

Towards a Wireless Physical-Layer Foundation Model: Challenges and Strategies

Jaron Fontaine, Adnan Shahid, *Senior Member* and Eli De Poorter

Abstract—Artificial intelligence (AI) plays an important role in the dynamic landscape of wireless communications, solving challenges unattainable by traditional approaches. This paper discusses the evolution of wireless AI, emphasizing the transition from isolated task-specific models to more generalizable and adaptable AI models inspired by recent successes in large language models (LLMs) and computer vision. To overcome task-specific AI strategies in wireless networks, we propose a unified wireless physical-layer foundation model (WPFM). Challenges include the design of effective pre-training tasks, support for embedding heterogeneous time series and human-understandable interaction. The paper presents a strategic framework, focusing on embedding wireless time series, self-supervised pre-training, and semantic representation learning. The proposed WPFM aims to understand and describe diverse wireless signals, allowing human interactivity with wireless networks. The paper concludes by outlining next research steps for WPFMs, including the integration with LLMs.

Index Terms—Foundation models, LLMs, wireless networks

I. INTRODUCTION

In the ever-evolving landscape of wireless communications and networking research, including the advancements of the upcoming 6G standard, AI has become the focal point for tackling issues that cannot be solved by traditional non-machine learning approaches [1]. Such approaches are based on traditional optimization theory techniques and only work if suitable mathematical models are available. With increasing user traffic and density, formulating such models is difficult [2]. Deep learning is suitable in such situations because it can find effective functions from a dataset, while aiming to be scalable and generalizable. It powers a wide range of applications such as recognizing wireless technologies, wireless optimization, classifying non-line-of-sight (NLOS) conditions, estimating environmental parameters and analyzing human behavior in sports and healthcare applications. [3]–[5]. Recently, significant efforts have been made by 3rd Generation Partnership Project (3GPP) to standardize machine learning (ML) in wireless networks. 3GPP has integrated ML into the 5G core architecture in releases 15 and 16, while ‘Open RAN’ embraces a ML-native approach [6].

However, there is a fundamental issue with the predominant deep learning approach. A large number of research papers and solutions already exist, but are often developed and trained from scratch. Each of these thousands individual AI models operate in isolation which leads to a lack of knowledge sharing and reuse. If we look at the current trend of deep learning, which is

presented in Figure 1, we can identify three phases and analyze how this issue evolved and can be addressed.

1) In the **first phase** of the development of wireless AI (see Figure 1), many researchers individually proposed ML models for different wireless communication tasks such as recognition of wireless technologies, management of radio resources, classification of (N)LOS, etc., which require domain expertise and expensive ML model training costs [7]. Although these models use popular architectures such as deep, convolutional, and long short-term memory neural networks, the idea of sharing knowledge (weights) across various wireless downstream tasks is vastly underexplored.

2) A **second phase** of advances in AI has been led by domains that have a lot of data available, such as neurolinguistic programming (NLP) and the computer vision domain. In such domains, neural networks have been thoroughly investigated and successfully demonstrated over the last decade. During this period, transfer learning has been proposed to leverage and synthesize the knowledge distilled within a task and use valuable experience accumulated in the past to facilitate the learning of new problems [8]. This requires less labeled data, ML can adapt quickly to new environments and can be more robust. However, this approach focuses on variations within single tasks, including those in the wireless domain.

3) Very recently, in the **third phase**, key AI domains have undergone a paradigm shift with the introduction of foundation models. A foundation model is a “paradigm for building AI systems” in which a model trained on a large amount of unlabeled data can be adapted to many different downstream tasks, even with different types of data [9]. For example, a foundation model for image generation can cope with a wide variety of styles and shapes. Upon showing just a few new samples of a new style, the foundation model is adapted towards a new downstream task (e.g., generation of images using the new style) without significant effort required. When we consider these rapid advances in AI, it becomes evident that current task-based ML approaches in wireless networks are no longer the way forward.

As such, the evolution of AI development reveals a transition from task-specific models to the emergence of adaptable AI models that work across many tasks. To this end, this paper aims to contribute significantly by proposing foundation models for physical-layer wireless networks AI across multiple downstream tasks, thereby enabling future advancements in this domain. The main contributions presented in this paper are the following:

- A brief overview of advances in foundation models and their applicability in the wireless domain.

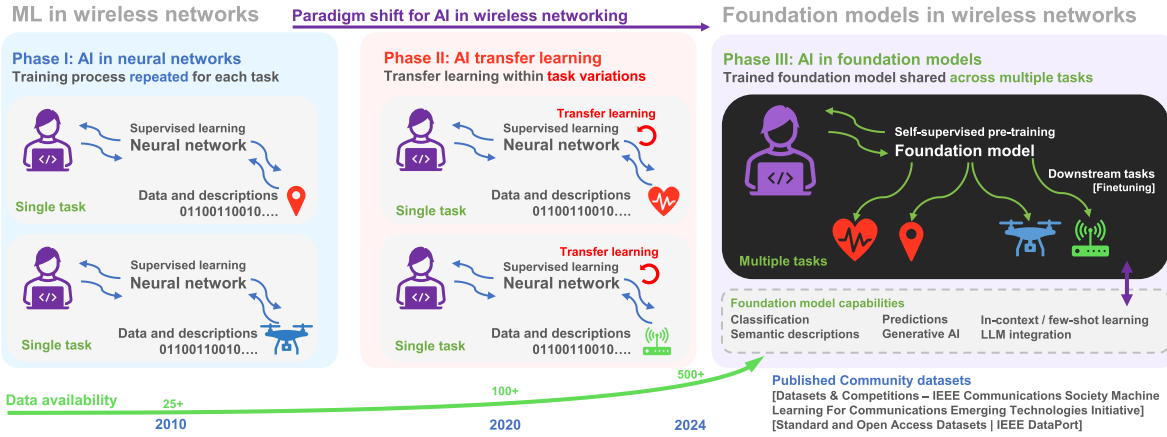


Fig. 1. An overview of the three phases of deep learning, where a WPFM aims to be a generalizable and adaptable model across multiple wireless applications.

- Analysis of missing steps and main challenges in the wireless domain to build a foundation model.
- A wireless physical-layer foundation model (WPFM) framework.
- Strategies to apply wireless use cases effectively.

In the next section, we explore the advances in foundation models and discuss the need for WPFMs to streamline AI development in various tasks in wireless communication. Next, Section III presents the challenges in the wireless domain of building a WPFM. Section IV outlines wireless applications, used to demonstrate the foundation model in Section V, where we present a general WPFM framework and implementation strategies. Next, Section VI discusses the next research steps for WPFMs and enabling human-interactive wireless networks. Finally, conclusions are drawn in Section VII.

II. ADVANCES IN FOUNDATION MODELS

Foundation models have gained a lot of interest in the field of natural language processing and computer vision with the introduction of models such as GPT3/4, ChatGPT, BERT, DALL-E, etc. [10]. These models have enabled significant progress and achieved state of the art (SOTA) accuracy in their fields. With the abundant availability of large datasets, foundation models can be seamlessly applied to a diverse set of downstream tasks. Innovations to such foundation models include unsupervised pre-training techniques that enables models to grasp complex patterns and relationships within massive datasets. Additionally, fine-tuning strategies have improved in recent years, e.g. few- and zero-shot learning for new applications.

To accommodate diverse data types, multimodality has become a prominent feature in machine learning and is frequently adapted by foundation models [11]. Models such as 'CLIP', designed for vision tasks, seamlessly merge text and image encodings, facilitating zero-shot image identification [12]. Additionally, text-to-image models like DALL-E demonstrate a profound synergy between language and vision models, incorporating encoded text prompts and image generation capabilities [13]. The autoregressive-trained transformer can simultaneously encode text and images, showcasing robust performance even

in zero-shot evaluation scenarios. This integration of modalities not only enhances versatility, but also underscores the adaptability of (transformer-based) neural network architectures to handle varied input types effectively.

Why have these remarkable advances in AI not been applied in other domains? Unfortunately, these advances have thrived with the availability of large amounts of data, primarily drawn from the Internet, trained on large models. Acquiring such data quantities proves challenging in numerous domains, since the Internet does not harbor the necessary data as abundantly as it does textual and visual content.

One domain facing this challenge, i.e. robotics, has started to embrace the collection large dataset to achieve a general-purpose (foundation) model [14]. Instead of relying on single-task AI, which only works well on a single robot involved in a single experiment, researchers have collaborated on achieving a general AI robot that has learned from a pool of many robots. Surprisingly, the authors found that multirobot data could be used with similar methods used in LLMs, provided that they follow the recipe of using large neural networks with large datasets. The dataset contains five hundred different skills and interactions with thousands of different objects, and allows training of a foundation model without requiring any special features for cross-embodiment. Remarkably, the global (foundation) model outperformed the robots trained in individual tasks. Finally, the authors have successfully integrated large vision and language models, which are finetuned to describe actions based on visual data from the robot. This allows prompt-based robotic actions, even with unseen objects.

In addressing the challenges posed by the advent of 6G networks, encompassing Non-Terrestrial Networks (NTN), Terrestrial Networks (TN), mmWave/THz network, underwater networks, and advancements in Wireless Local Area Networks (WLANs) [15], could a unified WPFM serve as a viable solution to streamline and reduce redundancy in AI development across diverse wireless networks? Much like in the domain of robotics, similar challenges exist, where large datasets sourced from the Internet are scarce or too simplistic to represent complex wireless conditions. However, the availability of data is quickly

catching up. Popular journals are soliciting papers specific to datasets [16], as depicted in Figure 1.

We believe it is crucial to start the development of a foundation model which focuses on the wireless physical layer. Unlike higher layers in wireless networks, the realization of this WPFM requires dealing with complex and dynamic data in the form of time series. The adoption of ML innovations can be significantly accelerated with a model that can understand and represent these time series. Trained foundation models using architectures such as transformer networks will eliminate the need for exhaustive research, domain expertise, expensive data collection, as it enables improved representation learning across multiple downstream tasks.

Next, it will be possible to integrate a WPFM with foundation models intended for higher layers of the network stack. In these layers, pre-trained LLMs, such as ChatGPT, BERT, and Llama, have been very recently investigated and can already perform general tasks quite well [9] [17] [18]. Examples of such tasks include answering healthcare-related questions, classifying 3GPP working group based on technical specifications, answering telecom-related questions, etc. However, these models lack an understanding of physical wireless signals. With a WPFM, we can integrate existing LLMs to open up a semantic understanding of the physical wireless environment. System operators will no longer solely rely on traditional rule-based configurations programmed by engineers for individual tasks (e.g. defined channel selection and power allocation parameters for each application); they will be able to simply instruct (prompt) the model to configure networks or build applications using in-context learning (giving input and output examples) and utilize automatic optimization (without explicit programming) using physical-layer sensing WPFMs, as illustrated in Figure 1.

III. CHALLENGES IN WIRELESS PHYSICAL-LAYER FOUNDATION MODELS

Recent scientific work has provided preliminary building blocks for WPFMs, such as transfer learning solutions and per-task data representations. However, since there is no general methodology to integrate these building blocks into an overall foundation model, significant research remains to be done. In addition, the usage of LLMs has been a recent research topic and even standardization within wireless communications, however, no physical-layer results have been presented and fundamental research challenges have yet to be identified [17]–[20]. This paper addresses the following fundamental research challenges:

1) *Challenge 1: Novel methods are required for wireless pre-training tasks:* Modern ML architectures are capable of handling complex pattern learning and scaling of many parameters. The transformer neural network [21], for example, excels in efficiently learning sequential data with parallel training. In other domains, foundation models exist which can perform general tasks, such as CLIP, DALL-E and LLMs such as GPT3, GPT4 and BERT, but also have been applied recently in time series [22], [23]. However, in wireless networks, the transformer architecture is missing its potential by being trained to perform

individual tasks. Instead, training large foundation transformer models requires effective un- and self-supervised pre-training tasks, e.g., in LLMs next-word predictions, masking, positional predictions, denoising, etc., are used [9]. This is key in enabling a shared foundation model for multiple downstream tasks (Figure 1). However, with limited data availability in the past and challenges in supporting heterogeneous data types, there is a gap in the wireless domain for effective pre-training tasks.

2) *Challenge 2: WPFMs need to support the embedding of heterogeneous wireless time series with different lengths, sampling rates and data types:* Creating a foundation model for wireless time series, such as in-phase and quadrature (IQ) samples and channel impulse responses (CIRs), diverges significantly from models in the NLP (i.e. semantic understanding) and vision domains (i.e. 2D / 3D patterns) due to the heterogeneous temporal nature of the data. Unlike text or images, time-series data unfold over time, which presents challenges related to capturing embedding temporal dependencies, modeling variations, and addressing issues like fading channels and dynamic network conditions. Another contrast with SOTA can be found in forecasting time series. Here, the focus is on predicting future trends based on historical data and seasonal trends, often seen in financial markets or climate studies, emphasizing precision and accuracy in predicting future outcomes. Analyzing wireless networks also proves to be much more difficult when dealing with heterogeneous wireless time series which are non-intuitive, in contrast to data in the aforementioned domains. Wireless SOTA embedding is limited to reducing the dimensionality (compression) or mapping (in)complete data in a homogeneous space [8]. Developing a WPFM demands a deep understanding of time-sensitive data dynamics heterogeneous, i.e. supporting samples from use cases with different lengths, sampling rates and data types (IQ, received signal strength indicator (RSSI), CIR, metadata etc.), setting it apart as a compelling and distinctive domain within the broader AI landscape.

3) *Challenge 3: To cope with the nonintuitive nature of wireless time series data, WPFMs need human-understandable interaction and prompt-based optimization:* The semantic description of wireless networks and their environments has been a recent topic for standalone (wireless) machine learning models [12], [24]. Combining textual descriptions with the first two challenges in a foundation model allows AI to be used in many downstream applications and opens up new possibilities. For example, by combining the embedded information from WPFMs with such semantic descriptions, we allow LLMs to autonomously understand wireless data from the physical layer, enable AI chain-of-thoughts and prompt-based applications and optimization. SOTA lacks the ability for wireless optimization (LLM + WPFM) and is currently limited to LLM-based configurations using standardization and specification documents [25].

IV. APPLICATIONS OF A WIRELESS PHYSICAL-LAYER FOUNDATION MODEL

To demonstrate the framework we propose in Section V and how it can address these challenges in wireless networks,

Physical layer foundation models in wireless networks

Proposed framework

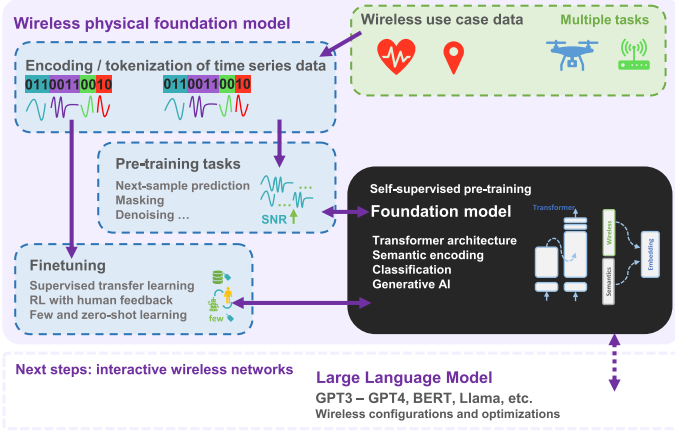


Fig. 2. The different framework strategies of a WPFM

we introduce two use cases where the AI improvements are predominately focused on wireless time series such as IQ samples, CIR with different sample rates, input lengths, etc.

1) **Activity recognition using UWB radar:** Activity recognition in healthcare leveraging ultra-wideband (UWB) radar can rely on CIR data for precise movement detection. The use of ML in activity recognition applications, often including IMU sensors, facilitates automated real-time movement detection and improves healthcare monitoring. Including UWB radar as a sensor can mitigate the need for persons to wear on-body sensors. Due to the complex nature of UWB CIR signals, a high cost will be associated to develop one of many individual activity recognition applications.

2) **Wireless spectrum management:** Wireless spectrum management involves recognizing coexisting technologies within the same spectrum using IQ samples, analysed by ML models. The increasing number of wireless technologies complicates AI-driven recognition. This becomes even more complicated by the diverse number of bandwidths at which the technologies are operating, which requires distinct sampling rates. Traditional training approaches for individual ML models become challenging and time-consuming due to these complexities.

As such, there is a need for a WPFM that can understand features in wireless time series, including UWB CIRs, IQ samples, etc. This can alleviate costly engineering of individual models, simplifying ML in existing and new wireless applications.

V. A WIRELESS PHYSICAL-LAYER FOUNDATION MODEL STRATEGIC FRAMEWORK

To address the research challenges, we present a strategic framework of a WPFM. This foundation model, illustrated in Figure 2 has a simple, but transformative goal: it can understand many types of physical wireless signals (time series) and meta-data, while enabling network configurations and optimization and allowing user interaction. This will enable easy transfer to new downstream tasks (e.g., CIR understanding to detect different types of objects using UWB radar, IQ pattern encoding to

recognize unseen wireless technologies in a spectrum manager and configuring a 6G network depending on the environmental conditions such as interfering signals, noise, etc.).

A. Embedding and tokenization of physical-layer time-series

In the wireless domain, technologies and applications generally consist of heterogeneous time series. This means that the length of the input data, its data type and dimensionality can vary across applications. To ensure a consistent input for foundation models, we propose using embedding or tokenizing of wireless time series data, which has several implementation options. One possibility is to use Byte-Pair Encoding (BPE) to merge frequently occurring signal or pulse IQ sample pairs, until a fixed model input size is obtained. Another possibility is to represent known pulses and short-term patterns in time series as tokens. Alternatively, Time Variable based Tokenization (TVT) can be used to tokenize time series where the token uniformity inductive bias would act on the variable dimension [26]. In addition to encoding, it is essential to define the vocabulary size (number of unique tokens) to support variable input lengths, without making the model unnecessary complex. By applying tokenization, we can provide the foundation model with a uniform sample distribution, irrespective of the sampling rate (reaching e.g., $< 10\%$ embedding difference) and is robust to input noise (e.g., $\text{SNR} > 10$ dB). Furthermore, it should support samples at different bandwidths or sample rates and allow generative AI of samples close (in embedded space) to a wireless time series for data augmentation or simulation purposes. The result of a robust tokenizer can serve as input for a foundation model based on, for example, transformers.

Use case applications In wireless use cases, these techniques allow CIRs with larger and shorter lengths to be understood by the framework, as well as technology recognition IQ streams with different sampling rates and sample lengths. The shape of pulses or sine waves contains information about the wireless technology and modulation used or represents reflections in UWB CIR data. These waves or pulses can be represented as tokens. To support longer or shorter time patterns in wireless applications, the accumulated token context size needs to be appropriate. Depending on the complexity of the transformer and its energy requirements, these can be extended or reduced.

B. Effective self-supervised pre-training tasks for a WPFM

A crucial part of the development of foundation models is to obtain novel wireless pre-training tasks. Pre-training tasks are essential because they allow the model, e.g. a transformer, to learn general features and representations from a vast amount of diverse data before fine-tuning on a specific task. Allowing self-supervised pre-training is especially interesting in the wireless domain, which suffers from a low volume of labeled datasets. Pre-training can (i) facilitate learning general representation and contextual information that are applicable in multiple wireless applications, (ii) it can facilitate transfer learning to downstream tasks and (iii) it mitigates the need for large labeled datasets. In wireless networks, we envision techniques

such as (i) next sample/pulse/multipath prediction, aiming at predicting sequential information, (ii) masking which can learn to predict missing samples/pulse/multipath within the signal, (iii) denoising learns to remove (additive) Gaussian noise from signals, (iv) sequence order prediction learns to order signals in chronological order and (v) generative adversarial networks learn internal representations of the signal to generate realistic new versions of the signal under different conditions. During training, several loss function strategies must be considered. One example is contrastive loss where, depending on the task, samples are assigned positive and negative labels. In the context of localization, samples collected near or at the same time and position can be considered positive, while others can be negative. Another approach is to assign positive labels to one sample with different augmentations and negative labels to other samples. By utilizing a pre-trained foundation model, we can effectively capture and extract common patterns within wireless time series data, enabling the application of generative AI techniques. Furthermore, it serves as a strong basis for further fine-tuning on specific wireless tasks.

Use case applications Given an existing context of (embedded) CIRs or IQ samples, the model can learn to predict the next likely pulse or sine wave samples, enhancing its ability to capture sequential information. Similarly, masking methods can teach the model to predict missing samples within the CIR signal or IQ samples, improving its robustness to incomplete or noisy data. Finally, denoising can help train the model to remove Gaussian noise from signals, making it more resilient to real-world environmental conditions. When pre-training, contrastive loss can be assigned to CIR samples collected at the same time and position, to capture spatial and temporal correlations.

C. Semantic physical-layer wireless representation learning

To generate semantic information, we need to integrate textual descriptions of the wireless network and environment into the foundation model. These descriptions can be obtained from experts or pre-trained LLMs. To fuse text and wireless time series, multimodal fusion foundation models (transformers) can be designed. A simple approach is to share the latent space which enables joint representations of text and time series modalities. In contrast, separated latent space representations can be investigated which are more flexible and allow different architectures or model reuse for both text and time series. The textual description is different from the labels as it represents semantic information that can be provided along the wireless time-series data. For example, labels are the wireless technologies shared in the considered spectrum, while semantic textual descriptions can be the size and type of the environment, similarly to image captions in the computer vision domain. Learning semantic representations in wireless networks enables the foundation model to produce semantic information about the wireless network and environment in a textual form. In addition, it can also generate time series variations based on semantic descriptions in new environments and wireless technologies.

Use case applications Metadata such as the environment dimensions (walls, ceiling height, etc.), type of environment

(outdoor, office indoor, industrial environment, etc.), number of obstacles, persons, etc. can be included, as it impacts the efficiency and performance of wireless applications. Such descriptions can be augmented by LLMs and allow foundation models to generatively provide context to new, unknown environments. Additionally, the generative capabilities can help with diagnostics or simulations of UWB and wireless deployments.

D. Fine-tuning WPFMs

Although the foundation model may already be able to perform general tasks and applications, fine-tuning allows it to adapt the model to specific downstream tasks or domains. To enable this fine-tuning, we believe the following techniques are vital: (i) supervised transfer learning with a small, labeled dataset (tens of samples), (ii) reinforcement learning with human feedback (grading the predictions made by the foundation model before and during model deployment), (iii) zero- and few-shot learning by providing context (data context augmentation), and (iv) example input-output pairs (in-context learning) of the expected downstream task. Additionally, generative AI capabilities can enrich small datasets and allow these be used for fine tuning the model for the considered downstream tasks.

Use case applications With reinforcement learning, a user of an activity recognition system can provide positive or negative feedback, while experts or network controllers can provide efficiency or performance feedback on wireless classification performance. In-context or zero- and few-shot learning can be integrated by giving in and output examples, e.g. a UWB CIR + 'falling down' movement, as part of a healthcare application. The model can take this example and explain new human activities detected by the UWB radar.

VI. NEXT STEPS: THE ROAD TO INTERACTIVE WIRELESS NETWORKS

The realization of a WPFM, evaluated on a number of wireless applications, sparks several future research opportunities:

- **LLM integration:** LLMs can be integrated with the WPFM. This allows users to interact in a natural way with wireless networks. When users prompt statistics or the status of physical-layer conditions, the LLM can request meta-data from the WPFM which includes classifications, semantic descriptions of the wireless network conditions, sensing applications, human behavior, etc. This interaction requires further research to increase efficiency and raises open questions such as whether the pre-trained LLM and WPFM need to be finetuned together (training both latent spaces) or can coexist and interact on an API-basis.
- **Multimodal WPFM:** Next to supporting wireless time series and semantic meta-data of the environment, another modality that can be included is image-based information. As such, the WPFM can incorporate and interact with images of floor plans, human activities, wireless access point or nodes topologies, etc.
- **Wireless network optimization:** With LLM integration, the WPFM enables continuous optimization of wireless

networks, considering environmental and wireless conditions and providing this information to the LLM. On the basis of this information, LLMs could output updated configurations and settings of the network. For example, when the WPFM notices increased in human activity in a room, the LLM can look at the UWB configuration and update the sampling rate and bandwidth for increased accuracy. Such automated optimization can be enabled on a prompt basis, following any data sheets and standardization given as a context to existing LLMs.

- **Addressing energy consumption:** Foundation models tend to have a large number of parameters, resulting in very high complexity and energy consumption. From a training perspective, trade-offs should be investigated whether this requires more energy than combining multiple traditional task-focused ML solutions. By sharing the WPFM and integrating in multiple domains and applications, the foundation model has the potential to save energy in the end.
- **Embedded and edge-based implementations:** Bringing foundation models closer to the end user is a trending topic within the research community. Especially in time critical wireless networks, it is crucial to investigate running the foundation model local on edge or embedded mobile devices, limiting data transfer and latency.

VII. CONCLUSIONS

This paper underscores the upcoming transformative work within the field of AI for wireless networks, evolving from task-specific models to the innovative paradigm of adaptable WPFMs. The challenges identified, such as effective pre-training tasks and embedding of heterogeneous time-series, highlight the complexities inherent in developing a unified model for wireless applications. The proposed WPFM architecture aims to revolutionize AI development in wireless networks, accelerating and sharing AI advances. We believe the semantic capabilities of a WPFM are a crucial step towards human interactive wireless networks. Such interactivity will be part of future research and can bridge the gap between expert-based manual configurations and automatic prompt-based configurations using LLMs. To realise the goal of a unified WPFM, shared across many downstream tasks, upcoming research should focus on refining, standardizing pre-training tasks, tailored for the wireless domain. Additionally, real-world implementations are essential to empirically validate the effectiveness of the proposed WPFM.

REFERENCES

- [1] J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, "Toward a 6g ai-native air interface," *IEEE Communications Magazine*, vol. 59, no. 5, pp. 76–81, 2021.
- [2] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, ai-based, or both?," *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7331–7376, 2019.
- [3] J. Fontaine, E. Fonseca, A. Shahid, M. Kist, L. A. DaSilva, I. Moerman, and E. De Poorter, "Towards low-complexity wireless technology classification across multiple environments," *Ad Hoc Networks*, vol. 91, p. 101881, 2019.
- [4] Y. Cheng, B. Yin, and S. Zhang, "Deep learning for wireless networking: The next frontier," *IEEE Wireless Communications*, vol. 28, no. 6, pp. 176–183, 2021.
- [5] J. Fontaine, F. Che, A. Shahid, B. Van Herbruggen, Q. Z. Ahmed, W. B. Abbas, and E. De Poorter, "Transfer learning for uwb error correction and (n) los classification in multiple environments," *IEEE Internet of Things Journal*, 2023.
- [6] M. K. Shehzad, L. Rose, M. M. Butt, I. Z. Kovács, M. Assaad, and M. Guizani, "Artificial intelligence for 6g networks: Technology advancement and standardization," *IEEE Vehicular Technology Magazine*, vol. 17, no. 3, pp. 16–25, 2022.
- [7] M. Kulin, T. Kazaz, E. De Poorter, and I. Moerman, "A survey on machine learning-based performance improvement of wireless networks: Phy, mac and network layer," *Electronics*, vol. 10, no. 3, p. 318, 2021.
- [8] C. T. Nguyen, N. Van Huynh, N. H. Chu, Y. M. Saputra, D. T. Hoang, D. N. Nguyen, Q.-V. Pham, D. Niyato, E. Dutkiewicz, and W.-J. Hwang, "Transfer learning for wireless networks: A comprehensive survey," *Proceedings of the IEEE*, vol. 110, no. 8, pp. 1073–1115, 2022.
- [9] C. Zhou, Q. Li, C. Li, J. Yu, Y. Liu, G. Wang, K. Zhang, C. Ji, Q. Yan, L. He, *et al.*, "A comprehensive survey on pretrained foundation models: A history from bert to chatgpt," *arXiv preprint arXiv:2302.09419*, 2023.
- [10] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, *et al.*, "Language models are few-shot learners," *Advances in neural information processing systems*, vol. 33, pp. 1877–1901, 2020.
- [11] Y. Liu, X. Gao, J. Han, L. Liu, and L. Shao, "Zero-shot learning via a specific rank-controlled semantic autoencoder," *Pattern Recognition*, vol. 122, p. 108237, 2022.
- [12] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, *et al.*, "Learning transferable visual models from natural language supervision," in *International conference on machine learning*, pp. 8748–8763, PMLR, 2021.
- [13] A. Ramesh, M. Pavlov, G. Goh, S. Gray, C. Voss, A. Radford, M. Chen, and I. Sutskever, "Zero-shot text-to-image generation," in *International Conference on Machine Learning*, pp. 8821–8831, PMLR, 2021.
- [14] A. Padalkar, A. Pooley, A. Jain, A. Bewley, A. Herzog, A. Irpan, A. Khazatsky, A. Rai, A. Singh, A. Brohan, *et al.*, "Open x-embodiment: Robotic learning datasets and rt-x models," *arXiv preprint arXiv:2310.08864*, 2023.
- [15] L.-H. Shen, K.-T. Feng, and L. Hanzo, "Five facets of 6g: Research challenges and opportunities," *ACM Comput. Surv.*, vol. 55, feb 2023.
- [16] C. Fischione, M. Chafii, Y. Deng, and M. Erol-Kantarci, "Data sets for machine learning in wireless communications and networks," *IEEE Communications Magazine*, vol. 61, no. 9, pp. 80–81, 2023.
- [17] Z. Lin, G. Qu, Q. Chen, X. Chen, Z. Chen, and K. Huang, "Pushing large language models to the 6g edge: Vision, challenges, and opportunities," *arXiv preprint arXiv:2309.16739*, 2023.
- [18] A. Maatouk, N. Piovesan, F. Ayed, A. De Domenico, and M. Debbah, "Large language models for telecom: Forthcoming impact on the industry," *arXiv preprint arXiv:2308.06013*, 2023.
- [19] L. Bariah, Q. Zhao, H. Zou, Y. Tian, F. Bader, and M. Debbah, "Large language models for telecom: The next big thing?," *arXiv preprint arXiv:2306.10249*, 2023.
- [20] W. Tong, C. Peng, T. Yang, F. Wang, J. Deng, R. Li, L. Yang, H. Zhang, D. Wang, M. Ai, *et al.*, "Ten issues of netgpt," *arXiv preprint arXiv:2311.13106*, 2023.
- [21] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
- [22] Y. Wang, Z. Gao, D. Zheng, S. Chen, D. Gunduz, and H. V. Poor, "Transformer-empowered 6g intelligent networks: From massive mimo processing to semantic communication," *IEEE Wireless Communications*, 2022.
- [23] P. Wang, Y. Cheng, B. Dong, R. Hu, and S. Li, "Wir-transformer: Using transformers for wireless interference recognition," *IEEE Wireless Communications Letters*, vol. 11, no. 12, pp. 2472–2476, 2022.
- [24] L. H. Li, M. Yatskar, D. Yin, C.-J. Hsieh, and K.-W. Chang, "Visualbert: A simple and performant baseline for vision and language," *arXiv preprint arXiv:1908.03557*, 2019.
- [25] M. Kotaru, "Adapting foundation models for information synthesis of wireless communication specifications," *arXiv preprint arXiv:2308.04033*, 2023.
- [26] Z. Zhou, R. Zhong, C. Yang, Y. Wang, X. Yang, and W. Shen, "A k-variate time series is worth k words: Evolution of the vanilla transformer architecture for long-term multivariate time series forecasting," *arXiv preprint arXiv:2212.02789*, 2022.