Abstract—Traditionally, a communication waveform is designed by experts based on communication theory and their experiences on a case-by-case basis. In this paper, we propose a new waveform design paradigm with the knowledge graph (KG)-based intelligent recommendation system. The proposed paradigm aims to improve the design efficiency by structural characterization of existing waveforms and intelligently utilizing the knowledge learned from them. To achieve this goal, we first build a communication waveform knowledge graph (CWKG) with a first-order neighbor node, for which both structured semantic knowledge and numerical parameters of a waveform are integrated by representation learning. Based on the developed CWKG, we further propose an intelligent communication waveform recommendation system (CWRS) to generate waveform candidates. In the CWRS, an improved convolutional operator is introduced according to the characteristics of KG-based waveform representation, and the multi-head self-attention is adopted to weigh the influence of various components. Meanwhile, multilayer perceptron-based collaborative filtering is used to evaluate the matching degree between the requirement and the waveform candidate. Simulation results show that the proposed CWKG-based CWRS can recommend waveform candidates with high reliability, and utilize existing waveform knowledge much more effectively than existing methods.

I. INTRODUCTION

For wireless communications, a communication waveform is usually composed of multiple access and duplex scheme, frame/slot structure, modulation, channel coding, and interleaving scheme, etc [1]. The task of communication waveform design is to determine these schemes and corresponding parameters so that the information transmission requirement under specific application scenarios and resource constraints can be efficiently met. For a new requirement, the communication waveform is commonly designed by experts with solid communication theory knowledge and rich experiences, which is usually laborious and time-consuming. For example, it takes thousands of experts worldwide several years to design 4G and 5G waveforms. Moreover, the optimality of the proposed waveform could not always be guaranteed due to theoretical and empirical limitations. Therefore, it is well-motivated to improve the efficiency of waveform design.

Model-based optimization approaches have been widely used to facilitate the design of communication waveforms. The adaptive modulation and coding (AMC) [1] is a typical one. In the regime of software-defined radio (SDR) and cognitive radio (CR), a spectrally modulated, spectrally encoded (SMSE) framework [2] is proposed to represent and analyze orthogonal frequency division multiplexing (OFDM)-based communication waveform. In [3], a framework for joint dynamic resource allocation and waveform adaptation is presented based on generalized signal expansion functions. With the development of machine learning, data-driven methods are proposed, for which the transceiver is considered a black box and part or all of the components are replaced by deep neural networks (DNNs) [4], [5]. Recently, the combination of model-driven and data-driven methods has been proposed for better performance, e.g., ComNet, RTN, ViterbiNet [5], [6].

However, these existing works mainly focus on communication waveform component design, such as the modulation and channel coding, while other crucial parts are not jointly optimized, e.g., the frame/slot structure. Moreover, waveform knowledge can not be fully leveraged even though the proposed waveforms will be applied in similar scenarios.

A knowledge graph is a structured representation of facts, consisting of entities, relationships, and semantic descriptions [7]. Recently, knowledge graph-based recommendation systems (KGRS) have attracted considerable research and development efforts and have been successfully applied in the fields of search, entertainment, and shopping [7], [8] due to the ability to improve recommendation accuracy by utilizing existing knowledge. For communication systems, the recommendation system has been used to recommend accessible channels [9] and channel state information (CSI) [10].

Inspired by the KGRS, we propose a new waveform design paradigm based on a communication waveform knowledge graph (CWKG), which facilitates the efficiency of waveform design and is embedded with the capability of utilizing the knowledge from existing waveforms. The existing waveform knowledge is characterized by the knowledge graph, and the CWKG is built by incorporating both the waveform scheme
and the corresponding performance under a specific environment. Based on the developed CWKG, we further propose an intelligent communication waveform recommendation system (CWRS) to generate waveform candidates according to the information transmission requirement, such as the application environment and quality-of-service (QoS). We adopt an improved involuition1D operator and multi-head self-attention to perform embedding representation enhancement (ERE) for feature extraction and fusion. Meanwhile, we use the multilayer perceptron (MLP)-based collaborative filtering (CF) to evaluate which waveform candidate matches the requirement. Simulation results show that the proposed CWKG-based CWRS can recommend waveform candidates with high reliability by fully utilizing existing waveform knowledge.

II. THE FRAMEWORK OF KG-BASED CWRS

The framework of CWKG aided CWRS is shown in Fig. 1. A CWKG is built with structured representation of existing communication waveforms, so as to systematically utilize the waveform knowledge. According to the information transmission requirement, the CWRS generates waveform candidates based on the CWKG. The performance of each waveform candidate is evaluated through the evaluation system. If one waveform candidate meets the requirement, it will be accepted and added to the CWKG. If the obtained waveform candidates could not fully meet the requirement under some particular environment, they can serve as foundations for further optimization to accelerate the design process, in which the existing model-based and data-based methods can be applied. As CWRS is the core of this new waveform design paradigm, this paper focuses on the CWKG and CWRS of this framework.

Mathematically, the waveform recommendation task is defined as “Given an environment $u$ and a target waveform $v$, the CWRS estimates the matching degree between them.” That is,

$$\hat{y}_{uv} = f_{\Theta}(u, v)$$  \hspace{1cm} (1)

where $f_{\Theta}$ represents the neural network with parameter $\Theta$ adopted in the CWRS, and $\hat{y}_{uv} \in [0, 1]$ denotes the probability score measuring the availability of target waveform $v$ under environment $u$.

As illustrated in Fig. 2, the framework of the CWRS can be divided into three parts: Knowledge Representation Learning (KRL), Embedding Representation Enhancement (ERE), and Collaborative Filtering (CF). Correspondingly, $f_{\Theta}(\cdot)$ can be divided into $f_{\Theta_1}(\cdot)$, $f_{\Theta_2}(\cdot)$, and $f_{\Theta_3}(\cdot)$ as following:

$$\begin{align*}
    (E_u, E_v) &= f_{\Theta_1}(u, v), (Z_u, Z_v) = f_{\Theta_2}(E_u, E_v) \\
    \hat{y}_{uv} &= f_{\Theta_3}(Z_u, Z_v)
\end{align*}$$  \hspace{1cm} (2)

where $f_{\Theta_1}$ represents the KRL model with parameter $\Theta_1$ to convert the waveform knowledge into a low-dimensional embedding representation vector $E_u$ and $E_v$. $f_{\Theta_2}$ represents the ERE model with parameter $\Theta_2$ to enhance the features of the above vector. $f_{\Theta_3}$ represents the CF model with parameter $\Theta_3$ to calculate the probability score $\hat{y}_{uv}$ according to enhanced features $Z_u$ and $Z_v$. Finally, the waveform candidates are sorted and recommended based on the probability scores.
$r_u$, and the specific values of parameters are defined as tail entity $t_u$. Similar to the WKG, the EKG can be expressed as triplets $\{(h_u, r_u, t_u) | h_u, r_u \in \mathcal{E}_u, t_u \in \mathcal{R}_u\}$. Some typical relationship types involved in the waveform are shown in Table 1.

### Table I

| Relationship | Values |
|--------------|--------|
| Modulation   | BPSK, QPSK, MSK, ... |
| Coding type  | RS, Turbo, LDPC, ... |
| Coding rate  | 2/3, 1/2, 1/3, ... |
| Jamming suppression | on/off |
| Soft demodulation | on/off |
| Bit rate (Rb) | 128kbps, 2Mbps, 64Mbps, ... |
| Channel type | Gaussian, Rician, Rayleigh, ... |
| Jamming type | single-tone, multi-tone, partial-band, Gaussian pulse, ... |
| Num of tones | single-tone: 1, multi-tone: >1 |
| Bandwidth factor | 0~1 |
| JSR (dB) | 0, 5, 10, ... |
| $E_b/N_0$ (dB) | 0, 1, 2, 3, ... |
| Bit rate (Rb) | 128kbps, 2Mbps, 64Mbps, ... |

C. Environment-Waveform Bipartite Graph (EWBG)

To connect the WKG and EKG, we further construct an EWBG, in which the virtual environment node and the waveform node are connected through a “feasible” relationship to form a triplet $(h_u, \text{feasible}, h_u)$ if the waveform can meet the information transmission QoS requirements of the communication system in a certain environment. Therefore, the CWKG can be expressed as $\mathcal{G} = \{(h, r, t) | h, t \in \mathcal{E}, r \in \mathcal{R}\}$, where $\mathcal{E} = \mathcal{E}_u \cup \mathcal{E}_w$, $\mathcal{R} = \mathcal{R}_u \cup \mathcal{R}_w \cup \{\text{feasible}\}$. For consistency, unless otherwise specified, the CWKG is the combination $\mathcal{G}$ of WKG, EKG, and EWBG as shown in Fig. 3.

In Fig. 3, we use $(E_1, r_0, W_1)$ to illustrate that the waveform $W_1$ can match environment $E_1$. Obviously, $E_1$ and $W_1$ consist of various parameters. For example, $(E_1, r_H, t_{k+3})$ can denote the jamming type $r_H$ of environment $E_1$ to be multi-tone jamming $t_{k+3}$. Meanwhile, $(W_1, r_2, t_2)$ can denote the modulation $r_2$ of waveform $W_1$ to be QPSK $t_2$.

In summary, the proposed knowledge graph representation of communication waveforms has the following features:

1. By representing the parameters of waveforms and environments in triplets, the difficulty of characterizing the communication waveform knowledge in high dimensional space is avoided.
2. Benefit from the same structure of WKG and EKG, a unified method can be used to perform data mining and fusion of the environment and waveform information.
3. By building the CWKG with first-order neighbors, the embedded propagation can be efficiently implemented.

IV. WAVEFORM CANDIDATES GENERATION BASED ON THE PROPOSED CWRS

As described in the previous section, the triplets in the CWKG represent the scheme with associated parameters of the existing communication waveforms and their achievable performance in a specific environment. By utilizing the developed CWKG, we describe the details of the CWRS to generate waveform candidates for a new environment in this section. As represented in the CWKG, the new environment consists of the propagation environment and QoS requirements.

A. Knowledge Representation Learning

As shown in Fig. 2, KRL is the first step and critical part of the CWRS, which is responsible for mapping the triplets in CWKG into a low-dimensional embedding representation vector. In this paper, the widely used TransD model [7] is adopted to extract the structured information of the KG. And the Word2vec model is further adopted to handle the textual information, e.g., the plain meaning of the word ‘Turbo’. In contrast to the knowledge graph used in other fields, numerical information, such as coding rate, is crucial for communication waveforms. Therefore, we simultaneously fuse textual information, numerical information, and structured information to obtain a multi-channel low-dimensional embedding representation vector shown in Fig. 4.

![Multi-channel representation of communication waveform knowledge.](image)

Specifically, ‘15dB’ means the JSR is 15dB, ‘2/3’ means the coding rate is 2/3, ‘8ms’ means the pulse period is 8ms, etc.

Specifically, for the waveform, the numerical feature vector, the output vectors of the TransD model, and the Word2vec model are cascaded into a 3-channel embedding representation vector $E_u$ with dimension $N_u \times N_{emb} \times 3$. Here, $N_u$ is the number of a waveform’s features (or relationships), and $N_{emb}$ is the dimension of embedding representation. For the environment, an embedding representation vector $E_e$ with dimension $N_e \times N_{emb} \times 2$ is obtained, where $N_e$ is the number of environment’s features (or relationships).
Note that the input of the environment may introduce new entities when applying the trained network to recommend waveform candidates. To avoid re-training the TransD model, the corresponding vectors are not included for the environment. For example, the environment changes when a new jamming type arises, and then we have to re-train the TransD model to learn the representation of the new entity. However, these issues barely occur in the waveform scheme because it remains quasi-static for a long time, as the waveform in CWKG is invariable until a new waveform has been designed.

The initial input of KRL is the triplet \((h, r, t) \in G\). The TransD model first initializes each triplet into two sets of vectors \((h_p, r_p, t_p)\), where the former is the embedding vector, and the latter is the corresponding projection vector. Then, the score is calculated as follows [7]:

\[
\begin{align*}
\hat{y} &= ||h_{\perp} + r - t_{\perp}||^2 \\
h_{\perp} &= (r_p h_p^T + I) h \\
t_{\perp} &= (r_p t_p^T + I) t \\
\end{align*}
\]

where \(\hat{y}\) is the score, \(I\) is the identity matrix, and \(h_{\perp}\) and \(t_{\perp}\) are the scores of head and tail entities, respectively.

Since the CWKG are all positive samples, the negative samples need to be generated automatically. To make the difference of the scores between the positive and negative sample as large as possible, the following Bayesian Personalized Ranking (BPR) loss function [11] is used to train the TransD model:

\[
L_1 = -\frac{1}{N_v} \sum_{n=1}^{N_v} \ln \left( \sigma \left( \hat{y}_{n}^{pos} - \hat{y}_{n}^{neg} \right) \right)
\]

where \(N_v\) is the number of samples, \(\hat{y}_{n}^{pos}\) and \(\hat{y}_{n}^{neg}\) are the scores of the positive sample and the negative sample, respectively, and \(\sigma(\cdot)\) is the Sigmoid activation function.

**B. Embedding Representation Enhancement**

Intuitively, the output vectors of KRL are raw data similar to an original image. Therefore, ERE is applied to highlight the features of a waveform or environment. To simultaneously consider the semantic information and keep the connection information, a propagation-based method [12] including both feature extraction and fusion is adopted for ERE.

It seems that the format of communication waveform embedding representation vector is similar to the image format in computer vision. Then, a convolutional neural network (CNN) may be considered for feature extraction in ERE. However, compared with the image, the obtained vector has the following characteristics:

- Each row of the vector is derived from independent waveform parameters, and there is no spatial continuity.
- Different channels of the vector describe the same object in various feature spaces.

According to the above characteristics, it is preferable to use different kernels among rows for feature extraction and share kernels among channels. Therefore, CNN is not suitable for communication waveform ERE as it is space-agnostic and channel-specific. Then, based on the involution operator presented in [13], which is space-specific and channel-agnostic, we propose a modified Involution1D operator to perform communication waveform ERE.

1) Involution1D: Let the previously obtained vector \(\mathbf{E}_v\) or \(\mathbf{E}_u\) take a slice of a coordinate point \((i, j)\) along the channel as \(\mathbf{X}_{ij} \in \mathbb{R}^{1 \times K \times C}\), and flatten it into a vector \(\mathbf{X}_{ij} \in \mathbb{R}^{1 \times KG}\). The basic idea of Involution1D is to use the generating function \(\varphi(\cdot)\) to generate a space-specific kernel \(\mathcal{K}_{ij} \in \mathbb{R}^{1 \times K \times G}\) for the input \(\mathbf{X}_{ij}\), and share the generated kernel \(\mathcal{K}_{ij}\) on all channels. Here, \(K\) is the size of the kernel, and \(G\) is the number of groups of the kernel (i.e., each spatial position shares \(G\) groups of different kernels). In particular, \(\varphi(\cdot)\) consists of two fully connected layers with LeakyReLU activation functions. The resulting \(\mathbf{e}_{inv}^{ij}\) for the generated kernel \(\mathcal{K}_{ij}\) and the corresponding input \(\mathbf{X}_{\Omega_{ij}}\) is given as follows,

\[
\mathbf{e}_{inv}^{ij} = \sum_{g=1}^{G} \sum_{k=1}^{K} (\mathcal{K}_{ij})_{g} \mathbf{X}_{\Omega_{ij} g}
\]

where the operator \([\mathbf{x}]^\mathbf{g}\) represents the matrix expansion product. It is defined as follows:

\[
[A][\mathbf{x}]_{g} = a_{k g} b_{c k}
\]

where \(a_{k g}\) is the \((k, g)\)th element of matrix \(A \in \mathbb{R}^{K \times G}\), and \(b_{c k}\) is the \((k, c)\)th element of matrix \(B \in \mathbb{R}^{K \times C}\).

2) Multi-head Self-Attention: Because each waveform parameter has a different influence on the communication waveform, it is necessary to emphasize the crucial waveform features by fusing various waveform parameters with different weights. It is difficult for graph convolution networks to assign different weights to various neighbor nodes, so we adopt an attention mechanism to merge various waveform parameters. Since the source and target of our problem are the same, the self-attention mechanism [14] is adopted. For a given input \(\mathbf{X}\), the self-attention is performed as follows:

\[
\mathbf{Z}_{\text{att}} = \text{softmax}(\mathbf{QK}^T) \mathbf{V}
\]

where \(\mathbf{Q}, \mathbf{K}, \mathbf{V}\) are vectors of query, key, and value, respectively. All of them are generated by the linear transformation of \(\mathbf{X}\), and \(\mathbf{X}\) is the output \(\mathbf{E}^{\text{inv}}\) or \(\mathbf{E}^{\text{inv}}\) of Involution1D.

Furthermore, we use a multi-head mechanism to improve the performance [14]. Each self-attention is treated as a head, and different heads can project the input to various representation subspaces. As a specific subspace is more prominent for some waveform parameters than others, combining multiple subspaces can highlight the waveform parameters with significant influence. The final output is given as follows:

\[
\mathbf{Z} = Z_1 \oplus Z_2 \oplus \cdots \oplus Z_H
\]

where \(Z_i\) represents the output of the \(i\)th self-attention, \(H\) is the number of heads, and ‘\(\oplus\)’ represents a cascading operation.

**C. Collaborative Filtering**

As mentioned before, we apply KRL and ERE to characterize the environment and the waveform, respectively. The characteristics of the waveform include both its label and natural language processing (NLP).
For the MLP-based CF, the characteristic representations $Z_u$ and $Z_v$ of the environment and the waveform are first cascaded. Then, the matching degree $s_{uv}$ is learned by feeding the resulting vector into the MLP. That is,

$$Z_u^{\text{MLP}} = Z_u \oplus Z_v$$

$$Z_1^{\text{MLP}} = a_1 (Z_u^{\text{MLP}} W_1 + b_1)$$

$$\ldots$$

$$Z_L^{\text{MLP}} = a_L (Z_L^{\text{MLP}} W_L + b_L)$$

where $W_m, b_m, a_i$ are weight matrix, bias vector, and activation function of the $i$th perceptron, respectively. $h$ is a learnable coefficients vector. Finally, the probability of each waveform concerning the environment is calculated as follows:

$$\hat{s}_u = \text{softmax}(s_u)$$

where $s_u = [s_{u1}, s_{u2}, \ldots, s_{uM}]^T$, $M$ is the total number of waveforms.

**D. Network Training Process**

For an environment, the score for an available waveform is 1, or 0 for unavailable or unknown waveforms. Then, the score $y_{uv} \in \{0, 1\}$, which is similar to the binary classification task. Therefore, we adopt the cross-entropy loss function in network training. It is given as follows:

$$L_2 = -\sum_{(u,i) \in O^+} \ln (\hat{y}_{ui}) - \sum_{(u,i) \in O^-} \ln (1 - \hat{y}_{ui})$$

$$L_2 = -\sum_{(u,i) \in O} (y_{ui} \ln (\hat{y}_{ui}) + (1 - y_{ui}) \ln (1 - \hat{y}_{ui}))$$

where $O = O^+ \cup O^-$, $O^+$ represents the sample set of available waveforms, $O^-$ is the sample set of unavailable or unknown waveforms, and satisfies $|O^+| = |O^-|$. We use the Adam optimizer to alternately optimize the loss $L_1$ in (4) and $L_2$ in (11).

**V. EXPERIMENTS**

Up to now, we have built a CWKG consisting of 46 waveform entities and 12470 environment entities. The waveforms can be divided into two categories, namely single-carrier-based low-bit-rate waveforms, such as the Link16 data link waveform [16], and multi-carrier-based high-bit-rate waveforms, such as OFDM. The jamming involved in environment includes single-tone, multi-tone, partial-band, and Gaussian pulse jamming [17].

In the experiments, the hyper-parameters are set as follows: the learning rate of the Adam optimizer is $lr=0.001$, and the parameters of Involution1D are $K=5, G=1$. The training set and test set are allocated at a ratio of 10:2, and the recommendation success rate is measured by Hit@1. It is defined as follows:

$$\text{Hit}@1 = \frac{N_{\text{Hit}}}{N_{\text{All}}}$$

where $N_{\text{Hit}}$ is the number of successful recommendations, and $N_{\text{All}}$ is the total number of recommendations. Specifically, if the recommended waveform belongs to the set of available waveforms (which means it can work under current environment), it will be counted as a successful recommendation. The average success rate is presented based on the last 100 epochs after the system converges.

**Fig. 5. The effect of different ERE methods**

Firstly, we investigate the effect of ERE with different methods. In Fig. 5, simulation results show that the $\text{Hit}@1$ performance without ERE and with individual ERE are 0.9401, 0.9771(Self-Attention), 0.9741(Involution1D), and 0.8479(CNN), respectively. Compared with the performance without ERE, it can be found that the recommendation success rate can be significantly improved by introducing ERE. It can be observed that the ERE with self-attention and involution1D can achieve nearly the same performance. Meanwhile, the performance will significantly deteriorate if the ERE with CNN is used. As discussed in Section IV, the Involution1D is preferable compared to CNN for our proposed CWKG.

**Fig. 6. The effect of different cascading modes**

Subsequently, we investigate the influence of multi-head self-attention and its cascading schemes with involution1D. The $\text{Hit}@1$ performance with different individual multi-head self-attention ERE is 0.9771(H=1), 0.9933(H=3), 0.9943(H=5), and 0.9959(H=8), respectively. It shows that $H=3$ is a reasonable choice, as the gain is negligible when $H$ is greater than 3. In Fig. 6, the $\text{Hit}@1$ performance with different cascading schemes is shown to be 0.9853(Involution1D+$H=1$), 0.9752(Involution1D+$H=1$+Involution1D), and 0.9951(Involution1D+$H=3$), respectively. Obviously, better performance can be achieved when Involution1D is first used to extract the features. Meanwhile, the cascading mode ‘Involution1D+$H=(=3)$’ can achieve a performance close to $H=8$, which means a less complex approach can achieve a nearly similar performance.

Finally, we compare the performance of the waveform recommended by our CWRS and the one generated by existing
waveform optimization methods, which utilize optimization algorithms to choose Modulation and Coding Schemes (MCSs) and transmit power. As the optimization problem is commonly non-convex, some heuristic algorithms are commonly adopted, such as genetic algorithm (GA) and particle swarm optimization (PSO) algorithm [18]. For the optimization algorithm, the available waveform parameters include modulation schemes with BPSK, QPSK, and 16QAM, and Turbo coding with rates 1/3, 1/2, 2/3, and 3/4. We use the notation ‘MCS(\cdot, \cdot)’ to denote the modulation and coding set. For example, MCS(1,1) means the waveform is configured with BPSK and 1/3 Turbo code and the bit rate is 350kbps.

In the experiment, the environment consists of additive white Gaussian noise (AWGN) channel, partial-band jamming with jamming-to-signal power ratio (JSR) 15dB, the required date rate $R_d=1200$kbps with bit-error-rate (BER) $10^{-5}$ and demodulation threshold $E_b/N_0=9$dB. Our CWRS recommends an single-carrier waveform candidate supporting $R_d=2015$kbps and consisting of CRC-12, 4CPM, $\frac{1}{2}, \frac{3}{2}, \frac{5}{2}$, Turbo code with a coding length 5248, random interleaver with interleave length 23808, soft demodulation and frequency-domain jamming suppression. Meanwhile, both the PSO algorithm and GA output the MCS(2,2), i.e., QPSK modulation and 1/2 Turbo coding, with bit rate is 1050kbps.

In Fig. 7, both CWRS and MCS(2,2) can meet the energy constraint and BER requirements, but the latter doesn’t satisfy bit rate requirements. Hence, we turn to the MCS(2,3) and MCS(3,1), whose bit rate is 1400kbps. Unfortunately, both of them can not satisfy the BER requirement. As a result, the candidate by CWRS is a appropriate waveform under current environment rather than the one generated by PSO or GA.

Compared with heuristic optimization algorithms, the advantages of CWRS are covering a more comprehensive waveform library rather than the one with limited MCSs, and fully utilizing the waveform knowledge. However, as the performance of CWRS highly relies on the knowledge covered in CWKG, building a database with rich knowledge is vital to applying CWRS.

VI. CONCLUSION

In this paper, we propose a new communication waveform design paradigm based on a communication waveform knowl-

edge graph (CWKG). By considering both waveform schemes and their performance under specific application environments, we build a CWKG integrating structured, textual, and numerical information of communication waveform knowledge. Based on the developed CWKG, we further propose a communication waveform recommendation system (CWRS) to generate waveform candidates for new requirements specified by both environment and QoS. Simulations show that the proposed CWKG-based CWRS can achieve a considerably high recommendation success rate, and can effectively utilize existing waveform knowledge.

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