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Stepan Kubiv, Dr Sc., Professor
National Aviation University.
orcid.org/0000-0002-2606-4550
e-mail: skubiv@gmail.com;

Bohdan Morklianyk, Dr Sc.
The National Agency for Higher
Education Quality Assurance
orcid.org/0009-0000-6564-6804
e-mail: bmorklianyk@naqa.gov.ua

FORMATION OF ENSEMBLES OF SIGNALS WITH TIME DIVISION USING A NEURAL NETWORK

Introduction

Within the vast domain of telecommunications, signals characterized by their temporal dynamics assume a role of utmost significance in the intricate landscape of information transmission and processing. These signals, which materialize as electromagnetic waves, serve as the primary vehicles for the transfer of data from one communication device to another, effectively constituting the lifeblood of modern communication networks. The defining feature that sets these signals apart is their temporal nature, or more precisely, the dynamic evolution they undergo over time. As they traverse the extensive web of telecommunications networks, these signals embody a rich spectrum of parameters, encompassing not only the familiar attributes of amplitude, frequency, and phase but extending into a multidimensional space of possibilities. This multifaceted parameterization affords telecommunication engineers the creative latitude to craft a diverse array of signal types, each meticulously tailored to convey a vast spectrum of information. However, it is not merely the transmission aspect of these signals that makes them so intriguing; rather, it is their dynamic metamorphosis over time that holds the key to evaluating signal quality and resilience during the intricate dance of transmission.

To delve deeper into the essence of these signals, we must embark on a comprehensive analysis of their temporal characteristics, a multifaceted journey that encompasses intricate elements such as time delays, noise, and various temporal attributes. These elements, often relegated to the background, form a critical determinant of the effectiveness with which information can be resurrected at the receiving end. This analysis, rooted in the fundamental principle of signal integrity, plays a pivotal role in the optimization of the intricate tapestry of signal

transmission and processing that unfolds within the sprawling landscape of telecommunications networks.

The optimization of this complex endeavor demands the deployment of an array of methods and cutting-edge technologies. Among these, the techniques of modulation, demodulation, coding, and decoding shine as beacons of sophistication. These sophisticated methodologies not only enhance the swiftness and efficiency of data transmission but also serve as formidable bastions against the encroachment of interference, ensuring the steadfast reliability of communication networks.

In the contemporary milieu, the omnipresent adoption of neural networks has ushered in a paradigm shift in complex problem-solving across diverse domains, and telecommunications stands as no exception to this transformative wave. The ascent of neural networks to the forefront of the telecommunications arena signals the dawn of a new era characterized by heightened efficiency, unwavering reliability, and elevated service quality within communication networks. This symbiosis between neural networks and telecommunications represents not just a union of convenience, but a dynamic partnership that promises to redefine the very fabric of communication networks. It underlines the inexorable march of technology toward a more interconnected, efficient, and responsive era in the field of telecommunications.

The utilization of neural networks for the formation of ensembles of complex telecommunications signals with temporal separation presents a multitude of noteworthy advantages and practical applications that merit further elaboration.

Signal Recognition Improvement. Complex telecommunications signals, such as radio and mobile signals, are often plagued by high levels of noise and susceptibility to distortion during transmission. Neural networks offer a powerful solution by providing

advanced signal analysis and reconstruction capabilities, significantly enhancing signal recognition and recovery. This, in turn, leads to more reliable and accurate data interpretation.

Demodulation and Decoding of Signals. Neural networks are proficient in developing intricate models for the efficient demodulation and decoding of signals. This is a critical aspect of signal processing, as it aids in the retrieval of the original data concealed within complex signal structures. Neural networks excel in deciphering these intricate codes, enhancing the accessibility of information embedded within the signals.

Error Detection and Correction. In the realm of telecommunications, maintaining high data transmission quality and ensuring resilience to errors are paramount. Neural networks play a pivotal role in error detection and correction processes. By employing these networks, the quality of data transmission is notably improved, and the robustness of the system is fortified, even in the face of potential disruptions.

Adaptation to Changing Transmission Conditions. Telecommunications networks are exposed to a multitude of variables, including interference, noise, and variations in the communication channels. Neural networks exhibit the capacity to learn and adapt to these dynamic conditions. This adaptability ensures that the system can maintain its functionality and reliability across diverse and evolving scenarios, making it an invaluable asset in the field.

Reduced Computational Costs. The adoption of neural networks for the analysis and processing of telecommunications signals brings about an additional advantage in the form of reduced computational costs. Neural networks have the potential to streamline and optimize signal processing, which can be notably more resource-efficient in comparison to traditional signal processing methodologies.

Enhanced Efficiency and Productivity. By integrating neural networks into telecommunications systems, a tangible boost in overall efficiency and productivity can be achieved. The reduction of errors and the improvement of data transmission accuracy result in systems that operate more smoothly and effectively. This contributes to a seamless and efficient communication infrastructure, critical in today's digitally connected world.

In light of the above, it is evident that the integration of neural networks into the formation and analysis of complex telecommunications signals with temporal separation is an issue of significant relevance. In the ever-evolving landscape of modern telecommunications networks, this approach offers a versatile and effective means of addressing a multitude of challenges. Neural networks hold the potential to revolutionize the field by enhancing the

recognition, recovery, and processing of complex signals, ultimately contributing to the development of more resilient and efficient telecommunications systems.

Analysis of recent research and publications

The research conducted in the realm of scientific and practical advancements concerning the formation of intricate signal ensembles distinguished by temporal separation through the employment of a neural network training system has yielded compelling insights. It reveals a unique dichotomy wherein the explorations, methodologies, and scientific innovations within this domain find partial application among foreign scholars [1-5], whereas Ukrainian researchers [6-7] approach the matter from a distinctive vantage point. The Ukrainian perspective is anchored in the conceptualization of the challenge as the creation of ensembles that encompass intricate signal-code structures woven into the tapestry of telecommunications signals, all within the expansive framework of telecommunications cognitive systems.

This divergence in approach underscores the multidimensionality of the challenge at hand. On the one hand, there is a rich tapestry of knowledge and methodologies disseminated across international borders, with foreign authors harnessing these insights to address the intricacies of signal ensembles with temporal separation. This cross-pollination of ideas leads to a dynamic exchange of knowledge, fostering a global synergy in the pursuit of solutions within this domain.

On the other hand, Ukrainian authors bring a distinct perspective to the forefront, encapsulating the essence of telecommunications cognitive systems. Their lens reframes the challenge, placing a strong emphasis on the intricacies of signal-code structures and their seamless integration within telecommunications signals. This approach serves as a testament to the multifaceted nature of this research, acknowledging the rich tapestry of challenges and opportunities that characterize the study of signal ensembles with temporal separation.

In essence, this research landscape is a testament to the diversity of thought and approach that exists within the scientific community. It underscores the global collaborative spirit in addressing complex challenges, while also highlighting the unique and nuanced perspectives that researchers bring to the table. As the field of forming complex signal ensembles continues to evolve, the amalgamation of these varied insights promises to drive innovation and broaden the horizons of knowledge in the realm of telecommunications and cognitive systems.

Problem Statement

Certainly, delving into the intricacies of forming complex signals with temporal separation through the application of neural networks is an imperative undertaking, primarily because this realm remains relatively underexplored. To comprehend the gravity of this pursuit, it is crucial to outline a comprehensive rationale for research in this domain.

First and foremost, the landscape of telecommunications is in a perpetual state of evolution. The continuous demand for faster, more reliable, and adaptable communication technologies necessitates innovation and novel approaches. In this context, the utilization of neural networks to craft ensembles of signals with temporal separation emerges as a compelling frontier that can be instrumental in optimizing telecommunications systems to meet modern requirements.

Modern telecommunications signals are characterized by their complexity and dynamic nature. These signals are not static entities; they undergo variations over time, which can present formidable challenges. Investigating and deciphering such signals, encompassing the intricacies of their encoding and ensemble formation, mandates the development of new methodologies and approaches. This facet of research is particularly significant as it has the potential to substantially enhance the performance and reliability of telecommunications systems. Ensuring uninterrupted and seamless communication is of paramount importance in our digitally connected world.

Furthermore, the implications of advancements in signal ensemble formation techniques extend beyond the realm of telecommunications. These innovations can reverberate throughout various domains, including wireless networks, medical technologies, data analysis, and more. Consequently, research in this field is not limited to its immediate applications but holds the promise of catalyzing broader technological advancements and innovations.

In essence, the pursuit of understanding and perfecting the formation of complex signal-code ensembles with temporal separation through the medium of neural networks is an imperative task. It represents an exciting avenue that not only addresses the current challenges in telecommunications but also offers new possibilities for innovation and progress in a continuously evolving technological landscape. As technologies perpetually advance, research in this domain is a catalyst for staying at the forefront of these transformations and ensuring that telecommunications systems remain agile, reliable, and adaptable to the ever-changing demands of our digital age.

The purpose of the article

The primary objective of the article, which delves into the intricacies of shaping intricate signals characterized by temporal separation through the utilization of neural networks, is to embark on a comprehensive exploration of the methodologies employed in the creation of these complex signals. This endeavor involves a multifaceted inquiry into various facets, including algorithms, approaches, and the architectural underpinnings of neural networks deployed for the generation of such signals. Additionally, it entails a meticulous scrutiny of the utilization of temporal separation and the profound ramifications it bears on the process of signal formation. Of paramount significance is the exploration of the role neural networks play in optimizing this intricate process.

In essence, this article serves as a beacon guiding us through the labyrinth of complexities inherent in the formation of signals that span a temporal dimension. It encapsulates a multifaceted research journey that encompasses not only the mechanics of neural networks but also the intricate choreography required to mold signals into sophisticated, time-varying constructs. This exploration shines a spotlight on the synergy between temporal separation and neural networks, shedding light on the potential for achieving unprecedented levels of optimization within this domain. As we delve into the inner workings of signal formation and the role of neural networks, we unlock a treasure trove of insights that promises to reshape the landscape of signal processing and pave the way for new horizons in the field.

Summary of the main material

In the field of telecommunications, signals with dynamic time separation play a decisive role in the transmission and processing of information. These signals are electromagnetic waves that carry data from one device to another. The main characteristic of such signals is their temporal nature, namely, how they change with time. In data transmission over telecommunication networks, signals can display various parameters such as amplitude, frequency, phase, etc. This variety of parameters makes it possible to create different types of signals for the transmission of various information.

The dynamic change of time parameters of signals is also important for evaluating their quality and immunity during transmission. Analysis of delays, noise, and other temporal characteristics of signals helps determine how effectively information can be recovered at the receiver. Various methods and technologies such as modulation, demodulation, encoding and decoding are used in telecommunication networks to optimize signal transmission and

processing. These techniques allow to increase transmission speed, reduce interference and ensure reliable communication.

As a result of the analysis of scientific and research sources, several aspects were found that substantiate the necessity and relevance of the use of neural networks in the field of communications: In the field of telecommunications, signals with dynamic time separation play a decisive role in the transmission and processing of information. These signals are electromagnetic waves that carry data from one device to another. The main characteristic of such signals is their temporal nature, namely, how they change with time. In data transmission over telecommunication networks, signals can display various parameters such as amplitude, frequency, phase, etc. This variety of parameters makes it possible to create different types of signals for the transmission of various information.

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As a result of the analysis of scientific and research sources, several aspects were found that substantiate the necessity and relevance of the use of neural networks in the field of communications.

1. Improving the quality of service. Neural networks help improve service quality by predicting and managing traffic. They can detect anomalies and predict network load, allowing operators to plan and optimize resources to provide the best customer service.

2. Automation of network operations. Neural networks help automate many network management tasks, including troubleshooting, optimizing traffic routing, and configuring network parameters. This improves network efficiency and reduces the risk of errors, contributing to the autonomous operation of the network.

3. Protection against security threats. Neural networks can be used to detect network security threats, such as DDoS attacks or other types of cybercrime. They can respond to potential threats in real time and help prevent or detect attacks.

4. Optimization of resources and reduction of costs: The use of neural networks for traffic prediction allows operators of telecommunication networks to reduce excessive reserves of resources

and optimize their use. This helps reduce costs and improve network efficiency.

5. Big data support: Telecommunication networks generate large amounts of data and neural networks help in analyzing this data to make predictions and make decisions. They can reveal patterns and dependencies that are not always obvious with traditional analysis.

The formation of ensembles of signals with dynamic changes in time parameters, using a neural network, is an advanced approach that opens up new opportunities for real-time data processing and analysis. This approach includes several important aspects that allow you to effectively use signals with dynamic changes in time parameters in various areas.

The basis for the determination is an approach that allows you to determine exactly which signals need to be combined into an ensemble. These can be measurements from sensors, data from various sources, or input signals from various devices. It is important to choose signals that interact with each other in an appropriate way. After selecting the appropriate signals, neural networks can be used to combine the selected signals into an ensemble. The criteria by which the ensemble of signals is formed may include a list of optimal weights for each signal to maximize the informativeness of the ensemble. Neural networks must be trained to take into account the temporal characteristics of signals and their mutual compatibility, in order to ensure that the ensemble is useful and appropriate for a specific task.

In addition, the use of neural networks allows you to use them to analyze changes in the time parameters of signals and detect anomalies in them. Neural networks can be trained to predict events based on this data, making them an effective tool for real-time decision-making. All these aspects of forming ensembles of signals with a change in time parameters using neural networks contribute to the automation and improvement of signal processing, ensuring high immunity and the use of more information to achieve the set goals. When forming ensembles of complex signals using neural networks, an important task is the choice of neural network architecture. That is, the definition of the type of neural network that best meets the defined task.

When forming ensembles for processing complex signals with dynamic changes in time parameters, different neural network architectures can be used, depending on specific tasks and data characteristics. Here are some architectures that can be useful in such cases.

1. Recurrent neural networks (RNN). RNNs are well suited for processing sequential data with dynamically changing time parameters. They have feedback loops that allow you to store previous states and use them to predict future values. LSTM

(Long Short-Term Memory) and GRU (Gated Recurrent Unit) are advanced versions of RNNs that help avoid the problem of gradient vanishing and gradient decay.

2. Convolutional neural networks (Convolutional Neural Networks, CNN) are a class of neural networks specially designed for processing grid-structured data, such as images. The main characteristic of CNNs is their ability to automatically detect and exploit features located in different parts of the input data. This is achieved through the use of convolutional layers, which apply filters to highlight important features, and pooling layers to reduce the dimensionality of the data. A key characteristic is their ability for deep learning due to the hierarchical structure of convolutional layers. All this makes CNN a powerful tool for various image processing tasks, such as object recognition, classification, segmentation and many others. An important feature is the ability to reuse pre-trained models and adapt them to different tasks in fields from medicine and the automotive industry to computer vision and art.

3. Long short-term memory (LSTM) networks are a special class of recurrent neural networks (RNNs) designed to solve the fading and gradient decay problems common to conventional RNNs when training on long data sequences. They are known for their ability to store and manage information on the network for long periods of time, which makes them ideal for processing sequential data with long time dependencies, such as speech, time series, text data, and many others. One of the key features of LSTM is the presence of three main gates or "gates" – a forget gate, an input gate, and an output gate. These gates allow the network to choose what information to store, what input information to consider, and what information to output. They control the flow of information through an LSTM cell, which makes them very powerful in working with long and complex sequences.

In addition, LSTMs have a relational structure that allows information to be passed across multiple time steps, making them ideal for analyzing and modeling temporal dependencies. They can be used for tasks such as forecasting future values in time series, and for processing and generating natural language.

In general, LSTMs have become an important tool in many fields where it is important to consider the dynamic change of temporal parameters of data and long-term dependence in time, and they continue to be relevant in the field of deep learning and processing of sequential data, such as speech, time series, text, etc.

1. Long term memory networks (GRUs), or Gated Recurrent Units, are another form of recurrent neural networks (RNNs) designed to process data sequences. They are similar to long-short-term memory (LSTM) networks and are used to solve the vanishing and gradient decay problem that can occur in conventional RNNs. The main idea of GRU is to simplify the structure of LSTM while preserving important information flow control functions. They also have gates, but they are combined into one update gate and one output gate (reset gate). The update gate determines how much information will be updated, and the output gate controls how much information will be output. One advantage of GRUs is their greater potential for parameter reduction, which allows them to be less computationally demanding compared to LSTMs. They can also be trained on relatively small datasets and perform well in many sequence processing tasks.

GRUs remain important in deep learning and sequence processing. They can be used in tasks where modeling of long-term dependencies is important, such as machine translation, speech recognition, speech synthesis, and many others. GRUs are an efficient tool for working with data sequences in various applications.

2. Grids with a reservoir (Reservoir Computing). These are architectures that are based on the idea that a large internal reservoir network that generates random connections can be used to process complex time signals. The effectiveness of tank computers is manifested in their ability to dynamically model complex signals in the time domain.

When choosing an architecture for an ensemble, it is important to consider the specific requirements of the scientific task and the particularities of the data. In addition, the combination of several different architectures in an ensemble can improve the results, since different models can solve different aspects of complex signals.

Recurrent Neural Networks (RNNs) are powerful tools for processing sequences and signals with dynamic time parameters, and they can be used to model mutual interference between signals. In this context, the following RNMs can be used:

1. RNM circles. One of the main ways to use RNM to model mutual interference is to create RNM chains (recurrent neural networks that are connected to each other). Each level of the RNM chain can model a specific aspect of the signal or interference. The information that one layer transmits to another layer can reflect interactions between signals and mutual interference.

2. Two- or multi-level RNM. To solve problems of high complexity, it is advisable to use multi-layer RNNs (Multi-layer RNNs), where each level

represents different characteristics of the signal and interference. Such networks can be more powerful in modeling mutual interference.

3. Modeling changes in time parameters. RNMs are well suited for modeling dynamic changes in the time parameters of signals. They can take into account the dependence between previous and future values of signals and disturbances.

4. Interaction between inputs. RNMs can be used to model the interaction between different inputs, which can be signals or disturbances. They can study how one signal affects another and the mutual interference between them.

5. Feedback: One of the important features of RNM is the presence of feedback, which allows information to be transmitted from the output to the input of the network. This allows RNMs to learn to take into account prior context and constraints when analyzing new data.

6. Training. Appropriate optimization methods and loss functions are used during RNM training, which allow taking into account the mutual influence between signals.

7. Evaluation of the results: After training the RNMs, it is important to evaluate their effectiveness in simulating mutual interference. This may include analysis of the accuracy of the predictions, as well as possible validation on real data with mutual interference.

The algorithm for forming ensembles of signals with dynamic changes in time parameters based on the use of a recurrent network (RNN) involves the use of RNNs to analyze and combine signals with time dependence. In general, its main steps can be described as follows (Fig. 1).

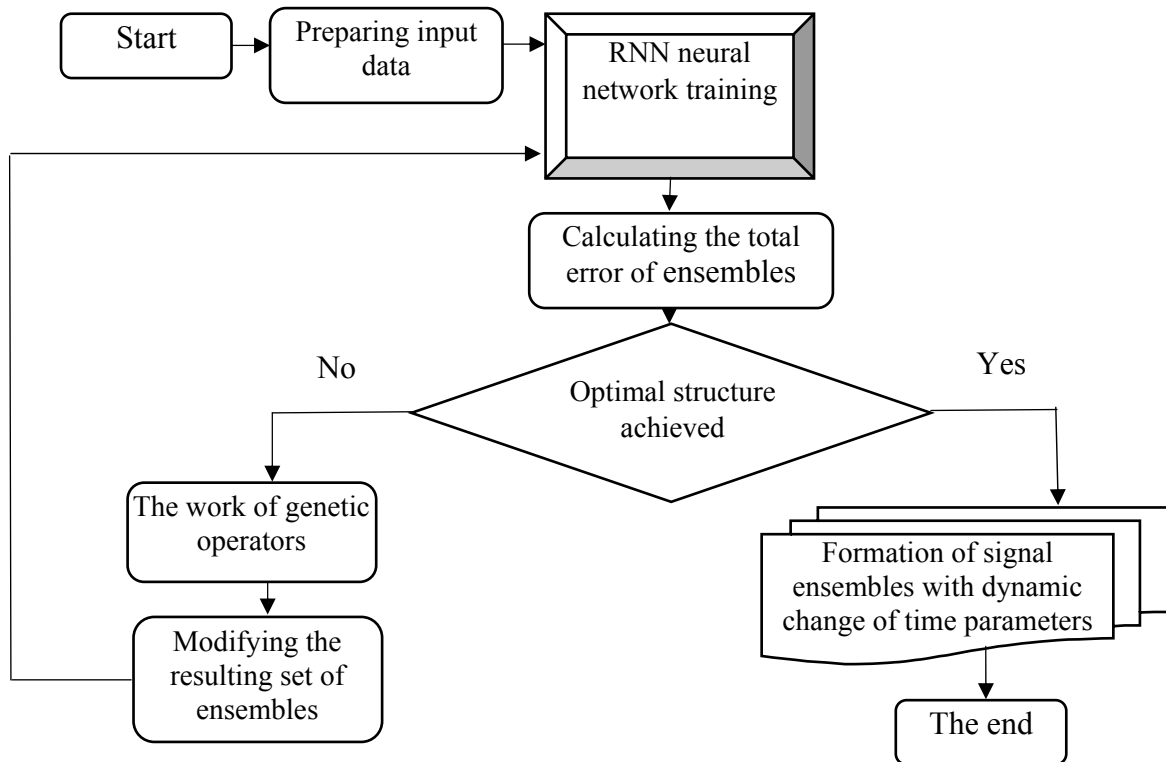


Fig. 1. Algorithm for forming ensembles of signals with dynamic changes in time parameters using a recurrent network (RNN)

Preparation of input data. This may include splitting the time series into windows (samples) that will be used to train the RNN. Each window should contain some number of time steps and a corresponding label or value to be predicted or analyzed.

1. RNN training. A recurrent network learns from the prepared data and analyzes the time dependences and patterns in the signals.

2. Error calculation for each signal. For each signal, the predicted value is compared to the true value in the case of regression, or the classification

results are compared to the true class in the case of classification. This helps to determine the prediction accuracy for each signal separately. After calculating the error for each signal, these errors are summed or the average error is calculated, depending on the specific metric. The total error gives a general idea of the accuracy and efficiency of the PNN network in forecasting an ensemble of signals with dynamic changes in time parameters.

In case of reaching the optimal structure of the ensemble, there is a transition to signal generation.

3. Ensemble formation. After the RNN is trained, it is used to analyze new signals. That is, new data is fed into the neural network, and the RNN generates responses or predictions for each time step.

4. Aggregation of results. Different approaches can be used to form an ensemble. One common method is to average the predictions from the RNN for each time step. Mathematically, the formula looks like:

$$Forecast_{average} = \frac{1}{T} \sum_{t=1}^T forecast_t, \quad (1)$$

where T – number of time steps; $\frac{1}{T} \sum_{t=1}^T forecast_t$ – forecast at a specified time step

1. Use of ensemble. The final step is to use the ensemble for decision making or signal analysis. For example, when predicting an event, you can use the average forecast to decide whether it will occur or not.

2. In the event that the PNN network does not provide the optimal composition of the ensembles, the transition to the next stages takes place.

3. Application of genetic operators. The choice of genetic operators depends on the specific task and the structure of the neural network. Crossover of architectures (Architecture Crossover) is well suited for neural networks with complex architecture, such as recurrent neural networks with dynamic changes in time parameters. Because it allows you to exchange blocks or layers between parent models, creating new combinations of architectures.

4. The next stage is the compilation of new modifications, which are cyclically sent as input data for learning with a neural network.

5. Methods of estimating the total error of ensembles of signals with dynamic changes in time parameters using PNN require separate attention and analysis.

6. Analysis methods include the use of appropriate metrics, the evaluation of which depends on a specific type of problem (regression or classification). The general methods of calculating the total error for ensembles of signals with dynamic changes in time parameters using PNN include the following [6].

Mean Squared Error (MSE) for regression:

$$MSE = \frac{1}{n} \sum_{n=1}^n (y_i - \hat{y}_i)^2, \quad (2)$$

where n – the number of signals in the ensemble with dynamic changes in time parameters; y_i – the true value for a signal with a dynamic change in time parameters i ; \hat{y}_i – predicted value predicted

value for the signal i ; $\frac{1}{n} \sum_{n=1}^n$ average value

$(y_i - \hat{y}_i)^2$ squared errors.

The calculation of the difference between the predicted values and the true values is performed for each signal in the ensemble and each difference is squared to avoid the influence of negative values. The smaller the MSE, the better the model of the ensemble of signals with dynamic changes in time parameters.

7. The overall classification error (Overall Classification Error – OCE) is defined as the percentage of incorrectly classified signals relative to the entire ensemble of signals and is calculated as follows [7]:

$$OCE = \frac{FP + FN}{NO} \times 100 \%, \quad (3)$$

where, *False Positives (FP)* – the number of signals that were falsely classified as positive (the classifier made a mistake by marking them as positive); *False Negatives (FN)* – the number of signals that were mistakenly classified as negative (the classifier made a mistake by marking them as negative); *Total Number of Observations (NO)* – the total number of observations in the data set.

The choice of the metric depends on the specific task of the scientific survey, taking into account the characteristics of the data necessary for the formation of ensembles of signals. After using the selected metrics, it is mandatory to evaluate the accuracy and efficiency of ensembles of signals with dynamic changes in time parameters, using the PNN neural network.

In the context of ensembles of neural networks that are designed to process signals with dynamic changes in time parameters, the possibility of formation or detection of multiple access interference (MAI) may depend on the specific structure and functionality of the ensemble, as well as on the method of signal processing.

MAI is a situation where signals from multiple sources are transmitted simultaneously in the same channel, and this can lead to overlapping and mutual influence of these signals. In a telecommunications context, this can be a problem because MAI interference can lead to false signal recognition and reduced reception quality. Whether an ensemble of neural networks will be able to effectively detect or shape MAI disturbances depends on the settings and characteristics of this ensemble. Some architectures and models may be well-suited to solving the MAI problem if they are trained or configured to do so. However, this may require special data processing

and the installation of algorithms to detect and compensate for MAI.

In practice, to solve the MAI problem in telecommunications, specialized methods and algorithms are usually used, such as CDMA (Code Division Multiple Access) or other methods of channel separation, which are designed to control and separate signals in multiple access networks. Neural networks can be used as an auxiliary tool for data processing, but their effectiveness depends on specific conditions and tasks.

Conclusions

In conclusion, the utilization of neural networks in forming ensembles for processing signals with temporal dynamics represents a highly pertinent and promising avenue within the realms of machine learning and signal processing. This approach offers a plethora of opportunities for addressing a wide spectrum of tasks related to the analysis and prediction of intricate temporal data, spanning from time series and audiovisual signals to medical records and beyond. One of the primary merits of employing neural networks in this context lies in their ability to tackle challenges that conventional methods may find daunting. Neural networks exhibit a remarkable proficiency in uncovering intricate patterns and nonlinear dependencies within temporal data, rendering them particularly effective for diverse tasks where traditional techniques might prove inadequate. The ongoing advancements in deep learning are affording the construction of intricate and deep-seated neural network architectures, allowing for a more accurate representation of the complex interrelations within temporal data. In certain scenarios, a single model may not suffice for solving complex tasks, and this is where ensembles of neural networks come into play, where multiple models collaborate, significantly ameliorating prediction outcomes and bolstering the system's resilience.

This research trajectory is not limited to machine learning and signal processing but also actively contributes to the development and optimization of telecommunication networks. The incorporation of neural networks in the realm of telecommunications has the potential to elevate the efficiency and reliability of communication systems, ensuring more seamless and robust connectivity.

Кубів С. І., Моркляник Б. В.

ФОРМУВАННЯ АНСАМБЛІВ СИГНАЛІВ З ЧАСОВИМ РОЗДІЛЕННЯМ З ВИКОРИСТАННЯМ НЕЙРОННОЇ МЕРЕЖІ

У телекомунікаціях сигнали з часовим розділенням, відіграють надзвичайно важливу в процесі передачі та обробки інформації. Ці сигнали, які представляються як електромагнітні хвилі, служать основними транспортним засобом для передачі даних від одного комунікаційного пристрою до іншого, фактично становлячи кровоносну систему сучасних комунікаційних мереж. Визначальною особливістю, яка відрізняє ці

Hence, it is evident that the utilization of neural networks in forming ensembles for processing signals with temporal dynamics remains a pertinent and promising endeavor across various domains. This field not only unlocks a vast realm of possibilities for further exploration but also holds substantial potential for practical implementation.

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сигнали, є їхня часова природа, або, точніше, зміни, які вони зазнають з часом в процесі передач по мережі. Ці сигнали містять багатий спектр параметрів, охоплюючи не лише атрибути амплітуди, частоти та фази, але й багато інших параметрів. В статті науково обґрунтовується доцільність та актуальність дослідження процесу формування ансамблів сигналів з часовим розділенням за допомогою нейронних мереж. Досліджено, що однією з ключових задач при формуванні ансамблів складних сигналів з часовим розділенням з застосуванням робити нейромережі є вибір оптимальної архітектури нейромережі. Це передбачає визначення типу нейромережі, що найефективніше відповідає конкретному науковому завданню. Розроблено алгоритм формування ансамблів сигналів з часовим розділенням з використанням рекурентної нейронної мережі (RNN). Особлива увага приділяється методам оцінки загальної помилки ансамблів сигналів з часовим розділенням з використанням PNN. Ці методи аналізу включають застосування відповідних метрик, оцінка яких залежить від конкретного типу завдання (регресія або класифікація). Результати цього дослідження сприятимуть подальшому розвитку методів формування ансамблів сигналів з часовим розділенням за допомогою нейронних мереж та покращенню їх застосування в сучасних телекомунікаційних системах.

Ключові слова: телекомунікації, ансамблі сигналів, часове розділення, нейронні мережі.

Kubiv S., Morklianyk B.

FORMATION OF ENSEMBLES OF SIGNALS WITH TIME DIVISION USING A NEURAL NETWORK

In telecommunications, time-division signals play an extremely important role in the process of information transmission and processing. These signals, which are presented as electromagnetic waves, serve as the main means of transport for the transmission of data from one communication device to another, effectively constituting the circulatory system of modern communication networks. The defining feature that distinguishes these signals is their temporal nature, or more precisely, the changes they undergo over time as they travel over the network. These signals contain a rich spectrum of parameters, covering not only the attributes of amplitude, frequency and phase, but also many other parameters. This article provides a scientific rationale for the feasibility and relevance of researching the process of forming signal ensembles with temporal separation using neural networks. It has been established that one of the key tasks in creating ensembles of complex signals with temporal separation through the application of neural networks is the selection of an optimal neural network architecture. This entails determining the type of neural network that best aligns with a specific research objective. An algorithm for forming signal ensembles with temporal separation using a recurrent neural network (RNN) has been developed. Special attention is devoted to methods for assessing the overall error of signal ensembles with temporal separation using PNN. These analytical methods encompass the utilization of pertinent metrics, the evaluation of which depends on the specific nature of the task, whether it involves regression or classification. The findings of this research will contribute to the further advancement of methods for forming signal ensembles with temporal separation through the utilization of neural networks and enhance their application in contemporary telecommunications systems.

Keywords: telecommunications, signal ensembles, time division, neural networks.

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