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Scheduling Algorithms for 5G Networks and Beyond: Classification and Survey

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ABSTRACT Over the years, several research groups have been developing effective and efficient scheduling algorithms to enhance the quality of service of mobile communication networks. The arrival of the fifth generation of mobile networks (5G) has demonstrated the importance of advanced scheduling techniques to manage the limited frequency spectrum available while achieving 5G transmission requirements. This issue has been picked up extensively within the research community due to the increasing demand for mobile communications and the desire for a fully connected world. Consequently, the scientific community has developed novel approaches and varied scheduling schemes to meet the needs of various applications and scenario conditions. In this context, this paper presents an overview of the state-of-the-art methods, highlights seminal and innovative research, and investigates the current state of 5G radio resource management. This review of literature compares emerging strategy methods based on their metrics, analyzes their performances, and emphasizes the existing works with a vision for the future of modern 5G and upcoming networks in terms of radio resource allocation to provide a thorough introspection of the literature. Furthermore, gaining a better understanding of the radio resource management state-of-the-art would provide valuable information for future work and might be helpful for new researchers in the field.

INDEX TERMS 5G, beyond 5G, scheduling algorithms, resource allocation, radio resource management, spectral efficiency, scheduling schemes.

I. INTRODUCTION

A. BACKGROUND

Our daily life has become much easier thanks to high technology that provides innovative services, applications, and intelligent devices. As new applications and technologies emerge, the demand for communication services grows. According to [1], [2], 5G and beyond communication systems will address this massive rise in services and applications requiring more efficient networks with higher data rates, reduced latencies, greater spectrum efficiencies, increased energy efficiency, and expanded network capacity. The fifth generation of mobile systems 5G intends to deliver higher data rates than its antecedent 4G of Gbps order, enhancing the users' perceived performances called quality of experience (QoE) [3], [4].

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The international union of telecommunication (IUT) has divided 5G applications into three prominent use cases, namely enhanced Mobile BroadBand (eMBB), massive Machine Type Communications(MTC), and Ultra-Reliable and Low Latency Communications (URLLC) [5], [6].

Enhanced mobile broadband (eMBB) extends 4G services to address end-user demand for extra mobile broadband. It is required to serve high data rate applications, provide a seamless transition for highway users, expand coverage zones, and maintain QoS standards for ultra-dense situations [7], [8]. This use case provides a wide range of services and apps, such as augmented and virtual reality (AR/VR), video streaming, and cloud computing [9].

On the other hand, the URLLC use case guarantees communications for crucial applications that need a low packet loss and low latency, such as remote medical care, automated industry, manufacturing, V2X communications, self-driving cars, and robots [10], [11]. As further detailed in [12], the

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competing demands of high reliability and low latency make it challenging to meet URLLC QoS criteria.

In addition to the EMBB and URLLC use cases, 5G systems transform machine-to-machine (M2M) applications used in previous generations of mobile communications into machine-type communications. In this use case, embedded technologies connect devices and enable them to interact with their internal states and exchange data with external nodes. Machine-type communications aim to satisfy the needs of certain services and applications, which can range from a wearable smart gadget to a connected house or a smart city [13], [14]. New challenges are being introduced to provide the necessary connectivity and boost resource efficiency to accommodate millions of devices transmitting low-volume, non-delay-sensitive data across the 5G network [15].

The main characteristic of 5G networks is their use of the millimeter-wave spectrum to serve a diversity of use cases. It employs low-band frequencies below 1 GHz for use cases requiring flawless coverage and high mobility, such as ultra-Reliable Low Latency Communications (uRLLC) and massive Machine Type Communications (mMTC) [17]. However, these low-band frequencies cannot serve enhanced Mobile Broadband (eMBB) services that require high peak data rates of 20 Gbps and experienced user data rates in the range of 100 Mbps, which necessitates the usage of high-band at mmWave frequencies. Aline with mmWaves, massive multiple inputs, and multiple outputs (mMIMO) remains a critical technology for 5G [18]. mMIMO employs several focused beams to improve coverage, speed, and capacity across the macro-assisted small cells, where a macro cell uses the lower bands to provide broad network coverage, and the small cells operate on the mmWave band to improve user performance [19].

Besides the new features and leading technologies that the 5G and beyond systems enable, the effective management of radio resources remains crucial to overcoming these constraints [20], [21]. Using an accurate allocation of radio assets strategy ensures fulfilling QoS targets and increases the quality of experience for heterogeneous users [22].

The variety of use cases presented by 5G systems necessitates consideration of many performance criteria to fulfill the technological requirements of the aforementioned use cases as depicted in Fig. 1.

In order to achieve communication targets, various models, approaches, metrics, and algorithms have been developed in the literature. Numerous factors influence the scheduling decision, namely the targeted data rate, the user channel conditions, power consumption, spectral efficiency, delay threshold tolerated, and packet loss ratio. Thus, selecting the appropriate scheduling scheme that meets the users' applications and requirements among the existing algorithms and procedures would be challenging. This paper analyzes the current strategies, highlights their promising and overlooked areas, and compares various research articles' application forms and metrics. The following paragraph discusses the associated survey articles.

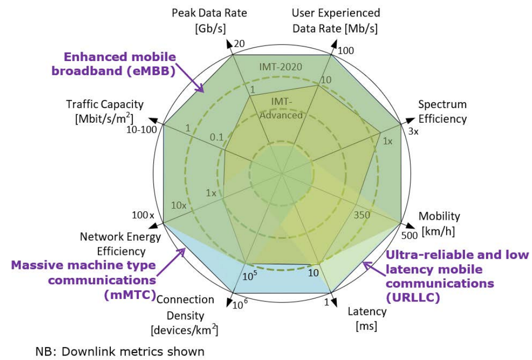

FIGURE 1. 5G performances [16].

B. RELATED REVIEWS

The resource allocation and scheduling methods issue has piqued the interest of academics and researchers. As a result, several scheduling algorithms and resource allocation methods have emerged. In this context, various surveys cover different aspects of resource allocation, as detailed in Table 1.

The survey published in [23] focuses on high-speed railway communication (HSR), its architecture, channel characterization, and ultimately on radio resource management methods (RRM) for HSR wireless communications from many perspectives: admission control, mobility management, power control, and resource allocation.

The authors of [24] provide a comprehensive overview of 5G's flexible multi-user scheduling features and summarize the 5G design standards of the 3GPP 5G studies. This survey gives an E2E standpoint, covering the increased QoS architecture and the diversified scheduling choices of the new radio. Nevertheless, this research focuses solely on the novel characteristics of 5G scheduling algorithms without discussing the state-of-the-art solutions. On the other hand, the resource allocation part was covered briefly, with HSR schedulers separated into three categories: interference-aware resource allocation, QoS-aware resource allocation, and cross-layer dynamic resource allocation. The authors of [25] provide a taxonomy of resource allocation in ultra-dense networks, including methodologies, methods, optimization criteria, and strategies.

Besides, the review in [26] also identifies and examines the main aspects of effective resource allocation and management in CRAN, including user assignment, remote radio heads selection, throughput maximization, spectrum management, network utility, and power allocation. However, these surveys lack a thorough examination of each scheduling system, its advantages, disadvantages, and suitability for 5G use cases.

The research in [27] provides a thorough literature analysis and taxonomy for content-aware and content-unaware downlink schedulers, focusing on the content-aware downlink scheduling methods for video streaming traffic over Long Term Evolution (LTE). Furthermore, the work in [28] provided a detailed overview of the downlink packet allocation techniques suggested for LTE networks.

TABLE 1. A review of the existing surveys.

Survey	Year	Resource allocation					Focus
		Procedure	Optimization criteria /method	Performance evaluation metric	KPI based taxonomy	5G use cases suitability	
[19]	2016			✓	✓	✓	Resource management for LTE networks with a 5G perspective
[24]	2018	✓					E2E standpoint on the novel characteristics of 5G scheduling algorithms
[26]	2020		✓				Resource allocation and management in CRAN for 5G and beyond
[25]	2021		✓		✓		Resource allocation in ultra-dense networks for LTE and 5G systems
Our survey	2022	✓	✓	✓	✓	✓	Radio resource allocation algorithms for 5G networks

The article detailed in [29] examines different radio resource management (RRM) approaches used in LTE-A networks for resource sharing, emphasizing the possibility of multi-objective optimization algorithms for attaining desirable QoS in LTE-A systems.

Notwithstanding, there is no discussion of the appropriateness of 5G applications in these studies [27]–[29], which are solely helpful for LTE networks and primarily cover scheduling techniques in the downlink stream. The authors of [30] investigate uplink scheduling techniques over LTE and LTE-A from the perspective of M2M. They focus on M2M communications characteristics like power efficiency, QoS support, multi-hop connectivity, and scalability for large devices. Nonetheless, it represents a limited number of scheduling techniques and is constrained to M2M communication systems in the uplink. Finally, [19] discusses how a limited number of scheduling schemes addressing spectrum-efficient (SE), interference-efficient (IE), and energy-efficient allocation issues may be suitable for meeting the QoS performance requirements of 5G RAN systems. Although the 5G suitability, the parameters used, and the adopted performance evaluation metrics could be more detailed.

Driven by the shortcomings mentioned above, our paper presents the 5G use cases and their requirements. We survey the development of the scheduling algorithm through the literature, analyze the existing strategies, determine their advantages and inconveniences, and compare their application forms and metrics across various research papers. This review paper takes the readers on a journey starting from the specifications of 5G technology to understand radio resource allocation techniques and their role by classifying existing scheduling algorithms, inspiring new researchers, and providing positive perspectives for upcoming works.

C. CONTRIBUTIONS

Our main contributions to this paper are summarized as follows:

- We define the scheduling procedure and their role.
- We determine the parameters that impact the radio resource allocation decision.
- We classify the existing schemes according to their parameters, their performance, and their suitability for 5G services.
- Finally, we identify the strengths and gaps in the literature algorithms.

D. ROAD MAP

Fig. 2 presents the outline of this survey. The remainder of this paper is organized as follows: Section 2 introduces the procedure of radio resource allocation, details the factors impacting the scheduling decision, and describes the performance evaluation metrics. Then we classify the scheduling strategies according to metric parameters, performance goals, traffic type, and implementations in Section 3. Section 4 provides an overview of the advantages and disadvantages of the scheduling techniques studied in this survey. We discuss the reviewed scheduling algorithms and emphasize new perspectives to fill the gaps in the existing solutions in Section 5. Finally, we summarize the paper in section 6.

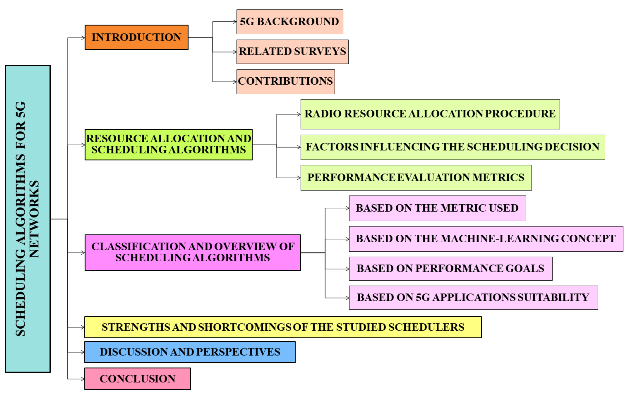

FIGURE 2. Paper map.

TABLE 2. List of acronyms.

Acronym	Definition
3GPP	3rd Generation Partnership Project
4G	4th Generation of mobile networks
5G	5th Generation of mobile networks
ACLA	Actor Critic Learning Automate
AMC	Adaptive Modulation and Coding
ANN	Artificial Neural Network
AR/VR	Augmented Reality/Virtual Reality
BSR	Buffer Status Reports
CIS	Channel Independent Scheduling
CPU	Central Processing Unit
CQI	Channel Quality Indicator
CSI	Channel State Information
DL	DownLink
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
E2E	End to end
eMBB	enhanced Mobile BroadBand
E-MQS	E model Maximum Queue Size
FDD	Frequency Division Duplex
GA	Genetic Algorithms
GBR	Guaranteed Bit Rate
gNB	Next Generation Node B
HOL	Head Of Line
IUT	International Union of Telecommunications
KPI	Key Performance Indicator
LP	Linear Programming
LTE	Long Term Evolution
LTE-A	Long Term Evolution - Advanced
MAC	Medium Access Control
MCS	Modulation and Coding Scheme
mMIMO	massive Multiple Input Multiple Output
MQS	Maximum Queue Size
NR	New Radio
OFDMA	Orthogonal Frequency Division Multiple Access
OS	Opinion Score
PGACL	Policy Gradient actor-critic Learning
PF	Proportional Fair
PSO	Particle Swarm Optimization
QAM	Quadrature Amplitude Modulation
QCI	QoS Class Indicator
QoE	Quality of Experience
QoS	Quality of Service
RB	Resource Block
RE	Resource Element
RGA	Resource Grid Allocation
RL	Reinforcement Learning
RR	Round Robin
RRC	Radio Resource Control
RRM	Radio resource management
RT	Real Time
SCS	Sub-Carrier Spacing
SINR	Signal to Interference Noise Ratio
TDD	Time Division Duplex
TTI	Transmission Time Interval
UE	User Equipment
UL	UpLink
URLLC	Ultra-Reliable Low Latency Communication

Table 2 provides all the acronyms used in this text, together with their meanings, to facilitate reading.

II. RESOURCE ALLOCATION AND SCHEDULING ALGORITHMS

A. RADIO RESOURCE ALLOCATION PROCEDURE

Radio resource management (RMM) procedures aim to manage, run, and share radio resources to deliver an optimized QoS [31]. A radio resource is characterized by frequency (bandwidth and carrier frequency) and time (duration of the transmission) [32]. It distributes the limited frequency spectrum resources efficiently among the connected devices in a radio network zone to meet the network's performance requirements. The scheduling procedure considers the KPI constraints defined for the scenario before allotting the radio resources [33]. The radio management process involves ranging the users according to their metric priority and generating a mapping table that links each resource block (RB) to a specific user and assigns sufficient resources according to QoS needs [34].

The papers in the literature discern channel-independent scheduling (CIS) and channel-dependent scheduling (dynamic scheduling). The CIS strategies, also known as the classical strategies, consist of sharing the radio resources among the users equally without considering their type of traffic or channel conditions [35]. Meanwhile, channel-dependent scheduling optimally allocates resources depending on the users' circumstances [36]. Scheduling decisions for these dynamic strategies consider the collected information received from the user equipment. Devices continuously send their current status to the gNB through the CSI Report (Channel State Information), the Buffer Status Reports (BSR), and the QoS attributes defined for each type of traffic [37], [38]. Fig. 3 details the scheduling process to make the appropriate resource allocation decision. The procedure starts by comparing the user's metrics per RB. At every TTI, the user (i) having the highest $w_{i,j}$ metric value sends its data through the jth RB. The metric computation varies from one scheduling scheme to another [39], [40].

B. THE FACTORS INFLUENCING THE SCHEDULING DECISION

As previously stated, the network often bases scheduling decisions on CSI reports provided by the devices. The scheduling algorithm collects various measures from the reports supplied by the user equipment to generate the metric to determine when the user can utilize the channel [41], [42]. This subsection details the scheduling inputs and shows how these parameters affect the outputs of the scheduling algorithms.

1) CHANNEL QUALITY INDICATOR

The Channel Quality Indicator is an integer coded in 4 bits, which means its value can vary from 0 to 15. 0 denotes a lousy channel condition, and 15 is the best case [37], [43]. The reported CQI values are essential for resource allocation decisions, as users having appropriate channel circumstances experience high performance. The AMC module selects the suitable modulation and coding scheme (MCS) that matches the CQI value to determine the number of bits per resource element (RE). Hence, the CQI affects the enabled throughput. Namely, a high CQI value provides high data rates [34], [44].

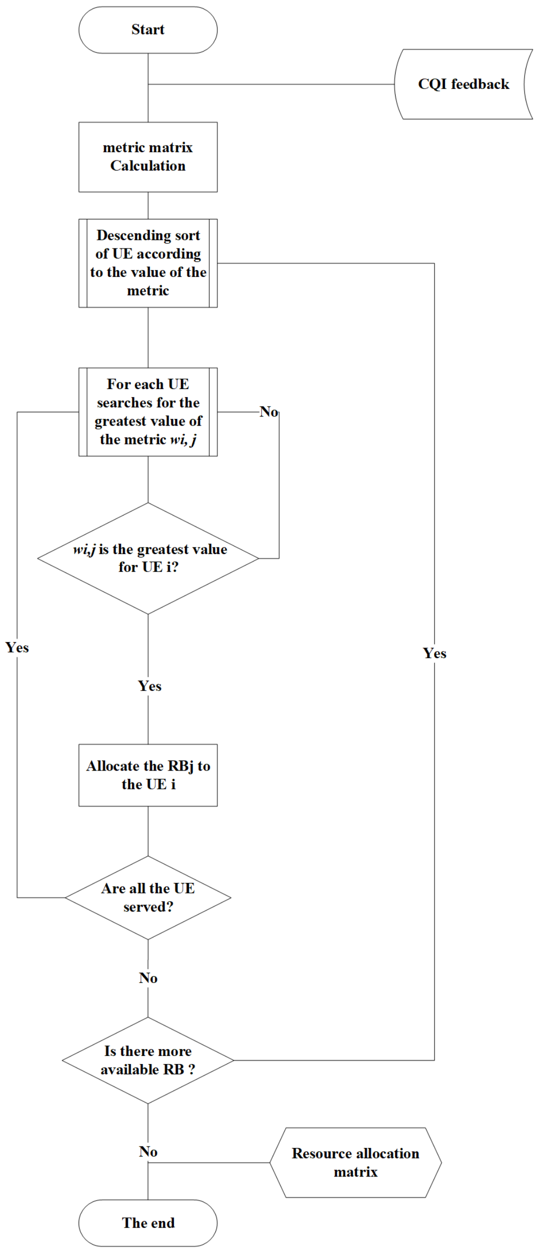

FIGURE 3. Radio resources scheduling process.

2) AVERAGE DATA RATE

The average data rate of user i in the previous TTI provides details about the history of resource allocation. It ameliorates the fairness of resource sharing by giving higher priority to the users with the lowest past achieved throughput. Based on the past achieved data rate $R_i(t-1)$, the instantaneous average achieved rate $R_i(t)$ is updated every TTI following (1) as detailed in [45]–[47]:

$$R_i(t) = (1 - 1/t_c)R_i(t-1) + (1/t_c)r_i(t) \tag{1}$$

Furthermore, the average data rate considers the current achievable transmission rate $r_i(t)$ based on the current CQI value of the user i. The constant t_c represents the memory of the averaging filter, whereas $1/t_c$ stands for the moving average data rate weight used to calculate the average data rate.

3) HEAD OF LINE PACKET DELAY (D_{HOL})

This parameter computes the time a packet spends in the buffer before being sent. The equation expressed in (2) calculates the D_{HOL} at the current time t, t_{enter} refers to the moment at which a packet enters the eNodeB buffer [48]. It maximizes the metric of the user having a long HOL queue to ensure packet delivery with a minimum latency [49].

$$D_{HOL} = t - t_{enter} \tag{2}$$

4) QUEUE STATUS AND BUFFER LEVELS

The queue status and the buffer level parameters provide information about the amount of data a scheduler needs to transfer on the downlink and uplink, respectively. These parameters ensure a flexible assignment of radio resources considering the flow existing in the buffer or the transmission queue of each user [50], [51]. Hence, the queue and the buffer status impact the resource allocation decision by assigning more resources to users having a large amount of data to transfer, which reduces latency and enhances reliability.

5) QUALITY OF SERVICE IDENTIFIER

QCI stands for QoS Class Identifier, also known as 5QI (5G QoS Indicator). It refers to the quality-of-service requirements of various use cases and applications. The QCI remains an essential input for QoS-aware schedulers since it describes the priority level, type of flow, tolerated packet budget delay, and packet error loss limits for each application [52], [53]. The QCI affects the resource allocation decision by prioritizing users having a short packet budget delay or a high priority level. In addition, it conditions the HARQ retransmissions to respond to the packet error loss limitations of certain services.

Furthermore, other configurable parameters may impact the scheduling decision, namely the RRC channel control of layer 3, the SINR, and the link adaptation parameters given by the physical layer.

C. PERFORMANCE EVALUATION METRICS

1) DELAY

Delay measures the time elapsed for a packet to be received by the end-user [54], [55]. This performance metric measures the perceived delay of successfully receiving the packets. The expression (3) details its computation [56]:

$$Delay = T_{rx} - T_{tx} \tag{3}$$

With T_{rx} the instant when the data arrive and T_{tx} is the transmission moment.

2) THROUGHPUT

High throughput presents the main performance target of mobile networks through all its generations [56], [57]. Equation (4) indicates that the throughput is the data transfer percentage over the sending time [58].

$$Throughput = \frac{\sum Rx\ Packet\ Size}{Delivery\ Time} \tag{4}$$

3) GOODPUT

Goodput presents a crucial performance indicator that classifies the schedulers regarding their effective data rate [59], [60]. It divides the payload bits delivered successfully to the user by the transfer time [61]. The difference between the throughput and the goodput is in the bits successfully delivered, where goodput does not consider the control bits of the header or the retransmitted packets [62]. We note that both goodput and throughput do not count lost packets [63]. According to [64], the goodput is expressed by (5):

$$Goodput = \frac{Original\_data}{Time} \tag{5}$$

4) FAIRNESS

The fairness metric evaluates the ability of the network to assign the available radio resources equally among the users [65]. Fairness computations differ from one article to another. The authors in [66], [67] detail the commonly used fairness metrics in the literature. The most frequently used index is Jain's index [68], which calculates the fairness as expressed in (6).

$$Fairness_{index} = \frac{(\sum x_i)^2}{n \times \sum x_i^2} \tag{6}$$

where x_i is the data of the i_{th} user, and n is the total number of devices.

5) SPECTRAL EFFICIENCY

Due to the limited radio resources, efficient spectrum usage is necessary to enhance the QoS. The spectral efficiency metric calculates the ratio of the average data rate to the bandwidth (bits per second per Hertz) via the expression in (7) to evaluate the efficacy of the network in managing the radio resources [63], [69].

$$spectral_{efficiency} = \frac{R}{B} \tag{7}$$

With R, the average bit rate, and B, the bandwidth needed for transmission.

6) PACKET LOSS RATIO

In the fifth generation of mobile networks, ultra-reliable and critical communication services require a low packet loss ratio. This metric computes the proportion of the packets successfully received within the transmission time as expressed in (8) [70], [71].

$$PLR = \frac{P_{sent} - P_{recieved}}{P_{sent}} \tag{8}$$

Table 3 presents an annotation table to facilitate the comprehension of our paper and enhance its readability.

TABLE 3. Annotation table.

Symbol	Definition
$R_i(t-1)$	the past average achieved rate
$r_i(t)$	the current achievable transmission rate
t_c	the memory of the averaging filter
t_{enter}	the moment at which a packet enters to the buffer
T_{rx}	the instant when the data arrive
T_{tx}	the transmission instant
Rx	received packets
x_i	the data transmitted by the user i
R	the average bit rate
B	refers to the bandwidth
P_{sent}	packets sent
$P_{recieved}$	packets received

III. CLASSIFICATION AND OVERVIEW OF SCHEDULING ALGORITHMS

Throughout the successive eras of mobile systems, the researchers developed several scheduling schemes and metrics to fulfill the various requirements proposed by the different scenarios and use cases. Motivated by the diversity of the scheduling solutions in the literature, this review aims to describe, summarize, evaluate, compare, and assess existing works in order to help readers, scientists, and future researchers in the field.

This section carries out a comparative analysis presented through four subsections. Firstly, we classify the metric-based schedulers according to the parameters used to make the scheduling decision, followed by an overview of the machine learning-based solutions. The third subsection analyzes the performance goals achieved by every studied scheduler. Finally, we investigate the suitability of the studied scheduler to meet the 5G criteria.

A. SCHEDULING ALGORITHMS CLASSIFICATION BASED ON THE METRIC USED

This section reviews the popular schemes considered as the ancestors of the scheduling field, namely Round Robin, Best-CQI, Proportional Fair, MLWDF, and EXP-PF, as well as other schemes newly developed according to their metrics as figures in Table 4. The Round Robin algorithm shares the resources equally to serve all UEs in the current cell [45], [72]. Many systems utilize it because it is the simplest scheduling method to implement [39]. Unlike the Round Robin method, the Best CQI scheme evaluates UE Channel Quality Indicator (CQI) and prioritizes users with the best channel quality as detailed in section II-B2 [73].

To properly allocate resources across high data rate systems known as CDMA-HDR, the proportional-fair metric (PF) divides the achieved data rate of each user by the past average data rate at each TTI, as earlier stated in the section. According to the PF metric, the user with the lowest data rate in the previous TTI will have the greatest priority in the current TTI. As a result, the PF ensures fairness between the users [74], [75].

TABLE 4. Classification according to the metric.

Scheduling algorithm	Metric	CQI	Average data rate	PLR probability	D_{HOL}	Delay threshold	Queue size	Other parameters
[72]	$w_{RR} = E\left(\frac{\sum RB}{\sum UE}\right)$							Shares the available RB among all users
[73]	$w_{BCQI} = max(CQI)$	✓						
[83]	$w_{i,j} = \frac{r_{i,j}}{R_i}$	✓	✓					
[76]	$w_{i,j} = \alpha_i D_{HOL,i} \frac{r_{i,j}}{R_i}$ With $\alpha_i = -\frac{log(\delta_i)}{\tau_i}$	✓	✓	✓	✓	✓		
[84]	$w_{i,j} = exp(\frac{\alpha_i D_{HOL,i} - X}{1+\sqrt{X}}) \frac{r_{i,j}}{R_i}$ with $X = \frac{1}{N_{rt}} \sum_{i=1}^{N_{rt}} \alpha_i D_{HOL,i}$	✓	✓		✓			The number of users in real-time services $N_r t$
[79]	$w_{i,j} = \alpha_i exp\left(\frac{\tau_i}{(\tau_i - D_{HOL,i})}\right) \frac{r_{i,j}}{R_i}$ With $\alpha_i = -\frac{log(\delta_i)}{\tau_i}$	✓	✓	✓	✓	✓		
[51]	$w_{i,j} = \alpha_i Q_i \frac{r_{i,j}}{R_i}$ with $\alpha_i = -\frac{log(\delta_i)}{\tau_i}$	✓	✓	✓		✓		
[81]	$w_{i,j} = \alpha_i D_{HOL,i} Q_i \frac{r_{i,j}}{R_i}$ with $\alpha_i = -\frac{log(\delta_i)}{\tau_i}$	✓	✓	✓	✓	✓	✓	
[82]	$w_{i,j} = \delta_i (Q_{i,max} - Q_i) \frac{D_{HOL,i}}{\tau_i - D_{HOL,i}} \frac{r_{i,j}}{R_i}$	✓	✓	✓	✓		✓	The maximum queue size $Q_{i,max}$
[85]	$w_{i,j} = \frac{MOS_i (Q_{i,max} - Q_i)}{\tau_i} \frac{r_{i,j}}{R_i}$	✓	✓		✓		✓	maximum queue size ; QCI; E-Model parameter MOS_i
[75]	$w_{i,j} = \frac{r_{i,j}{}^{\beta}}{R_i{}^{\gamma}}$	✓	✓					γ and β impact changing factors
[86]	$\frac{r_{i,j}}{R_i} * \left(\frac{1}{\Omega_i(t)}\right)^{\rho}$ with $\rho \geq 0$ and $\Omega_i(t) = \begin{cases} 1 - \left(\frac{n_i}{M}\right), & M > 0\ n_i \neq M \\ b, & M > 0 n_i = M \\ 1, & M = 0 \end{cases}$	✓	✓					$\Omega_i(t)$ neighborhood metric ; n_i the neighboring nodes for the UEi; M presents the uncoordinated nodes; ρ optimization constant to emphasize $\Omega_i(t)$; b constant
[87]	$w_{i,j} = \alpha_{RRE} * log(\frac{r_{i,j}}{R_i}) + \alpha_F * log(\frac{CQI_k}{CQI_{max}})$	✓	✓					α_{RRE} and α_F are weighting factors for radio resource and flow efficiencies respectively
[50]	$w_{i,j} = \frac{r_{i,j}}{R_i} \times b_i$	✓	✓					b_i refers to the buffer status of the UE i
[88]	$UE_{Ci,j} = PF_C + \sum_{i=1}^{N_{UE}} FU_{Ci}$	✓	✓					$UE_{Ci,j}$ the chance that UEi uses RBj ; PF_C the PF selection ; FU_{Ci} the cell-edge user chances
[89]	$w_{i,j} = SINR_{i,j} p$ with $p = \frac{Q_i}{\sum Q_i}$	✓					✓	Signal Interference Noise Ratio (SINR)
[90]	$m_{uc} = y_u + (BW_{uc})/(BW_u)$	✓	✓		✓			m_{uc} associates UE to the appropriate cell; y_u the one way latency ; BW_{uc} bandwidth estimated for the UE u at the cell c; $BW_u$the sum bandwidth of all the serving cells for the user u

The M-LWDF presented in [76] prioritizes streaming services and affords a maximum delivery time for packages with a limited shelf life τ_i. The M-LWDF scheduler associates the packet loss probability δ_i and the delay of transmitted data to the achieved data rate ratio $\frac{r_{i,j}}{R_i}$ used by the PF [77], [78]. Furthermore, different scheduling methods based on the MLWDF have been developed, such as the EXP-MLWDF, which combines the MLWDF metric with an exponential term to promote users with poor channel conditions, as illustrated in Table 4 [79]. On the other hand, the Virtual Token MLWDF associates a virtual queue parameter to the MLWDF metric in order to achieve real-time requirements and guarantee a minimum bit rate for non-real-time traffic [80]. The Queue-HOL-MLWDF scheduler associates packet delay and the queue size parameters with the MLWDF metric to avoid packet expiration and prevent buffer overflows [81]. The Channel-and QoS-Aware Scheduling metric associates the MQS(Maximum Queue Size) to the metrics of M-LWDF, VT-MLWDF, and Queue-HOL-MLWDF schemes [51], [82].

The E-model Maximum Queue Size (E-MQS) scheduler introduced in [85] is another queue-based scheduler. To assess the quality perceived by the user, it utilizes the E-Model Mean Opinion Score (MOS) obtained from the receiver.

As a result, it improves the quality of the experience for users.

Besides, many other schedulers base their metrics on the proportional fair (PF) metric, namely the EXP/PF, the GPF, and the N-PF. The Exponential/PF (EXP/PF) takes advantage of the exponential function properties and the performance provided by the PF scheduler to improve the user experience. It combines the EXP rule to fulfill latency constraints for streaming services with the PF rule to serve best-effort services to enhance the throughput and maximize fairness among users [48], [82], [84], [91].

The Generalized Proportional Fair (GPF) adds two impact factors: β and γ, to the numerator and denominator of the PF metric, respectively. When the value of β increases, it raises the impact of the instantaneous data rate. As a consequence, it prioritizes users with the best channel conditions. However, γ increases the average past data rate to guarantee equity among users [75].

Furthermore, Charles Katila developed in [86]Neighbors-Aware Proportional Fair (N-PF) method for heterogeneous systems, including eMBB users and massive internet of things devices. In order to maximize the packet transmission success rate, the N-PF combines the PF metric with the number of IoT devices (uncoordinated nodes) adjacent to each scheduled node (UE).

Similarly, the technique provided in [50] associates the buffer size parameter with the PF metric to allow a flexible resource assignment based on the quantity of the pending data. Besides, the scheduling algorithm proposed in [88] divides the user set into cell-centric and cell-edge users. It uses the proportional-fair metric as a first step, then involves the cell-edge users, selected by the PF, in a second round of ranking to choose the appropriate users for each RB. Then, the scheduler assesses the odds of assigning resources based on the PF measure or adjusting its metric to be prioritized based on the equation shown in table 4.

The authors in [89] developed a scheduler for eMBB and URLLC, prioritizing URLLC flows. It bases RB allocation on the signal-to-noise ratio multiplied by the normalized queue state parameter denoted p to avoid accumulating data in the buffer.

In addition, the centralized scheduler suggested in [90] seeks to identify UEs and cell assignments first. After that, the scheduler prioritizes scheduling HARQ procedures to avoid further queuing delays and reduce the need for additional retransmissions, followed by scheduling UEs with waiting data. The UE/cell allocation is carried out successively by identifying the UE/cell combination with the highest scheduling metric (m_{uc}). The selected users are scheduled through the PF metric for each cell.

Besides, the work in [92] suggests a massive MIMO scheduling technique based on mean channel gain. It calculates the difference between each user's channel gain and the mean channel gain and prioritizes the user whose channel gain is closest to the mean channel gain. On the other hand, the authors in [93] suggest a scheduling approach that extends the earliest deadline first (EDF) task scheduling, used primarily in operating systems, into slice scheduling by modeling delayed traffic as a task instance, substituting CPU time with radio resources, and responding to changes in radio resource needs. Considering the Lean production methodology initially proposed for the automotive industry, the authors in [87] proposed a 5G NR eMBB downlink lean scheduler that associates the resources with the production goal through a Lean matrix. In this scheduler, they used the log of the PF metric to express the radio resource usage and the log rule of the CQI of each user divided by the max CQI among all users to determine the flow efficiency.

B. SCHEDULING ALGORITHMS CLASSIFICATION BASED ON THE MACHINE-LEARNING CONCEPT

Machine learning approaches make the right decision by directly collecting the relevant information from data samples. As a result, the researchers employ several machine learning methodologies, such as deep learning, reinforcement learning, and supervised learning, to improve resource allocations and address the QoS needs of upcoming 5G and B5G wireless networks [94]. This section examines the recently established machine learning-based schedulers in terms of methodology, algorithm, and objective functions. Table 5 summarizes the algorithms studied in this section.

The reinforcement learning scheduler suggested in [95] uses the Q-learning approach to reduce end-to-end latency by allocating compute resources while imposing the maximum tolerated latency requirement constraint. Whereas the scheduling method [96] employs two types of neural networks to estimate the best policy for allocating radio resources: FNN (Fully connected Neural Networks) for resource allocation and Cascade NN to increase approximation accuracy and ensure QoS criteria.

The approach given in [97] employs many reinforcement learning (RL) concepts such as QV, QV2, QVMax, and ACLA algorithms to accomplish low-complexity real-time scheduling. The scheduler cited in [98] aims to achieve dynamic scheduling and fulfill QoS criteria. It selects and learns the strategy to be employed at each TTI depending on current conditions, including traffic volume, QCI, and application requirements.

Moreover, the reinforcement learning-based radio resource scheduling technique presented in [99] ensures a low-latency constraint for limited radio resources by utilizing the Q-learning algorithm and deep neural network to reach the latency objective in a reduced time.

TABLE 5. Recent machine learning-based scheduling algorithms.

Scheduler	Method	Learning algorithm	Objective function
[95]	Reinforcement Learning	Q-learning	latency
[96]	Supervised Deep Learning	Cascade neural network (CNN) + Fully connected Neural Networks (FNN)	Energy efficient power allocation + QoS requirements for delay-tolerant, delay-sensitive, and URLLC services
[97]	Reinforcement Learning	QV algorithms / ACLA algorithm	Latency + packet loss
[99]	Reinforcement learning	DNN Q-learning	Latency
[100]	Reinforcement learning	Q-learning	Data rate for vehicular network + packet loss
[101]	Deep reinforcement learning	PGACL algorithm	Data rate + reliability + latency
[102]	Supervised Deep Learning	Feed Forward Back Propagation (FFBP) neural network	QoE
[103]	Deep reinforcement learning	dueling deep Q network (Dueling DQN)	Energy efficiency (EE) and spectral efficiency (SE)
[104]	Multi-agent reinforcement learning	Q-learning	Improve reliability + minimize latency of URLLC users
[105]	Deep reinforcement learning	Q-learning	Improve throughput + minimize packet loss ratio + Dynamic TDD allocation

The RL-based solution in [100] utilizes a Q-learning algorithm to optimize radio resource usage, provide high throughput, and ensure an efficient and dynamic UL/DL TDD configuration. Alsenwi *et al.* suggested a scheduling approach that assures eMBB and URLLC slicing by using an optimization problem for eMBB users combined with a PGACL deep RL algorithm for URLLC [101]. The authors of [102] employed the Feed Forward Back Propagation (FFBP) neural network algorithm to assess the QoE score by mapping the QoS and Opinion Score (OS). After that, it determines the optimal values for the service priority factor through a Particle Genetic Algorithm (PGA), which is a combination of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to appropriately allocate radio resources and maintain the QoE threshold of each service. The article suggested in [103] adopts a deep reinforcement learning approach called the Dueling Deep Q Network (Dueling DQN) that considers energy efficiency (EE) and spectral efficiency (SE) of the system while allocating radio resources. The reinforcement learning scheduler proposed in [104] employs a multi-agent Q-learning algorithm to achieve a joint power and resource allocation scheme. The authors of [105] suggest a deep reinforcement learning-based method that extracts the network's properties to construct an intelligent and dynamic TDD Up/Downlink resource allocation technique for high-mobility heterogeneous networks.

C. SCHEDULING ALGORITHMS CLASSIFICATION BASED ON PERFORMANCE GOALS

Generally, scheduling schemes aim to satisfy specific performance requirements. Proof of this, the round-robin algorithm was introduced to guarantee an unconditional fair sharing of resources between the users of the same cell [106], [107]. At the same time, the best CQI attributes the radio resource only to users having the best channel conditions. Thus, it maximizes the spectral efficiency and increases cell throughput to the detriment of fairness [108]. In this context, the Proportional Fair algorithm evaluates the history of resource allocation of each data flow and then allocates RBs to UEs that were neglected in previous iterations to address the fairness issue, avoid resource starvation, and improve the data rate [74], [109].

The MLWDF associates the HOL packet delay (DHOL) and the channel quality indicator to maximize the metric of users transmitting time-sensitive traffic. It aims to reduce latency and avoid packet loss [61], [110]. Based on the MLWDF metric and the exponential function, the EXP-MLWDF [80] scheduling scheme considers the QoS information to increase the overall throughput while decreasing the packet loss ratio and the delay value. The EXP-PF [111], [112] combines two scheduling techniques: the exponential rule, which reduces latency, and the PF metric, which maximizes throughput and maintains fairness among the UEs.

The virtual token MLWDF (VT-MLWDF) metric combines the queue length and packet delay used in the MLWDF measure to maintain low latency while increasing total data throughput and decreasing packet loss [113], [114]. The Queue-HOL-MLWDF combines packet delay, queue size, and average data rate to reduce packet loss ratio, enhance throughput, and maintain fairness for RT and NRT systems [81]. The channel-QoS-aware scheduler intends to incorporate the MQS factor into the metric using a mix of the M-LWDF, VT-MLWDF, and Queue-HOL-MLWDF metrics. This scheduler meets the QoS standards for real-time applications by lowering the PLR while increasing cell throughput, fairness, and spectral efficiency [115].

The E-MQS scheduler considers the MQS ($Q_{i,max}$ - Q_i) and the MOS parameter, which reflects user perception, to schedule services sensitive to packet loss and delay [85].

The GPF scheduler guarantees a compromise between the high throughput provided by the BCQI and the PF's fairness performance [75].

The authors in [86]developed a new scheduling scheme based on the PF classic N-PF metric. It distinguishes a typical user and IoT device to ensure continuous transmission among IoT devices and increase the data rate for mobile phones.

Alternatively, the scheduler provided in [50] based its scheduling decision on the buffer size in conjunction with the PF measure to prioritize flows with larger buffer sizes. As a result, it increases the achievable throughput while ensuring fairness among all cell users.

In the same token, the scheduler presented in [88] enhances cell-edge throughput while preserving the needed data rate for cell-centric users to ensure satisfactory performance and maintain equity among users. The heuristic algorithm developed in [89] manages the radio interface and shares it between URLLC and eMBB users by enhancing the overall throughput for eMBB services and reducing latency for URLLC applications. Furthermore, the low-complexity scheduler suggested for 5G URLLC achieves a 99 percent increase in dynamic point selection and reduces URLLC latency by 90 percent when compared to distributed scheduling [90]. In table 6, we summarize the scheduling algorithms aforementioned, sorted by their performance goals. The lean scheduler presented in [87] uses the Lean efficiency matrix to ensure the trade-off between the spectral efficiency and the throughput enhancement.

Furthermore, the scheduler proposed in [95] assigns necessary resources in time to provide ongoing compliance with the low latency needs of applications under dynamic workloads. The spectrum scheduling approach introduced in [99] combines the Q-learning reinforcement learning technique with deep neural networks to satisfy a low latency performance goal. In addition, [96] proposes a machine learning-based scheduling approach that reduces total power usage for 5G traffic. Furthermore, it meets the various QoS requirements in non-stationary wireless networks for delay-tolerant, delay-sensitive, and URLLC services. Besides, the scheduling scheme suggested by [97] combines multiple parameters to reduce latency, avoid packet loss, and enhance the overall QoS.

The approach proposed in [100] aims to achieve high data speeds with minimal packet loss. In addition, the authors of [101] developed an optimization-aided DRL-based framework that aims at maximizing the eMBB data rate while improving reliability for URLLC. Besides, the approach submitted in [104] balances the latency and the reliability of URLLC users by allocating compute resources while imposing the maximum tolerated latency requirement constraint, which enhances the reliability, transmission, and queuing delays of URLLC users. The paper proposed in [103] intends to optimize the balance between energy efficiency and spectral efficiency in the Ultra-Dense Network. The proposed channel gain-based scheduling method enhances error performance, increases overall throughput, and ensures user fairness [92]. Whereas the solution proposed in [93] reduces latency, provides an accurate resource share, and improves resource utilization. The last work to be studied in this section is the scheduler given in [105] adjusting TDD configuration dynamically to enhance uplink and downlink radio resource allocation by improving network throughput and reducing packet loss rate.

TABLE 6. Classification based on performance goals.

Work	Throughput	Latency	Goodput	Fairness	Spectral efficiency	Packet loss ratio	Power efficacy
[72]				✓			
[73]	✓				✓		
[83]	✓		✓	✓	✓		
[76]	✓	✓				✓	
[84]	✓	✓		✓	✓		
[79]	✓	✓				✓	
[51]	✓	✓				✓	
[81]	✓	✓	✓			✓	
[82]	✓			✓	✓	✓	
[85]	✓	✓	✓			✓	
[75]	✓			✓			
[86]	✓			✓	✓		
[87]	✓		✓		✓		
[50]	✓		✓	✓	✓		
[88]	✓		✓	✓			
[89]	✓	✓	✓		✓	✓	
[90]		✓	✓	✓	✓	✓	
[92]	✓			✓		✓	
[93]		✓		✓	✓		
[95]		✓			✓		
[96]		✓			✓		✓
[97]		✓				✓	
[99]		✓					
[100]	✓		✓			✓	
[101]	✓		✓		✓	✓	
[103]					✓		✓
[104]		✓				✓	✓
[105]	✓					✓	

D. SCHEDULING ALGORITHMS CLASSIFICATION BASED ON 5G APPLICATIONS SUITABILITY

An efficient scheduling algorithm must support the service target and fulfill the QoS needs based on the application criteria. For instance, when a scheduling algorithm serves non-real-time flows, such as surfing the internet or texting, the reliability of transmitted data is critical. Whereas for real-time flows, the latency is not tolerable as it influences the QoS of the communication. Similarly, a slight delay may be fatal in the medical field or vehicular communications. The scheduling schemes' efficiency is highly dependent on the use case, the scenario adopted, and the application concerned. There are two types of scheduling algorithms: real-time and non-real-time schedulers, based on the specifications of transmitted data. As detailed in Table 7, the Round Robin and Best CQI were initially developed to schedule non-real-time services [84], [116]. Furthermore, the PF metric does not consider packet delay or queue length, making it unsuitable for real-time applications and delay-sensitive services. The GPF serves the users transmitting a best-effort flow and requiring a high data rate. Therefore, the RR, BCQI, PF, and GPF are suitable for some eMBB scenarios, namely virtual shopping, virtual staff assistance, and heavy downloads.

Edge User-Friendly Scheduler [88] seeks to improve the performance of devices near cell borders or in poor channel conditions without taking into account QoS requirements or any other constraints. As a result, it is appropriate for non-real-time and elemental traffic.

The modified largest weighted delay first (MLWDF) and its modified variants, EXP-MLWDF and VT-MLWDF, provide high reliability and decrease latency [35], [113]. In addition, the Queue-HOL-MLWDF attempts to improve performance metrics for video services while preserving the minimal QoS required for non-real-time services in the network at the same time [82]. E-MQS scheme offers low latency and a low packet loss ratio to real-time, delay-sensitive, and ultra-reliable services [85]. As a result, they can handle critical RT traffic and low-latency communications while still maintaining minimum requirements for non-time-sensitive applications [117].

Moreover, the EXP-PF combines two scheduling techniques. The PF rule maximizes system throughput while maintaining fairness for non-real-time services. Meanwhile, the EXP rule is applied to real-time, demanding services. The channel-QoS-aware presented in [82] meets the PLR, cell throughput, fairness, and spectral efficiency KPIs for real-time flows. These hybrid schedulers are suitable for both eMBB and URLLC use cases.

Since the Neighbors are aware PF shares radio resources between the users' mobile phones (UE) and their connected devices, it seems the most appropriate scheduler for the massive machine-type communications [86]. The low-complexity heuristic scheduling approach described in [89] seeks to multiplex URLLC efficiently while transmitting eMBB traffic over the same radio node. Likewise, the scheduling strategy suggested in [104] improves URLLC reliability, which results in fewer re-transmissions and reduced transmission delays to address the problem of multiplexing URLLC and eMBB traffic. Besides, the heuristic scheduler described in [90] intends to serve the URLLC traffic and meet the QoS criteria specified for this use case. Meanwhile, the PF-buffer scheduler explained in [50] was created to ensure eMBB communication downstream. Similarly, the lean scheduler [87] was designed to handle eMBB traffic because it maintains a balance between radio resource use and the throughput required for this use case.

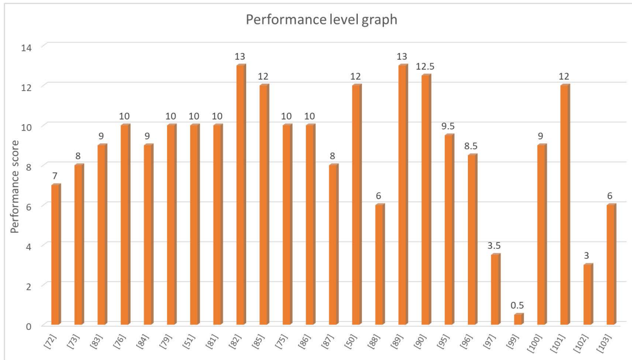

FIGURE 4. Performance level graph.

The Q-learning-based scheduler is appropriate for URLLC since it provides low latency for varied traffic loads [95]. In addition to URLLC, the deep learning-based scheduling scheme described in [96] is suitable for mMTC given that it reduces power consumption and ensures low-latency URLLC communication. The reinforcement learning-based schedulers described in [97], [99] will enhance the QoS for URLLC and critical communications since they aim to minimize latency and reduce packet drop ratio.

Although the scheduler described in [100] schedules vehicular networks, it could also serve some eMBB applications because it attempts to increase user throughput. The method presented in [101] meets the demanding URLLC reliability requirements, improves the Jain fairness index, and boosts data rates for eMBB traffic. The work provided in [102] enhances QoE for video, VoIP, and best-effort applications while optimizing radio resource allocation, making it appropriate for eMBB applications. In [103], the authors optimized the spectral and energy efficiency to serve the dense infrastructure of the Internet of Things (IoT) applications and massive machine-type communications (mMTC). Similarly, the performance requirements of the scheduler introduced in [93] present the number of resources needed for each use case: eMBB, uRLLC, and mMTC. The scheduler introduced in [105] improves the user's throughput and minimizes the packet loss ratio to present a reliable transmission to its users. Besides, it ensures dynamic TDD switching, making it suitable for eMBB and URLLC applications. To facilitate readers' comprehension, we scored the performances in ascending order of the performance level for each scheduler. Then we calculated the score corresponding to each scheduling scheme. Where 0.5 corresponds to "very low," 1 means "low," 2 stands for "medium," and 3 refers to "high."

The resulting graph is depicted in Fig. 4.

IV. STRENGTHS AND SHORTCOMINGS OF THE STUDIED SCHEDULERS

The previous sections discussed the metric parameters, performance goals, and methods used in the current algorithms and their suitability for the 5G use cases. This section pro-

TABLE 7. Classification based on applications suitability.

Scheduling algorithm	Flow type	Achievable 5G performance requirements							Use case suitability
		Fairness	Peak data rate	Experienced data rate	Latency	Spectrum efficiency	Reliability	other parameter	
[72]	NRT	High	Medium	Medium	N/A	N/A	N/A	N/A	eMBB (NRT scenarios)
[73]	NRT	Low	High	Low	N/A	High	N/A	N/A	eMBB (NRT scenarios)
[83]	NRT	High	Medium	Medium	N/A	Medium	N/A	N/A	eMBB (NRT scenarios)
[76]	RT/ NRT	N/A	Medium	Medium	Low	Medium	High (reduced PLR)	N/A	URLLC
[84]	RT/ NRT	Medium	Medium	Medium	Low	Medium	N/A	N/A	eMBB/ URLLC
[79]	RT/ NRT	N/A	Medium	Medium	Low	Medium	High (reduced PLR)	N/A	URLLC
[51]	RT/ NRT	N/A	Medium	Medium	Low	Medium	High (reduced PLR)	N/A	URLLC
[81]	RT/ NRT	N/A	Medium	Medium	Low	Medium	High (reduced PLR)	N/A	URLLC
[82]	RT	Medium	Medium	Medium	Medium	Medium	High (reduced PLR)	N/A	eMBB/ URLLC
[85]	RT	N/A	High	High	Low	Medium	High (reduced PLR)	N/A	URLLC
[75]	NRT	High	Medium	Medium	N/A	High	N/A	N/A	eMBB (NRT scenarios)
[86]	NRT	High	Medium	Medium	N/A	High	N/A	High connection density	eMBB / IoT(mMTC)
[87]	RT/NRT	Low	Medium	Medium	N/A	High	N/A	N/A	eMBB
[50]	NRT/RT	High	High	High	N/A	High	N/A	N/A	eMBB
[88]	NRT	High	Medium	Low	N/A	N/A	N/A	N/A	eMBB (NRT basic scenarios)
[89]	RT/NRT	N/A	High	High	Low	High	High (reduced PLR)	N/A	eMBB/ URLLC
[90]	RT	Medium	Medium	Medium	very Low	High	High (reduced PLR)	N/A	URLLC
[95]	RT	Medium	Medium	Medium	very Low	High	N/A	N/A	URLLC
[96]	RT	Medium	Medium	Medium	very Low	Medium	N/A	Low power consumption	URLLC / IoT(mMTC)
[97]	RT	N/A	N/A	N/A	very Low	N/A	High (reduced PLR)	N/A	URLLC
[99]	RT	N/A	N/A	N/A	very Low	N/A	N/A	N/A	URLLC
[100]	RT	N/A	High	High	N/A	N/A	High (reduced PLR)	N/A	URLLC (V2V) eMBB
[101]	RT	High	High	High	N/A	N/A	High (reduced PLR)	N/A	URLLC / eMBB
[102]	RT	N/A	N/A	N/A	N/A	N/A	N/A	High QoE Video and VoIP	eMBB
[103]	RT/NRT	N/A	N/A	N/A	N/A	High	N/A	High connection density + High power efficiency	mMTC

vides an overview of the advantages and disadvantages of scheduling techniques reviewed in this survey.

The first studied algorithm is the Round Robin [72], renowned for ensuring absolute fairness between all users regarding the number of resource blocks assigned to each user. However, it disregards the channel conditions or the service requirements. Meanwhile, the best CQI scheduler provides the highest data rate for users with good link conditions and a high SNIR, but it condemns cell edge users or those with poor coverage [73].

The proportional fair combines high throughput for users with the highest CQI value while ensuring fair resource sharing. Despite the throughput-fairness compromise, the PF consumes more spectral resources than other techniques and forces users with good channel conditions to stick to a limited level of throughput, even less than their needs [83].

The MLWDF prioritizes users with real-time traffic and limited DHOL timing while ignoring the QoS of each service in real-time traffic, besides the NRT users, who might suffer from starvation [76]. The EXP/PF prioritizes real-time traffic; however, the exponential rule increases the algorithm's complexity and makes it hard to implement [84]. The EXP-MLWDF also suffers from high complexity due to exponential use. Meanwhile, it promotes users with terrible channel conditions [79].

The Virtual Token MLWDF [51], the Queue-HOL-MLWDF [81], and Channel-QoS-Aware [82] assign resources to long-sized traffic while considering the timing threshold to serve delay-sensitive applications and avoid buffer overloads. However, they ignore the QoS requirements of each service and limit the RBs allocated to NRT users. Besides, the Queue-HOL-MLWDF [81] and Channel-QoS-Aware [82] use unbalanced parameters since they associate the DHOL in ms with the queue size in KBs.

Furthermore, Channel-QoS-Aware affords minimum fairness among real-time applications by considering the maximum queue size.

The E-model Maximum Queue Size (E-MQS) scheduler [85] is a QoS-aware scheduler that improves the quality of the experience for real-time users. It affords minimum fairness among real-time applications by considering the maximum queue size. Meanwhile, it uses many parameters, which may increase the computation time and make it hard to implement.

The GPF [75] scheduler balances the performance of the BCQI and the PF in terms of throughput and fairness. It prioritizes users with the best channel conditions and guarantees minimum user equity. Yet, the users with bad channel conditions suffer from starvation, and it does not consider QoS. Furthermore, the factors changing from BCQI to PF should be adjusted manually, which means it does not offer dynamic scheduling. The N-PF scheduler presented in [86] overlooks the QoS of each flow and uses numerous parameters to schedule eMBB traffic along with mMTC applications. Hence, the expanded computation time makes it hard to implement.

The lean scheduler [87] provides the lowest complexity of all schedulers since it associates the log rule with the PF metric and the CQI of each user divided by the max CQI among all users. It enhances spectral efficiency and ensures equity among users. Nevertheless, it is a QoS-aware scheduler and works only for the downstream.

The proportional fair buffer [50] avoids buffer overload, affords equity, and enhances the overall throughput; however, it is a QoS-aware scheduling scheme. Edge User-Friendly Scheduler (EUFS) [88] protects cell-edge users from starvation. Regardless, this scheduler suffers from many limitations; it is QoS-unaware, hard to implement, and wastes many radio resources.

The scheduler in [89] schedules eMBB and URLLC traffic and prioritizes URLLC flows. It is a channel conditions-aware scheduler that avoids accumulating data in the buffer. Meanwhile, it does not consider the QoS of each service in the studied use cases.

The centralized scheduler suggested in [90] avoids queuing delays and reduces the need for additional retransmissions. Yet, it is unsuitable for the TDD duplex, and it overlooks the QoS requirements. Likewise, the reinforcement learning scheduler suggested in [95] reduces the overall end-to-end latency and imitates human decisions to assign radio resources dynamically to the delay-sensitive users. Nonetheless, it is hard to implement due to the unavailability of the input data. Besides, using machine learning principles increases the algorithm's complexity.

The scheduling method in [96] employs two types of neural networks to increase approximation accuracy and ensure QoS criteria. Despite that, it suffers from high complexity and a challenging implementation. On the other hand, the scheduler in [97] accomplishes low-complexity real-time scheduling and allows a dynamic allocation of radio resources based on the QCI of each flow. Meanwhile, it employs numerous reinforcement learning (RL) concepts that increase the computation time and cause high latency.

The scheduling technique presented in [99] reduces latency and enhances spectral efficiency. Besides, The solution in [100] utilizes a Q-learning algorithm to provide high throughput and ensure an efficient and dynamic UL/DL TDD configuration. Nonetheless, potential weaknesses of these algorithms are unavailability of the input data to the learning algorithms, advanced complexity, and difficulty of usage.

The scheduling scheme presented in [101] ensures the eMBB and URLLC slicing. It aims to maximize the eMBB data rate and improve reliability for URLLC by using an optimization problem for eMBB and a PGACL deep RL algorithm for URLLC. Hence, the algorithm's complexity increases and causes a challenging implementation. In addition, this scheduler neglects the QoS requirements of the different applications in each use case.

The main limitation of the work cited in [102] consists of the increased complexity of implementation due to the usage of Feed Forward Back Propagation (FFBP) combined with Genetic Algorithms (GA) and Particle Swarm Optimization

TABLE 8. Strengths and shortcomings of the studied schedulers.

Work	Strengths	Limitations
[72]	- Absolute fairness	- Channel conditions not considered - Service requirements not considered
[73]	- Very high data rate - Channel conditions aware	- Condemns the cell- edge users - QoS unaware and unfair
[83]	- Avoids users starvation - Enhances coverage	- Consumes more spectral resources - Limited data rates - QoS unaware
[76]	- Delay sensitive - Channel conditions aware	- Packet loss after deadline expiration - NRT users might suffer from starvation. - QoS unaware
[84]	- Delay sensitive - Avoids packet expiration	- The use of exponential rule increases the complexity - NRT users might suffer from starvation. - QoS unaware - Hard to implement
[79]	- Delay sensitive - Avoids packet expiration - Minimum resource for lowest CQI users	- The use of exponential rule increases the complexity - QoS unaware - Hard to implement
[51]	- Delay sensitive - Reliable	- QoS unaware - NRT users might suffer from starvation.
[81]	- Delay sensitive - Avoids packet expiration - Avoids buffer overload	- QoS unaware - NRT users might suffer from starvation. - Unbalanced parameters
[82]	- Delay sensitive - Avoids packet expiration - Avoids buffer overload - Affords minimum fairness for real-time applications	- QoS unaware - NRT users might suffer from starvation. - Unbalanced parameters - Many parameters' usage may increase the computation time.
[85]	- Improves the quality of the experience for real-time users - Affords minimum fairness for real-time applications - QoS aware	- Many parameters' usage may increase the computation time. - Hard to implement
[75]	- Ensures balance the performance of the BCQI and the PF in terms of throughput and fairness	- The users with bad channel conditions suffer from starvation - It does not take the QoS into account - static scheduling
[86]	- Schedules eMBB traffic along with mMTC applications	- QoS unaware - Many parameters' usage may increase the computation time. - Hard to implement
[87]	- Very low complexity - Enhances spectral efficiency - Ensures equity among users.	- QoS unaware - Works only for the downstream
[50]	- Avoids buffer overload - Afford equity - Enhances the overall throughput	- QoS unaware scheduling scheme - FDD only
[88]	- Avoids cell- edge users from starvation	- QoS unaware scheduler - Hard to implement - Wastes so many radio resources
[89]	- Channel conditions aware - Avoids accumulating data in the buffer.	- Does not consider the QoS of each service in the studied use cases.
[90]	- Avoids queuing delays - Reduces the need for additional retransmissions	- FDD only - QoS unaware
[95]	- Reduce overall end- to- end latency - Flexible and can imitate human decision	- Hard to implement due to the unavailability of the input data - High complexity - QoS unaware
[96]	- QoS aware - Flexible and can imitate human decision - Increased approximation accuracy	- High complexity - Hard implementation
[97]	- Low- complexity - Real- time scheduling - QCI based (QoS aware)	- High computation time - Increased latency
[99]	- Reduces latency - Enhances spectral efficiency	- QoS unaware - Increased complexity - Hard to implement
[100]	- High throughput - Efficient and dynamic UL/DL TDD	- Hard to implement due to the unavailability of the input data - High complexity - QoS unaware
[101]	- Ensures eMBB and URLLC slicing - Maximizes the eMBB data rate - Improves reliability for URLLC	- Hard to implement due to the unavailability of the input data - High complexity - QoS unaware
[102]	- High spectral efficiency - Improve QoE and QoS aware	- Hard to implement - Very high complexity
[103]	- Improves the energy efficiency - High spectral efficiency	- Hard to implement - High complexity

(PSO). However, it allocates radio resources appropriately and maintains the QoE threshold of each service. The work in [103] improves energy efficiency (EE) and spectral efficiency (SE). Nevertheless, it might be hard to implement since it uses a deep reinforcement learning approach, making it a high-complexity scheduler. The gain-based method presented in [92] ensures spectral efficiency and efficient spectrum usage. However, it is concerned solely with downlink traffic and does not consider the quality of service needed for each user. Besides, the reinforcement learning method introduced in [104] prioritizes the URLLC flows by reducing the latency and enhancing the power efficiency. Nevertheless, it might be classed as high complexity scheduler since it uses multi-agent Q-learning to achieve its goals. Table 8 summarizes the weaknesses and the strengths of the studied scheduling algorithms.

V. DISCUSSION AND PERSPECTIVES

The main flaw of the well-known algorithm, Round Robin, is that it ensures absolute fairness regardless of channel conditions. Numerous channel-dependent schedulers have been developed to address this issue. Such as the best CQI scheduler, which considers channel quality but penalizes users at the cell edge or those having inadequate coverage. Therefore, it does not share radio resources equally among users. In this context, the proportional fair, combining fair sharing of resources with knowledge of the state of the canals, was developed. However, it consumes more spectral resources and ignores service requirements.

In light of this, many scheduling algorithms have been developed based on the stream type requirements, whether for real-time or non-real-time streams. PF-based delay-aware schedulers, namely EXP-PF, MLWDF, and their variants, focus on real-time traffic to reduce latency and packet loss rate.

Unfortunately, these schedulers suffer from many shortcomings, such as starvation of NRT users and high complexity due to many parameters' usage. Moreover, they only perform downlink transmissions and ignore the quality-of-service requirements required for each application.

On the other hand, recent scheduling methods developed for 5G networks only work on frequency division duplex (FDD), while the 5G NR 2 (FR2) frequency range uses only frequency division duplex (TDD). Also, most 5G planners design their metrics to meet a particular requirement.

Given these points, radio resource allocation for 5G networks and beyond remains challenging and needs further investigation, considering the following perspectives:

- Resource allocation with flexible duplexing, particularly dynamic TDD
- Radio resource management issues related to carrier aggregation
- Multi-criteria schedulers
- A generalized scheduling scheme that considers all 5G use cases

VI. CONCLUSION

Scheduling algorithms are crucial to effectively and efficiently managing the limited radio resources. Consequently, they aroused the interest of numerous scholars who proposed diverse solutions. Several scheduling schemes and metrics are designed to allocate radio resources efficiently to various flow types and applications in different fields like multimedia, industry, medical fields, and virtual reality. This article describes and reviews the latest developments in resource allocation managing strategies. Intending to understand further the process of resource allocation and the importance of scheduling algorithms, we studied, compared, and classified the scheduling schemes according to the parameters used to calculate their metrics, performance goals and objectives, and application suitability. In summary, we started by identifying the 5G use cases, characteristics, and requirements. Subsequently, we explained the radio resource scheduling process. After that, this survey discusses the input parameters considered for scheduling algorithms and their impact on the outputs. Then, it introduces the metrics used to evaluate the schedulers' performances. The classification section includes four subsections to categorize the studied schemes on the basis of their metrics, the machine learning algorithm used, their performance, and their suitability for 5G use cases. The last two sections discussed the strengths and shortcomings of the state-of-the-art solutions and introduced the remaining challenges in the literature. The perspectives section shows that all the existing scheduling schemes in the literature need to be improved and modified to address the requirements of the diverse use cases proposed by 5G and beyond communication systems. In addition, it presents outstanding issues that require further study.

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