



6G VISION AND RESEARCH CHALLENGES

PERIAL COLLEGE SEMINARS SERIES ON FUTURE COMMUNICATION

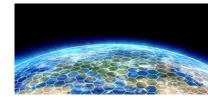
REGIUS, FRENG PROFESSOR RAHIM TAFAZOLLI DIRECTOR INSTITUTE FOR COMMUNICATION SYSTEMS (ICS), 5GIC & 6GIC



- MOBILE CELLULAR
- WIFI
- SATELLITE COMMUNICATIONS & BROADCAST
 - Broadband Fixed
 - Broadband Mobile BB on the move
 - Broadcast passenger vehicles
- INTERNET OF THINGS
- VEHICLE COMMUNICATIONS
- FUTURE INTERNET

FROM THEORY TO INNOVATION

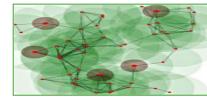
















TESTBED: 4G & 5G MULTI-RADIO ACCESS NETWORK ENVIRONMENT COVERAGE

OUTDOOR

- 4KM² COVERAGE OF DENSE CELLS
- Ultra dense C-RAN of 44 4G-TDD sites & 66 Cells
- CELL CLUSTER OPERATED AS 1XMACRO & 15XSMALLCELL SITE/CLUSTER
- EMBB D-RAN OF 7 5G-TDD(3.5G) SITES & 9 CELLS
- URLLC RAN of 1 5G-TDD(3.5G) site & single cell
- 700MHz 4G-FDD 1 SITE
- 60GHz backhaul system
- Combination of SDR & 60GHz supported on a drone for Popup-Network
- SATELLITE BACKHAULING

INDOOR - OVER 2 FLOORS

- C-RAN OF 4G-TDD 6 CELLS
- 4G-FDD FEMTOS CELLS
- 6 X WI-FI-A







5•6G

CENTRE

INNOVATION





5GIC: World's first 5G Centre

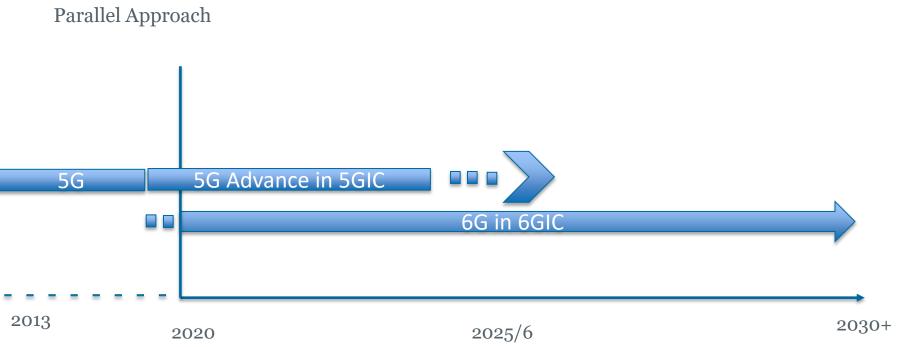
ART OF POSSIBLE

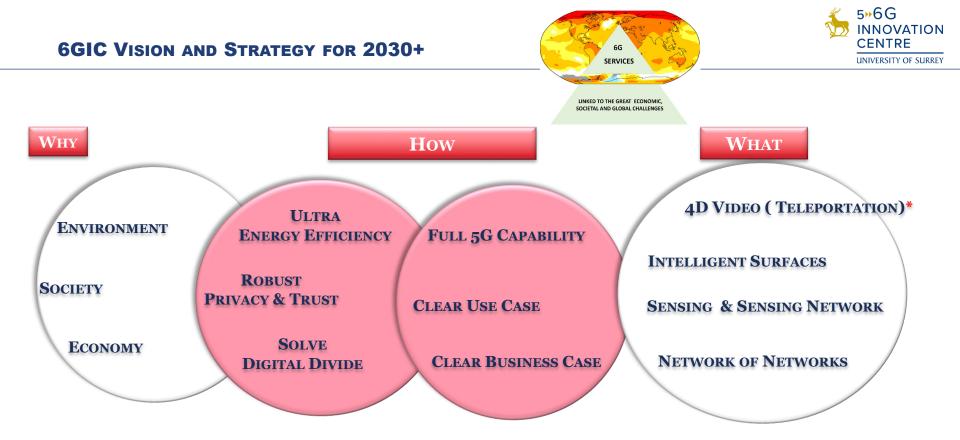


WINNER OF ROYAL ACADEMY OF ENGINEERING (RAENG) 2021 FOR BEST INDUSTRY-ACADEMIA COLLABORATION

Research Strategy



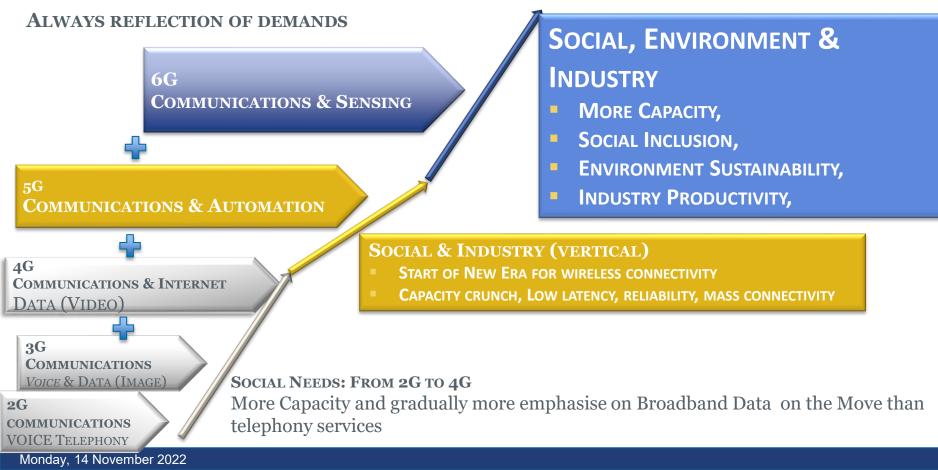




* R. TAFAZOLLI, FUTURE WIRELESS WORLD, TEDX 2015

MOBILE SYSTEM GENERATIONS EVOLUTION

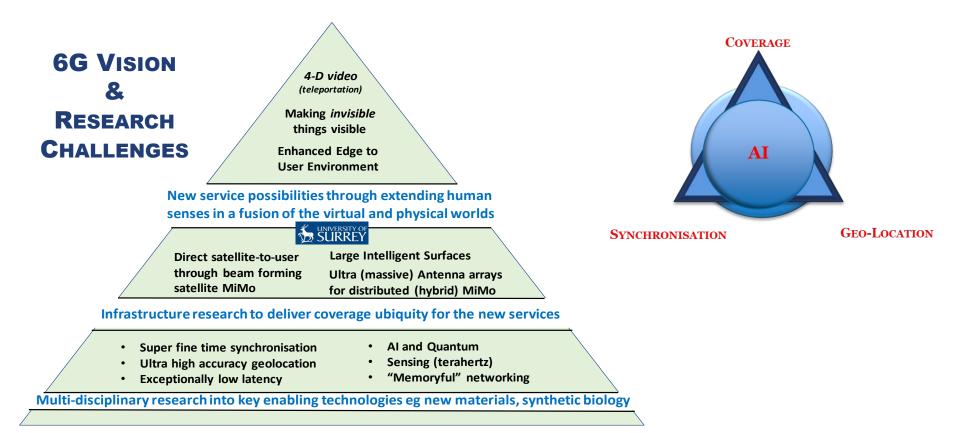




INTEGRATED COMMUNICATION AND SENSING (ICS)

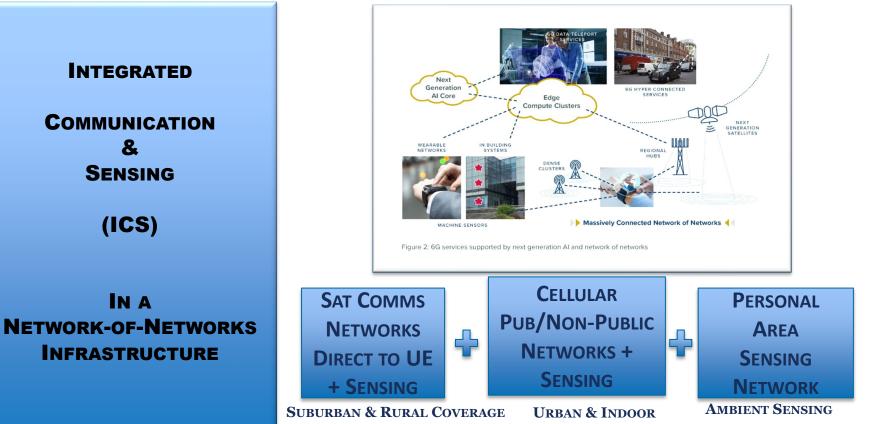
Figure 1: 6G vision supported by new cross-functional research and development programme





6G System Architecture: 3D Network





PRINCIPLE TECHNOLOGIES FOR 6G

• Computing & Intelligence (AI)=========

• Block Chain & Time Synchronisation (Heartbeat)========

- - Semantics & AI (Inference & learning)=======



5•6G





Freedom



INTERACTIVITY BETWEEN AND WITHIN

VIRTUAL AND PHYSICAL WORLDS





INTERACTIVITY IN CYBER WORLD WITH AMBIENT SENSES AROUND A USER



Teleportation



Live and interactive teleportation of multiple objects from different network locations

New Generation of Use cases with enabled with Interactivity



5G

ENABLED BY LOW LATENCY AND RELIABILITY



- CONNECTED VEHICLES
- MANUFACTURING
- GAMES/ENTERTAINMENT
- HEALTH

. . .

EDUCATION



6G ENABLED BY LOW LATENCY + TIME SYNCHRONISATION + SENSING INFORMATION

- HIGH SPEED DRIVER-LESS AND COOPERATIVE DRIVING
- INTERACTIVE COOPERATIVE MANUFACTURING
- INTERACTIVE AGRICULTURE
- INTERACTIVE ENTERTAINMENT
- INTERACTIVE TELECARE
- INTERACTIVE TELE-EDUCATION
- TELEPORTATION







.....





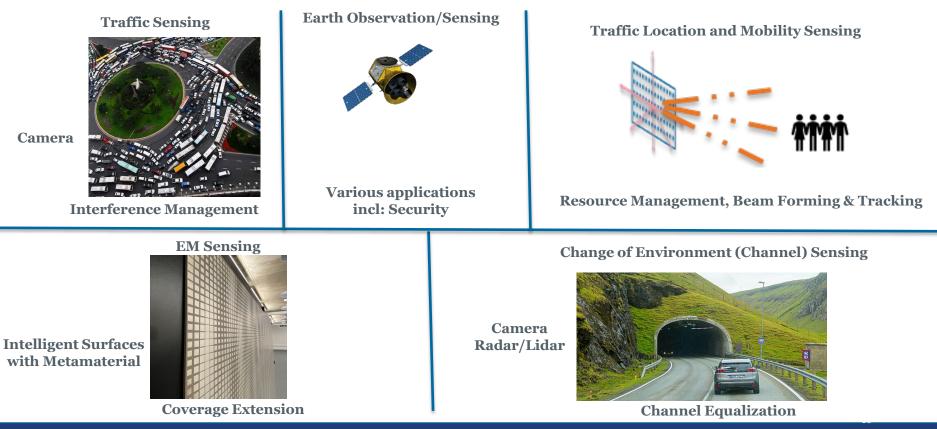
- ENHANCES EFFICIENCY AT ALL LAYERS OF COMMUNICATIONS: PHY, MAC, NET,..& SYSTEM
- IMPROVES ENERGY & SPECTRUM EFFICIENCY
- ENABLE SMARTER APPLICATIONS

- Two broad categories of Sensing:
 - SYSTEM LEVEL
 - USER LEVEL (AMBIENT INFORMATION)

SYSTEM-LEVEL SENSING & COMMUNICATION: ENVIRONMENT CONTEXT INFORMATION

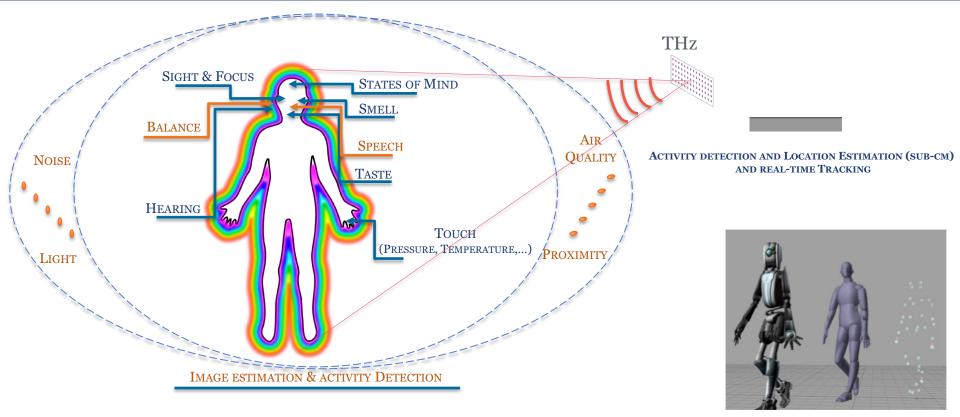
SOME EXAMPLES





ADDING USER-LEVEL SENSING TO INTERACTIVE VR



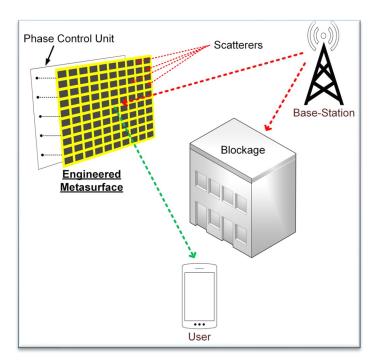


THZ IMAGING



- **OPTIMUM RESOURCES BALANCING FOR SENSING AND COMMUNICATIONS**
 - HOW MUCH FOR SENSING AND HOW MUCH FOR COMMUNICATIONS AND HOW MUCH FOR AI
- How to Integrate sensing information with communications
- HIGH QUALITY TIME/FREQUENCY SYNCHRONISATION
- EDGE PROCESSING AND COMPUTING AND TASK OFFLOADING BETWEEN UE AND NETWORKS
- SEMANTIC COMMUNICATION AND SENSING
- PRIVACY PRESERVING AND BILATERAL (DISTRIBUTED) AUTHENTICATION PROTOCOLS BETWEEN SENSING NODES





RECONFIGURABLE REFLECTING/TRANSMITTING SURFACES

ENERGY EFFICIENT COVERAGE: OUTDOOR 2 OUTDOOR OUTDOOR 2 INDOOR INDOOR 2 INDOOR

r.tafazolli@surrey.ac.uk

1

6GIC- WORLD'S FIRST WORKING RIS BASED ON HOLOGRAPHY PRINCIPLE









REFLECTIVE INTELLIGENT SURFACES (RIS)





- THICKNESS: 3mm
- UNIT CELLS: 11000
- BEAMS: 2 REFLECTED BEAMS TOWARDS ±45^o
- MEASURED GAIN: 20 dB
- BANDWIDTH: 400MHz (3.3 GHz- 3.7 GHz)
- INPUT POWER: ZERO

DYNAMIC RIS





- SUBSTRATE THICKNESS: 1.524mm
- UNIT CELLS: 3000
- MEASURED GAIN: 17dB
- BANDWIDTH:700MHz (3.1 GHz- 3.8 GHz)

TRANSMISSIVE (CONDUCTIVE GLASS) AND REFLECTIVE RIS



 INTERROGATES 3.3~3.7 GHz FROM OUTDOOR

• POLARIZATION INSENSITIVE



Single glazing



• WIDE INCIDENT ANGLE INSENSITIVE

• Passive and small $(\sim 15\lambda \times \sim 15\lambda)$

EASY TO IMPLEMENT

SATELLITE ROLE: APPLICATIONS & USE CASES



RURAL LAND, SEA AND AIR

- **MOBILE BROADBAND**
- **INTERNET OF THING**
- **5G** (Communications & Automation) NARROW-MEDIUM-BROADBAND APPLICATIONS
 - CONNECTED TRANSPORTATION, E-AGRI, E-MANUFACTURING,....
- **PNT**
- **QUANTUM KEY DISTRIBUTION**
- BEYOND LOS FOR UAV
- **DIRECT SAT-TO- UE**



EARTH OBSERVATION

6G (Communications & Sensing)

















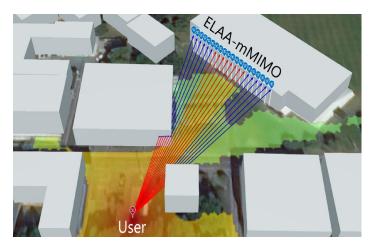


- **AI/ML FOR WIRELESS NETWORKS**
 - DEEP NEURAL NETWORK (DNN)S FOR JOINT SOURCE CHANNEL CODING (JSCC)
 - MIMO CHANNEL ESTIMATION AND FEEDBACK
 - NEURAL MMWAVE BEAM MANAGEMENT FOR SENSING-AIDED COMMUNICATIONS
 - MODEL-BASED LEARNING FOR COMMUNICATIONS
 - **DNN-BASED SEMANTIC AND EFFECTIVE COMMUNICATIONS**
 - NETWORK AUTOMATION E.G, 6GANA



MIMO, mMIMO or umMIMO are important components of 5G, 6G,..... Why there is so much gap between theoretical and practical performances?



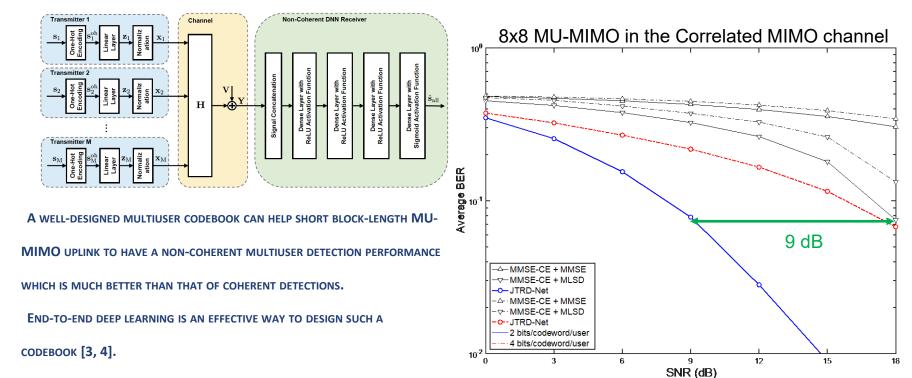


- Channel <u>Spatial Non-Stationarity</u> in MIMO with an extremely large aperture array
- Non-Linear distortions (analog-to-digital conversion, power amplifier, etc.)
- Non-Gaussian noise and interferences due to device nonlinearities
- Non-Ergodic communication due to shot finite-length transmissions

MU-MIMO (Non-Ergodic)



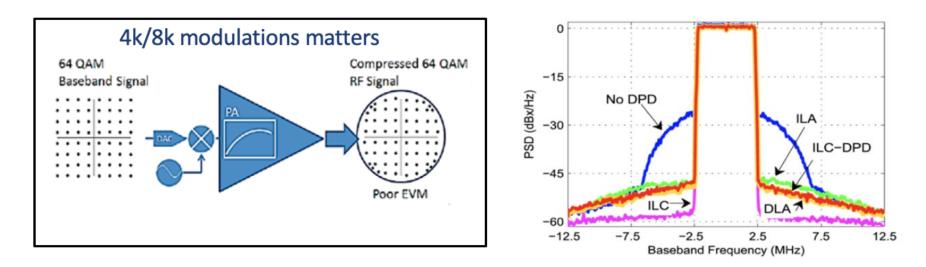
END-TO-END DEEP LEARNING FOR MULTIUSER-MIMO JOINT TX-RX DESIGN



USE CONTINUOUS LEARNING TO IMPROVE THE SYSTEM ADAPTABILITY [5].



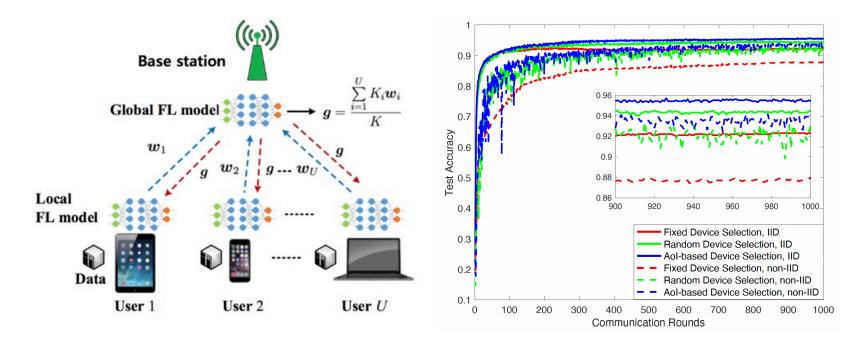
NEW DEEP LEARNING ARCHITECTURE FOR PA LINEARISATION



USING ITERATIVE LEARNING CONTROL (ILC) PRINCIPLE IN DEEP LEARNING FOR DPD CAN SIGNIFICANTLY IMPROVE THE PA LINEARIZATION PERFORMANCE (10 – 15 dB GAIN IN PSD)

COMMUNICATIONS OPTIMISED FOR FEDERATED LEARNING



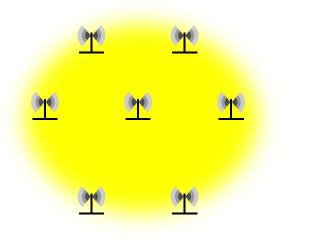


AGE OF INFORMATION (AOI) AWARE DEVICE SELECTION CAN OFFER FASTER CONVERGENCE AND HIGHER TEST ACCURACY IN FEDERATED LEARNING BECAUSE AGED INFORMATION IS MORE CRITICAL PARTICULARLY FOR NON-IID DATA.



SCENARIO & PROBLEM

- SCENARIO: A SET OF BASE STATIONS WHICH CAN CHOOSE A PARTICULAR SCHEDULING SCHEME TO OPERATE
- QUESTION: WHAT COMBINATION OF SCHEDULERS WILL DELIVER THE USER EXPERIENCE?



IEEE Transactions on Cognitive Communications and Networking (2020)

IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING, VOL. 6, NO. 2, JUNE 2020

575

Dynamic Scheduler Management Using Deep Learning

James Hall[®], Klaus Moessner[®], *Senior Member, IEEE*, Richard MacKenzie, Francois Carrez, and Chuan Heng Foh[®], *Senior Member, IEEE*

Abstract—The ability to manage the distributed functionality of large multi-vendor networks will be an important step towards ultra-dense 5G networks. Managing distributed scheduling functionality is particularly important, due to its influence over inter-cell interference and the lack of standardization for schedulers. In this paper, we formulate a method of managing distributed scheduling methods across a small cluster of cells by dynamically selecting schedulers to be implemented at each cell. We use deep reinforcement learning methods to identify suitable joint scheduling policies, based on the current state of the network observed from data already available in the RAN.

influences the high level performance metrics used to assess the network, including throughput, fairness and latency. These indicators are monitored because of their influence on the quality of service provided to users in the network.

A large body of literature exists around scheduling methods for the LTE network architecture. These methods are evaluated by a number of surveys of the most commonly used scheduling methods for LTE networks, highlighting the key themes and the limitations imposed by the network architecture [1], [2].

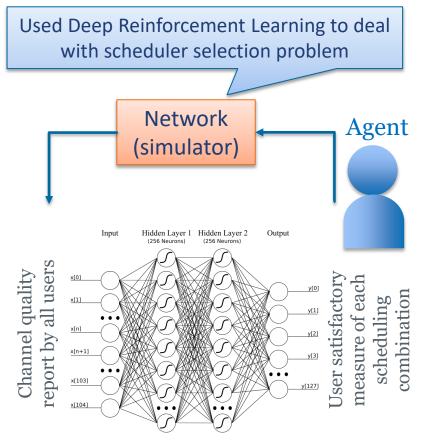
USER SCHEDULING



Results

- WE USE DEEP NN AS A FUNCTION APPROXIMATOR
- DISTRIBUTED SCHEDULER SELECTION (DSS):
 - DEEP RL & GENETIC ALGORITHM (GA)
- TESTED AGAINST TWO CASES:
 - σ_0 : All Proportional Fair Case
 - σ_{127} : All Margin Adaptive Case

	Deep RL	GA
DSS better than σ_0	92.4 %	87.2 %
DSS better than σ_{127}	83.5 %	84.2%





- **F**OR USER SCHEDULING, WE APPLIED **DRL** TO LEARN THE BEST SCHEDULER SELECTION MEETING USER SATISFACTION.
- BY DEVELOPING A PARALLEL MODEL, WE CAN EXPLAIN OUR RNN MODEL AND BETTER INTERPRET THE OUTCOMES.
- HUGE OPPORTUNITIES IN NETWORK AUTOMATION FOR RAN USING ML ALGORITHMS



• TECHNICAL CHALLENGES:

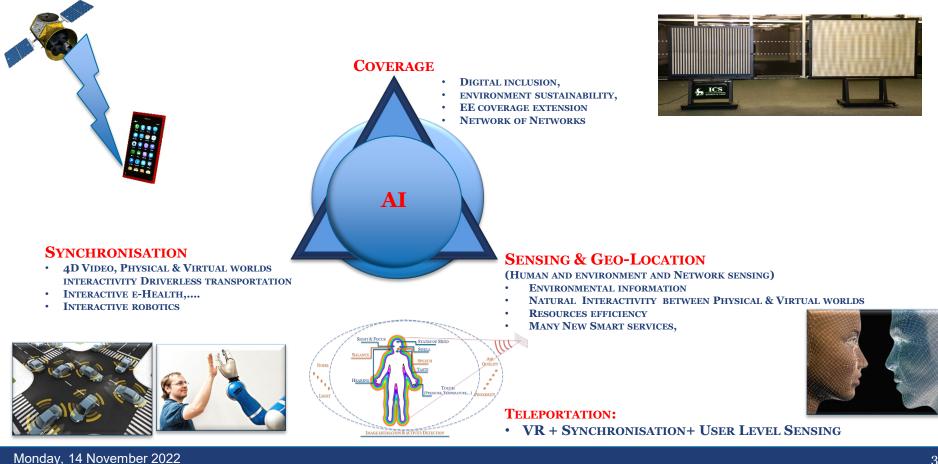
- DATA COLLECTION AND TRAINING (MOSTLY OFFLINE) OVERHEAD
- RUNNING RESOURCE-HUNGRY AI/ML MODELS ON HANDHELD DEVICES
- RUNTIME LATENCY OF AI/ML MODELS
- SITUATION OR LOCATION/... SPECIFIC AI/ML MODELS, E.G., EACH BS NEEDS TO TRAIN ITS OWN NN
- ADAPTABILITY CHALLENGE
- MODEL-BASED LEARNING FOR COMMUNICATIONS
 - MODEL-BASED INFERENCE → ANALYTICALLY UNDERSTANDABLE BUT REQUIRES SIMPLIFYING CHANNEL ASSUMPTIONS
 - DATA-DRIVEN INFERENCE → MODEL-AGNOSTIC BUT NEEDS DATASET COLLECTION AND TRAINING
 - BEST OF BOTH WORLDS: MODEL-BASED LEARNING FOR COMMUNICATIONS

FUTURE DIRECTIONS:

- ONLINE TRAINING/ADAPTATION OF AI/ML MODELS DURING NORMAL OPERATION OF THE WIRELESS NETWORK (META-LEARNING, FEW-SHOT LEARNING, NN SIMPLIFICATION TECHNIQUES)
- SPECTRUM, ENERGY EFFICIENT, AND GREEN DISTRIBUTED AI/ML (OTA LEARNING, KNOWLEDGE DISTILLATION)
- WIRELESS NETWORKS FOR AI/ML
 - COLLABORATIVE LEARNING (CL) OVER WIRELESS NETWORKS
 - OVER-THE-AIR COMPUTATION (OTAC) FOR DISTRIBUTED LEARNING OVER WIRELESS NETWORKS

INTEGRATED COMMUNICATION AND SENSING IN 3D NETWORK







[1] J. LIU, Y. MA, ET AL, "A NOVEL STOCHASTIC SPATIALLY NON-STATIONARY CHANNEL MODEL AND CAPACITY ANALYSIS FOR ELAA," IEEE GLOBECOM 2021(SUBMITTED).

- [2] L. LIU, Y. MA, N. YI AND R. TAFAZOLLI, "HERMITE EXPANSION MODEL AND LMMSE ANALYSIS FOR LOW-RESOLUTION QUANTIZED MIMO DETECTION," **IEEE TRANS. SIGNAL PROCESS.**, 2021 (UNDER REVIEW)
- [3] S. XUE, Y. MA, AND N. YI, "UNSUPERVISED DEEP LEARNING FOR MU-SIMO JOINT TRANSMITTER AND NON-COHERENT RECEIVER DESIGN," **IEEE WIRELESS COMMUN. LETTS.**, 2018.
- [4] S. XUE, Y. MA, AND N. YI, "END-TO-END LEARNING FOR UPLINK MU-SIMO JOINT TRANSMITTER AND NON-COHERENT RECEIVER DESIGN IN FADING CHANNELS," IEEE TRANS. WIRELESS COMMUN., 2021 (XPLORE EARLY ACCESS).
- [5] S. XUE, Y. MA, R. TAFAZOLLI, "AN ORTHOGONAL-SGD BASED LEARNING APPROACH FOR MIMO DETECTION UNDER MULTIPLE CHANNEL MODELS," **IEEE ICC2020 WORKSHOPS**.





DR YI MA Y.MA@SURREY.AC.UK

DR MAHDI BOLOURSAZ M.BOLOURSAZMASHHADI@SURREY.AC.UK

> DR CHUAN FOH C.FOH@SURREY.AC.UK



https://www.surrey.ac.uk/sites/default/files/2020-11/6g-wireless-a-new-strategic-vision-paper.pdf



#Surrey5GIC



6 G WIRELESS: A NEW STRATEGIC VISION



