

# Applications of Artificial Intelligence for Telecom Signal Processing

G. Peng<sup>1</sup>, N. Leung<sup>2</sup>, R. Lechowicz<sup>3\*</sup>

<sup>1-3</sup>Department of Computing, British Columbia Institute of Technology, Vancouver, BC V5G 3H2, Canada

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## ABSTRACT

Artificial Intelligence (AI) convergence and signal processing are changing the way Telecommunications work and it is happening now as the industry is undergoing a paradigm shift towards the new era of better efficiency and reliability, and better innovation. Through AI powered signal processing techniques, next generation telecommunications systems are emerging as key enablers of faster, more reliable communication networks as demand continues to grow. In this article, we explore how AI is changing the signal processing for telecommunication networks to reduce network performance and enable new application/services. Telecommunications have long relied on signal processing to transmit, receive and manipulate information carrying signals. At present, the analysis and modification of signals has been traditionally done using mathematical models and algorithms. While conventional methods still work great for basic communication networks, increasing complexity of modern networks, and exponential growth of data, have overwhelmed conventional methods.

Author e-mail: lechowiczr@bcit.ca

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## INTRODUCTION

There arise artificial intelligence, the ability to learn from enormous databases, from learning conditions. The current state of the art in AI powered signal processing techniques allow for the processing of complex, non linear problems that were previously intractable. The paradigm shift is making it possible for telecommunications companies to fine tune their networks, optimize the service quality and create innovative applications which were once impossible.<sup>[1-4]</sup>

### Noise Reduction and Signal Enhancement with AI

Noise and interference are some of the most extraordinary challenges faced in telecommunications when it comes to degrading signal quality. It is found that AI algorithms can be used to solve this problem better than traditional methods is proven, and their noise reduction and signal enhancement capability is higher than the traditional methods.

### Adaptive Noise Cancellation using Machine Learning

Large datasets of noisy signals can be trained onto machine learning models (i.e. deep neural networks) such that they learn optimal strategies for the noise

cancelling. Fixed filters have been up to now, these AI driven noise cancellers can learn to adapt to diverse types of noise and interference in real time to offer a more effective and flexible solutions.

### Beamforming enhanced with AI for 5G Networks

AI is used in 5G to enable optimization of beam forming techniques, that focus wireless signals in particular directions to boost coverage and minimise interference. In the first instance, AI algorithms can take into account network conditions as well as user behaviors in order to dynamically adjust the beamforming parameters to maximize signal strength and minimize interference to enhance the network performance and users experience. Radio frequency spectrum is a limited resource, it ought to be properly managed to maintain the level of interference and optimize the use of resource. In telecommunications networks spectrum management and resource allocation are increasingly relying on AI.<sup>[5-8]</sup>

## COGNITIVE RADIO NETWORKS

Such systems exploit wide opportunities and challenges related to the dynamic adaptation of intelligent sensing

and dynamic spectrum access, aided by cognitive radio platforms powered by AI. Machine learning algorithms are used to predict spectrum usage patterns and to make real time decisions on frequency allocation, with the resulting improvement in spectrum efficiency.

### AI Driven Network Slicing in 5G and Beyond

The ability to slice network is a key feature of 5G and future networks, enabling the operator to create multiple virtual networks atop the same physical infrastructure. The allocation of network resources across these slices are being optimized using on Real Time demands and service requirements to maximize network capacity utilization and fulfill diverse quality of service (QoS) needs based on real time using AI algorithms.<sup>[9-13]</sup>

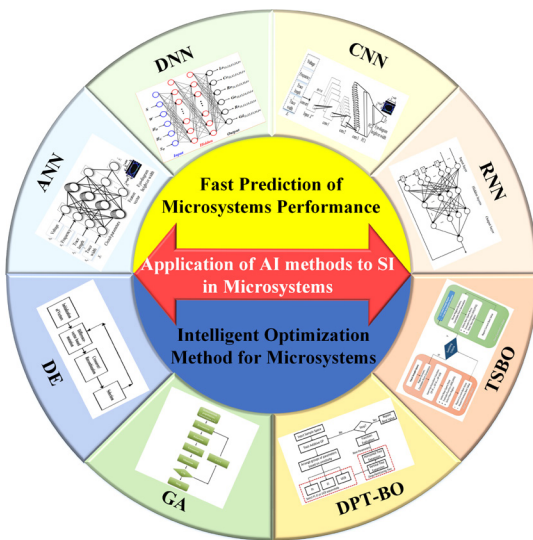


Fig. 1: Cognitive Radio Networks

### Channel Estimation and Equalization with AI capacity.

As wireless environments become more challenging, maintaining reliable communication links requires accurate channel estimation, equalization. These processes are proving to be highly improved by AI techniques.

### Channel Estimation Using Deep Learning

Even under complex, time-varying environments, we demonstrate that deep learning models can be trained to accurately predict channel characteristics. Resulting from the use of these AI driven channel estimators, their capacity to quickly and effectively adapt to changing channel conditions improves signal quality and reduces bit error rates.

### Reinforcement Learning Based Adaptive Equalization

Adaptive equalizers are being developed with reinforcement learning algorithms to use the

received signal as feedback, and then adapt their parameters in real time. The non linear channel distortions can be handled better by these AI powered equalizers than conventional linear equalizers due to better signal quality and better communication reliability.

Table 1: Artificial Intelligence Techniques Used in Telecom Signal Processing

Technique	Functionality
Neural Networks	Neural networks are used for pattern recognition in telecom signals, enhancing the ability to detect and filter noise in data transmission.
Support Vector Machines	Support vector machines are employed for classifying telecom signal data, improving error correction and optimizing signal quality in real-time.
Decision Trees	Decision trees are applied for decision-making processes in signal routing, helping optimize the allocation of bandwidth and improve signal flow efficiency.
Reinforcement Learning	Reinforcement learning optimizes signal transmission in dynamic environments, adjusting parameters based on real-time feedback to enhance overall system performance.
Deep Learning	Deep learning techniques are used to improve signal processing by recognizing complex patterns in telecom data, leading to more accurate predictions and data recovery.
Genetic Algorithms	Genetic algorithms are employed for optimizing the parameters of telecom signal processing systems, enabling efficient search for optimal configurations.

### Network Optimization and Predictive Maintenance

Telecommunications networks are challenged by ever evolving and multiplying services, the proliferation of wireless devices, and increasingly sophisticated users, demanding rapid, transparent and adaptive adaptation to those changes.

### Predictive Maintenance: Driven by AI

Machine learning models can go beyond and analyze large amounts of network data to predict equipment failure and degradation in performance before impacting service quality. Using this predictive maintenance approach, operators are able to schedule less downtime and more efficiently perform maintenance activities, increasing network reliability overall.

### AI powered Real-Time Network Optimization

Network performance metrics can be continuously monitored by AI algorithms, and network parameters can continuously be adjusted by the AI algorithms to optimize performance. This real time optimisation can improve network congestion, provide network load balancing and generally improve the quality of service for users.

### Improved Security and Fraud detection

Due to the ever increasing complexity and interconnectivity of telecommunications network, the security of such network, detection of fraud and other guilty activities has become more difficult. Network security as well as fraud detection capabilities are among new possibilities to illustrate how AI is now playing a crucial role.<sup>[14-17]</sup>

### INTRUSION DETECTION SYSTEMS USING ARTIFICIAL INTELLIGENCE

Applied network traffic patterns to detect anomalies and potential security threats in the real time. However, AI driven intrusion detection systems are increasingly powerful in predicting and responding to sophisticated cyber attacks more effectively than conventional rule based systems.

### Deep Learning for Fraud Detection

Due to the capability of deep learning models to analyse large volumes of call data records and other telecommunications data, it is possible through the process of deep learning models to identify patterns indicating non-legitimate activities. Frankly speaking these AI based fraud detection system can learn with new fraud problem and can be more accurate and timely than the conventional way.

### Quality of Experience (QoE) Management by AI

Telecommunications providers put a high importance on a high quality of experience for users. Our discussion shows how AI is enabling new and more sophisticated approaches to QoE management whereby operators can more proactively adapt to issues and improve service delivery.

### Predictive QoE Modeling

Knowing different network and user related factors, machine learning models can predict the quality of experience for different services and applications. Through the use this predictive approach, operators

are able to take preemptive actions to ensure high QoE levels and to avoid customer dissatisfaction.<sup>[18-19]</sup>

### CONTENT CACHING AND DELIVERY POWERED BY THE AI

The content caching and delivery strategies can be further optimized using the user behavior patterns and the content popularization trends by AI algorithms. An intelligent caching approach to this can reduce network congestion and speed content deliverance as well as improve user experience.<sup>[20-23]</sup>

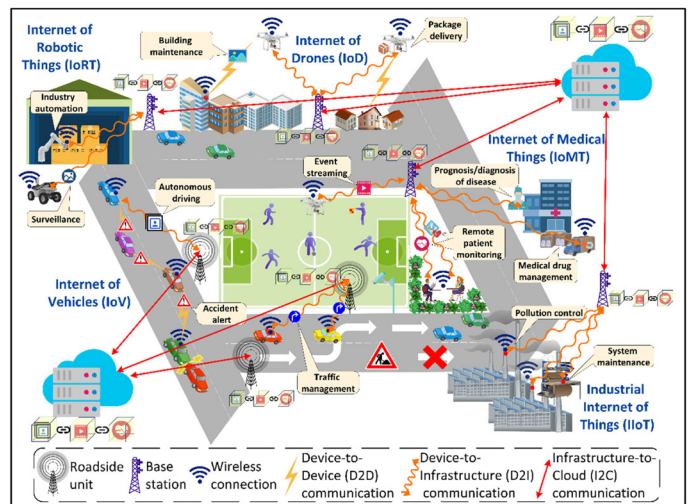


Fig. 2: Content Caching and Delivery Powered by the AI

### An Advanced Signal Processing for IoT and Edge Computing

IoT devices proliferation and emerging edge computing are shaping new signals processing challenges and opportunities in telecommunications. More efficient and intelligent signal processing at the network edge is becoming possible due to AI.

### Introduction of lightweight AI models for IoT devices

This work is focused on compact, energy efficient AI models that can run on resource constrained IoT devices. They offer us lightweight models for intelligent signal processing and decision making at the edge, that do not require continual communication to centralized servers, for efficient system as a whole.

### Distributed Signal Processing Using Federated Learning

By using techniques that soften the federated learning paradigm, AI models can be trained across multiple edge devices by training across them without centralizing all the data. This still benefits from the collective

intelligence of the network while making more privacy preserving and efficient distributed signal processing possible in IoT networks.

### Speech and Audio Processing by AI

Speech and audio processing in telecommunications is being revolutionized by AI and speech and audio quality are improved through more natural and efficient voice based interactions in challenging environments.

## SPEECH RECOGNITION AND SYNTHESIS

### Experimental Evidence of Advanced Speech Recognition and Synthesis

Over the past few years, speech recognition and synthesis systems have improved dramatically in accuracy and naturalness with the help of deep learning models. Aided by the power of these AI engines, these voice interfaces are becoming more and even more sophisticated in benefiting the telecommunications business by facilitating use of articulable voice services and applications.<sup>[24]</sup>

### Audio Quality Improvement Supported by AI

In real time, audio signals can be analyzed to find and eliminate background noise, improve clarity of speech and increase audio quality. In mobile and conferencing applications, these AI driven audio processing techniques are particularly valuable.

### Integrated Network Planning and Optimization

AI is fundamentally changing the way telecommunications networks are planned, designed and optimized to better and more economically deploy network.

### AI-Driven Network Planning

Network infrastructure can be optimally placed based on various factors such as terrain, population density and traffic pattern via machine learning models. Using this AI powered approach, network design could be more efficient and coverage would be better (Table 2).

### Automated Network Configuration and Optimization

Network performance is monitored by AI algorithms resolutely and the configurations of the network set would be adjusted automatically to optimize the performance and resource utilization. This self-optimizing method reduces the need for manual intervention significantly, and increases overall network efficiency.

### Satellite Communications with AI

Alternative application domains where artificial intelligence is also insinuating itself include satellite communications, providing unique solutions to problems and bringing new capabilities to this domain.

### Resource allocation and Intelligent Beam Hopping

Satellite resource allocation can be optimally planned using real time demand and atmospheric conditions based on AI's optimization of frequency bands and power. Such intelligent resource management both improves efficiency and capacity of satellite communication systems.

### Analysis of Ground Constellations, with Applications to AI-Enhanced Signal Processing for LEO Constellations

The rapid movement and ever changing network topology make Low Earth Orbit (LEO) satellite constellations unique from the other radio communications that we address in the rest of this thesis. These challenges are

Table 2: Artificial Intelligence in Telecom Signal Processing

Benefit	Advantage
Improved Signal Quality	Improved signal quality is achieved through AI algorithms that reduce noise, distortion, and interference, resulting in clearer communication.
Real-Time Processing	Real-time processing capabilities of AI ensure quick decision-making and signal adjustment, which is essential for uninterrupted communication in telecom networks.
Bandwidth Optimization	Bandwidth optimization helps in managing network traffic, reducing congestion, and ensuring that signal data is efficiently transmitted with minimal latency.
Error Detection and Correction	Error detection and correction techniques enabled by AI enhance data integrity, automatically identifying and correcting signal errors during transmission.
Network Efficiency	Network efficiency is maximized by AI algorithms that dynamically adjust network resources to balance load and improve performance in congested conditions.
Predictive Maintenance	Predictive maintenance powered by AI helps identify potential failures in signal transmission systems, enabling timely intervention and reducing downtime.

being addressed with the development of AI techniques to reduce handovers between satellites, and improve LEO communications signal quality.

## FUTURE TRENDS AND CHALLENGES

Even if AI is constantly growing older, it will continue to have greater impact on the signal processing in telecommunications. Some key trends and challenges to watch include:

### Signal processing with Quantum AI

New AI algorithms may emerge for solving complex signal processing problems which are intractable to classical computers because of the emergence of quantum computing. Quantum AI could seemingly rework societies such as cryptography and secure communications.

### AI for Regulatory Compliance\_ Explainable AI

With the increasing use of AI in critical telecommunications infrastructure, we will see an increased demand for explainable AI models that support transparency and responsibility over the decision making processes.

### AI-Driven 6G Network Design

As super-fast, low latency communications and increasingly sophisticated applications like holographic telepresence, and brain computer interfaces continue to develop, producible smart network design and optimization is called for and where AI can be expected to be a central part of the networks of the future.

## CONCLUSION

The joining of artificial intelligence with signal processing is revolutionize telecommunications both in terms of innovation and efficiency. AI is revolutionizing the telecommunications industry from state-of-the-art applications and services to enhance network performance and security. With these technologies continuing to improve, we can anticipate even farther reaching advancements than ever before in the events that will radically transform global communication. However, these are serious challenges, including rising energy consumption in AI algorithm, protecting the privacy and security of AI systems, and designing AI model would cover them well in a highly dynamic and complex telecommunications. Nevertheless, the implications for AI enhanced signal processing in telecommunications are huge with the capability of offering faster, more reliable, and more intelligent communication networks that underpin the digital economy of tomorrow.

Together, researchers, engineers, and industry leaders are consistently setting the boundary further and further while advancing AI and signal processing for smooth, intelligent communication around the world .

## REFERENCES:

1. Mitra, D., & Paul, R. K. (2017). Hybrid time-series models for forecasting agricultural commodity prices. *Model Assisted Statistics and Applications*, 12(3), 255-264.
2. O'reilly, G., Bezuidenhout, C. C., & Bezuidenhout, J. J. (2018). Artificial neural networks: applications in the drinking water sector. *Water Science and Technology: Water Supply*, 18(6), 1869-1887.
3. Huang, C., Fujisawa, S., De Lima, T. F., Tait, A. N., Blow, E., Tian, Y., ... & Prucnal, P. R. (2020, March). Demonstration of photonic neural network for fiber nonlinearity compensation in long-haul transmission systems. In *2020 optical fiber communications conference and exhibition (OFC)* (pp. 1-3). IEEE.
4. Zhang, S., Yaman, F., Nakamura, K., Inoue, T., Kamalov, V., Jovanovski, L., ... & Wang, T. (2019). Field and lab experimental demonstration of nonlinear impairment compensation using neural networks. *Nature communications*, 10(1), 3033.
5. Kravtsov, K., Fok, M. P., Rosenbluth, D., & Prucnal, P. R. (2011). Ultrafast all-optical implementation of a leaky integrate-and-fire neuron. *Optics express*, 19(3), 2133-2147.
6. Chen, Y., Chen, D., & Jiang, T. (2021, March). Beam-squint mitigating in reconfigurable intelligent surface aided wideband mmWave communications. In *2021 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1-6). IEEE.
7. Huang, C., Zappone, A., Alexandropoulos, G. C., Debbah, M., & Yuen, C. (2019). Reconfigurable intelligent surfaces for energy efficiency in wireless communication. *IEEE transactions on wireless communications*, 18(8), 4157-4170.
8. Pittala, C. S., Sravana, J., Ajitha, G., Saritha, P., Khadir, M., Vijay, V., ... & Vallabhuni, R. R. (2021, September). Novel methodology to validate DUTs using single access structure. In *2021 5th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMEN-Tech)* (pp. 1-5). IEEE.
9. Wu, Q., & Zhang, R. (2019). Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network. *IEEE communications magazine*, 58(1), 106-112.
10. Gomes, I. R., Gomes, C. R., Gomes, H. S., & Cavalcante, G. P. D. S. (2018). Empirical radio propagation model for DTV applied to non-homogeneous paths and different climates using machine learning techniques. *PloS one*, 13(3), e0194511.
11. Graham, A., Kirkman, N. C., & Paul, P. M. (2007). *Mobile radio network design in the VHF and UHF bands: a practical approach*. John Wiley & Sons.

12. Ghanavi, R., Kalantari, E., Sabbaghian, M., Yanikomeroğlu, H., & Yongacoglu, A. (2018, April). Efficient 3D aerial base station placement considering users mobility by reinforcement learning. In *2018 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1-6). IEEE.
13. Mismar, F. B., Choi, J., & Evans, B. L. (2019). A framework for automated cellular network tuning with reinforcement learning. *IEEE Transactions on Communications*, *67*(10), 7152-7167.
14. Liao, Y., Hua, Y., Dai, X., Yao, H., & Yang, X. (2019, May). ChanEstNet: A deep learning based channel estimation for high-speed scenarios. In *ICC 2019-2019 IEEE international conference on communications (ICC)* (p p. 1-6). IEEE.
15. Ullah, I., Raza, B., Malik, A. K., Imran, M., Islam, S. U., & Kim, S. W. (2019). A churn prediction model using random forest: analysis of machine learning techniques for churn prediction and factor identification in telecom sector. *IEEE access*, *7*, 60134-60149.
16. Babu, P. A., Nagaraju, V. S., & Vallabhuni, R. R. (2022). 8-Bit Carry Look Ahead Adder Using MGDI Technique. In *IoT and Analytics for Sensor Networks: Proceedings of ICWSNUCA 2021* (pp. 243-253). Springer Singapore.
17. Wisesa, O., Adriansyah, A., & Khalaf, O. I. (2020, September). Prediction analysis sales for corporate services telecommunications company using gradient boost algorithm. In *2020 2nd international conference on broadband communications, wireless sensors and powering (BCWSP)* (pp. 101-106). IEEE.
18. Dong, P., Zhang, H., Li, G. Y., Gaspar, I. S., & NaderiAlizadeh, N. (2019). Deep CNN-based channel estimation for mmWave massive MIMO systems. *IEEE Journal of Selected Topics in Signal Processing*, *13*(5), 989-1000.
19. Soltani, M., Pourahmadi, V., Mirzaei, A., & Sheikhzadeh, H. (2019). Deep learning-based channel estimation. *IEEE Communications Letters*, *23*(4), 652-655.
20. Min, B., Ross, H., Sulem, E., Veyseh, A. P. B., Nguyen, T. H., Sainz, O., ... & Roth, D. (2023). Recent advances in natural language processing via large pre-trained language models: A survey. *ACM Computing Surveys*, *56*(2), 1-40.
21. Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., ... & Sun, L. (2024). A comprehensive survey on pretrained foundation models: A history from bert to chatgpt. *International Journal of Machine Learning and Cybernetics*, 1-65.
22. Gollamandala, U. B., Midasala, V., & Ratna, V. R. (2022). FPGA implementation of hybrid recursive reversible box filter-based fast adaptive bilateral filter for image denoising. *Microprocessors and Microsystems*, *90*, 104520.
23. Ejaz, M., Kumar, T., Ylianttila, M., & Harjula, E. (2020, March). Performance and efficiency optimization of multi-layer IoT edge architecture. In *2020 2nd 6G Wireless Summit (6G SUMMIT)* (pp. 1-5). IEEE.
24. Fu, Y., Wang, S., Wang, C. X., Hong, X., & McLaughlin, S. (2018). Artificial intelligence to manage network traffic of 5G wireless networks. *IEEE network*, *32*(6), 58-64.
25. Sathish Kumar, T. M. (2024). Low-power design techniques for Internet of Things (IoT) devices: Current trends and future directions. *Progress in Electronics and Communication Engineering*, *1*(1), 19-25. <https://doi.org/10.31838/PECE/01.01.04>
26. Kumar, T. M. S. (2024). Security challenges and solutions in RF-based IoT networks: A comprehensive review. *SCCTS Journal of Embedded Systems Design and Applications*, *1*(1), 19-24. <https://doi.org/10.31838/ESA/01.01.04>
27. Uvarajan, K. P. (2024). Integration of blockchain technology with wireless sensor networks for enhanced IoT security. *Journal of Wireless Sensor Networks and IoT*, *1*(1), 23-30. <https://doi.org/10.31838/WSNIOT/01.01.04>
28. Kavitha, M. (2024). Enhancing security and privacy in reconfigurable computing: Challenges and methods. *SCCTS Transactions on Reconfigurable Computing*, *1*(1), 16-20. <https://doi.org/10.31838/RCC/01.01.04>
29. Kavitha, M. (2024). Energy-efficient algorithms for machine learning on embedded systems. *Journal of Integrated VLSI, Embedded and Computing Technologies*, *1*(1), 16-20. <https://doi.org/10.31838/JIVCT/01.01.04>
30. Kavitha, M. (2023). Beamforming techniques for optimizing massive MIMO and spatial multiplexing. *National Journal of RF Engineering and Wireless Communication*, *1*(1), 30-38. <https://doi.org/10.31838/RFMW/01.01.04>
31. Roper, S., & Bar, P. (2024). Secure computing protocols without revealing the inputs to each of the various participants. *International Journal of Communication and Computer Technologies*, *12*(2), 31-39. <https://doi.org/10.31838/IJCCTS/12.02.04>
32. Anandhi, S., Rajendrakumar, R., Padmapriya, T., Manikanthan, S. V., Jebanazer, J. J., & Rajasekhar, J. (2024). Implementation of VLSI Systems Incorporating Advanced Cryptography Model for FPGA-IoT Application. *Journal of VLSI Circuits and Systems*, *6*(2), 107-114. <https://doi.org/10.31838/jvcs/06.02.12>
33. Klavin, C. (2024). Analysing antennas with artificial electromagnetic structures for advanced performance in communication system architectures. *National Journal of Antennas and Propagation*, *6*(1), 23-30.