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An Analytical Framework for Effective Joint Scheduling Over TDD-Based Mobile Networks

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ABSTRACT The growing demand for data along with the emergence of new communication standards have reshaped wireless networks through a denser base station deployment, an increasing traffic heterogeneity, and an additional complexity in quality of service (QoS) assurance. Orthogonal Frequency Division Multiple Access (OFDMA) is considered as one technique to be used in next generation wireless networks. Utilizing time division duplexing (TDD) aids the management of resources and providing effective QoS. In the literature, common approaches in assessing effectiveness attempt to capture performance using single indicators that reflect one aspect of the network's operation. consequently, multi-objective evaluations are not easy and require intuitively considering isolated descriptions, plots, visualizations, and holistically performing multiple comparisons. In this paper, we propose an analytical framework that aims to classify the effectiveness of joint scheduling algorithms over TDD-OFDMA networks per combined heterogeneous properties. In the suggested framework, a designer benefits from a bouquet of carefully customized indicators that can lead to quality evaluations, performance classifications beyond traditional approaches, and accurate improvements. Validation includes exhaustive simulations and the assessment of different scheduling and performance classification schemes. The obtained results confirm the validity of the framework and confirms its effectiveness in application.

INDEX TERMS Performance, classification, networks, joint scheduling, mobile networks.

I. INTRODUCTION

The telecommunication industry has been recently witnessing shake-ups on different fronts. Operators have replaced their reliance on voice as a main source of revenue with data services to bridge the gap between network execution and operation costs from one side and profit from the other. Concurrently, data consumption of subscribers has been increasing exponentially and putting notable strain on the existing network infrastructure. To this end, next generation wireless standard proposals have focused on developing a scalable network capable of providing significantly high data rates and low latencies to the largest number of subscribers. Modern networks use ingenious techniques including network function virtualization, software-defined radio interfaces, and advanced scheduling algorithms capable of optimally handling resources.

The witnessed reform in the network design philosophy must notably cater for the advent of services with heterogeneous uplink and downlink requirements. These services include legacy applications with either downlink (e.g., video streaming) or uplink (e.g., upload services) constraints, and newer services with bidirectional requirements such as multiplayer gaming platforms and interactive applications (e.g., video conferencing). Such heterogeneity poses major challenges on the network design in terms of interference management and traffic adaptability.Well-known legacy resource management techniques such as the round robin, proportional fairness and max-throughput algorithms fail to satisfy such requirements. Therefore, scheduling algorithms designed for future generalized network shall try to find the Pareto optimal point that involves the fulfilment of users' bidirectional requirements while guaranteeing adequate network

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performance in terms of interference minimization and throughput (TH) maximization. As orthogonal frequency division multiple access (OFDMA) is considered as one technique to be used in next generation wireless networks, utilizing time division duplexing (TDD) in conjunction with this multiple access scheme enables the management of uplink and downlink resources through a flexible switching point configuration mechanism. The process involves determining whether each timeslot in a given frame and in a particular cell is configured for uplink or downlink transmission.

Recently, the interest in investigating the effectiveness of jointly determining the switching point configuration and allocating resources, in cellular networks, has been on the rise [1]–[3]. The complex nature of joint scheduling challenges its effective deployment and the sound evaluation of its impact on network performance. The performance of joint scheduling is observed through different metrics such as throughput, delay, interference, to name but a few. Throughout the literature of joint scheduling over TDD-OFDMA, performance analysis of deployments is usually done using simple and individual indicators that capture single network properties. Accordingly, it would be difficult to observe how the variations of different parameters are related to each other. To that end, multi-objective evaluations are not easy and require considering isolated descriptions, plots, visualizations, and comparisons. The difficulty of assessing the overall efficiency of the scheduling algorithm is tightly related to the unavailability of a comprehensive approach for assessing performance.

Based on a careful review of the literature (See Section II), limited or no investigations are reported to adopt mathematical frameworks that aim to classify and rank joint scheduling according to heterogeneous properties. In addition, limited or no investigations are reported to combine qualitative and quantitative measurements holistically to aid the multifaceted performance evaluation of joint scheduling. Moreover, no evaluation in communication systems has been reported to classify deployments holistically under a scale that captures different levels of performance, such as, highly effective, effective, somewhat effective, and ineffective. To that end, we propose the Joint Scheduling Effectiveness Indicator (JoSEI) framework to capture the various aspects of joint scheduling algorithms and enable their sound evaluation, sorting, ranking, and classification. The proposed analytical framework comprises qualitative and quantitative simple indicators that capture ''atomic'' characteristics, such as, throughput, fairness, interference, algorithm complexity, network size and more. In addition, the proposed framework proposes a set of combined measurement indicators (CMIs) that amalgamates several simple indicators; the suggested CMIs include JoSEI as a main indicator that combines the largest set of metrics.

This paper is organized as follows. Section II presents related work with focus on the adopted framework. Section III summarizes the motivation for developing the framework and the subsequent research objectives. Section IV describes the analytical framework including the performance indicators and their mathematical formulation. Section V provides extensive results illustrating the merits of the proposed mathematical framework along with a thorough discussion of the findings. In addition, the usefulness of the developed framework is discussed in the wider networking context. Section VI concludes the paper and identifies future work.

II. RELATED WORK

Research work on TDD-based scheduling and resource allocation has focused on a subset of the simple metrics to optimize as highlighted in Table 1. For instance in [4], an interference-aware resource management algorithm is proposed and assessed in terms of the resulting interference, delay, and spectral efficiency. On the other hand, the approach in [5] aims at improving the network throughput and refining the uplink and downlink user association, that is, defining for each user the base station it is connected to for transmission.

The problem of resource allocation in general, and in the context of TDD-based networks in particular, is a multidimensional problem that is difficult to fully characterize using simple metrics such as throughput, interference, etc. The approach of using simple metrics fails to illustrate the existing interactions among indicators. Such an illustration limitation is addressed, in this investigation, through the development of a novel composite indicators.

The choice of scheduling metrics can also be associated to type of network being optimized. In [6], a scheduling algorithm is developed for massive Machine Type Communications (mMTC). As mMTC scenarios create some traffic imbalances with a notable increase in uplink traffic, the authors rely on customized frame structures with additional low power slots to address the traffic requirements. However, the resulting interference in the network is not properly analyzed. Another scheduling algorithm is developed in the context of ultradense networks in [7]. The developed approach relies on deep learning principles to have a proactive congestion-free network operation. Simulations are done using a single cell thus eliminating one important dimension in TDD networks which is interference.

The aforementioned papers along with others mentioned in Table 1 demonstrate the difficulty in having a unified mathematical framework that would provide a holistic and effective vision of the TDD-based network operation under various scheduling algorithms and for different network configurations. Thus, this paper follows a new methodology in assessing network's performance. The assessment paradigm concurrently considers simple metrics along with high-order composite metrics which enables the characterization and evaluation of the performance of any scheduling algorithm for any network scenario. In addition, this characterization is done through a unified mathematical framework. The different investigation techniques highlighted in Table 1 (optimization, probability analysis, etc.) will be overlooked in favor of a set of tractable mathematical rules normalizing the comparison process.

TABLE 1. Summary of related work.

Ref.	Year	Objective	Technique	Indicators	Results	Comparative Issues
[4]	2019	Centralized joint allocation with MIMO rank adaptation	Optimization; Clustering	Delay; Interference; MIMO rank; spectral efficiency	Clustering with flexible configuration	Fixed and small-sized clusters
[8]	2018	Resource allocation; TDD 5G nets.	Graphs; MATLAB	TH; Spectral Efficiency (SE)	Dynamic configuration per slice; reduced interference; high TH and SE	Optimality
[9]	2018	Design distributed TDD schemes for decoupled uplink and downlink trans.	Optimization, Monte Carlo Simulations	TH; outage probability	Channel-aware TH-maximizing dynamic configuration	Scalability
[10]	2018	Minimize interference; dynamic TDD 5G nets.	Probabilistic analysis	Signal to interference and noise ratios; Data rate	Improved signal quality and TH	Scheduling
[5]	2018	Joint dynamic TDD configuration and user association	Optimization; MATLAB	TH; User association	Improved dynamic configuration; high TH	Algo. complexity
[6]	2018	Asymmetric resource allocation in mMTC	Stochastic geometry, sub-gradient descent algo.	TH; traffic adaptation; queue length	Queue-aware resource allocation	Additional slots needed for interference cancellation
[7]	2018	Resource allocation in ultra-dense nets.	Deep learning; Python	Packet loss rate; TH; MOS	Proactive resource allocation algo.	Interference not considered
[11]	2016	Slicing mechanism for TDD-based nets.	Heuristics; scheduling; network simulator	Mean opinion score; resource utilization	Improved QoS and QoE	Fixed subset of TDD frames

III. MOTIVATION AND RESEARCH OBJECTIVES

A variety of aspects motivates proposing JoSEI as an analytical framework for joint scheduling over TDD-OFDMA networks. Joint scheduling algorithms are usually quite complex and therefore can become a performance hurdle when the network size is large. Joint scheduling becomes a challenging network slicing and virtualization problem as it involves the distribution of physical and virtual resources amongst different slices. Furthermore, the proper assessment of scheduling algorithms is essential in determining its suitability for next generation virtualized networks. Among others, the scalability and comprehensiveness of scheduling algorithms compromise their overall performance. In addition, the impact of the scheduling algorithm on the network performance can be observed through different quantifiable metrics such as throughput, delay, interference and other QoS and Quality of Experience (QoE) measures. However, it would be difficult to observe how the variations of different parameters are related to each other. Consequently, the difficulty of assessing the overall efficiency of the scheduling algorithm is tightly related to the unavailability of a comprehensive performance indicator. It is evident that scheduling is a multi-faceted problem. Therefore, any developed algorithm cannot capture all the intricacies of the process but rather focus on one or a certain number of parameters. For example, key performance aspects include maximizing throughput, minimizing interference, satisfying trade-offs, to name a few.

To the best of our knowledge, no benchmark is available in the literature that could be used to "objectively" assess the performance of a set of algorithms used in communications networks. Moreover, based on careful survey of the literature, limited or no investigations are reported to adopt mathematical frameworks that aim to classify and rank algorithms according to heterogeneous properties. Finally, limited or no investigations are reported to combine qualitative and quantitative measurements holistically. To that end, our research objectives are as follows:

- Develop an analytical framework that captures the various aspects of joint scheduling algorithms and enable their sound evaluation, sorting, ranking, and classification as per their attained performance. The targeted analysis model comprise qualitative and quantitative indicators that capture prime characteristics, such as, throughput, reliability, fairness, traffic adaptability, algorithm complexity, network size and topology.
- Target a selection of scheduling paradigms.The mathematical framework presented in the sequel considers the algorithms proposed in [1] where optimal and meta-heuristic sub-optimal techniques are presented. Two flavors of the sub-optimal algorithm, namely, full and cluster-coordination are analyzed and compared to the traditional full-synchronization technique. This will be further discussed in Section V.

- Propose a systematic and robust procedure for the rapid assessment of a scheduling algorithm in terms of its adaptability and predicted performance for any given network through a sound mathematical analysis using tailored indicators.
- Present a discussion on the usefulness and applicability of the developed set of performance indicators, in the wider networks context.

The proposed analytical framework is heterogeneous in the sense that it is based on different qualitative and quantitative measurements that capture various performance-related aspects. Therefore, the proposed JoSEI is intended to provide a comprehensive indication of scheduling performance over TDD-OFDMA networks. The proposed analytical framework aims at being scalable for any problem size or algorithm class. In addition, the framework aims at being portable for any network topology and being generic in the sense that it is applicable in the wider quality assurance of networks.

The methodology towards achieving our research objectives is outlined as follows:

1) Develop the analytical framework using the Generic Benchmark Model (GBM) of Damaj and Kasbah [12].
2) Simulate the operation of the proposed algorithms.
3) Analyze and evaluate the findings
4) Validate JoSEI and other indicator classifications through comparisons with classifications produced by scheduling algorithms from [1].

IV. JOSEI ANALYTICAL FRAMEWORK

To present the development of the proposed analytical framework, the GBM of Damaj and Kasbah [12] is adopted. The GBM comprises six elements that define the Goal, Input, Activities, Output, Outcomes, and the desired Performance profile of the proposed analytical framework. The model defines the relationships among the analysis aims, available resources, target implementations, statistical formulations, and the obtained results. The six elements of the GBM are described as follows:

- The **Goal** defines the aim of the analysis framework.
- The **Input** identifies the algorithms under study, implementation systems, reference algorithm, performance metrics, etc.
- The **Activities** present the algorithm implementations and the results.
- The **Output** is the formulation of the key indicators and development of any needed rubric.
- The **Outcomes** are the formulations of the statistical assessment as combinations of the Output.
- The **Performance** dimension is the application of the framework to sort, rank, and classify target algorithms according to the obtained results.

A. GOAL, INPUT, AND ACTIVITIES

The **Goal** is to develop an analytic model that captures the characteristics of joint scheduling algorithms under TDD-OFDMA and enable their effective evaluation, ranking, and classification.

The **Input** identifies the targeted algorithms and the performance metrics. The analytic framework targets a selection of scheduling paradigms ranging from optimal to metaheuristic algorithms. In particular, two joint algorithms are selected; an optimal solution that works for small networks and a sub-optimal algorithm that scales for large networks.

The identified performance metrics are classified into **Algorithmic Profile** (AlgoP), **Network Profile** (NetP) and **Operational Profile** (OP). The AlgoP includes the complexity of the algorithms. Moreover, the NetP captures the network specification in terms of density and communication interference. The OP includes throughput, fairness, and base and mobile stations communication interference power.

B. ACTIVITIES

The **Activities** include simulations and validations under MATLAB.

C. OUTPUT

The **Outputs** of the analysis framework are three sets for indicators that belong to the AlgoP, NetP, and OP. The main Key Indicator (KI) of the AlgoP is the **Algorithm Complexity** (AC), which is defined as the asymptotic complexity analysis using the Big-O, small-ω, and Θ notations. To analyze the complexity of the targeted algorithms, we study their asymptotic behavior. The asymptotic behavior classifies algorithms according to their rate of growth with respect to the increase in input size. The following complexity analysis classification is based on the rubric presented in [12]. However, an additional level is introduced to capture exponential complexity [13].

- $O(f(n))$: The rate of growth of an algorithm is asymptotically no worse than the function $f(n)$ but can be equal to it.
- $\Omega(f(n))$: The rate of growth of an algorithm is asymptotically no better than the function $f(n)$ but can be equal to it.
- $\Theta(f(n))$: The rate of growth of an algorithm is asymptotically equal to the function $f(n)$.

Here, n is the size of input.

As the framework in development relies on quantities, we map the qualitative scale points onto numbers [14]. The scale points are uniformly mapped to a range between 0 and 1. To that end, the quantitative scale points are the values 17%, 34%, 51%, 68%, 85%, and 100%; respectively.

The **NetP** comprises two KIs, namely, the **Communication Interference** (CI) and **Network Density** (ND). The CI and ND are defined as follows:

- **Communication Interference** (CI): The total interference resulting from the adopted switching point configuration. This indicator is essential in profiling the performance of the wireless network. item **Network Density** (ND): The network density, in terms of base stations, users, and resource allocation variables

TABLE 2. The rubric of the algorithm complexity indicator.

General Indicator	Levels					
	Logarithmic Low (LL)	Logarithmic High (LH)	Linear (L)	Almost Quadratic (AQ)	Higher than Quadratic (HQ)	Exponential (E)
Algorithm Complexity	$O(logn)$	$\omega(logn)$ but better than Linear	$\Theta(n)$	$O(n^2)$ but worse than Linear	$\omega(n^2)$ but better than exponential	$\Omega(2^n)$
Mapping to Quantities	0.17	0.34	0.51	0.68	0.85	1

(subcarriers, power, switching points, etc.) conveys information about how the proposed algorithm would adapt to a dense environment with closer nodes (and thus higher possibility of interference) by satisfying traffic requirements while maintaining interference at minimum levels. This is the optimal scenario in the case of a practical network operation.

The OP includes the KIs that aid the analysis of the behaviour of a network in terms of throughput, fairness, and Base Station (BS)-BS Interference Power. The OP KIs are defined as follows:

- **Throughput** (TH): The number of bits communicated over a network per second (bps); either as an Uplink Throughput (UTH), or a Downlink Througput (DTH) of a transmission.
- **Fairness** (FN): The Fairness reflects the faithfulness in satisfying the users' QoS and QoE requirements, and the efficacy of the scheduling algorithm in providing an adequate distribution of the resources.
- **BS-BS Interference Power** (BSIP): BS-BS interference is a critical metric in the operation of asynchronous TDD networks. A low BSIP usually stems from a full-synchronization in the scheduling process or an efficient asynchronous switching point configuration outcome.

D. OUTCOMES

The **Outcomes** element presents the equations of CMIs as functions of the proposed KIs. As mentioned earlier, the main CMI in the proposed framework is JoSEI. The mathematical formulation of CMIs uses the Geometric Mean of KI ratios to provide a holistic calculation that captures the performance of joint scheduling. The generic equation of CMIs from [12] is as follows:

$$CMI = \sqrt[n]{ratio_1 \times ratio_2 \times \ldots ratio_n} \tag{1}$$

where,

$ratio_i = \dfrac{KI_{i.j}}{KI_{i.j}^{ref}}$

$KI_{i.j}$ is the i^{th} *KI* of the j^{th} *profile*,

$i \in \{1..n\}$ and $j \in \{1..2\}$,

$KI_{i.j}^{ref}$ is the reference measurement of the indicator $KI_{i.j}$

To calculate a CMI, the Geometric Mean is used as it is able to measure the central tendency of data values that are obtained from ratios. The attraction for using the Geometric Mean is that its ratio is equal to the Geometric Mean of performance ratios; which implies that when comparing two different implementations' performance, the choice of the reference implementation is irrelevant [12], [15]. In the current investigation, the reference measurements are considered as an execution that attains a satisfactory performance as compared to all performed executions.

JoSEI enables the classification of a joint scheduling execution at different uplink and downlink cell indices, equal and optimal power schemes; clustering weights; equal and channel-based assignments; and scheduling schemes that include full-coordination, cluster-coordination, and full-synchronization. The main JoSEI equation, using the seven developed indicators, is shown in Equations (2), (3), (4) and (5).

$$JoSEI = \sqrt[7]{AlgoP \cdot NetP \cdot OP} \tag{2}$$

where,

$$AlgoP = \frac{AC_{ref}}{AC} \tag{3}$$

$$NetP = \frac{CI_{ref}}{CI} \cdot \frac{ND}{ND_{ref}} \tag{4}$$

$$OP = \frac{UTH}{UTH_{ref}} \cdot \frac{DTH}{DTH_{ref}} \cdot \frac{FN}{FN_{ref}} \cdot \frac{BSIPref}{BSIP} \tag{5}$$

Based on the calculation of JoSEI, three additional CMIs are proposed to capture the performance of an execution as related to the developed profiles; the additional CMIs are as follows:

- **Network Profile Indicator** (NetPI): Captures the performance resulting from the execution of the joint scheduling algorithm for a given distribution of base stations and users and the network size. As shown in (6), the network performance is higher when the resulting interference (including BS-BS, MS-MS, MS-BS, BS-MS) does not increase dramatically with a denser network setup thus reflecting a highly adaptable scheduling algorithm.

$$NetPI = \sqrt[2]{\frac{CI_{ref}}{CI} \cdot \frac{ND}{ND_{ref}}} \tag{6}$$

- **Operational Profile Indicator** (OPI): Captures the compounded performance effect of the scheduling technique through the achieved throughput, fairness, and measured interference (See Equation (7)).

$$OPI = \sqrt[4]{\frac{UTH}{UTH_{ref}} \cdot \frac{DTH}{DTH_{ref}} \cdot \frac{FN}{FN_{ref}} \cdot \frac{BSIPref}{BSIP}} \tag{7}$$

TABLE 3. The proposed levels of performance of simple indicators and the values of the reference measurement.

	Levels				
Indicator	**Low**	**Somewhat Satisfactory**	**Satisfactory**	**High**	**Ref.**
Algorithm Complexity	1	0.85	0.68	≤ 0.51	0.68
Communication Interference	$> 10^{-9}$	$(8 \cdot 10^{-10}, 10^{-9}]$	$(3 \cdot 10^{-10}, 8 \cdot 10^{-10}]$	$\leq 3 \cdot 10^{-10}$	$5.5 \cdot 10^{-9}$
Network Density	≤ 1700	(1700,4000]	(4000,7500]	> 7500	5750
Downlink Throughput	≤ 150	(150,200]	(200,500]	> 500	350
Uplink Throughput	≤ 75	(75,150]	(150,250]	> 250	200
Fairness	≤ 0.4	(0.4,0.60]	(0.6,0.8]	> 0.8	0.7
BS-BS interference	> 0.9	(0.5,0.9]	(0.2,0.5]	≤ 0.2	0.35

- **Algorithmic Profile Indicator** (AlgoPI): Captures the complexity of the scheduling algorithm (See Equation (7)).

$$AlgoPI = \frac{AC_{ref}}{AC} \tag{8}$$

Considering the aggregate uplink and downlink data rate requirements in a given cell, the scheduling performance can be assessed through the traffic adaptability, that is, by comparing the achieved data rates in the uplink and downlink to the required one. For a cell l, and a ratio of uplink (R_l^U) to downlink (R_l^D) traffic θ_l, the coarse traffic adaptation index for that cell can be estimated as in Equation (9).

$$x_l = \left| \frac{R_l^U}{R_l^D} - \theta_l \right| \tag{9}$$

This defined index can be used to define the network's **Fairness** (FN) given by the Jain's fairness index ($\mathcal{J}$) defined as in Equation (10) [1].

$$FN = \mathcal{J}(x_1, \cdots, x_n) = \frac{(\sum_{i=1}^{n} x_i)^2}{n \cdot \sum_{i=1}^{n} x_i^2} \tag{10}$$

At this point, a **Reliability Indicator** (RLI) can be defined to capture the reliability of joint scheduling in terms of interference and traffic adaptability. the calculation of the RLI adopts the geometric mean of ratios as in JoSEI (See Equation (11).

$$RLI = \sqrt{\frac{CI\,ref}{CI} \cdot \frac{BSIPref}{BSIP}} \tag{11}$$

Two additional CMIs are proposed to capture the efficiency of joint scheduling in terms of throughput and interference power; the CMI is the **BS-BS Efficiency Indicator** (BFI) that is defined in Equation (12).

$$BFI = \frac{UTH \cdot DTH}{BSIP} \tag{12}$$

E. PERFORMANCE

The **Performance** analysis based on the JoSEI system provides measurements for all KIs and enables the calculation of the defined CMIs. The results enable sorting, ranking, and classifying the targeted algorithms. Sorting executions per the attained performance is straightforward using the obtained indicator results. Executions with high JoSEI values holistically attain higher performance than those of low values.

1) PERFORMANCE LEVELS

To enable ranking and classifying executions according to their performance, we develop an analytical scheme based on the levels proposed in Table 3. The proposed ranges were determined heuristically through a careful assessment of the results in [1]. The suggested ranges are for a performance scale of four levels, namely, Low, Somewhat Satisfactory, Satisfactory, and High. The proposed ranges are fine tuned to provide the ratio breakpoints of 0.5, 0.8, and 1.6 among the identified scale levels. In this investigation, the adopted reference measurement is for an execution that attains the middle score within the range of the Satisfactory performance level—as shown in Table 3. To that end, classifying executions per indicator scores becomes possible. For example, an execution with a Downlink Throughput (DTH) score of 700 bps produces a ratio of 2 that reflects attaining a higher performance than the selected reference.

The defined ranges in Table 3 are justified as follows:

- **Algorithmic Complexity:** A complexity of Almost Quadratic, as mapped to the value 0.68, is considered to attain a Satisfactory Performance. In addition, a Linear complexity, as mapped to the value 0.51, or better is considered to attain a High Performance. The remaining complexity levels are considered to attain Somewhat Satisfactory and Low performance as shown in Table 3. A low algorithmic complexity usually reflects higher scalability to high network sizes and facilitates the practical implementation of the algorithm. In the context of JoSEI, the algorithmic complexity only affects the temporal effectiveness highlighted by the indicator AlgoP while not affecting the quality of service (QoS) shown through the indicators NeTP and OP.
- **Communication Interference:** The communication interference is defined as the total interference per cell including BS-MS, MS-BS, BS-BS, and MS-MS interference.
- **Network Density:** The network size is a major defining factor of the scalabililty of the scheduling algorithm to an increasing number of users and base station. The main reason is that the variables including temporal switching points, spectral and power allocation increase drastically with the network size. Another dimension could be added in terms of the clustering decisions. In fact, as the number of nodes increases for a given area, the size of the cluster increases due to the large proximity between transmitting nodes until it

TABLE 4. The ANM Scheme; the mean, standard deviation, kurtosis, and skewness of ratios and JoSEI qualitative interpretations.

Calculation	Levels			
JoSEI	Effectiveness is lower than the reference execution (0,0.5)	Effectiveness is somewhat lower than the reference execution [0.5,0.8)	Effectiveness is similar to the reference execution [0.8,1.6)	Effectiveness is higher than the reference execution ≥ 1.6
Mean (μ)	Low: (0,0.5)	Somewhat Satisfactory: [0.5,0.8)	Satisfactory: [0.8,1.6)	High: $\geq$1.6
Standard Deviation (σ)	Uniform *Almost no variation in the obtained results* (0,0.3)	Somewhat Disperse: *Small variation in the obtained results* [0.3,0.6)	Disperse: *Significant variation in the obtained results* [0.6,0.9)	Highly Disperse: *Large variation in the obtained results* $\geq$ 0.9
Kurtosis (κ)	Flat: *Almost no variation in the obtained results* < 0	Normal: *Small variation in the obtained results* [0]	Turbulent: *Large variation in the obtained results* > 0	
Skewness (ζ)	Skewed towards low scores < 0	Normal with no skewness [0]	Skewed towards high scores > 0	

converges to the traditional full-synchronization solution. The quality of the scheduling algorithm therefore relates to all the aforementioned parameters as $D = C^{-1}T \cdot \left(L \cdot M^U \cdot K + L \cdot \cdot M^D \cdot K\right)$ where C is the number of clusters resulting from clustering process in the sub-optimal joint resource allocation algorithm described in [1], T the number of slots to be configured, L the number of base stations, M^U and M^D the number of connected devices in the uplink and downlink, and K is the number of subcarriers. A larger network density with a low total interference (See Equation (6)) reflects the efficacy of the scheduling algorithm in optimizing the performance with an increasingly dense network.

- **Throughput:** The achieved throughput is a main metric in scheduling algorithms as a highly performing scheduling algorithm should achieve the highest attainable throughput possible. The throughput ranges is different between the uplink and downlink (UTH and DTH). The values presented in Table 3 are in bps per Hz per cell.
- **Fairness:** The fairness is defined based on the Jain's index. A value close to one ensures the highest performance in terms of a faithful adaptation to a given cell's uplink and downlink traffic requirements.
- **BS-BS Interference:** To estimate the performance of the scheduling algorithm in terms of minimizing the BS-BS interference, the defined indicator is characterized as a function of the MS-BS interference which is present in a synchronized operation of a TDD system. As such, the performance spectrum ranges from being highly satisfactory when the normalized BS-BS interference is less than 20% of the normalized MS-BS interference to being unsatisfactory when it much greater than the achieved MS-BS interference. The normalization procedure involves dividing the values by the average over all cells and is necessary to reduce the variability in the results.

2) EVALUATION SCHEMES

Although the JoSEI holistically enables sorting executions according to their effective performance, capturing an attained performance level requires additional information about the KIs. Besides the JoSEI, an analytical scheme, based on Aggregate Numerical Measures (**ANM**), is created to comprise the mean (μ), statistical dispersion (standard deviation, σ), kurtosis (κ), and skewness (ζ) of ratios. The proposed scheme and its qualitative interpretations are shown

TABLE 5. The JoSEI ANM evaluation chart wrt a reference execution with measurements of satisfactory performance.

Level	Execution Effectiveness
Highly Effective: The execution holistically attains high performance	• The JoSEI score is **higher** than the reference execution • The Mean (μ) is **high** • The Standard Deviation (σ) is no higher than **somewhat disperse** • The Kurtosis (κ) is no higher than **normal** • The Skewness (ζ) is no lower than **normal**
Effective: The execution holistically attains satisfactory performance	• The JoSEI score is **higher** than the reference execution • For **any** Mean (μ) • For **any** Standard Deviation (σ) • For **any** Kurtosis (κ) • For **any** Skewness (ζ) • While below the **Highly Effective** score levels or • The JoSEI score is **similar** to the reference execution • The Mean (μ) is at least **satisfactory** • The Standard Deviation (σ) is no higher than **somewhat disperse** • The Kurtosis (κ) is no higher than **normal** • The Skewness (ζ) is no lower than **normal**
Somewhat Effective: The execution holistically attains somewhat satisfactory performance	• The JoSEI score is **similar** to the reference execution • For **any** Mean (μ) • For **any** Standard Deviation (σ) • For **any** Kurtosis (κ) • For **any** Skewness (ζ) • While below the **Effective** score levels or • The JoSEI score is **somewhat lower** than the reference execution • The Mean (μ) is at least **somewhat satisfactory** • The Standard Deviation (σ) is no higher than **somewhat disperse** • The Kurtosis (κ) is no higher than **normal** • The Skewness (ζ) is no lower than **normal**
Ineffective: The execution holistically attains low performance	Otherwise

TABLE 6. The ISS Scheme; the PoS and JoSEI qualitative interpretations.

Calculation	Levels			
JoSEI	Effectiveness is lower than the reference execution (0,0.5)	Effectiveness is somewhat lower than the reference execution [0.5,0.8)	Effectiveness is similar to the reference execution [0.8,1.6)	Effectiveness is higher than the reference execution ≥ 1.6
PoS	Low: (0, 50%)	Somewhat Satisfactory: [50%,70%)	Satisfactory: [70%,90%)	High: $\geq$ 90%

in Table 4. The scheme provides additional information about the calculated ratios of KIs, beyond the single JoSEI index, to enable the ranking and classification of an execution per a chart of performance effectiveness. The chart has a scale that comprises four levels, namely, Ineffective, Somewhat Effective, Effective, and Highly Effective. The description of chart is shown in Table 5. The qualitative interpretation of the chart levels is based on the ANM Scheme and ranges of Tables 3 and 4. Accordingly, an execution attains specific JoSEI, mean, dispersion, kurtosis, and skewness scores that successfully ranks the effectiveness of the attained performance.

Besides the ANM Scheme, another Indicator Status Scheme (**ISS**) comprise the Percentage of Satisfaction (**PoS**) that equals the percentage of KIs that attain a rank of Satisfactory and above. For instance, a PoS that is greater than 90% is ranked as High. The proposed ISS Scheme and its qualitative interpretations are shown in Table 6. The scheme provides additional information about the calculated ratios of KIs, beyond the single JoSEI index, to enable the ranking and classification of a scheduling execution per an ISS chart of performance effectiveness. The ISS chart has a scale that comprises four levels, namely, Ineffective, Somewhat Effective, Effective, and Highly Effective. The description of chart is shown in Table 7. The qualitative interpretation of the chart levels is based on the scheme and ranges of Tables 3 and 6. Accordingly, an execution attains specific JoSEI and PoS scores that successfully ranks the effectiveness of the attained performance. The ANM and ISS make two different classification rules with different sensitivities to outliers in measurements; a thorough discussion, the rationale of choice, and identification of limitations are presented in Section V-C.

TABLE 7. The JoSEI ISS evaluation chart wrt a reference execution with measurements of satisfactory performance.

Level	Execution Effectiveness
Highly Effective: The execution holistically attains high performance	• The PoS is **high** • The JoSEI score is **higher** than the reference execution
Effective: The execution holistically attains satisfactory performance	• The PoS is **high** • The JoSEI score is at most **similar** to the reference execution or • The PoS is **satisfactory** • The JoSEI score is at least **similar** to the reference execution
Somewhat Effective: The execution holistically attains somewhat satisfactory performance	• The PoS is **satisfactory** • The JoSEI score is at most **somewhat lower** than the reference execution or • The PoS is **somewhat satisfactory** • The JoSEI score is at least **somewhat lower** than the reference execution
Ineffective: The execution holistically attains low performance	Otherwise

V. PERFORMANCE ANALYSIS AND EVALUATION

This paper considers three joint uplink and downlink scheduling techniques within the context of TDD-OFDMA systems. The first is the full-synchronization approach which is considered the technique of choice for current TDD-LTE networks ([16]); mainly, because it partially satisfies traffic requirements with minimal impact on the resulting interference. This approach calculates the aggregate uplink and downlink traffic requirements in a given network and uses a fixed switching point configuration in all cells of the network. The second approach is a dynamic joint configuration scheduling algorithm [1], which tries to satisfy the per-cell uplink and downlink traffic requirements while minimizing interference through clustering the cells into different groups depending on the susceptibility of cells to interfere on each other with emphasis on BS-BS and MS-MS interference. Then, switching point configuration and multicell resource allocation are performed independently. The final approach is a cluster-coordination scheduling technique that simplifies the proposal of [1] by mitigating interference only at the cluster level.

The three approaches are simulated in MATLAB using the same network setup and parameters as described in [1]. The evaluation and analysis results presented in this sequel paper builds on the simulation results in [1] as the main purpose of this work is to showcase the effectiveness of the presented analytical framework in providing a better benchmark paradigm for scheduling algorithms and in particular, for the joint algorithms discussed in [1].

A. ANALYSIS AND EVALUATION

The presented results illustrate the defined indicators as well as the output of the employed classification methodology. Figs. 1-5 show the obtained indicators for a network composed of 30 cells with 30 users randomly distributed in each cell. Without loss of generality, a TDD frame structure with 10 slots is considered along with $K = 90$ subcarriers to be assigned in the uplink or downlink based on the resulting frame configuration. Additional parameters related to channel models can be found in Section 2 of [1]. The presented

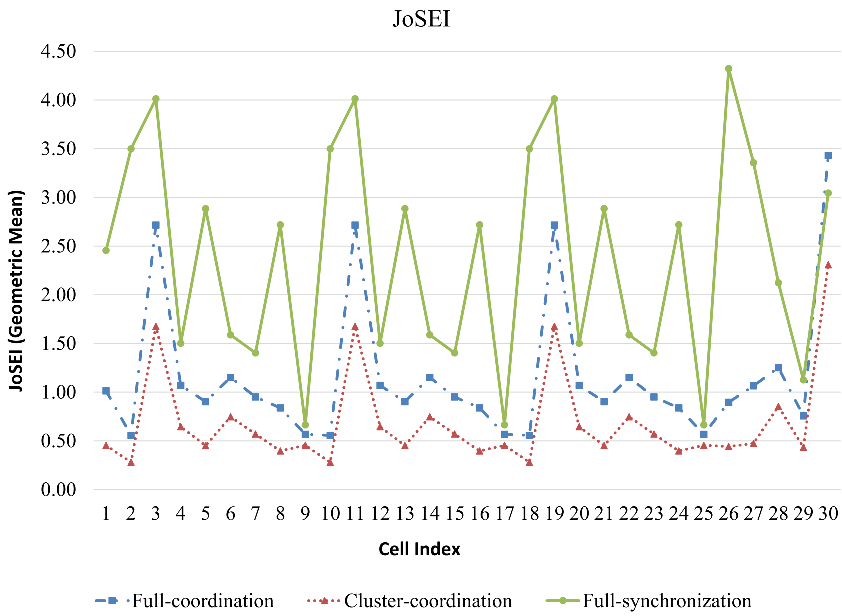

FIGURE 1. JoSEI scores versus cell index for scheduling under Full-coordination, Cluster-coordination, and Full-synchronization.

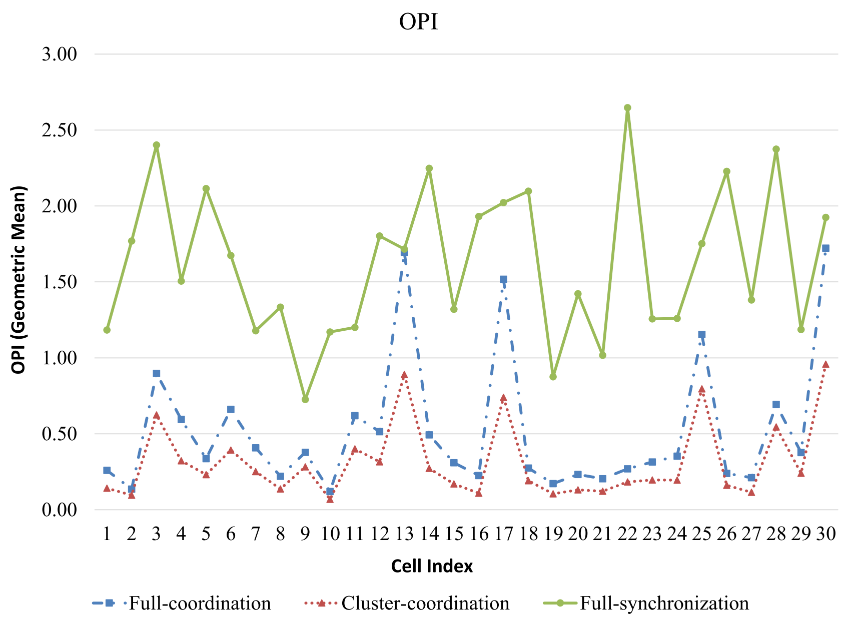

FIGURE 2. OPI scores versus cell index for scheduling under Full-coordination, Cluster-coordination, and Full-synchronization.

values in Figs. 1-5 reflect the network performance under each of the simulated joint scheduling algorithms.

Fig. 1 demonstrates the holistic performance of the three algorithms. Reading this figure in conjunction with Equation (2) provides several insights. The full-synchronization algorithm achieves the highest score as expected. It has the lowest algorithmic complexity due to the network-wide adoption of a unified switching point configuration, thus simplifying the scheduling process. This synchronized approach results as well in an elimination of the BS-BS interference which is considered as the highest component among all interference types in TDD systems. This conclusion can be clearly seen in Figs. 2, 3, and 4 representing the OPI, NetPI and RLI indicators which have interference components in their definitions.

In fact, looking at Equations (6), (7), and (11), the major constituents in the definition of the NetPI, OPI and RLI indicators depend on the resulting interference in the network. This corroborates the performance advantage in that regard of the full synchronization approach. The performance

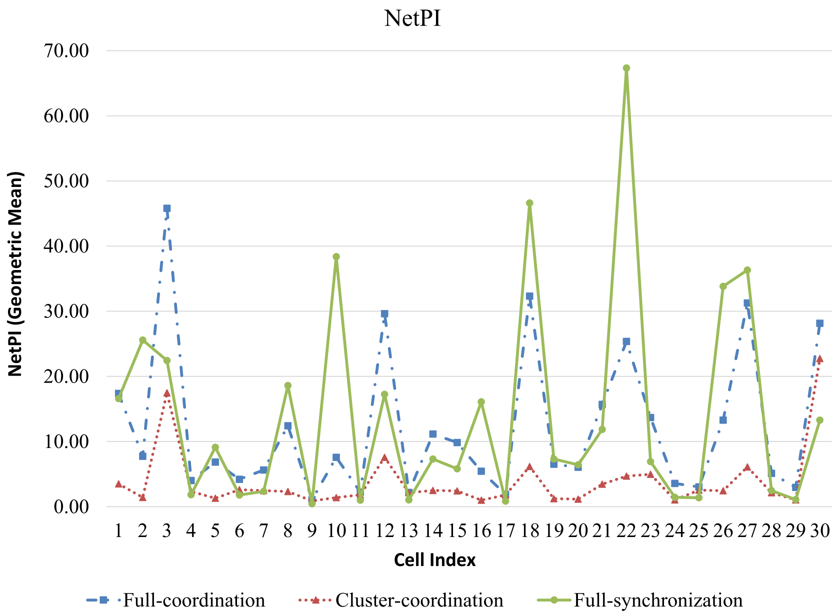

FIGURE 3. NetPI scores versus cell index for scheduling under Full-coordination, Cluster-coordination, and Full-synchronization.

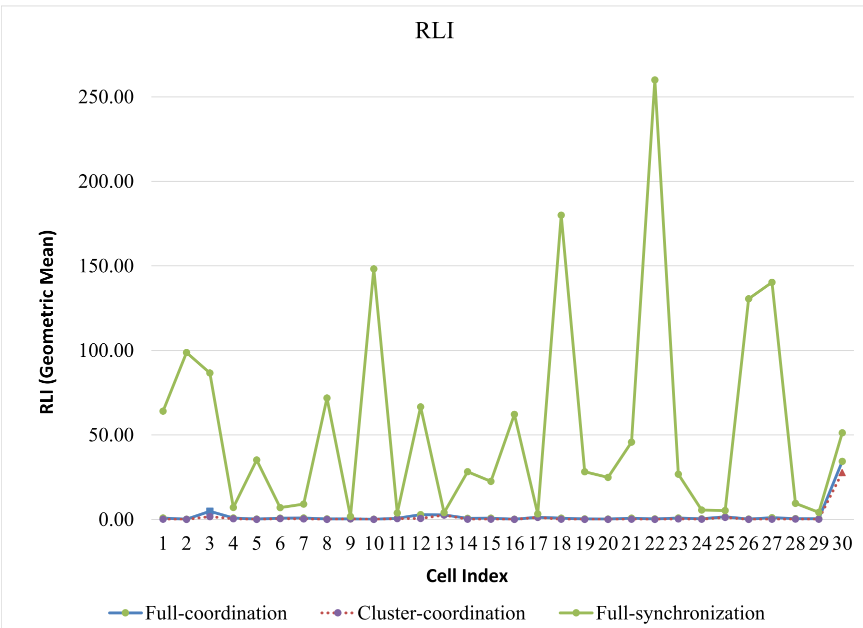

FIGURE 4. RLI scores versus cell index for scheduling under Full-coordination, Cluster-coordination, and Full-synchronization.

gap reduces, however, with the OPI and NetPI indicators as the achieved throughput, fairness and network density are taken into consideration. This is depictable particularly in Fig. 3 with the NetPI indicator. Indeed. this notable advantage does not provide the full picture regarding the network performance.

Looking at Fig. 5, the full-coordination approach outperforms the full-synchronization technique in the BFI indicator. The BFI indicator was defined as the ratio of the product of the uplink and downlink throughput to the BS-BS interference indicator. This reflects the capability of the scheduling algorithm of maximizing throughput and satisfying the per-cell uplink and downlink traffic requirements while keeping the BS-BS interference at a minimum level. Indeed, the full-coordination scheme outperforms the other two techniques in this category mainly due to the hybrid

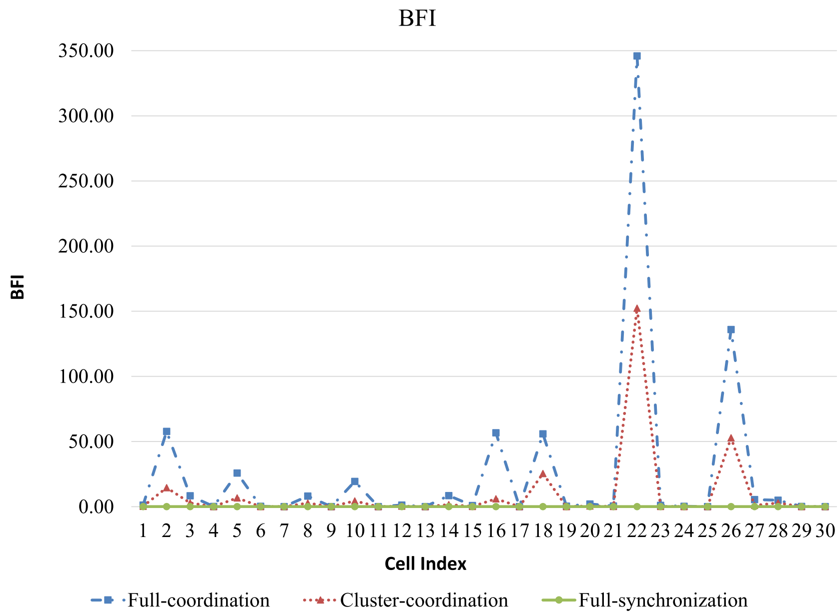

FIGURE 5. BFI scores versus cell index for scheduling under Full-coordination, Cluster-coordination, and Full-synchronization.

dynamic switching point configuration/clustering approach which tries to find the sweet spot in terms of QoS assurance and network performance optimization. The NetPI indicator also captures this observation. Fig. 3 demonstrates that the full-coordination scheme is relatively close to the full-synchronization one. This is due to the fact that even if the network deployment is dense (which should normally result in high interference), the adopted dynamic approach still reduces the overall interference to an acceptable level enabling an acceptable overall network performance.

The cluster-coordination scheme was conceived as a benchmark algorithm as it does not provide network-wide interference coordination while employing a clustering technique similar to the full-coordination scheme. Consequently, in the provided figures, it can be seen that it ranks last for all indicators.

Figures 6 and 7 illustrate the classification outcome based on the described ANM and ISS schemes, respectively. The classification schemes are based on a statistical analysis of the resulting indicators and a set of rules to interpret the statistical outputs. The ANM classification outcome in Fig. 6 corroborates the previously indicator-based analysis showing a high percentage of effectiveness for the fully synchronized scheduling technique. The full-coordination case shows, however, effectiveness for a large number of cells despite the use of various and sometimes aggressive switching point configurations in the network. The ISS classification schemes captures the performance trade-offs in the full-coordination case in a better way as it relies less on the obtained statistics and more on the percentage of satisfaction (PoS) and the JoSEI indicator. Fig.7 demonstrates that for most of the cells, full-coordination outperforms the

TABLE 8. The scale and corresponding values of the difference in classification (δ_c) metric.

Rank	δ_c
Nil	0
Small	1
Somewhat Significant	2
Significant	3

full-synchronization scheduling algorithm for a large number of cells in the network illustrating the high level of satisfaction achieved.

To quantify the difference between the two classification schemes, Fig. 8 highlights the gap in the classification through the Difference in Classification (δ_c) metric. The metric δ_c is the absolute difference in scale levels between two classifications; it classifies differences as Nil, Small, Somewhat Significant, and Significant as per Table 8. Based on the shown results, the difference in the classification ranges from small to somewhat significant (only for a couple of cells).

In all, the results presented in Section V-A have showcased a novel benchmarking mechanism for scheduling algorithms that captures, the implications of the adopted algorithm on the network performance. The process goes gradually from defining key performance indicators, to more complex composite indicators, ending with a classification paradigm. The results have shown that the standardized full-synchronization scheduling algorithm possesses several merits mainly due to the interference mitigation it provides while the full-coordination approach performs better in terms of traffic adaptability at the expense of a slight increase in interference, notably BS-BS interference. This approach

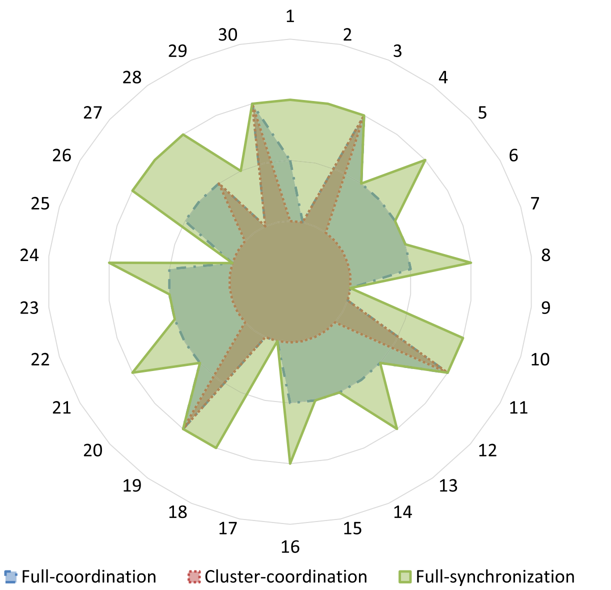

FIGURE 6. ANM classification versus cell index. Concentric circles depict the scale Ineffective (innermost circle), Somewhat Effective, Effective, and Highly Effective.

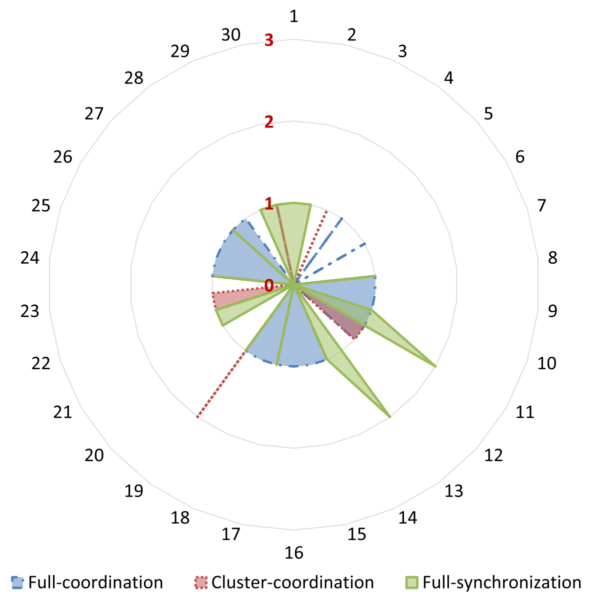

FIGURE 8. Difference in Classification (δ_C). The concentric circles depict the scale Nil (0), Small (1), Somewhat Significant (2), and Significant (3).

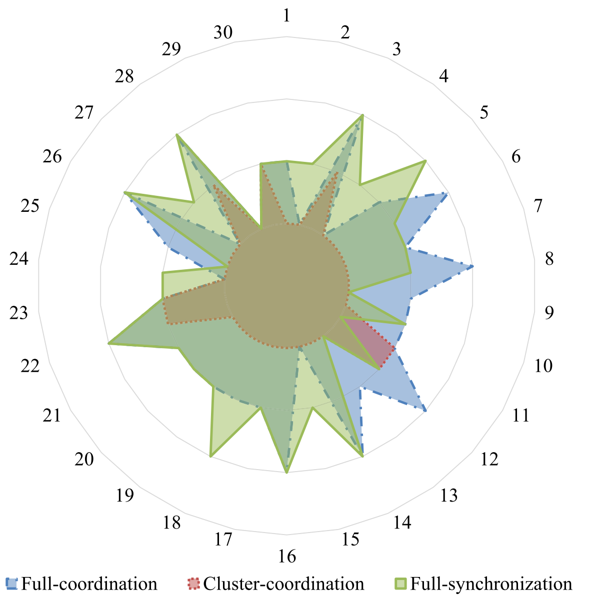

FIGURE 7. ISS classification versus cell index. Concentric circles depict the scale Ineffective (innermost circle), Somewhat Effective, Effective, and Highly Effective.

results in worse scores in many indicators except the BFI. Without the proposed mathematical framework, gauging the impact of a scheduling algorithm becomes harder as the relationship among the different network metrics cannot be clearly seen.

B. CLOSELY RELATED WORK

In [1], the authors present a through performance analysis of joint scheduling over TDD-OFDMA networks based on single indicators. The adopted indicators include throughput, interference, and traffic adaptation. The provided result visualizations enable the identifications of good performance aspects but in an almost isolated fashion among other metrics. In [1], three separate analysis scenarios are presented, namely, rate analysis, interference analysis, and traffic adaptability analysis. In the rate analysis scenario, the authors had to reason about the system behavior with focus on downlink and uplink throughput, while intuitively relating to the significant effect of interference power. Indeed, the BFI, as presented in this paper, nicely captures the result while analytically combining the throughput and interference. In the second scenario, the focus is on interference analysis. Again, the authors had to intuitively link back to the throughput results to draw specific conclusions. The third scenario focused on traffic adaptability. Clearly, the authors had to relate to the throughput and interference results to identify aspects of effective performance. In this investigation, throughput, interference, and traffic adaptability (fairness) are carefully combined and captured as the OPI. With not doubt, the remaining CMIs, namely JoSEI, NetPI, and AlgoP provide added values to the evaluation and provide a wide view of the attained network performance. The investigations in [4]–[11] follows a similar per-indicator performance evaluation approach as in [1]. The summary of limitations presented in Table 1 reveals the fact that common evaluations in the literature may overlook the use of some indicators that can affect the quest for high or optimal performance. In this paper, the proposed CMIs, and JoSEI's corresponding ANM and ISS schemes, elevate the discussions to the next level of performance evaluation through systematic, accurate, and convenient-to-deploy classification patterns of network performance that can surely lead to automated benchmarks within the context of application. The developed framework doesn't call for the elimination of the use of simple indicators, however, it stresses and enables the effective use of CMIs and classifiers in the evaluation process and the assurance of QoS.

C. LIMITATIONS AND FUTURE WORK

This section presents the limitations and future work as related to the choice of classifiers and the target application on joint scheduling over TDD-OFDMA.

1) CLASSIFICATION

The presented framework centers its analytics on standard statistical ANMs and the frequency of indicator's attainment of satisfaction–also referred to as the ISS. As for the ANM Scheme, it utilizes the calculations for the geometric mean, arithmetic mean, standard deviation, kurtosis, and skewness in defining the evaluation and classification chart. Although the effectiveness of the ANM scheme is validated and confirmed; by their very nature; there are always limitations to summary measures, and this applies to the mean, variance, skewness, as well as kurtosis [17], [18]. For instance, outliers, such as extreme values, can affect the aggregated results and accordingly the classification. The ISS scheme attempts to reduce or eliminate the effect of outliers through counting the number of indicators that achieve satisfactory performance. To that end, the rationale of classification rule choices is focused on what makes an execution effective and to what extent the classification decision is sensitive to the variability in the measured scores of individual indicators.

Although the attained Difference in Classification (δ_c); as in Fig. 8; is small or nil in most cases, the ANM and ISS still justify two different classifications that provide different evaluations in application and conclusions. In all, and among the three execution scenarios of the application in hand, 17.78% of executions are classified differently between the two proposed rules. The three executions that attain Somewhat Significant δ_c values are for cell indices of 11 and 13 under Cluster-coordination, and 19 under Full-synchronization (See Fig. 8). Reflecting on the scores of individual indicators confirms that the cause of differences are the individual low scores attained by several indicators. Accordingly, the several low indicator scores result in ISS ranks lower than those of the ANM. As explained in Section V-A, the ANM classification outcome in Fig. 6 shows a high percentage of effectiveness for the fully synchronized scheduling technique. However, the ISS classification scheme proficiently captures the performance trade-offs in the full-coordination case as it relies less on the obtained statistics and more on the percentage of satisfaction. Future work can include exploring the use of different statistical formulations or machine learning algorithms to develop additional classifiers at an added accuracy, convenience of deployment, and reduced computational complexity of classifiers.

2) APPLICATION

While the merits of the scheduling algorithm can be assessed through proper simulations, the performance of the practical implementation of the algorithm, such as on actual hardware, cannot be projected from the performed simulations. To that end, future work can include the hardware implementation of joint scheduling algorithms. JoSEI framework expansions can then include a hardware profile that captures additional performance characteristics, such as, area, throughput, power, etc. The proposed performance profiles can be made further diverse by including various options within a heterogeneous computing system. Combining heterogeneous performance indicators is an intrinsic feature of our proposed methodology. Accordingly, additional profiles can include indicators to capture the performance under Graphical Processing Units (GPUs), Field Programmable Gate Arrays (FPGAs), to name but a few [12], [19], [20]. Moreover, another direction of this work would be in a practical implementation of the joint algorithms using full-stack LTE simulators. The proposed mathematical framework would consequently allow the classification and ranking of joint scheduling algorithms in a realistic environment with standard-compliant simple and composite indicators.

At the application level, the developed framework can be used to examine qualities of importance and interest to developers or users in the wider networks context and beyond. For instance, the presented framework enables the ranking and classification of joint scheduling algorithms. Here, in JoSEI, the qualities of importance are algorithm complexity, network density, fairness, throughput and communication interference. The identified indicators are reusable in the wider networks context of applications. Work in progress includes developing an indicator for routing with low power over lossy networks (RPL) protocols [21], [22].

The framework proposed in this paper is reusable beyond computer networks. Damaj and Kasbah in [12] presented a customization within the area of computer security—cryptography in particular. The developed framework aimed at classifying cryptography algorithms according to their lightness. To that end, lightness is assumed to comprise high throughput at low hardware area utilization and power consumption. Future work can include developing classifiers for signal processing algorithms. The performance of signal processing algorithms is usually related to their accuracy and reliability [12]. Future work can include the development of a *Reliability and Accuracy Indicator* (*RAI*) to combine context-specific indicators that aid ranking and classifying signal processing algorithms per their effectiveness in application.

3) DECISION MAKING MODELS

The proposed analytical framework is developed upon the need to evaluate performance based on multiple, and sometimes conflicting, quantitative and qualitative indicators. The framework enables ranking executions according to their effectiveness and therefore can support a dependant decision making process. In some aspects, the proposed framework is similar to Multiple Criteria Decision Making (MCDM)—a sub-discipline of operations research [23], [24].

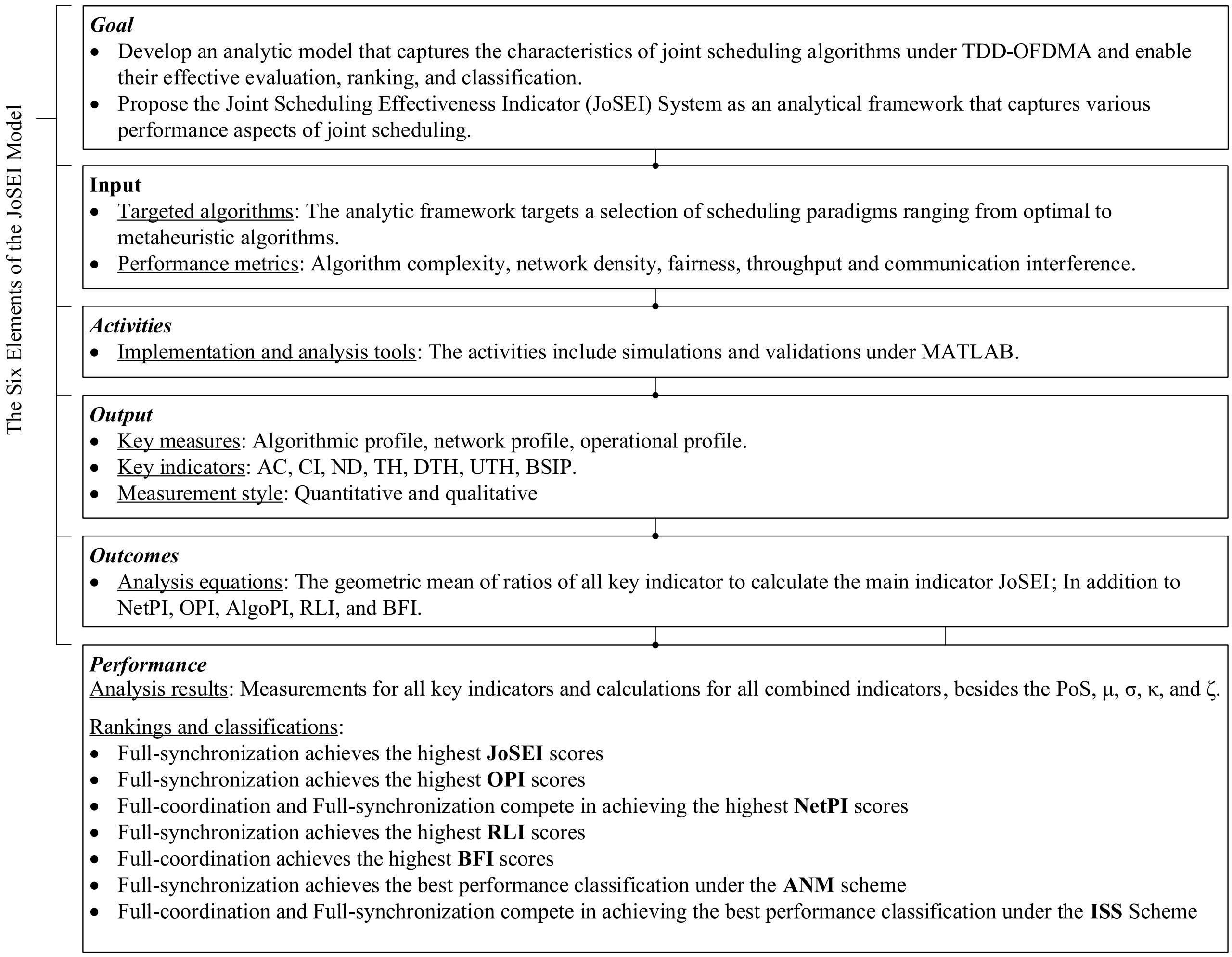

FIGURE 9. The six elements diagram of the JoSEI analytical framework.

MCDM techniques; such as VIKOR, TOPSIS, PROMETHEE, etc. [23]; and our proposed framework share a similar problem solving approach that can be summarized as follows:

1) Identify criteria, attributes, or indicators
2) Collect the appropriate information
3) Build a set of possible alternatives to guarantee that the goal is reachable
4) Identify an appropriate method to evaluate and rank alternatives

The main difference between existing MCDM techniques and the proposed framework is in the method to rank and evaluate alternatives. JoSEI framework enjoys several characteristics that are not necessarily part of traditional MCDM techniques. For instance, the proposed framework heavily relies on rubrics in an attempt to capture qualitative indicators, such as the algorithm complexity indicator (See Table 2), categorized performance levels, aggregate statistics, and performance grades (See Tables 3 through 8). Moreover, the proposed framework adopts the geometric mean calculation to determine its main CMIs; such a use is found in MCDM techniques, like the extended Analytic Hierarchy Process (AHP), to enable considering fuzzy linguistic variables. However, our proposed framework supports the use of geometric mean with aggregate statistics to accurately arrive at performance rankings and reduce the effect of outliers (See Section V-C). Indeed, the AHP technique is concerned with decision making based on hierarchical alternatives; this differs from the purpose of JoSEI to rank algorithm executions that does not necessarily follow a structured model.

The similarity in approach and characteristics between the proposed framework and MCDM enables several future work opportunities. Firstly, MCDM techniques can be further customized and applied to rank and classify the presented joint scheduling measurements. In addition, the proposed framework can be extended to consider weights and support hierarchical structures and accordingly be used as a Multiple Attribute Decision Making (MADM) technique. To that end, investigations to use the proposed framework within MCDM's traditional areas, such as economy and finance, can be carried out.

On the application level, to the best of our knowledge, the use of MCDM theory in the context of mobile communication systems has been scarce. This has been mainly due to the difficulty of establishing a set of mutually exclusive criteria, assigning weights and optimally solving the decision making problem.

The main attempts in the wireless communications literature are focused on specific problems, where a finite set of criteria can be established and traditional MCDM techniques can be used as is or slightly altered to solve the problem in hand. In [25], the TOPSIS algorithm is used to establish a cell selection paradigm during the handover process in LTE systems. The admission control problem in wireless heterogeneous networks is solved in [26] using the VIKOR method. Finally, TOPSIS is again used to establish proper content multicasting strategies in [27]. In the particular case of ranking scheduling algorithms, finding a finite set of criteria is problematic. Infinitesimally varying the initial problem definition leads to a different set of criteria and results in a different final solution. A future extension of this work would therefore consist of establishing and validating a set of criteria and then casting the problem as an MCDM one. Due to the intricacies of the resource allocation problem, a tailor-made MCDM technique needs to be developed to attempt reaching optimality in the decision making process.

VI. CONCLUSION

This work has presented a novel mathematical framework that aims at providing an objective and unified mechanism for benchmarking scheduling algorithms. The developed approach builds on traditional algorithm assessment techniques by identifying key performance indicators that reflect the network's operation under the considered scheduling paradigm. The defined indicators are then combined into composite indicators, aiming at identifying the intricate relation among the predefined performance measures. Then, rule-based classification schemes are utilized to assess the effectiveness of the scheduling algorithms. Numerical and analytical results presented in the sequel demonstrate how the proposed framework uncovers hidden links among the performance indicators, which traditional assessment techniques are usually oblivious to. This indeed provides a platform for more accurate and objective comparison among different scheduling approaches. In the case of TDD-OFDMA networks, the framework has in particular highlighted, in an automated manner, the trade-offs between interference from one side and throughput maximization and traffic adaptability from the other. The overall JoSEI framework and its six elements are summarized in Fig. 9. In all, the classification results confirm the competition between the full-synchronization and full-coordination schemes in achieving the best performance classifications. Future work includes developing additional schemes that comprise different statistical formulations and explore the effectiveness of machine learning algorithms in performing classifications.

APPENDIX
LIST OF ACRONYMS

Acronym	Definition
AlgoP	Algorithmic Profile
AC	Algorithm Complexity
AHP	Analytic Hierarchy Process
ANM	Aggregate Numerical Measures
AQ	Almost Quadratic
BFI	BS-BS Efficiency Indicator
BSIP	BS-BS Interference Power
CI	Communication Interference
CMI	Combined Measurement Indicator
DTH	Downlink Throughput
ET	Execution Time
E	Exponential
FN	Fairness
GBM	Generic Benchmark Model
ISS	Indicator Status Scheme
$\mathcal{J}$	Jain's Fairness Index
μ	Mean
JoSEI	Joint Scheduling Effectiveness Indicator
KI	Key Indicator
κ	Kurtosis
L	Linear
LH	Logarithmic High
LL	Logarithmic Low
MCDM	Multiple Criteria Decision Making
mMTC	Massive Machine Type Communications
NetP	Network Profile
ND	Network Density
OFDMA	Orthogonal Frequency Division Multiple Access
OP	Operational Profile
PoS	Percentage of Satisfaction
Q	Quadratic
RLI	Reliability Indicator
σ	Standard Deviation
ζ	Skewness
TDD	Time Division Duplexing
TH	Throughput
UTH	Uplink Throughput

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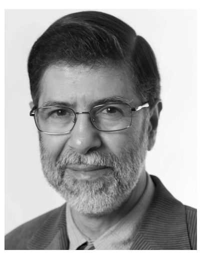

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