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(71) Applicant: **NOKIA SOLUTIONS AND NETWORKS OY** [FI/FI]; Karakaari 7, 02610 Espoo (FI).

(72) Inventor: **KELA, Kalle Petteri**; Kukkolankatu 4, 20780 Kaarina (FI).

(74) Agent: **NOKIA EPO REPRESENTATIVES**; Nokia Technologies Oy, Karakaari 7, 02610 Espoo (FI).

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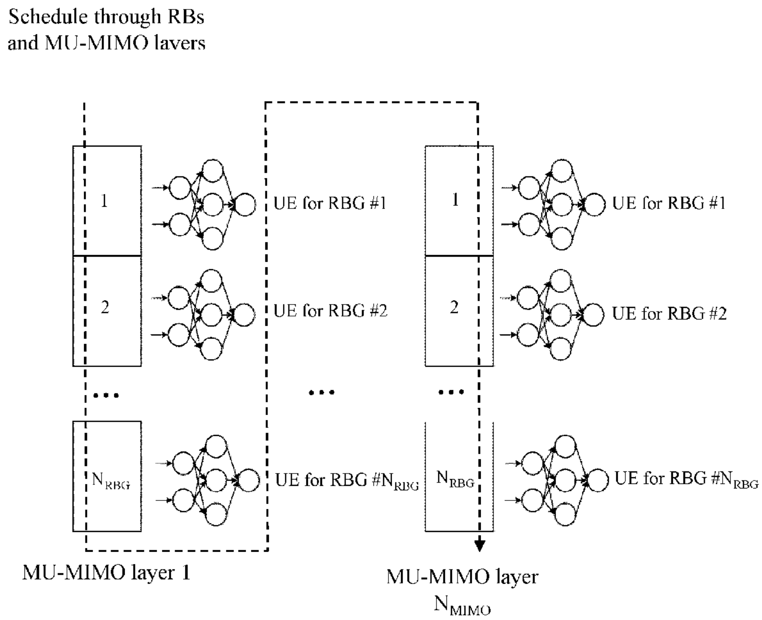

FIG. 4

(57) Abstract: A technical solution is provided, which allows Resource Blocks (RBs) or RB Groups (RBGs) to be scheduled simultaneously in frequency and spatial domains for UEs in a MU-MIMO-supported network. For this purpose, a list of UEs is obtained, for which available RBs or RBGs are to be scheduled for use in MU-MIMO layers for a target TTI. Each MU-MIMO layer is assigned to a different UE and comprises the available RBs or RBGs. Then, a data vector for each RB or RBG in each MU-MIMO layer is obtained. The data vector comprises frequency-specific information indicating a channel state of each of the UEs and a spatial correlation value indicating whether the UEs are spatially separable by using beamforming. Next, the RBs or RBGs are scheduled for the UEs for the TTI by using an ML model configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG. Each scheduling decision indicates whether a certain RB or RBG is to be scheduled for one or more of the UEs.

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RESOURCE BLOCK SCHEDULING IN WIRELESS COMMUNICATION NETWORK

TECHNICAL FIELD

The present disclosure relates generally to the field of wireless communications. In particular, the present disclosure relates to a Resource Block (RB) scheduling apparatus and method in a wireless communication network, as well as to a corresponding computer program product.

BACKGROUND

It has been recently shown that a properly configured machine learning (ML) model can learn to efficiently allocate Resource Blocks (RBs) (i.e., time-frequency resources) or Resource Block Groups (RBGs) (each typically including 4-16 continuous RBs) to User Equipments (UEs). In this sense, a ML-based RB scheduler can replace the existing RB schedulers relying on heuristic algorithms. More specifically, it has been also shown that the ML-based RB scheduler can outperform the heuristic RB schedulers in spectral efficiency. Furthermore, the ML-based RB scheduler has been proved to dominate in scheduling execution time, by doing real-time RB scheduling decisions for uplink approximately 70-80% faster than the existing RB schedulers using pretty complex state-of-the-art heuristic uplink scheduling algorithms.

Despite the above-indicated domination of the ML-based RB scheduler in the spectral efficiency and the real-time execution time, there is room for further improvements of the ML-based RB scheduler. In particular, one significant question is still left open, namely: how to embed spatial domain (SD) scheduling into the concept of the ML-based RB scheduler. If several UEs can be spatially multiplexed or separated in the same RB, the ML-based RB scheduler must perform such co-scheduling such that it does not degrade the overall network performance.

SUMMARY

This summary is provided to introduce a selection of concepts in a simplified form that are further described below in the detailed description. This summary is not intended to identify key features of the present disclosure, nor is it intended to be used to limit the scope of the present disclosure.

It is an objective of the present disclosure to provide a technical solution that allows RBs or RBGs to be scheduled simultaneously in frequency and spatial domains for UEs in a wireless communication network supporting the MU-MIMO technology.

The objective above is achieved by the features of the independent claims in the appended claims. Further embodiments and examples are apparent from the dependent claims, the detailed description, and the accompanying drawings.

According to a first aspect, an RB scheduling apparatus in a wireless communication network is provided. The apparatus comprises at least one processor and at least one memory storing instructions that, when executed by the at least one processor, cause the apparatus to operate at least as follows. At first, the apparatus obtains a list of UEs for which a set of RBs or RBGs is to be scheduled for a target Transmission Time Interval (TTI). The set of RBs or RBGs is shared by a set of MU-MIMO layers supported by a network node in the wireless communication network. Each MU-MIMO layer of the set of MU-MIMO layers is assigned to a different UE of the list of UEs. Then, the apparatus obtains a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers. The data vector comprises a frequency-specific value and a spatial correlation value. The frequency-specific value indicates a channel state of each UE of the list of UEs. The spatial correlation value indicates whether the UEs of the list of UEs are spatially separable by using beamforming. After that, the apparatus schedules the set of RBs for the list of UEs for the target TTI by using a ML model. The ML model comprises at least one Neural Network (NN) configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs. The scheduling decision indicates whether the RB or RBG is to be scheduled for one or more UEs of the list of UEs. The apparatus thus configured may take MU-MIMO aspects (i.e., the spatial diversity of the UEs) into account when scheduling (both downlink (DL) and uplink (UL)) RBs or RBGs for the UEs. Furthermore, the apparatus thus configured may perform the frequency and spatial domain RB scheduling regardless of: a maximum number of UEs to be scheduled to RBs or RBGs, a physical layer numerology/bandwidth (i.e., a number of RBs or RBGs per TTI), (digital/analog/hybrid) conventional and/or ML-based beamformers used in the MU-MIMO network, and a number of Radio Frequency (RF) chains determining a maximum number of spatially scheduled UEs.

In one example embodiment of the first aspect, the spatial correlation value comprises at least one of: a singular value decomposition of combined precoders of the UEs of the list of UEs, a Power Normalization Loss (PLN) value calculated for each UE of the list of UEs, and an estimation of a throughput increase caused by scheduling each UE to an additional MU-MIMO layer. By using these spatial correlation values, the NN(s) may obtain efficient (in terms of spatial domain (SD) scheduling) decisions for the set of RBs or RBGs.

In one example embodiment of the first aspect, the frequency-specific value comprises at least one of: Channel State Information (CSI) in the RB or RBG, a past average DL throughput in the RB or RBG, a past average UL throughput in the RB or RBG, a number of already scheduled other RBs or RBGs of the set of RBs or RBGs, an average size of transmitted DL packets in the RB or RBG, an average size of transmitted UL packets in the RB or RBG, a Modulation and Coding Scheme (MCS), and a scheduling decision made for the previous RB or RBG of the set of RBs or RBGs. By using this additional information, the NN(s) may obtain the most efficient (in terms of the combined FD and SD scheduling) decisions for the set of RBs or RBGs.

In one example embodiment of the first aspect, the CSI comprises at least one of: a Radio Resource Management (RRM) measurement for the RB or RBG, a RRM measurement for a sub-band comprising the RB or RBG, and a RRM measurement averaged over an entire bandwidth comprising the sub-band. The RRM measurement may comprise a Signal-to-Interference-plus-Noise (SINR), a Received Signal Received Power (RSRP), a Received Signal Received Quality (RSRQ), a Channel Quality Indicator (CQI), and/or any other signal quality parameter. By using this CSI, the efficiency of the scheduling decisions outputted by the NN(s) may be improved even more.

In one embodiment of the first aspect, the at least one NN is trained based on a sequence of tuples by using a reinforcement learning algorithm. Each tuple of the sequence of tuples comprises: a data vector obtained for a target RB or RBG of the set of RBs or RBGs for a target MU-MIMO layer of the set of MU-MIMO layers for the target TTI; a scheduling decision outputted by the at least one NN for the target RB or RBG; a performance reward resulted from the scheduling decision for the target RB or RBG; and a data vector obtained for one of: (i) a subsequent RB or RBG of the set of RBs or RBGs for the target MU-MIMO layer for the target TTI; (ii) the target RB or RBG for a subsequent MU-MIMO layer of the set of MU-MIMO layers for the target TTI; and (iii) the target RB or RBG for the target MU-MIMO layer for a subsequent TTI. By doing so, it is possible to train the NN(s) for the FD and SD RB scheduling in the most efficient way (i.e., with good performance vs complexity characteristics). Furthermore, since the fourth element in each tuple can be either a next RB for the same MU-MIMO layer, the same RB for a next MU-MIMO layer, or the same RB for a next TTI, it is possible to train the NN(s) to achieve a high long-term reward by performing seamless transitions over either the RBs or RBGs, or the MU-MIMO layers, or the TTIs (in all cases, the training performance is similar, but if the transitions are performed over the RBs or RBGs, it may provide better performance when training continuous RB or RBG allocations, for example, for single carrier waveforms, such as DFT-s-OFDM).

In one example embodiment of the first aspect, the at least one NN comprises a set of NNs each configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs but for a different MU-MIMO layer of the set of MU-MIMO layers. By using the set of NNs, it is possible to obtain the scheduling decisions for all MU-MIMO layers in parallel, thereby decreasing the time required for the whole RB scheduling process.

In another example embodiment of the first aspect, the at least one NN comprises a single NN configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers. This embodiment can be used when it is impossible to use a different NN for each MU-MIMO layer (e.g., due to computing resource exhaustion).

According a second aspect, an RB scheduling method in a wireless communication network is provided. The method starts with the step of obtaining a list of UEs for which a set of RBs or RBGs is to be scheduled for a target TTI. The set of RBs or RBGs is shared by a set of MU-MIMO layers supported by a network node in the wireless communication network. Each MU-MIMO layer of the set of MU-MIMO layers is assigned to a different UE of the list of UEs. Then, the method proceeds to the step of obtaining a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers. The data vector comprises frequency-specific information and a spatial correlation value. The frequency-specific information indicates a channel state of each UE of the list of UEs. The spatial correlation value indicates whether the UEs of the list of UEs are spatially separable by using beamforming. After that, the method goes on to the step of scheduling the set of RBs or RBGs for the list of UEs for the target TTI by using an ML model. The ML model comprises at least one NN configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs. The scheduling decision indicates whether the RB or RBG is to be scheduled for one or more UEs of the list of UEs. By doing so, it is possible to take MU-MIMO aspects (i.e., the spatial diversity of the UEs) into account when scheduling (either DL or UL) RBs or RBGs for the UEs. Furthermore, the frequency and spatial domain RB or RBG scheduling may be performed regardless of: a maximum number of UEs to be scheduled to RBs or RBGs, a physical layer numerology/bandwidth (i.e., a number of RBs or RBGs per TTI), (digital/analog/hybrid) conventional and/or ML-based beamformers used in the MU-MIMO network, and a number of RF chains determining a maximum number of spatially scheduled UEs.

In one example embodiment of the second aspect, the spatial correlation value comprises at least one of: a singular value decomposition of combined precoders of the UEs of the list of UEs; and a PLN value calculated for each UE of the list of UEs. By using these spatial correlation values, the NN(s) may obtain efficient (in terms of the SD scheduling) decisions for the set of RBs or RBGs.

In one example embodiment of the second aspect, the frequency-specific information comprises at least one of: CSI in the RB or RBG, a past average DL throughput in the RB or RBG, a past average UL throughput in the RB or RBG, a number of already scheduled other RBs or RBGs of the set of RBs or RBGs, an average size of transmitted DL packets in the RB or RBG, an average size of transmitted UL packets in the RB or RBG, a MCS, and a scheduling decision made for the previous RB or RBG of the set of RBs or RBGs. By using this additional information, the NN(s) may obtain the most efficient (in terms of the combined FD and SD scheduling) decisions for the set of RBs or RBGs.

In one example embodiment of the second aspect, the CSI comprises at least one of: a RRM measurement for the RB or RBG, a RRM measurement for a sub-band comprising the RB or RBG, and a RRM measurement averaged over an entire bandwidth comprising the sub-band. The RRM measurement may comprise a SINR, a RSRP, a RSRQ, a CQI, and/or any other signal quality parameter. By using this CSI, the efficiency of the scheduling decisions outputted by the NN(s) may be improved even more.

In one example embodiment of the second aspect, the at least one NN is trained based on a sequence of tuples by using a reinforcement learning algorithm. Each tuple of the sequence of tuples comprises: a data vector obtained for a target RB or RBG of the set of RBs or RBGs for a target MU-MIMO layer of the set of MU-MIMO layers for the target TTI; a scheduling decision outputted by the at least one NN for the target RB or RBG; a performance reward resulted from the scheduling decision for the target RB or RBG; and a data vector obtained for one of: (i) a subsequent RB or RBG of the set of RBs or RBGs for the target MU-MIMO layer for the target TTI, (ii) the target RB or RBG for a subsequent MU-MIMO layer of the set of MU-MIMO layers for the target TTI, and (iii) the target RB or RBG for the target MU-MIMO layer for a subsequent TTI. By doing so, it is possible to train the NN(s) for the FD and SD RB or RBG scheduling in the most efficient way (i.e., with good performance vs complexity characteristics). Furthermore, since the fourth element in each tuple can be either a next RB for the same MU-MIMO layer, the same RB for a next MU-MIMO layer, or the same RB for a next TTI, it is possible to train the NN(s) to achieve a high long-term reward by performing seamless transitions over either the RBs or RBGs, or the MU-MIMO layers, or the TTIs (in all cases, the training performance is similar, but if the transitions are performed over the RBs or RBGs, it may provide better performance when training continuous RB or RBG allocations, for example, for single carrier waveforms, such as DFT-s-OFDM).

In one example embodiment of the second aspect, the at least one NN comprises a set of NNs each configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs but for a different MU-MIMO layer of the set of MU-MIMO layers. By using the set of NNs, it is possible to obtain the scheduling decisions for all MU-MIMO layers in parallel, thereby decreasing the time required for the whole RB scheduling process.

In another example embodiment of the second aspect, the at least one NN comprises a single NN configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers. This embodiment can be used when it is impossible to use a different NN for each MU-MIMO layer (e.g., due to computing resource exhaustion).

According to a third aspect, a computer program product is provided. The computer program product comprises a computer-readable storage medium that stores a computer code. Being executed by at least one processor, the computer code causes the at least one processor to perform the method according to the second aspect. By using such a computer program product, it is possible to simplify the implementation of the method according to the second aspect in any computing device, like the apparatus according to the first aspect.

According to a fourth aspect, an RB scheduling apparatus in a wireless communication network is provided. The apparatus comprises a means for obtaining a list of UEs for which a set of RBs or RBGs is to be scheduled for a target TTI. The set of RBs or RBGs is shared by a set of MU-MIMO layers supported by a network node in the wireless communication network. Each MU-MIMO layer of the set of MU-MIMO layers is assigned to a different UE of the list of UEs. The apparatus further comprises a means for obtaining a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers. The data vector comprises frequency-specific information and a spatial correlation value. The frequency-specific information indicates a channel state of each UE of the list of UEs. The spatial correlation value indicates whether the UEs of the list of UEs are spatially separable by using beamforming. The apparatus further comprises a means for scheduling the set of RBs or RBGs for the list of UEs for the target TTI by using a ML model. The ML model comprises at least one NN configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs. The scheduling decision indicates whether the RB or RBG is to be scheduled to one or more UEs of the list of UEs. The apparatus thus configured may take MU-MIMO aspects (i.e., the spatial diversity of the UEs) into account when scheduling (both DL and UL) RBs or RBGs for the UEs. Furthermore, the apparatus thus configured may perform the frequency and spatial domain RB or RBG scheduling regardless of: a maximum number of UEs to be scheduled to RBs or RBGs, a physical layer numerology/bandwidth (i.e., a number of RBs or RBGs per TTI), (digital/analog/hybrid) conventional and/or ML-based beamformers used in the MU-MIMO network, and a number of RF chains determining a maximum number of spatially scheduled UEs.

Other features and advantages of the present disclosure will be apparent upon reading the following detailed description and reviewing the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

The present disclosure is explained below with reference to the accompanying drawings in which:

FIG. 1 shows a block diagram of a wireless communication system in accordance with the prior art;

FIG. 2 shows a block diagram of a Resource Block (RB) scheduling apparatus in a wireless communication network in accordance with one example embodiment;

FIG. 3 shows a flowchart of a method for operating the apparatus of FIG. 2 in accordance with one example embodiment;

FIG. 4 explains how a Neural Network (NN) used in the method of FIG. 3 may process data vectors obtained for RBs or RBGs for each MU-MIMO layer to make RB or RBG scheduling decisions;

FIG. 5 shows an exemplary RB scheduling table comprising the scheduling decisions made by the NN used in the method of FIG. 3 and rewards for the scheduling decisions;

FIG. 6 shows two possible options how a processor included in the apparatus of FIG. 2 may construct tuples to be fed to the NN for its training;

FIG. 7 shows a Cumulative Distribution Function (CDF) versus the CPU execution time required for doing the scheduling decisions per TTI in a system level simulator for two cases: the frequency selective even RB scheduling (dashed curve) and the RB scheduling based on the method of FIG. 3 (solid curve);

FIGs. 8A and 8B show a throughput performance of Spatial Domain (SD) scheduling for a UE throughput and a cell throughput, respectively;

FIG. 9 shows a reward evolution with 1000 step observation windows during the first 300000 simulation steps equal to ~21 seconds in real time; and

FIGs. 10A and 10B show, respectively, a DL windowed UE throughput and first MU-MIMO layer scheduling CPU time which are obtained by using the apparatus of FIG. 2 in accordance with the method of FIG. 3 and the prior art Proportional Fair (PF) FD scheduler with a decoupled greedy SD scheduler.

DETAILED DESCRIPTION

Various embodiments of the present disclosure are further described in more detail with reference to the accompanying drawings. However, the present disclosure can be embodied in many other forms and should not be construed as limited to any certain structure or function discussed in the following description. In contrast, these embodiments are provided to make the description of the present disclosure detailed and complete.

According to the detailed description, it will be apparent to the ones skilled in the art that the scope of the present disclosure encompasses any embodiment thereof, which is disclosed herein, irrespective of whether this embodiment is implemented independently or in concert with any other embodiment of the present disclosure. For example, the apparatus and method disclosed herein can be implemented in practice by using any numbers of the embodiments provided herein. Furthermore, it should be understood that any embodiment of the present disclosure can be implemented using one or more of the elements presented in the appended claims.

Unless otherwise stated, any embodiment recited herein as “example embodiment” should not be construed as preferable or having an advantage over other embodiments.

According to the example embodiments disclosed herein, a User Equipment (UE) may refer to an electronic computing device that is configured to perform wireless communications. The UE may be implemented as a mobile station, a mobile terminal, a mobile subscriber unit, a mobile phone, a cellular phone, a smart phone, a cordless phone, a personal digital assistant (PDA), a wireless communication device, a desktop computer, a laptop computer, a tablet computer, a gaming device, a netbook, a smartbook, an ultrabook, a medical mobile device or equipment, a biometric sensor, a wearable device (e.g., a smart watch, smart glasses, a smart wrist band, etc.), an entertainment device (e.g., an audio player, a video player, etc.), a vehicular component or sensor (e.g., a driver-assistance system), a smart meter/sensor, an unmanned vehicle (e.g., an industrial robot, a quadcopter, etc.) and its component (e.g., a self-driving car computer), industrial manufacturing equipment, a global positioning system (GPS) device, an Internet-of-Things (IoT) device, an Industrial IoT (IIoT) device, a machine-type communication (MTC) device, a group of Massive IoT (MIoT) or Massive MTC (mMTC) devices/sensors, or any other suitable mobile device configured to support wireless communications. In some embodiments, the UE may refer to at least two collocated and inter-connected UEs thus defined.

As used in the example embodiments disclosed herein, a network node may refer to a node in any of a Radio Access Network (RAN) and a Core Network (CN). It should be noted that the CN may refer to a network intended for connecting different RAN nodes by providing proper interfaces therebetween. The CN may also provide a gateway to other networks, for example, a Data Network (DN).

Being part of the RAN, the network node may be implemented as a fixed point of communication/communication node for a UE in a particular wireless communication network. More specifically, the RAN node may be used to connect the UE to the DN through the CN and may be referred to as a base transceiver station (BTS) in terms of the 2G communication technology, a NodeB in terms of the 3G communication technology, an evolved NodeB (eNodeB) in terms of the 4G communication technology, and a gNB in terms of the 5G New Radio (NR) communication technology. The RAN node may serve different cells, such as a macrocell, a microcell, a picocell, a femtocell, and/or other types of cells. The macrocell may cover a relatively large geographic area (for example, at least several kilometers in radius). The microcell may cover a geographic area less than two kilometers in radius, for example. The picocell may cover a relatively small geographic area, such, for example, as offices, shopping malls, train stations, stock exchanges, etc. The femtocell may cover an even smaller geographic area (for example, a home).

Being part of the CN, the network node may also refer to any of CN network functions, such as an Access and Mobility Management Function (AMF), a Session Management Function (SMF), Unified Data Management (UDM), User Plane Function (UPF), Policy Control Function (PCF), etc. The AMF supports termination of Non-Access Stratum (NAS) signalling, NAS ciphering and integrity protection, registration management, connection management, mobility management, access authentication and authorization, security context management. The SMF supports session management (session establishment, modification, release), UE IP address allocation and management, Dynamic Host Configuration Protocol (DHCP) functions, termination of NAS signalling related to the session management, downlink (DL) data notification, traffic steering configuration for the UPF for proper traffic routing. UDM supports Authentication and Key Agreement (AKA) credentials generation, user identification handling, access authorization, subscription management. The UPF supports packet routing and forwarding, packet inspection, Quality of Service (QoS) handling, acts as an external Protocol Data Unit (PDU) session point of interconnect to the DN, and is an anchor point for intra- and inter- Radio Access Technology (RAT) mobility. The PCF supports a unified policy framework, providing policy rules to Control Plane (CP) functions, access subscription information for policy decisions in a Unified Data Repository (UDR).

According to the example embodiments disclosed herein, a wireless communication network, in which one or more network nodes communicate with each other and/or with one or more UEs, may refer to a cellular or mobile network, a Wireless Local Area Network (WLAN), a Wireless Personal Area Networks (WPAN), a Wireless Wide Area Network (WWAN), a satellite communication (SATCOM) system, or any other type of wireless communication networks. Each of these types of wireless communication networks supports wireless communications according to one or more communication protocol standards. For example, the cellular network may operate according to the Global System for Mobile Communications (GSM) standard, the Code-Division Multiple Access (CDMA) standard, the Wide-Band Code-Division Multiple Access (WCDM) standard, the Time-Division Multiple Access (TDMA) standard, or any other communication protocol standard, the WLAN may operate according to one or more versions of the IEEE 802.11 standards, the WPAN may operate according to the Infrared Data Association (IrDA), Wireless USB, Bluetooth, or ZigBee standard, and the WWAN may operate according to the Worldwide Interoperability for Microwave Access (WiMAX) standard.

In the example embodiments disclosed herein, Multi-User Multiple Input Multiple Output (MU-MIMO) may refer to a communication technology at which a plurality of UEs communicate with a network node by using the same time-frequency resources (i.e., resource blocks (RBs) or RB Groups (RBGs), and the network node considers communication signals from the UEs as MIMO signals and separates the signals accordingly. The MU-MIMO technology may be considered as Space-Division Multiple Access (SDMA) using a spatial channel as a resource in addition to the conventional time-frequency resources. In the MU-MIMO technology, two or more UEs are appropriately (by specially designed DL and UL schedulers usually resided in a RAN node) selected to transmit and receive data at the same time by using the same RBs or RBGs. With this, a large multi-user diversity effect can be obtained, and the cell capacity of the whole wireless communication system can be improved.

FIG. 1 shows a block diagram of a wireless communication system 100 in accordance with the prior art. The system 100 comprises a (conventional or ML-based) receiver 102, a (conventional or ML-based) transmitter 104, and a ML-based RB scheduler 106. The ML-based RB scheduler 106 is typically provided in a RAN node (e.g., gNB). The receiver 102 and the transmitter 104 are assumed to be implemented in a single UE, and the ML-based RB scheduler 106 is assumed to communicate with them by using a Single-User MIMO (SU-MIMO) technology. As shown in FIG. 1, the ML-based RB scheduler 106 is configured to rule both the receiver 102 and the transmitter 104. In other words, the ML-based RB scheduler 106 can perform both DL and UL RB or RBG scheduling for any number of MIMO layers in the SU-MIMO network. However, if the SU-MIMO technology is replaced with a MU-MIMO technology in the system 100, the ML-based RB scheduler 106 will need to be further improved such that it is able to consider the MU-MIMO aspects (i.e., spatial diversity or spatial correlation) when performing the DL and UL RB or RBG scheduling for multiple UEs.

The example embodiments disclosed herein provide a technical solution that allows RBs or RBGs to be scheduled in both frequency and spatial domains for UEs in a wireless communication network supporting the MU-MIMO technology. For this purpose, a list of UEs is obtained, for which a set of RBs or RBGs is to be scheduled for a target TTI. The set of RBs or RBGs is shared by a set of MU-MIMO layers each assigned to a different UE of the list of UEs. Then, a data vector for each RB or RBG for each MU-MIMO layer is obtained. The data vector comprises frequency-specific information and a spatial correlation value. The frequency-specific information indicates a channel state of each UE of the list of UEs for the corresponding RB or RBG, while the spatial correlation value indicates whether the UEs of the lists of UEs are spatially separable for the corresponding RB or RBG by using beamforming. After that, the set of RBs or RBGs is scheduled for the list of UEs for the target TTI by using an ML model. The ML model comprises at least one NN configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs. Each scheduling decision indicates whether a certain RB or RBG of the set of RBs or RBGs is to be scheduled for one or more UEs of the list of UEs.

FIG. 2 shows a block diagram of an RB scheduling apparatus 200 in a wireless communication network in accordance with one example embodiment. The apparatus 200 may be used instead of the ML-based RB scheduler 106 in the system 100 to take account of the MU-MIMO aspects when performing the DL and UL RB or RBG scheduling. It should be noted that the apparatus 200 may be implemented either as part of a network node (RAN or CN node) or as an individual apparatus connected to the network node by means of wire or wirelessly. As shown in FIG. 2, the apparatus 200 comprises a processor 202 and a memory 204. The memory 204 stores processor-executable instructions 206 which, when executed by the processor 202, cause the processor 202 to perform the aspects of the present disclosure, as will be described below in more detail. It should be noted that the number, arrangement, and interconnection of the constructive elements constituting the apparatus 200, which are shown in FIG. 2, are not intended to be any limitation of the present disclosure, but merely used to provide a general idea of how the constructive elements may be implemented within the apparatus 200. For example, the processor 202 may be replaced with several processors, as well as the memory 204 may be replaced with several removable and/or fixed storage devices, depending on particular applications. Furthermore, in some embodiments, the processor 202 may perform different operations required to perform data reception and transmission, such, for example, as signal modulation/demodulation, encoding/decoding, etc. Alternatively, the apparatus 200 may further comprise an individual transceiver which can be configured to perform the required operations for data reception and transmission based on commands from the processor 202.

The processor 202 may be implemented as a CPU, general-purpose processor, single-purpose processor, microcontroller, microprocessor, application specific integrated circuit (ASIC), field programmable gate array (FPGA), digital signal processor (DSP), complex programmable logic device, etc. It should be also noted that the processor 202 may be implemented as any combination of one or more of the aforesaid. As an example, the processor 202 may be a combination of two or more microprocessors.

The memory 204 may be implemented as a classical nonvolatile or volatile memory used in the modern electronic computing machines. As an example, the nonvolatile memory may include Read-Only Memory (ROM), ferroelectric Random-Access Memory (RAM), Programmable ROM (PROM), Electrically Erasable PROM (EEPROM), solid state drive (SSD), flash memory, magnetic disk storage (such as hard drives and magnetic tapes), optical disc storage (such as CD, DVD and Blu-ray discs), etc. As for the volatile memory, examples thereof include Dynamic RAM, Synchronous DRAM (SDRAM), Double Data Rate SDRAM (DDR SDRAM), Static RAM, etc.

The processor-executable instructions 206 stored in the memory 204 may be configured as a computer-executable program code which causes the processor 202 to perform the aspects of the present disclosure. The computer-executable program code for carrying out operations or steps for the aspects of the present disclosure may be written in any combination of one or more programming languages, such as Java, C++, Python, or the like. In some examples, the computer-executable program code may be in the form of a high-level language or in a pre-compiled form and be generated by an interpreter (also pre-stored in the memory 204) on the fly.

FIG. 3 shows a flowchart of a method 300 for operating the apparatus 200 in accordance with one example embodiment.

The method 300 starts with a step S302, in which the processor 202 obtains a list of UEs for which a set of RBs or RBGs is to be scheduled for a target TTI. The set of RBs or RBGs is shared by a set of MU-MIMO layers each assigned to a different UE of the list of UEs. The list of UEs may comprise all UEs that have or is expected to have data in a DL or UL transmission buffer, respectively. Furthermore, the list of UEs may be a shortlisted subset of all UEs with non-empty transmission buffers. Said subset may be generated by calculating scheduling priority metrics. Such metrics may be based on randomization, expected throughput, past average throughput, channel state information, or anything derived from these metrics. Additionally, the list of UEs may be obtained based on a priority value assigned to each UE in the network. On top of that, the selection of UEs for which the set of RBs or RGs is to be scheduled may be selected randomly, by using a round robin principle, proportional-fair scheduling, Quality-of-Service (QoS) priority-based approach, or any combination thereof. It should be noted that the processor 202 may obtain the list of UEs by itself or, if the apparatus 200 is implemented as an individual apparatus, may receive it from a network node (e.g., a gNB).

Then, the method 300 proceeds to a step S304, in which the processor 202 obtains a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-

MIMO layers. The data vector comprises frequency-specific information and a spatial correlation value. The frequency-specific information is assumed to indicate a channel state of each UE of the list of UEs, while the spatial correlation value is assumed to indicate whether the UEs of the list of UEs are spatially separable by using beamforming. Similarly, the processor 202 may create the data vector by itself or may receive it from the network node. The spatial correlation value should hint towards the spatial correlation of UEs to be potentially spatially co-scheduled to the same RB or RBG with the already scheduled UEs on the same RB or RBG.

For example, for each RB or RBG, the spatial correlation value may be represented by a Singular Value Decomposition (SVD) of combined precoders of the UEs of the list of UEs. When scheduling the first MU-MIMO layer, a default value of 0 or 1.0 may be used as the spatial correlation value. For other MU-MIMO layers, the SVD is calculated with already scheduled (for the same RB/RBG) UEs' precoders and a new UE whose input value is calculated. Furthermore, the spatial correlation value may be additionally or alternatively represented by a Power Normalization Loss (PLN) value calculated for each UE of the list of UEs. Alternatively or additionally, the spatial correlation value may be based on an estimated throughput calculated for each UE. However, the throughput estimation would increase computational complexity due to required MU-MIMO precoder calculations. If a certain UE of the list of UEs is already scheduled for a certain RB or RBG of the set of RBs or RBGs, all the inputs for that UE may be masked to zero for remaining the MU-MIMO layers for that particular RB or RBG.

Any other spatial correlation values may be used. The principle is that a single value should hint towards channel correlation between the already scheduled UEs and a new scheduling candidate UE. As one more additional or alternative example, an estimation of a throughput increase caused by scheduling each UE to an additional MU-MIMO layer may be used as (part of) the spatial correlation value. For doing that, the processor 202 has to calculate new MU-MIMO precoders (e.g., zero forcing precoders) for scheduling a candidate UE taking into account the already scheduled UEs for the RB or RBG and the candidate UE. Then, by calculating the precoder's estimated effect on a SINR and selecting an appropriate MCS for that SINR, throughput estimations can be derived for each UE for the RB/RBG. The same can also be calculated without new candidate UEs to have a value by which to compare whether the sum throughput increases or not by scheduling a new UE to an additional MU-MIMO layer.

All of this may be done separately for each candidate UE to see, e.g., which scheduling selections increase the sum throughput estimate and which not.

In some embodiments, the frequency-specific information may comprise at least one of: Channel State Information (CSI) in the RB or RBG, a past average DL throughput in the RB or RBG, a past average UL throughput in the RB or RBG, a number of already scheduled other RBs or RBGs of the set of RBs or RBGs, an average size of transmitted DL packets in the RB or RBG, an average size of transmitted UL packets in the RB or RBG, a Modulation and Coding Scheme (MCS), and a scheduling decision made for the previous RB or RBG of the set of RBs or RBGs. The CSI may comprise at least one of a Radio Resource Management (RRM) measurement for the RB or RBG, a RRM measurement for a sub-band comprising the RB or RBG, and a RRM measurement averaged over an entire bandwidth comprising the sub-band. The RRM measurement may comprise a SINR, a RSRP, a RSRQ, a CQI, and/or any other signal quality parameter. The knowledge of the scheduling decision made for the previous RB or RBG of the set of RBs or RBGs may help the processor 202 provide continuous RB or RBG allocations required for continuous waveforms.

After the step S304, the method 300 goes on to a step S306, in which the processor 202 schedules the set of RBs or RBGs for the list of UEs for the target TTI by using an ML model. The ML model comprises at least one NN configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs. The scheduling decision indicates whether the RB or RBG is to be scheduled for one or more UEs of the list of UEs. In other words, the NN(s) output(s) optimal UE selection for each RB or RBG and each MU-MIMO layer.

FIG. 4 explains how the NN used in the method 300 may process the data vectors obtained for the RBs or RBGs for each MU-MIMO layer to make the scheduling decisions for the RBs or RBGs. In FIG. 4, it is assumed that only one NN is used, which may process the data vectors one by one, thereby outputting the scheduling decisions for the RBs or RBGs one by one in the order of the RBs or the RBGs in each MU-MIMO layer (see the dashed line in FIG. 4). If a set of NNs is used with each of them being assigned to a different MU-MIMO layer, the scheduling decisions may be outputted for the RBs or RBGs in parallel.

In one example embodiment, the NN used in the step S306 may be trained (in advance or online during the method 300) based on a sequence of tuples by using a reinforcement learning algorithm (e.g., a DDQN based reinforcement learning algorithm). Each tuple of the sequence of tuples comprises: (a) a data vector obtained for a target RB or RBG of the set of RBs or RBGs for a target MU-MIMO layer of the set of MU-MIMO layers for the target TTI; (b) a scheduling decision outputted by the NN for the target RB or RBG; (c) a performance reward resulted from the scheduling decision for the target RB or RBG; and (d) a data vector obtained for one of: (i) a subsequent RB or RBG of the set of RBs or RBGs for the target MU-MIMO layer for the target TTI, (ii) the target RB or RBG for a subsequent MU-MIMO layer of the set of MU-MIMO layers for the target TTI, and (iii) the target RB or RBG for the target MU-MIMO layer for a subsequent TTI.

Once the step S306 is finished, the ML model may output a table of all scheduling decisions each indicating N optimal UEs of the list of UEs for each RB or RBG for each MU-MIMO layer, where N is the maximum number of beams that may be formed/selected spatially for the same RB(s) or RBG(s).

FIG. 5 shows an exemplary RB scheduling table 500 comprising the scheduling decisions made by the NN used in the step S306 of the method 300 and rewards for the scheduling decisions. In the table 500, each column corresponds to one MU-MIMO layer of the set of MU-MIMO layers, while each row corresponds to one RB of the set of RBs. As can be seen, the scheduling decision for UE1 consists in that each of the RBs should be scheduled for UE1 in the first MU-MIMO layer, the scheduling decision for UE2 consists in that only the first two RBs should be scheduled for UE2 in the second MU-MIMO layer, and the scheduling decision for UE3 consists in that only the second and last RBs should be scheduled for UE3 in the last MU-MIMO layer. To utilize the MU-MIMO aspects efficiently, the table 500 may also comprise common performance rewards maximized for each RB. In other words, the same performance reward may be used for all the MU-MIMO layers for a single RB, regardless of whether the NN has decided to allocate it or not. This way, the NN also learns not to schedule if further co-schedulings on the same RB would decrease the overall performance. The performance reward r_i for i-th UE may be, e.g., defined as follows:

$$r_i = \frac{b_i}{n_{RBs}},$$

where b_i are the successfully transmitted/received bits during a given TTI per a number of allocated/scheduled RBs n_{RBs}.

However, if one wants to introduce proportional fairness, things become a bit more complicated due to the MU-MIMO aspects. If one just divides the bytes per RB with past average throughputs for each co-scheduled UE and sum them over the MU-MIMO layers, it will not capture a MU-MIMO gain very well. Therefore, to capture the MU-MIMO gain with proportional fairness for I UEs that were spatially co-scheduled for the same RB, the reward function should sum the bytes per RB and use the max past average throughput of the co-scheduled UEs on the same RB, namely:

$$R_{RB} = \frac{\sum_{i=0}^{I} b_i / n_{RBs}}{\max_{i \in I} t_i},$$

where t_i is the past average throughput (bytes per RB) of i-th UE. This way, the proportional fairness is ensured, and the MU-MIMO gain always increases the reward.

Hence, the processor 202 may collect the above-mentioned tuples and train the NN based by using the tuples one by one.

In one alternative embodiment, the reward may be based on an expert scheduler, which may be any well performing heuristic scheduler algorithm. For example, the NN may be trained to mimic such existing expert schedulers by rewarding a positive reward if the scheduling decision given by the NN is the same as that provided by the expert scheduler. Accordingly, a negative reward may be given if the scheduling decision does not match the expert decision. This way, the scheduling logic of the expert scheduler may be transferred into the ML model. The benefit of this is to achieve a much less computationally complex scheduler that may at least match the performance of the expert scheduler.

FIG. 6 shows two possible options how the processor 202 may construct the tuples to be fed to the NN for its training. The ML model may use the so-called replay memory for storing the tuples. If the first and last elements in each tuple (i.e., elements (a) and (d)) correspond, respectively, to the previous and next (in sequence) RBs for the same MU-MIMO layer, then the NN may be trained by performing seamless state transitions over all RBs in one MU-MIMO (as schematically shown by using the vertical arrows in FIG. 6). However, if the first and last elements in each tuple (i.e., elements (a) and (d)) correspond to the same RB but for the previous and next (in sequence) MU-MIMO layers, respectively, then the NN may be trained by performing seamless state transitions for the same RB over all the MU-MIMO layers (as schematically shown by using the horizontal arrows in FIG. 6). It should be also noted that the present disclosure is not limited to these two options shown in FIG. 6 – in one other option, the first and last elements in each tuple (i.e., elements (a) and (d)) may correspond to the same RB in the same MU-MIMO layer but in the previous and next (in sequence) TTIs (this will imply the combination of this option with one of those shown in FIG. 6).

Furthermore, it is optionally possible to use separate ML models (i.e., separate NNs) per MU-MIMO layer (instead of just a single ML model) and combine their outputs (i.e., scheduling decisions) to a single RB scheduling table (like the table 500).

Simulation results

In order to show that the apparatus 200 can be integrated into the system 100, a fully digital beamformer using regularized zero forcing (ZF) as a beamformer was assumed. A dynamic system level simulator with state-of-the-art MU-MIMO baseline parameterization was used for benchmarking the ML-based scheduling solution. The maximum number of MU-MIMO layers in the system level simulator was set to 4 in a macro cell simulation scenario.

The used ML model specific parameters for a DDQN (implemented in C++) are given in Table 1. Neural networks were fully connected. In PoC simulations, 10 UEs at maximum are scheduled per TTI. For each UE, 7 input values are obtained. Hence, the size of an input layer was 10x7 = 70 neurons. A first hidden layer had 220 neurons. A second hidden layer had 88 neurons. An output layer has output neuron for each candidate (i.e., each RB) plus possibility set empty allocation. Hence, the output layer had 11 neurons. This basic parameterization is just one example that works well enough. Parameters can be still further optimized.

Parameter	Value
Algorithms	Double Deep Q Network (DDQN)
Learning rate	0.001
Discount	0.95
Replay memory size	10 000
Epochs per training occasion	1
Target network soft update rate	0.001
Batch size	25
Training interval	1 TTI
Neural network topology	From input to output: 70-220-88-11 Additionally single bias neurons per layer, except output.

To maximize spectral efficiency, bits per RB was used as a UE reward. Such a reward alone would make the apparatus 200 to select all the time just UEs that maximize sum-throughput over all MU-MIMO layers. Therefore, when scheduling the first MU-MIMO layer, the maximum number of RBs per UE was calculated by dividing the number of available RBs with the number of scheduling candidates. Once a certain UE had a maximum number of RBs scheduled for the first MU-MIMO layer, it was marked as invalid, and its input values were masked with zeros. For the subsequent MU-MIMO layer, scheduling rounds all the candidates, except the ones scheduled already for the RB, were valid again.

FIG. 7 shows a Cumulative Distribution Function (CDF) versus the CPU execution time required for doing the scheduling decisions per TTI for two cases: the frequency selective even RB scheduling (dashed curve) and the RB scheduling based on the method 300 (solid curve). As follows from FIG. 7, the method 300 demonstrates absolute dominance in the real-time scheduling execution time. The execution times are shown for a single downlink MU-MIMO layer scheduling all RBs. The difference would be even more ludicrous if the prior art heuristic SD scheduler would be taken into account in total execution time or the more complex prior art heuristic FD scheduler would be used. “Even RB scheduling” is one of the simplest frequency selective scheduling algorithms, and still the method 300 can outperform it in the execution time due to the lack of sub-band channel state information processing, downlink throughput estimation calculations for each UE for each RB.

FIGs. 8A and 8B show a throughput performance of SD scheduling for a UE throughput and a cell throughput, respectively. In order to mimic the even resources scheduling algorithm, the UE was set as an invalid candidate and UE’s input values to be fed to the NN were masked with zeros once a number of scheduling candidates per total number of available RBs were reached for the UE. If the NN used in the method 300 picks an invalid candidate UE, it generates an empty allocation for the RB for the current MU-MIMO layer.

FIG. 9 shows a reward evolution with 1000 step observation windows during the first 300 000 simulation steps equal to ~21 seconds in real time. After 150 000 steps, the processor 202 has collected and trained the NN with bit more than 10000 tuples (as described above). The simulation was started with 100% exploration rate. In other words, all the scheduling decisions are randomly picked. The exploration rate is linearly decreased to zero before 75000 steps. After 150000 steps the NN is considered to be enough stabilized for the start of the actual simulation and its result collection. Whether the training was stopped or continued after that point did not much affect to the simulation results.

FIGs. 10A and 10B show, respectively, a DL windowed UE throughput and first MU-MIMO layer scheduling CPU time which are obtained by using the apparatus 200 in accordance with the method 300 and the prior art Proportional Fair (PF) FD scheduler with a decoupled greedy SD scheduler. As can be seen, if the proposed PF MU-MIMO reward function is used and compared against the prior art heuristic PF FD scheduler with the decoupled greedy SD scheduler, one can obtain similar spectral efficiency with ~90% less computational complexity. Because the state-of-the-art scheduling is decoupled into the separate FD and SD schedulers, only first MU-MIMO layer scheduling CPU time was compared to have apples to apples comparison. Nevertheless, the scheduling complexity reduction of all MU-MIMO layers is in the same ballpark, because the apparatus 200 does the same for all MU-MIMO layers, whereas the heuristic SD scheduler keeps re-calculating precoders, re-calculating throughput estimations, reselecting MCSs, etc. (i.e., everything that the apparatus 200 does only once after the scheduling decisions).

It should be noted that each step or operation of the method 300, or any combinations of the steps or operations, can be implemented by various means, such as hardware, firmware, and/or software. As an example, one or more of the steps or operations described above can be embodied by processor executable instructions, data structures, program modules, and other suitable data representations. Furthermore, the processor-executable instructions which embody the steps or operations described above can be stored on a corresponding data carrier and executed by the processor 202. This data carrier can be implemented as any computer-readable storage medium configured to be readable by said at least one processor to execute the processor executable instructions. Such computer-readable storage media can include both volatile and nonvolatile media, removable and non-removable media. By way of example, and not limitation, the computer-readable media comprise media implemented in any method or technology suitable for storing information. In more detail, the practical examples of the computer-readable media include, but are not limited to information-delivery media, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile discs (DVD), holographic media or other optical disc storage, magnetic tape, magnetic cassettes, magnetic disk storage, and other magnetic storage devices.

Although the example embodiments of the present disclosure are described herein, it should be noted that any various changes and modifications could be made in the embodiments of the present disclosure, without departing from the scope of legal protection which is defined by the appended claims. In the appended claims, the word “comprising” does not exclude other elements or operations, and the indefinite article “a” or “an” does not exclude a plurality. The mere fact that certain measures are recited in mutually different dependent claims does not indicate that a combination of these measures cannot be used to advantage.

CLAIMS

1. A Resource Block (RB) scheduling apparatus in a wireless communication network, comprising:

   at least one processor; and

   at least one memory storing instructions that, when executed by the at least one processor, cause the apparatus at least to:

   obtain a list of User Equipments (UEs) for which a set of RBs or RB Groups (RBGs) is to be scheduled for a target Transmission Time Interval (TTI), the set of RBs or RGBs being shared by a set of Multi-User Multiple Input Multiple Output (MU-MIMO) layers supported by a network node in the wireless communication network, each MU-MIMO layer of the set of MU-MIMO layers being assigned to a different UE of the list of UEs;

   obtain a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers, the data vector comprising frequency-specific information and a spatial correlation value, the frequency-specific information indicating a channel state of each UE of the list of UEs, the spatial correlation value indicating whether the UEs of the list of UEs are spatially separable by using beamforming; and

   schedule the set of RBs or RBGs for the list of UEs for the target TTI by using a machine-learning (ML) model, the ML model comprising at least one Neural Network (NN) configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs, the scheduling decision indicating whether the RB or RBG is to be scheduled for one or more UEs of the list of UEs.

2. The apparatus of claim 1, wherein the spatial correlation value comprises at least one of:

   a singular value decomposition of combined precoders of the UEs of the list of UEs; and

   a Power Normalization Loss (PLN) value calculated for each UE of the list of UEs.

3. The apparatus of claim 1 or 2, wherein the frequency-specific information comprises at least one of:

   Channel State Information (CSI) in the RB or RBG;

   a past average Downlink (DL) throughput in the RB or RBG;

   a past average Uplink (UL) throughput in the RB or RBG;

   a number of already scheduled other RBs or RBGs of the set of RBs or RBGs;

   an average size of transmitted DL packets in the RB or RBG;

   an average size of transmitted UL packets in the RB or RBG;

   a Modulation and Coding Scheme (MCS); and

   a scheduling decision made for the previous RB or RBG of the set of RBs or RBGs.

4. The apparatus of claim 3, wherein the CSI comprises at least one of:

   a Radio Resource Management (RRM) measurement for the RB or RBG;

   a RRM measurement for a sub-band comprising the RB or RBG; and

   a RRM measurement averaged over an entire bandwidth comprising the sub-band.

5. The apparatus of any one of claims 1 to 4, wherein the at least one NN is trained based on a sequence of tuples by using a reinforcement learning algorithm, each tuple of the sequence of tuples comprising:

   a data vector obtained for a target RB or RBG of the set of RBs or RBGs for a target MU-MIMO layer of the set of MU-MIMO layers for the target TTI;

   a scheduling decision outputted by the at least one NN for the target RB or RBG;

   a performance reward resulted from the scheduling decision for the target RB or RBG; and

   a data vector obtained for one of: (i) a subsequent RB or RBG of the set of RBs or RGBs for the target MU-MIMO layer for the target TTI, (ii) the target RB or RBG for a subsequent MU-MIMO layer of the set of MU-MIMO layers for the target TTI, and (iii) the target RB or RBG for the target MU-MIMO layer for a subsequent TTI.

6. The apparatus of any one of claims 1 to 5, wherein the at least one NN comprises a set of NNs each configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs but for a different MU-MIMO layer of the set of MU-MIMO layers.

7. The apparatus of any one of claims 1 to 5, wherein the at least one NN comprises a single NN configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers.

8. A Resource Block (RB) scheduling method in a wireless communication network, comprising:

obtaining a list of User Equipments (UEs) for which a set of RBs or RB Groups (RBGs) is to be scheduled for a target Transmission Time Interval (TTI), the set of RBs or RBGs being shared by a set of Multi-User Multiple Input Multiple Output (MU-MIMO) layers supported by a network node in the wireless communication network, each MU-MIMO layer of the set of MU-MIMO layers being assigned to a different UE of the list of UEs;

obtaining a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers, the data vector comprising frequency-specific information and a spatial correlation value, the frequency-specific information indicating a channel state of each UE of the list of UEs , the spatial correlation value indicating whether the UEs of the list of UEs are spatially separable by using beamforming; and

scheduling the set of RBs or RBGs for the list of UEs for the target TTI by using a machine-learning (ML) model, the ML model comprising at least one Neural Network (NN) configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG of the set of RBs or RBGs, the scheduling decision indicating whether the RB or RBG is to be scheduled for one or more UEs of the list of UEs.

9. The method of claim 8, wherein the spatial correlation value comprises at least one of:

a singular value decomposition of combined precoders of the UEs of the list of UEs; and a Power Normalization Loss (PLN) value calculated for each UE of the list of UEs.

10. The method of claim 8 or 9, wherein the frequency-specific information comprises at least one of:

Channel State Information (CSI) in the RB or RBG;

a past average Downlink (DL) throughput in the RB or RBG;

a past average Uplink (UL) throughput in the RB or RBG;

a number of already scheduled other RBs or RBGs of the set of RBs or RBGs;

an average size of transmitted DL packets in the RB or RBG;

an average size of transmitted UL packets in the RB or RBG;

a Modulation and Coding Scheme (MCS); and

a scheduling decision made for the previous RB or RBG of the set of RBs or RBGs.

11. The method of claim 10, wherein the CSI comprises at least one of:

a Radio Resource Management (RRM) for the RB or RBG;

a RRM for a sub-band comprising the RB or RBG; and

a RRM averaged over an entire bandwidth comprising the sub-band.

12. The method of any one of claims 8 to 11, wherein the at least one NN is trained based on a sequence of tuples by using a reinforcement learning algorithm, each tuple of the sequence of tuples comprising:

a data vector obtained for a target RB or RBG of the set of RBs or RBGs for a target MU-MIMO layer of the set of MU-MIMO layers for the target TTI;

a scheduling decision outputted by the at least one NN for the target RB or RBG;

a performance reward resulted from the scheduling decision for the target RB or RBG; and

a data vector obtained for one of: (i) a subsequent RB or RBG of the set of RBs or RBGs for the target MU-MIMO layer for the target TTI, (ii) the target RB or RBG for a subsequent MU-MIMO layer of the set of MU-MIMO layers for the target TTI, and (iii) the target RB or RBG for the target MU-MIMO layer for a subsequent TTI.

13. The method of any one of claims 8 to 12, wherein the at least one NN comprises a set of NNs each configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs but for a different MU-MIMO layer of the set of MU-MIMO layers.

14. The method of any one of claims 8 to 12, wherein the at least one NN comprises a single NN configured to output the scheduling decision for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers.

15. A computer program product comprising a computer-readable storage medium, wherein the computer-readable storage medium stores a computer code which, when executed by at least one processor, causes the at least one processor to perform the method according to any one of claims 8 to 14.

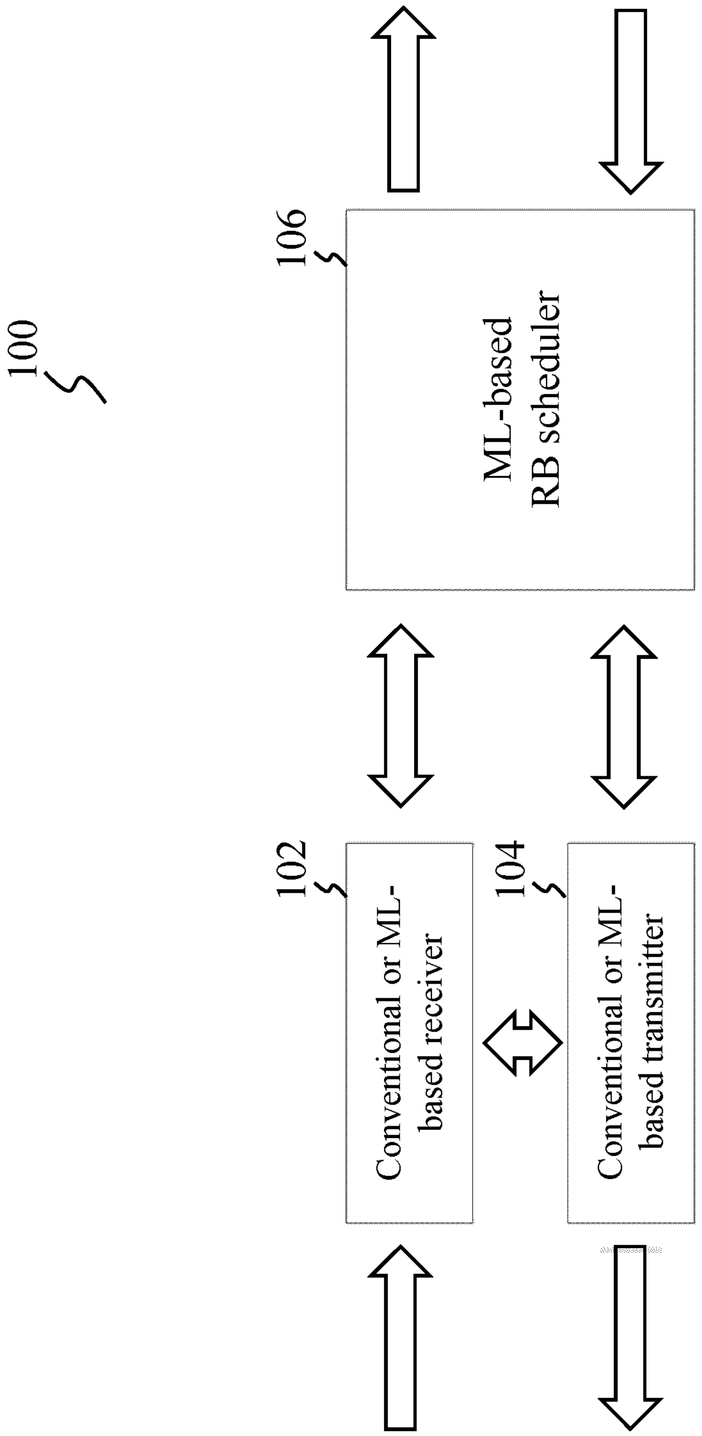
100
106
ML-based
RB scheduler
102
Conventional or ML-based receiver
104
Conventional or ML-based transmitter

FIG. 1

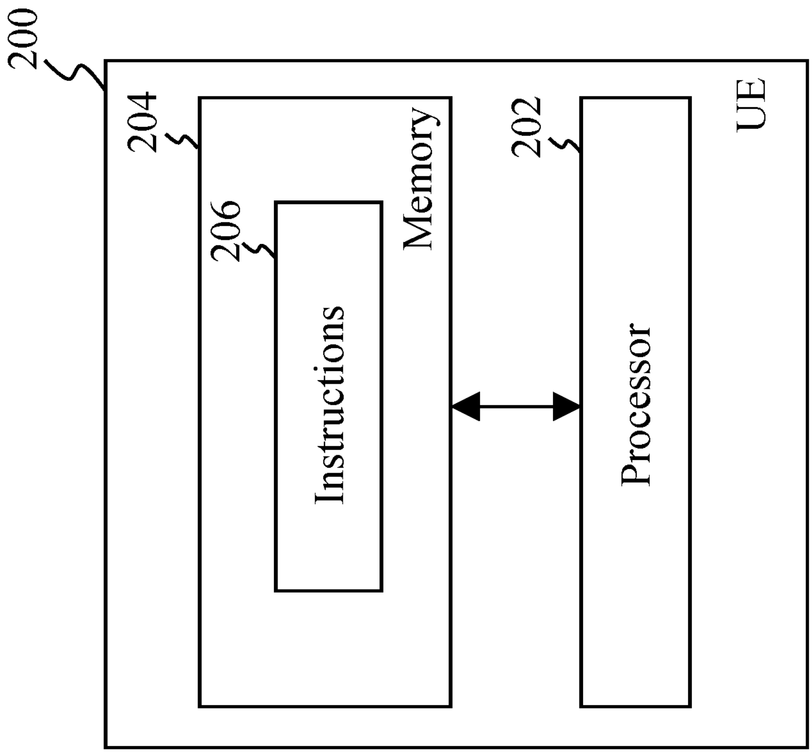

FIG. 2

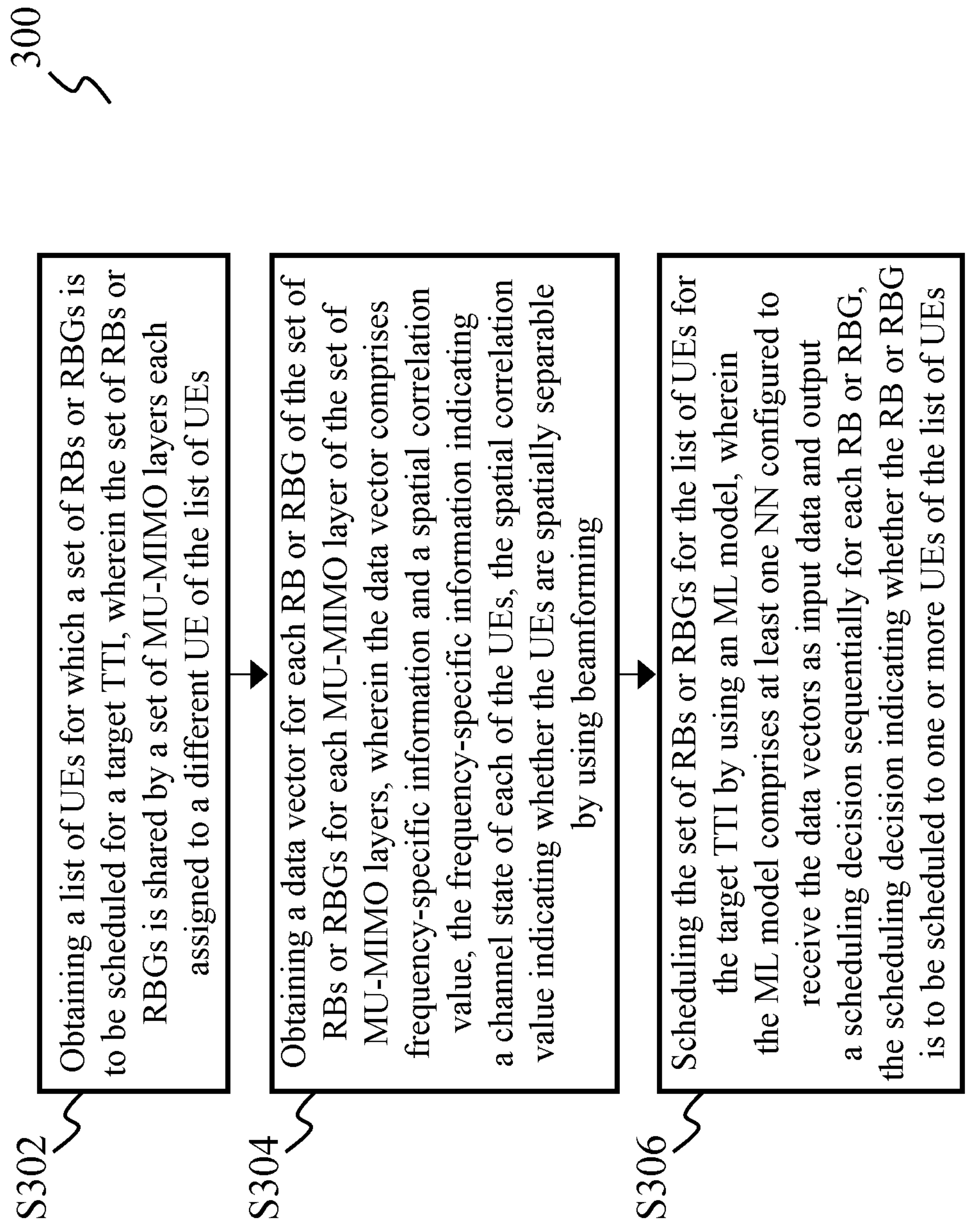
300
S302
Obtaining a list of UEs for which a set of RBs or RBGs is to be scheduled for a target TTI, wherein the set of RBs or RBGs is shared by a set of MU-MIMO layers each assigned to a different UE of the list of UEs
S304
Obtaining a data vector for each RB or RBG of the set of RBs or RBGs for each MU-MIMO layer of the set of MU-MIMO layers, wherein the data vector comprises frequency-specific information and a spatial correlation value, the frequency-specific information indicating a channel state of each of the UEs, the spatial correlation value indicating whether the UEs are spatially separable by using beamforming
S306
Scheduling the set of RBs or RBGs for the list of UEs for the target TTI by using an ML model, wherein the ML model comprises at least one NN configured to receive the data vectors as input data and output a scheduling decision sequentially for each RB or RBG, the scheduling decision indicating whether the RB or RBG is to be scheduled to one or more UEs of the list of UEs

FIG. 3

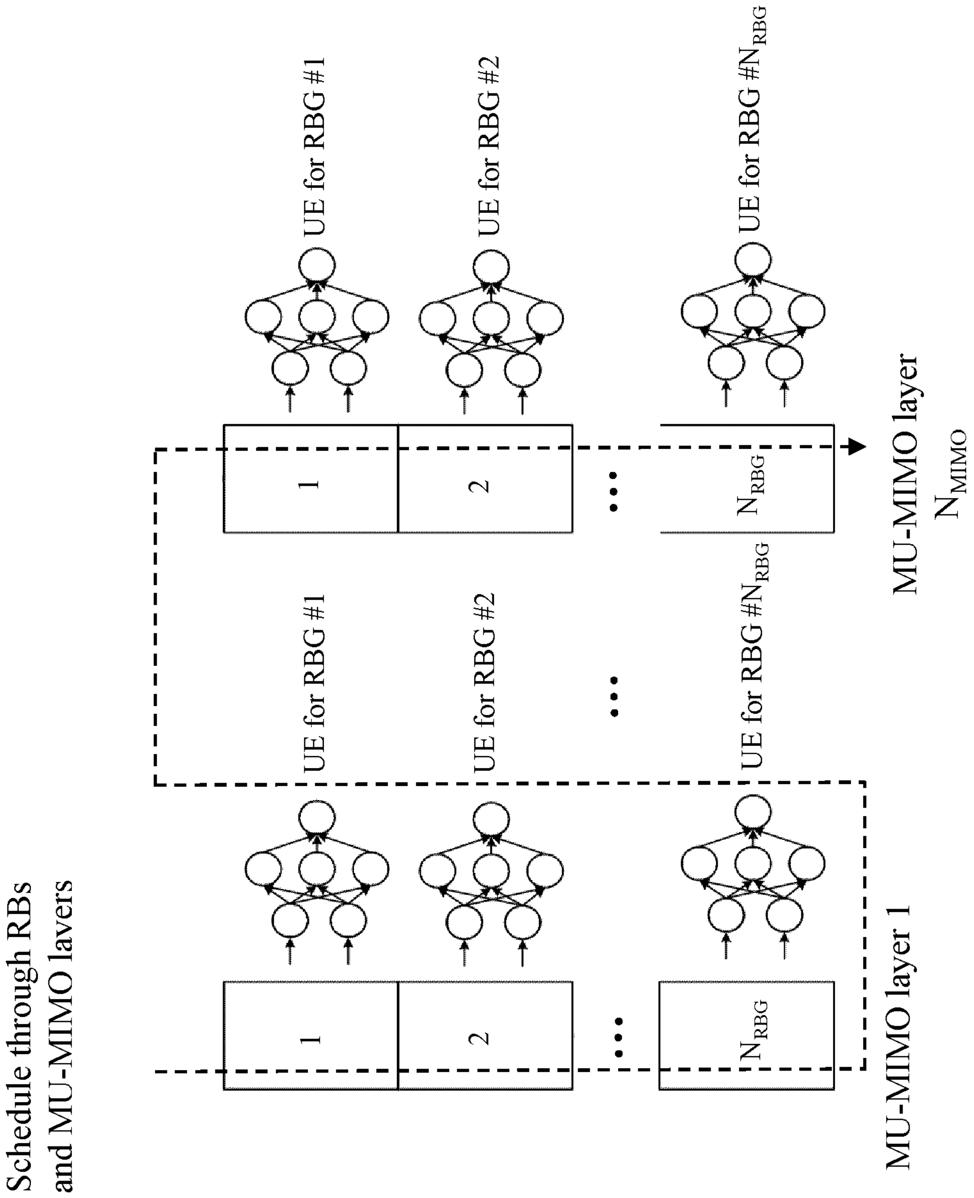
Schedule through RBs
and MU-MIMO layers
1
2
N_RBG
UE for RBG #1
UE for RBG #2
UE for RBG #N_RBG
MU-MIMO layer 1
MU-MIMO layer
N_MIMO

FIG. 4

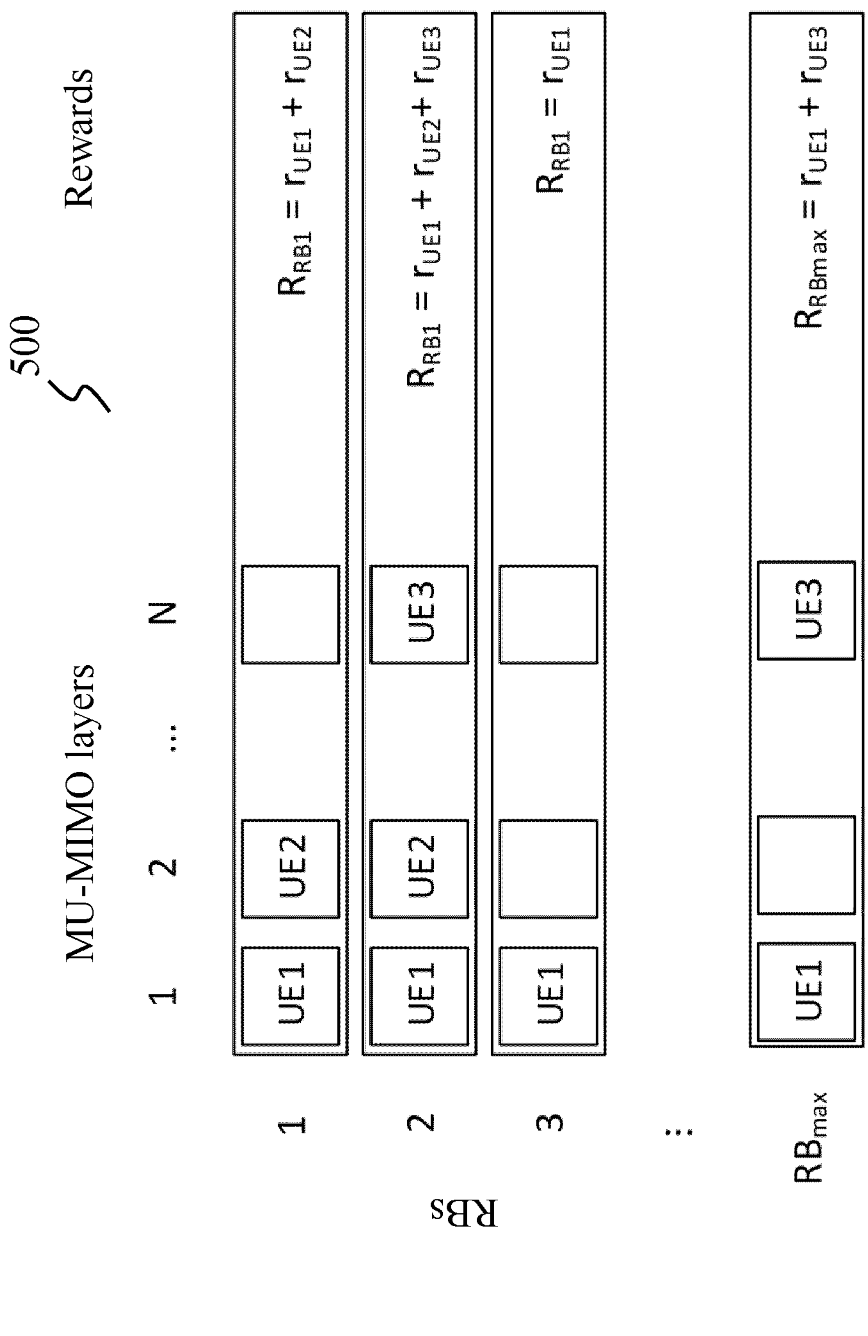
500
MU-MIMO layers
Rewards
1
2
...
N
RBs
1
2
3
...
RB_{max}
UE1
UE2
UE3
$R_{RB1} = r_{UE1} + r_{UE2}$
$R_{RB1} = r_{UE1} + r_{UE2} + r_{UE3}$
$R_{RB1} = r_{UE1}$
$R_{RBmax} = r_{UE1} + r_{UE3}$

FIG. 5

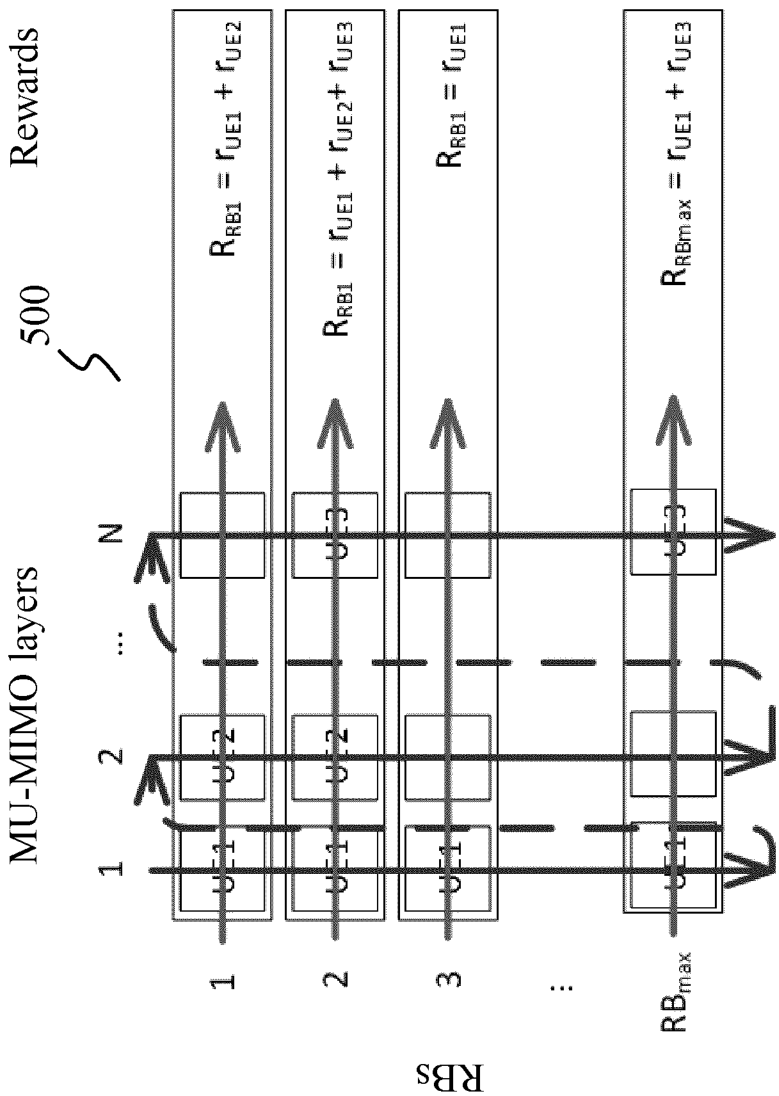
Rewards
MU-MIMO layers
500
1
2
...
N
RBs
1
2
3
...
RB_{max}
$R_{RB1} = r_{UE1} + r_{UE2}$
$R_{RB1} = r_{UE1} + r_{UE2} + r_{UE3}$
$R_{RB1} = r_{UE1}$
$R_{RBmax} = r_{UE1} + r_{UE3}$

FIG. 6

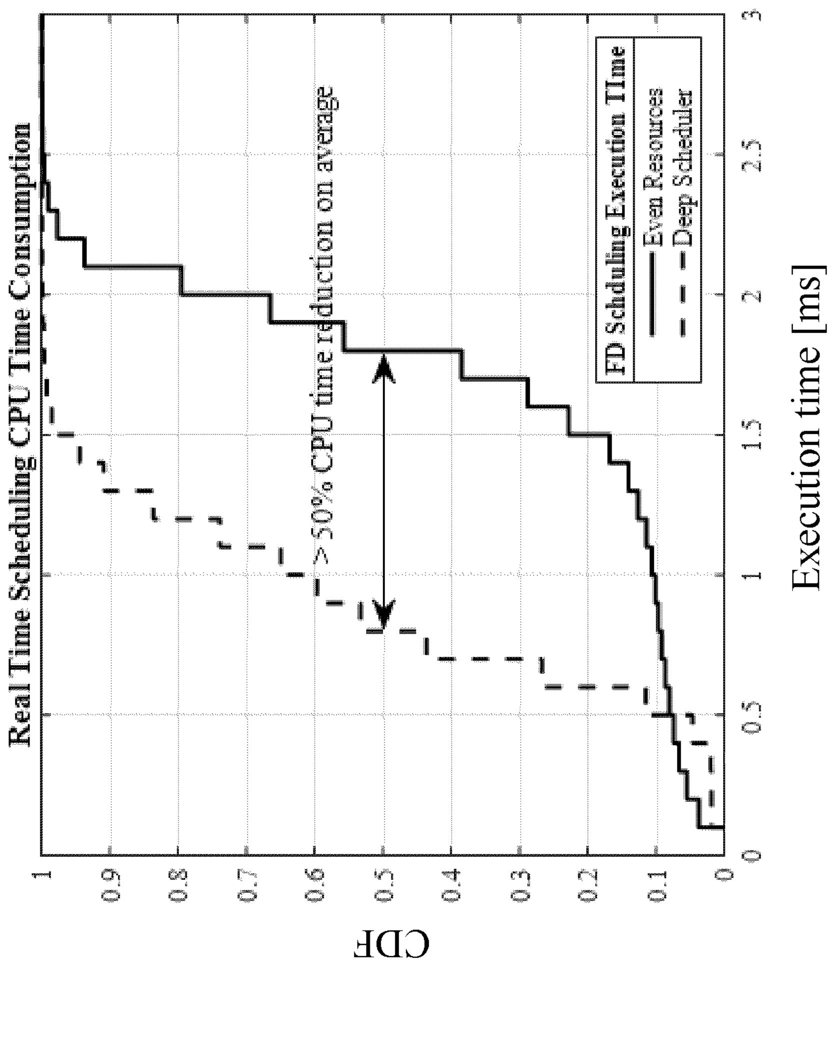
Real Time Scheduling CPU Time Consumption
> 50% CPU time reduction on average
FD Scheduling Execution TIme
Even Resources
Deep Scheduler
CDF
Execution time [ms]
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0.5
1.5
2
2.5
3

FIG. 7

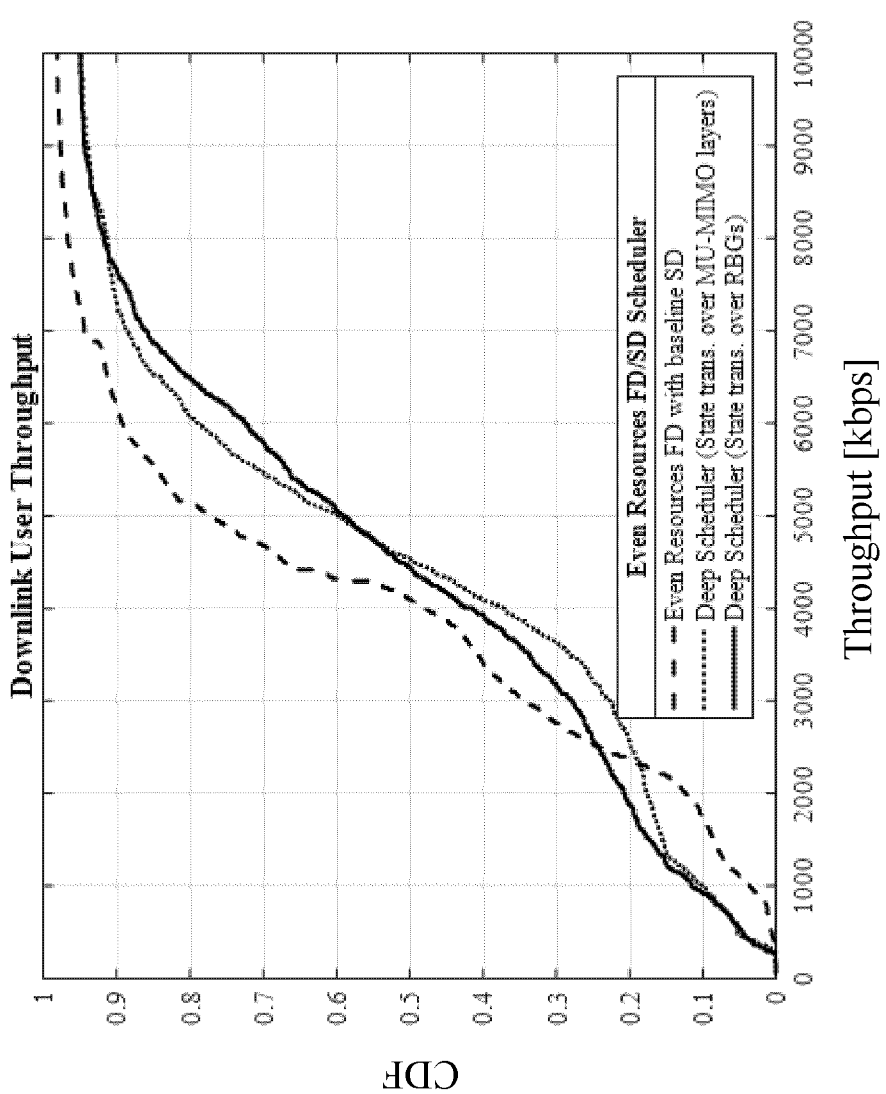
Downlink User Throughput
CDF
Throughput [kbps]
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Even Resources FD/SD Scheduler
Even Resources FD with baseline SD
Deep Scheduler (State trans. over MU-MIMO layers)
Deep Scheduler (State trans. over RBGs)

FIG. 8A

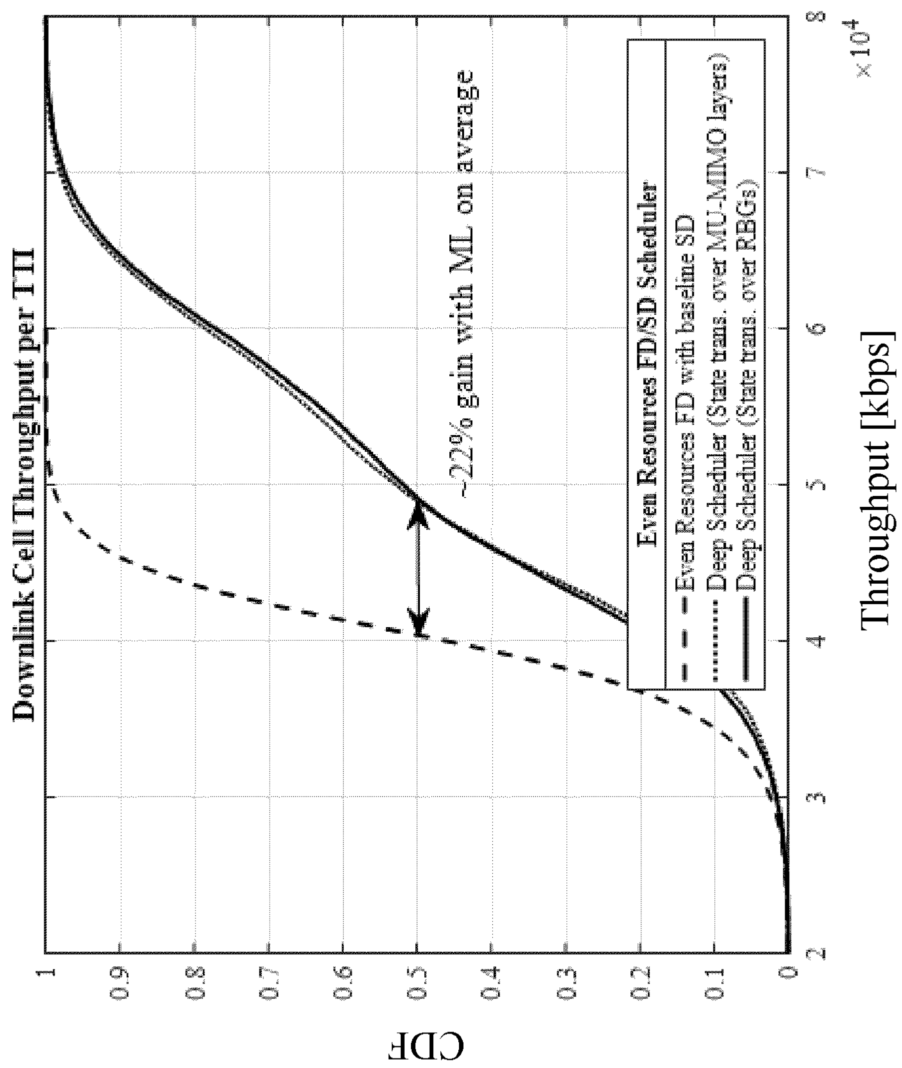
Downlink Cell Throughput per TTI
~22% gain with ML on average
Even Resources FD/SD Scheduler
Even Resources FD with baseline SD
Deep Scheduler (State trans. over MU-MIMO layers)
Deep Scheduler (State trans. over RBGs)
CDF
Throughput [kbps]
$\times 10^4$
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
2
3
4
5
6
7
8

FIG. 8B

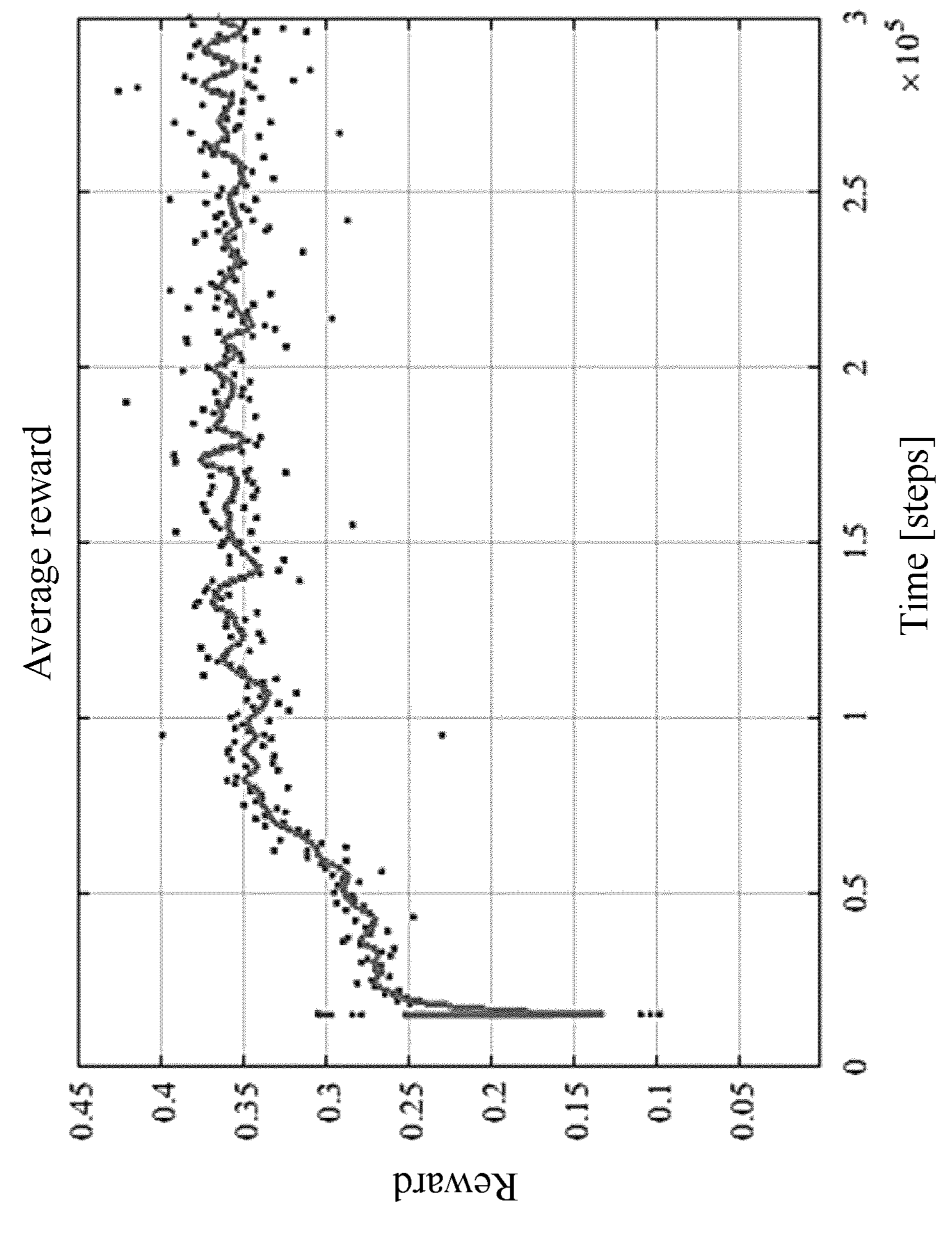
Average reward
Reward
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.5
1
1.5
2
2.5
3
$\times 10^5$
Time [steps]

FIG. 9

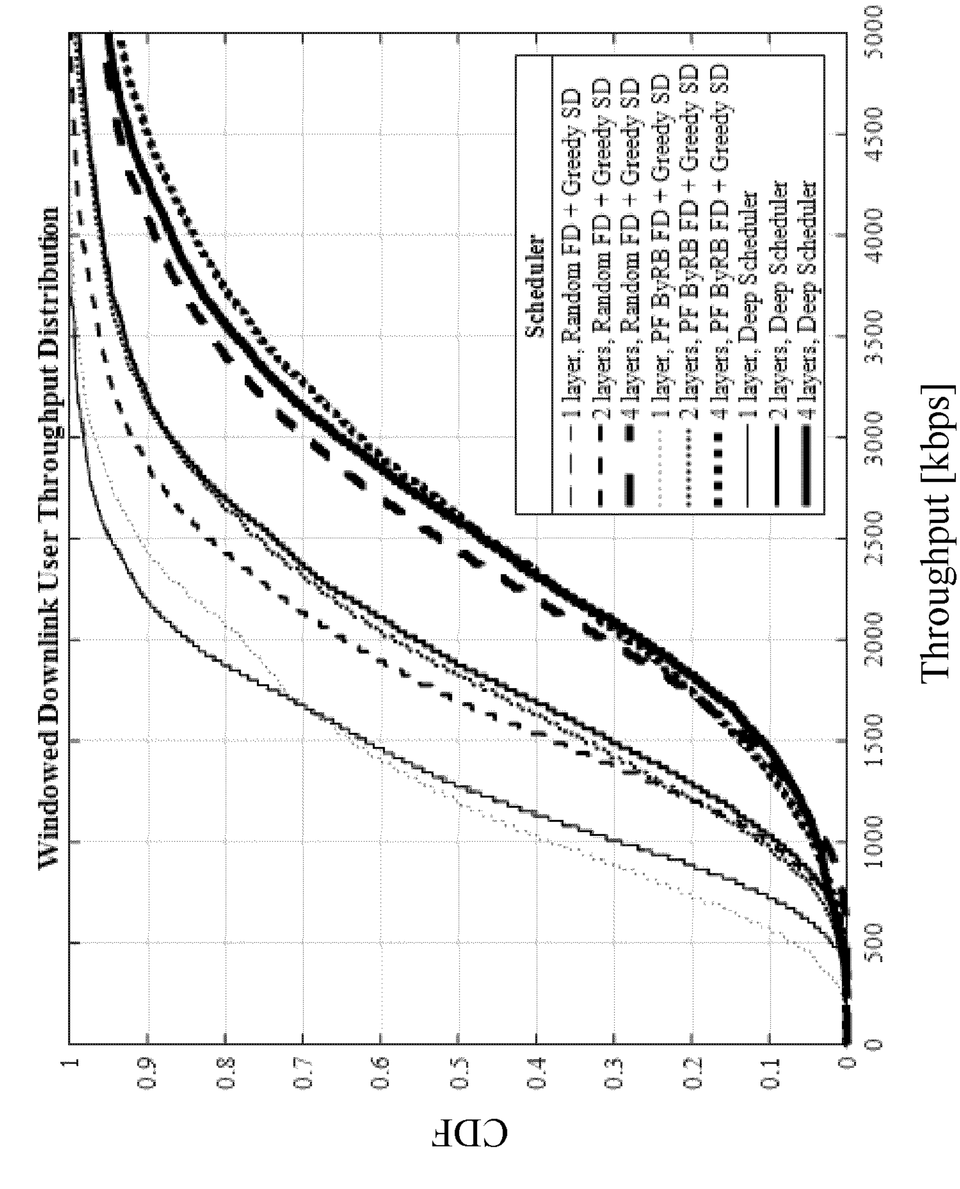
Windowed Downlink User Throughput Distribution
CDF
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
Throughput [kbps]
Scheduler
1 layer, Random FD + Greedy SD
2 layers, Random FD + Greedy SD
4 layers, Random FD + Greedy SD
1 layer, PF ByRB FD + Greedy SD
2 layers, PF ByRB FD + Greedy SD
4 layers, PF ByRB FD + Greedy SD
1 layer, Deep Scheduler
2 layers, Deep Scheduler
4 layers, Deep Scheduler

FIG. 10A

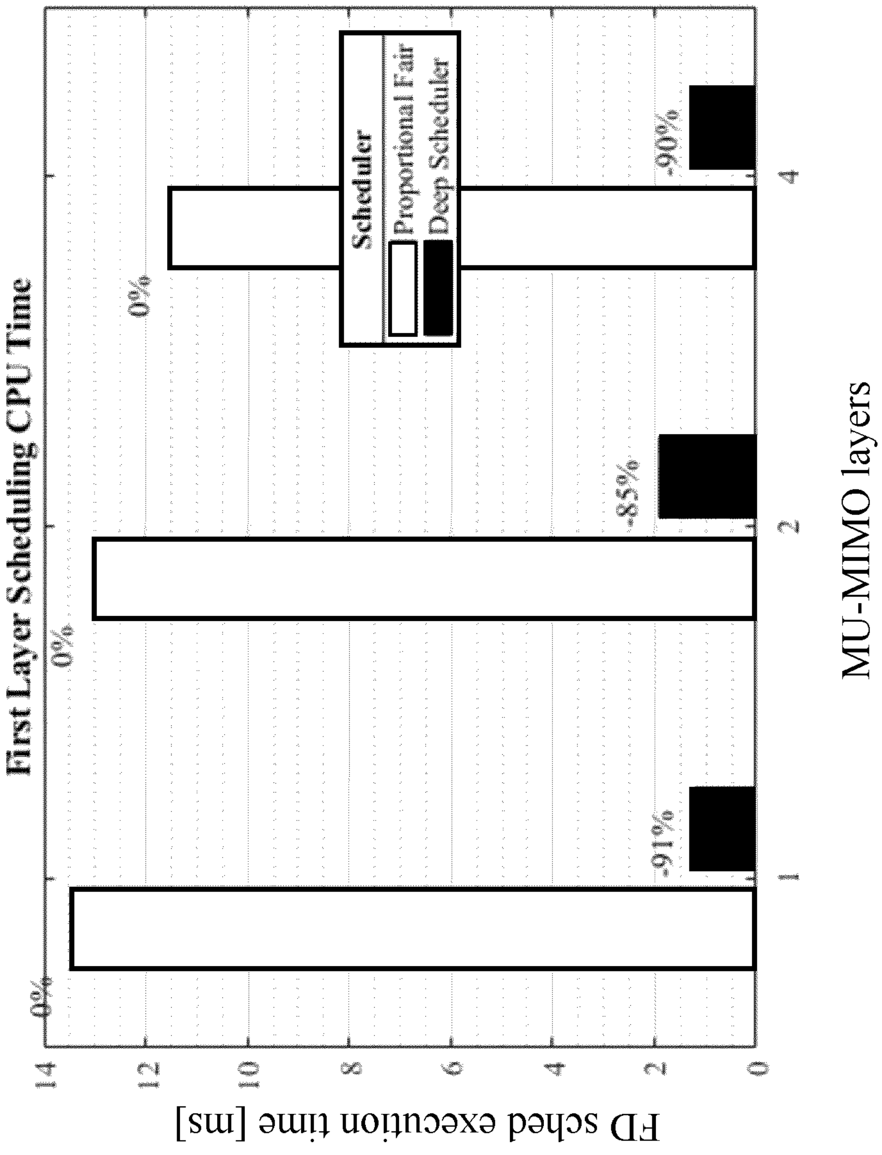
First Layer Scheduling CPU Time
FD sched execution time [ms]
0
2
4
6
8
10
12
14
MU-MIMO layers
1
2
4
0%
-91%
0%
-85%
0%
-90%
Scheduler
Proportional Fair
Deep Scheduler

FIG. 10B

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2023/066263

A. CLASSIFICATION OF SUBJECT MATTER
INV. H04B7/0452
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
H04B

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 2023/189317 A1 (NARASIMHA SWAMY VASUKI [US] ET AL) 15 June 2023 (2023-06-15) paragraphs [0067], [0078] - [0088], [0102] - [0105], [0117] - [0124], [0134] - [0135]; figures 2A,2B,3A,3B -----	1-15

☐ Further documents are listed in the continuation of Box C.

☒ See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance;; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance;; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
10 January 2024	24/01/2024

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Sälzer, Thomas

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/EP2023/066263

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2023189317 A1	15-06-2023	DE 102022129882 A1	15-06-2023
		US 2023189317 A1	15-06-2023