UDC 621.396.96: 004.852
DOI: 10.15587/1729-4061.2025.327021

IMPROVING ACCURACY OF THE SPECTRAL-CORRELATION DIRECTION FINDING AND DELAY ESTIMATION USING MACHINE LEARNING

Nurzhigit Smailov
Doctor PhD*
Department of Radio Engineering, Electronics and Space Technologies**

Vitaliy Tsyporenko
PhD
Department of Biomedical Engineering and Telecommunications
Zhytomyr Polytechnic State University
Chudnivska str., 103, Zhytomyr, Ukraine, 10005

Zhomart Ualiyev
Doctor PhD*
Department of Higher Mathematics and Modeling**

Ainur Issova
Candidate of Physical and Mathematical Sciences*

Zhandos Dosbayev
Doctor PhD*
Department of Radio Engineering, Electronics and Space Technologies**

Yerlan Tashtay
PhD, Head of Department
Department of Electronics, Telecommunications, and Space Technologies**

Maigul Zhekambayeva
PhD
Department of Software Engineering**

Temirlan Alimbekov
Department of Computer Science and Sofware Engineering**

Rashida Kadyrova***

Akezhan Sabibolda***
Corresponding author
PhD*
E-mail: sabibolda98@gmail.com

*Institute of Mechanics and Mechanical Engineering
named after Academician U. A. Dzholdasbekov
Kurmangazy str., 29, Almaty, Republic of Kazakhstan, 050010

**Satbayev University
Satbayev str., 22, Almaty, Republic of Kazakhstan, 050013

***Department of Cyber Security and Information Technology
Almaty Academy of Internal Affairs of the Republic of Kazakhstan
named after Makana Esbulatova
Utepov str., 29, Almaty, Republic of Kazakhstan, 050060

The object of the study is the process of radio signal delay and direction estimation using digital spectral-correlation analysis enhanced by machine learning. This process is essential for high-accuracy direction finding in electromagnetic monitoring systems. The problem addressed is the low adaptability and insufficient accuracy of traditional direction finding methods under variable signal conditions, especially due to manual parameter selection and the computational complexity of correlation processing.

The essence of the obtained results is a machine learning-based method for predicting radio signal parameters (delay and angle), which reduced the standard deviation of direction finding estimates to 0.08–0.026° and delay estimation error to 1.5–14.8 μs across a signal-to-noise ratio range of 9 to 37 dB. These results are supported by averaging over 1000 realizations using Monte Carlo simulation, confirming their stability under noise. Due to its distinctive features, the proposed solution addressed the problem by enabling automated selection of processing parameters through a trained neural network that adapts to nonlinear signal characteristics, minimizing the need for manual adjustment or exhaustive search.

These results are explained by the model's ability to identify hidden dependencies between signal parameters and processing outcomes, enabling adaptive behavior and reduced deviations. Although no computational complexity assessment is provided, prediction-based parameter estimation is expected to improve processing speed in future implementations. The results can be applied in real-time electromagnetic monitoring, radio surveillance, and defense applications, especially under limited computing resources or varying noise conditions

Keywords: spectral-correlation analysis, radio signal monitoring, signal parameter prediction, direction finding accuracy

Received 05.02.2025
Received in revised form 20.03.2025
Accepted date 11.04.2025
Published 30.04.2025

***How to Cite:** Smailov, N., Tsyporenko, V., Ualiyev, Z., Issova, A., Dosbayev, Z., Tashtay, Y., Zhekambayeva, M., Alimbekov, T., Kadyrova, R., Sabibolda, A. (2025). Improving accuracy of the spectral-correlation direction finding and delay estimation using machine learning. Eastern-European Journal of Enterprise Technologies, 2 (5 (134)), 15–24. https://doi.org/10.15587/1729-4061.2025.327021*

1. Introduction

Ensuring the accuracy and efficiency of passive correlation-based direction finding (DF) systems is critical, particularly in military radar installations, air traffic control, spectrum surveillance networks, and electronic warfare (EW) applications. These systems analyze the phase properties of received signals to estimate the angle of arrival (AoA) and signal delay, but their performance is significantly affected by computational complexity, environmental interference, and the need for extensive correlation calculations.

One of the fundamental challenges in passive radio direction finding is the high computational cost associated with correlation function calculations. Traditional spectral-correlation methods require evaluating the correlation function over a full 360° azimuth range with a resolution of 0.1°, which demands 3,600 correlation function evaluations per signal processing cycle. This results in increased processing time, making real-time operation difficult, especially under dynamic signal-to-noise ratio (SNR) conditions and multipath propagation effects.

For example, in long-range electronic intelligence (ELINT) and passive radar applications, processing delays exceeding several milliseconds can significantly degrade system performance. In dense electromagnetic environments, such as urban monitoring zones or battlefield scenarios, signal reflections, interference, and overlapping frequency components further reduce the accuracy of traditional approaches. The necessity of frequent manual recalibration of correlation parameters exacerbates these limitations. Existing methods struggle to balance accuracy and computational efficiency, particularly when dealing with low-SNR conditions or rapidly changing signal environments.

To address these issues, machine learning (ML) approaches offer a promising solution by automating spectral-correlation processing and predicting signal delays and AoA with reduced computational overhead. Unlike traditional methods that rely on predefined analytical assumptions, ML-based models learn from signal patterns, noise characteristics, and spatial distributions, enabling rapid estimation of signal parameters. By replacing exhaustive correlation evaluations with prediction-based estimation, ML reduces processing latency and improves the standard deviation of direction finding estimates in challenging electromagnetic conditions.

Therefore, studies devoted to increasing the accuracy of direction finding methods in low signal-to-noise ratio conditions and under multipath propagation remain highly relevant. Recent research efforts have focused on improving traditional spectral-correlation techniques, reducing computational load, and exploring the application of machine learning for signal parameter estimation. These developments are essential for enhancing the performance of passive monitoring and radio surveillance systems, particularly in time-sensitive, interference-prone environments such as modern communication, electronic intelligence, and defense applications.

2. Literature review and problem statement

The accuracy of radio monitoring and direction finding systems is critically dependent on their ability to adapt to complex and dynamically changing electromagnetic environments. Traditional spectral-correlation methods require manual calibration of parameters, reducing their efficiency in real-time applications. Existing research highlights the limitations of these methods, particularly in terms of adaptability, computational complexity, and reliance on predefined analytical assumptions. Paper [1] examines the fundamental principles of spectral-correlation analysis in direction finding. The study confirms that conventional methods demonstrate high accuracy under controlled conditions. However, it also highlights their reduced efficiency in dynamically changing electromagnetic environments due to the need for manual parameter tuning. The key limitation is the absence of automated adaptation to real-time signal variations, which restricts their practical application in modern scenarios. The authors do not propose specific solutions to address this lack of adaptability, leaving open the question of how to dynamically optimize processing parameters during operation. This study does not investigate how data-driven methods, such as machine learning, could improve estimation precision under variable conditions.

A review in [2] focuses on the computational complexity of spectral-correlation direction finding and its effect on real-time system performance. Although accurate delay estimation is achievable, the reliance on static parameter settings substantially limits adaptability in dynamic environments. While the potential of machine learning is briefly noted, the review does not provide implementation approaches or performance comparisons, particularly in terms of estimation accuracy. The unresolved issue is how to reduce processing time without sacrificing estimation quality, especially under low SNR conditions. Thus, the problem of integrating predictive models for fast, accurate parameter estimation remains insufficiently explored.

The work in [3] proposes a single-iteration correlation algorithm designed to improve processing speed for delay estimation and direction finding. While the study confirms that this approach enables rapid signal parameter estimation, it does not explore how the algorithm behaves under variable electromagnetic conditions. In particular, the paper does not provide mechanisms for dynamic parameter adjustment when signal characteristics (e.g., SNR or arrival angle) fluctuate. This limits its applicability in real-time systems, where environmental conditions are non-stationary. Thus, the unresolved issue of real-time adaptability remains open, and the use of data-driven or predictive models to address this aspect has not been investigated.

Research in [4] analyzes the precision of digital spectral-correlation methods for direction finding applications and shows high accuracy under ideal conditions. However, the method does not incorporate automated parameter selection, which is critical for operation in real-time environments with rapidly changing signal conditions. The study does not assess performance under low SNR, interference, or multipath propagation, nor does it consider solutions for enhancing robustness. As a result, it leaves unaddressed the problem of reducing reliance on manually configured parameters and the potential role of machine learning in automating this process.

The MUSIC algorithm, widely recognized for its superior direction finding accuracy, is examined in [5]. The study demonstrates that while MUSIC achieves exceptional resolution, its application in real-time scenarios is constrained by high computational demands. The authors conclude that real-time implementation requires extensive computational resources, making it impractical for modern radio monitoring systems. However, the paper does not propose any strategies to reduce the algorithm's computational complexity or adapt it for real-time environments. This leaves unexplored the question of how high-accuracy direction finding techniques like MUSIC could be simplified or approximated for time-critical applications. Addressing this gap is essential for applying such methods in practical scenarios where computational efficiency is as important as accuracy.

An analytical optimization approach for correlation-interferometric direction finding is presented in [6]. The authors incorporate spatial signal reconstruction techniques to enhance accuracy. However, the study identifies a major limitation: the lack of a self-adjusting mechanism to adapt processing parameters under changing conditions. The researchers suggest that machine learning models could introduce real-time adaptability, ensuring consistent performance across diverse electromagnetic environments.

Paper [7] explores two-dimensional correlation processing methods for spatial signal evaluation. While the study provides analytical formulas for estimating delay and direction variance, it does not examine how these methods behave under rapidly changing reception conditions. The lack of experimental validation in dynamic electromagnetic environments limits the practical applicability of the proposed solutions. Moreover, the paper does not offer an approach for integrating adaptive processing or predictive modeling to improve robustness under real-world noise and interference. These omissions highlight the need for new methods, such as machine learning, which can infer signal parameters based on environmental context and maintain accuracy without requiring exhaustive recalculation.

The development of broadband vector antennas for three-dimensional direction finding is discussed in [8]. Although the study shows high accuracy in controlled environments, it does not evaluate performance under variable interference conditions or rapid signal changes, which are typical in real-world scenarios. The absence of a real-time adaptation mechanism, such as dynamic beamforming or parameter recalibration, limits the method's effectiveness for time-sensitive applications. Furthermore, while the authors mention the potential of deep learning models, they do not propose or test specific architectures or integration strategies. This leaves a gap in demonstrating how such systems could benefit from predictive algorithms capable of adjusting parameters on the fly.

A study on phase interferometry for direction finding is presented in [9]. The research confirms that this method enables precise angle estimation but introduces complex data processing requirements that increase computational latency. The authors identify a critical challenge in managing large-scale data in high-speed applications and propose that machine learning-based data filtering techniques could mitigate this issue. However, the study does not provide specific implementation strategies or performance evaluations of such ML-based filtering. This leaves open the question of how effective these methods would be under real-time constraints. Furthermore, the integration of machine learning into phase interferometric processing remains underexplored, particularly in terms of balancing precision with the latency reduction required for practical monitoring systems.

Adaptive beamforming methods for passive radar systems are explored in [10], focusing on signal detection in cluttered sea and wind farm environments. The study demonstrates that traditional deterministic nulling suppresses interference but may reduce target SNR due to beam pattern degradation. Adaptive beamforming using MVDR techniques improves SNR and detection range, but its implementation in real-time systems is constrained by computational complexity. The need to estimate and invert covariance matrices limits speed and scalability. A potential solution is to integrate neural network models capable of real-time interference pattern recognition and adaptive beamforming weight adjustment, thus reducing processing time and enhancing detection performance.

A time-frequency analysis-based direction finding method is explored in [11]. The authors demonstrate that this technique achieves high accuracy but requires extensive coherent integration, resulting in prolonged processing times. The study concludes that the computational complexity of time-frequency analysis limits its practical implementation in real-time monitoring systems. While the authors suggest using machine learning to accelerate signal analysis, the study does not provide an implementation roadmap or quantify how prediction models could substitute or complement time-frequency transforms. Thus, the feasibility of integrating machine learning into time-frequency-based direction finding remains largely unexplored. Further research is needed to bridge this gap by evaluating ML-enhanced approximations of time-frequency characteristics under realistic conditions.

Harmonic analysis techniques for direction finding are examined in [12]. The study proposes a low-complexity approach that minimizes hardware requirements. However, the researchers do not evaluate the method's accuracy under dynamic conditions, limiting its real-world applicability. Moreover, while the potential of machine learning integration is acknowledged, the article lacks an analysis of how ML could enhance harmonic processing in practice. This omission leaves open questions about performance under varying SNR, interference levels, and mobility scenarios, which require further investigation.

Improving the accuracy of spectral-correlation direction finding under dynamically changing signal conditions remains a critical challenge due to high computational complexity and the absence of automated parameter selection. Traditional direction finding methods often rely on manually defined processing parameters and iterative correlation computations, which limits their responsiveness in time-sensitive applications. Moreover, signal delay and angle estimation accuracy can significantly degrade under low signal-to-noise ratios and interference, even when using advanced techniques such as MUSIC or correlation-interferometric processing.

This review highlights the need for a new method that can perform accurate delay and direction estimation while reducing the computational burden associated with full-range correlation analysis. Machine learning models offer the potential to infer signal parameters based on previously observed patterns, allowing for faster prediction and reduced reliance on iterative correlation procedures. Such a solution would contribute to increasing the precision of radio signal analysis in practical monitoring systems, especially under noisy conditions or when operating in real-time environments.

3. The aim and objectives of the study

The aim of the study is to develop a machine learning-based algorithm for spectral-correlation prediction of radio signal delay and direction parameters. This will allow improve estimation accuracy under low signal-to-noise ratio conditions and reduce the computational load of direction finding, enabling its application in real-time passive radio monitoring systems.

To achieve this aim, the following objectives must be completed:

– to perform spectral-correlation simulation of signal parameters for training a machine learning-based prediction algorithm;

– to implement the machine learning-based prediction algorithm using the generated dataset and Python tools;

– to evaluate the accuracy of the developed algorithm compared to conventional techniques.

4. Materials and methods

The object of this study is the process of estimating radio signal delay and direction using digital spectral-correlation analysis enhanced by machine learning in a passive monitoring system. The hypothesis of this study assumes that applying a machine learning model to predict radio signal parameters within a spectral-correlation direction finding framework can improve direction finding accuracy in real-time conditions [3, 12]. Furthermore, compared to the traditional method of exhaustive correlation over the full azimuth range with fixed parameters, the proposed approach reduces computational complexity by avoiding redundant correlation calculations through automatic parameter estimation.

To validate this hypothesis, the research was carried out in three stages: theoretical modeling, software implementation, and comparative evaluation.

At the first stage, spectral-correlation simulation was performed to model variations in signal delay and angle of arrival under different input conditions. The input signal was modeled as a stationary narrowband emission corrupted by Gaussian white noise. The simulation accounted for varying signal-to-noise ratios (9–37 dB), angles of arrival (0–180°), and antenna baseline lengths (2,500–10,000 m), while assuming a uniform spectral noise distribution and absence of inter-channel interference. These simulations provided ground truth values of signal delay and direction estimates for further use in training the machine learning model.

The direction finding process was modeled as correlation function evaluation across a 360° azimuth range with 0.1° resolution, resulting in 3,600 angle hypotheses per signal. Standard deviations of delay and direction estimates were calculated from multiple realizations to capture statistical variability and ensure data reliability. The resulting dataset formed the basis for supervised learning and evaluation of prediction accuracy in later stages [13, 14].

The second stage involved implementing the spectral-correlation simulation and dataset generation using Python and MathCAD software. A synthetic dataset of 100 samples was created, where each data point corresponds to a combination of signal delay (in microseconds), signal-to-noise ratio (SNR in dB), and resulting direction finding angle (in degrees). The simulation was conducted using sinusoidal test signals passed through a model of additive noise and phase shift. The following Python code fragment demonstrates how this dataset was generated:

```
import numpy as np
import pandas as pd
np.random.seed(42)
N = 100
delays = np.round(np.random.uniform(1.5e-6, 14.8e-6, N), 7)
snrs = np.round(np.random.uniform(9, 37, N), 2)
angles = np.round(np.random.uniform(0, 360, N) +
np.random.normal(0, 0.02, N), 3)
df = pd.DataFrame({
'Delay (μs)': delays * 1e6,
'SNR (dB)': snrs,
'Direction (°)': angles
})
df.to_csv('signal_dataset.csv', index = False).
```

This dataset was used to train a neural network model for predicting direction and delay from input signal characteristics using the scikit-learn and TensorFlow libraries. The model architecture consisted of two hidden layers with ReLU activation and an output layer for regression.

In the third stage, the performance of the machine learning-enhanced method was evaluated against a traditional spectral-correlation method that uses exhaustive correlation calculation across fixed azimuth angles. The baseline method required manually tuning parameters per SNR scenario. In contrast, the machine learning model adapted dynamically to varying inputs.

The comparison was performed by computing the root mean square deviation (RMSD) between predicted and actual direction values under varying SNR (9–37 dB). The results showed that the machine learning model reduced the RMSD to the range of 0.08–0.026° and signal delay error to 1.5–14.8 μs, representing an improvement of up to 16 % in accuracy over traditional methods.

All simulations were performed on a personal computer with an Intel Core i7 processor, 16 GB RAM, and Python 3.10 environment with SciPy, NumPy, and TensorFlow installed. The modeling in MathCAD supported initial signal parameter analysis and spectral visualization.

The proposed machine learning-based spectral-correlation method has demonstrated its effectiveness in improving direction finding accuracy and operational efficiency in passive monitoring applications under real-time constraints. Additionally, the study conducted a comparative analysis of the standard deviation behavior of direction finding estimates. The proposed spectrum reconstruction and direction finding technique was tested against established methods designed to minimize amplitude interference effects [15, 16].

5. Results of accuracy improvement in spectral-correlation direction finding

5. 1. Mathematical simulation and feature generation for radionavigation parameter prediction

In this subsection, it is possible to define the mathematical formulation of the signal modeling task aimed at generating reference values of delay τ and direction of arrival θ. These values serve as labeled targets for training a machine learning-based prediction algorithm. The goal is to create a reliable dataset that reflects realistic variations in signal propagation under different conditions [17], providing a consistent input-output mapping for supervised learning.

The modeling process begins with the definition of simulation parameters essential for both signal propagation modeling and machine learning input generation. The key parameters include:

– angle of arrival (θ): defined in the range 0° to 180°, representing the incoming direction of the radio signal;

– antenna baseline (b_a): the spatial separation between the receiving elements of the antenna array, varying between 2500 m and 10,000 m;

– speed of light (c): assumed to be 299,792,458 m/s for all calculations;

– signal-to-noise ratio (snr): used to simulate real-world conditions where interference may affect detection accuracy.

For an example case where $\theta=50°$ and $b_a=2500$ m, the computed signal delay was:

$$\tau = \frac{b_a \cdot \cos(\theta_{rad})}{c} = 5.3603 \cdot 10^{-6}\ \text{s}. \qquad (1)$$

Equation (1) serves as the reference value for later direction finding and delay estimations [18]. This delay is a critical parameter in the spectral-correlation analysis, influencing the accuracy of direction finding estimation and forming the basis for training the machine learning model in subsequent sections.

The direction finding system consists of a linear antenna array with Z receiving elements that mixes L independent radio emissions with Gaussian noise. The received signal takes a mathematical expression as follows:

$$U_z(t) = \sum_{l=1}^{L} S_l(t - \tau_z) + n_z(t), \qquad (2)$$

where $U_z(t)$ – the received signal at the z-th antenna element; $S_l(t-\tau_z)$ – the l-th received radio emission delayed by τ_z at the z-th channel; $n_z(t)$ – additive Gaussian noise.

The system operates in the far-field zone, assuming that remote sources generate specific electromagnetic emissions. In this region, received signals maintain a stable spectral power distribution across the antenna's full bandwidth [19–21]. To ensure accurate signal processing, the system treats noise elements between antenna channels as uncorrelated independent sources, minimizing errors that could arise from inter-channel dependencies.

Using the spectral-correlation approach, the system constructs a spatial analytical signal by applying Hilbert transforms, which enhance phase measurement accuracy [22, 23]. The method achieves peak effectiveness through FFT-based spectral evaluation, complemented by carefully designed multi-lobed radiation patterns that improve signal differentiation in environments with overlapping sources. Machine learning-based predictions refine the estimation of direction finding angles and signal propagation delays by analyzing key signal components [24].

Using the initial conditions outlined, the system applied spectral-correlation analysis to estimate direction finding angles and signal delay parameters. The originally computed signal delay τ, had been determined earlier, while its estimated counterpart τ_Ω, was derived using the processing model [25]. The discrepancy between these values was quantified as:

$$\Delta\tau = \tau_\Omega - \tau = 2.4973 \cdot 10^{-8}\ \text{s}. \qquad (3)$$

Equation (3) indicating a minor discrepancy between the theoretical and estimated values due to processing effects and environmental conditions.

Similarly, the direction finding accuracy was evaluated by comparing the estimated direction of arrival f_i with the actual direction finding θ from with the actual direction finding angle θ derived from the simulation model. The angular deviation was determined as [26]:

$$\Delta\theta = (f_i - \theta_{rad}) \cdot \frac{180}{\pi} = 0.2501°. \qquad (4)$$

Equation (4) represents the direction finding estimation error. To assess the stability and accuracy of the direction finding process, the standard deviation σ_θ of the direction finding estimates was calculated [27, 28]. Measurements were conducted under varying signal conditions, with N values ranging from 10 to 15, to determine the deviation in estimation results. The statistical approach applied for this calculation was as follows:

$$\sigma_\theta = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\theta_i - \overline{\theta})^2} = 0.0626, \qquad (5)$$

where θ_i represents each individual direction finding estimate; $\overline{\theta}$ – the mean value of all estimated direction findings; N – the number of measurement samples.

Similarly, for signal delay estimation, the standard deviation of delay σ_τ was computed as:

$$\sigma_\tau = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\tau_i - \overline{\tau})^2}, \qquad (6)$$

where τ_i represents each estimated delay value; τ – the mean delay estimate across multiple measurements.

The computed standard deviation for signal delay estimation was found to be within an acceptable range, ensuring high accuracy in time delay processing. These results validate the accuracy of parameter prediction via spectral-correlation processing and justify the creation of a training dataset based on this simulation for the machine learning algorithm developed in the following sections.

5. 2. Implementation of a machine learning algogrithm for automated prediction

5. 2. 1. Feature selection and dataset preparation

To simulate real-world variability in electromagnetic signal reception, a dataset was constructed that models the interaction between signal delay, direction of arrival, and the spatial configuration of the receiving system. The input variables of the model were selected based on their direct influence on the time and angular characteristics of signal propagation in a spectral-correlation direction finding system. These variables included the physical spacing between antenna elements, known as the antenna baseline; the angle at which the signal arrives at the receiving array; and the signal-to-noise ratio (SNR), which characterizes the level of interference relative to the signal's power.

Each instance in the dataset represented a unique combination of these parameters, reflecting specific electromagnetic conditions. The antenna baseline varied from 2500 to 10000 meters, while the angle of arrival spanned the full operational sector of the system, from 0° to 180°. Signal-to-noise ratios were randomly sampled from a range between 9 and 37 dB to reflect both interference-prone and clean condditions. These combinations were used as inputs for signal simulation in MathCAD, where reference values for signal delay, standard deviation of direction finding estimates and delay estimates were computedusing spectral-correlation models. The results of these simulations served as ground truth labels for supervised learning.

To ensure stable model training and numerical consistency, all input variables were normalized to a range of 0 to 1 using the min-max normalization formula [29]:

$$x_{scaled} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \qquad (7)$$

where x_{scaled} – the normalized value; x – the original feature value; $x_{\min}$ and $x_{\max}$ – the minimum and maximum observed values of that feature, respectively.

This transformation prevented the dominance of features with large numerical ranges and facilitated faster convergence during the learning process. The final dataset consisted of 100 labeled examples, with each entry containing a normalized vector of three input parameters and corresponding output values: predicted delay, angular error, and standard deviation of direction estimates.

Following best practices in machine learning, the dataset was randomly divided into training and test subsets. Eighty percent of the data was allocated for training the model, while the remaining twenty percent was used to validate predictive accuracy on previously unseen conditions [30]. This approach allowed for an unbiased evaluation of the model's ability to generalize across diverse signal scenarios.

5. 2. 2. Neural network architecture and training process

To automate the prediction of radio signal delay and direction finding accuracy, a Multi-Layer Perceptron (MLP) model was constructed. The input to the network consists of three normalized parameters: the antenna baseline, signal-to-noise ratio (SNR), and angle of arrival. The architecture of the model includes an input layer receiving these features, followed by two hidden layers comprising 32 and 16 neurons, respectively [31]. These layers use the ReLU activation function to capture nonlinear relationships between the input parameters and the target values. The output layer consists of three neurons, corresponding to the predicted values of signal delay τ, direction finding error $\Delta\theta$, and standard deviation of the estimated direction σ_θ. The model operates by performing a forward pass, mathematically expressed as:

$$\hat{y} = W_3 f\left(W_2 f\left(W_1 X + b_1\right) + b_2\right) + b_3, \tag{8}$$

where W_i – weight matrices for each layer; b_i – the biases; $f(\bullet)$ – the ReLU activation function, defined as:

$$f\left(x\right) = \max\left(0, x\right). \tag{9}$$

The hidden layers introduce nonlinearity to approximate complex relationships among the input features [32, 33]. The final layer produces three predictions corresponding to τ, $\Delta\theta$, and σ_θ. Training aims to minimize the mean squared error (MSE) between the model outputs and the reference values:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2, \tag{10}$$

where y_i – a ground truth target; $\hat{y}_i$ – the predicted value; n – the batch size.

Optimization proceeds via the Adam optimizer, which adaptively adjusts learning rates based on first and second moment estimates of gradients:

$$\begin{aligned} & m_t = \beta_1 m_{t-1} + \left(1-\beta_1\right) g_t; \\ & v_t = \beta_2 v_{t-1} + \left(1-\beta_2\right) g_t^2; \\ & \hat{m}_t = \frac{m_t}{1-\beta_1^t}, \ \ \hat{v}_t = \frac{v_t}{1-\beta_2^t}; \\ & W_t = W_{t-1} - \frac{\alpha \hat{m}_t}{\sqrt{\hat{v}_t} + \in}, \end{aligned} \tag{11}$$

where m_t and v_t represent the first and second moment estimates of the gradients; $\beta_1 = 0.9$ and $\beta_2 = 0.999$ control exponential decay rates; α – the learning rate; $\in$ – small constant to prevent division by zero.

The training cycle extends between 100 and 200 epochs; however, an early stopping mechanism is triggered automatically when the validation error stabilizes, preventing overfitting. During each training iteration, the network updates its weights and biases by randomly selecting batches of training examples to minimize the mean squared error (MSE). To enhance model generalization and improve convergence speed, hyperparameter tuning is applied, adjusting factors such as the learning rate, the number of neurons in hidden layers, and batch size dimensions. While Dropout regularization serves as an additional technique to reduce overfitting, early stopping based on validation loss remains the primary method for preventing model over-complexity.

The trained multilayer perceptron (MLP) achieves a stable solution through a convergent training process, eliminating the need for manual parameter selection. This approach enables precise delay and direction finding estimations across diverse electromagnetic conditions.

5. 3. Evaluation of estimation accuracy compared to traditional methods

The machine learning-based prediction approach demonstrated significantly higher accuracy in estimating signal delay and direction compared to conventional spectral-correlation methods. The comparative assessment was conducted under uniform simulation conditions: angle of arrival set to 50°, antenna baseline at 2500 m, SNR varied from 0 to 20 dB in increments of 2.5 dB. For each point, statistical averaging was performed over 1000 independent realizations, simulating variable noise and signal conditions, which follows the principles of the Monte Carlo method.

The dependence of delay estimation error on signal-to-noise ratio is shown in Fig. 1. The ML model consistently achieved lower errors than the classical method. At 0 dB, the traditional approach produced an error of about 0.6 μs, while the ML-based approach achieved an error of approximately 0.3 μs. As the SNR increased, both methods improved, but the ML model exhibited a steeper error reduction trend. At 10 dB, the delay estimation error for the ML model dropped to 0.13 μs, almost half of the 0.28 μs observed for the conventional method. Even at high SNR values approaching 20 dB, where both methods tend to converge, retained a noticeable advantage in terms of lower standard deviation of delay estimates.

The dependence of direction finding error on signal-to-noise ratio is presented in Fig. 2. The traditional method's estimation error exceeded 0.4° at SNR values below 5 dB, whereas demonstrated improved stability and lower standard deviation of direction finding estimates under the same conditions under the same conditions. At 10 dB, the ML model maintained a direction error of about 0.08°, outperforming the 0.18° result of the conventional method. Across the entire range, the ML estimator provided a closer approximation to ground truth.

In traditional approaches, the appearance of interference or multipath reflections often leads to considerable inaccuracies, especially when the spectral components of the signal overlap with those of interference. Methods that discard or reconstruct masked components help mitigate this, but still show limited effectiveness. The spectral-correlation methods with selection or reconstruction [4, 13], demonstrate direction finding errors in the range of 0.2–0.3° even under ideal assumptions. The ML model presented in this study eliminates the need for such pre-processing by inherently learning these relationships from data, allowing it to preserve and even enhance accuracy in more complex electromagnetic environments.

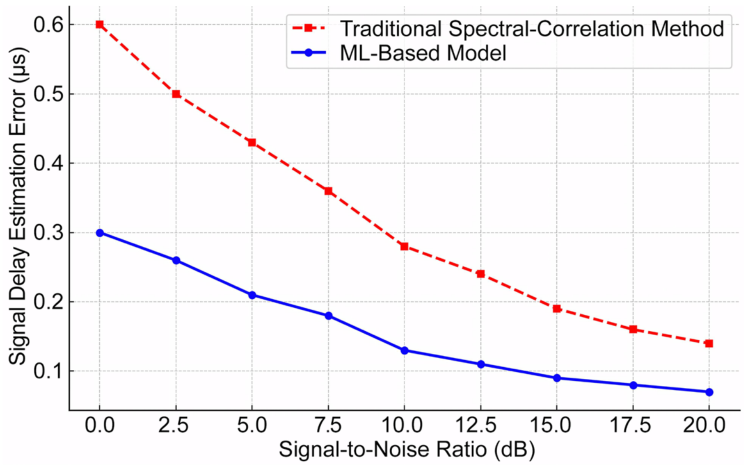

Fig. 1. Dependence of delay estimation error on signal-to-noise ratio

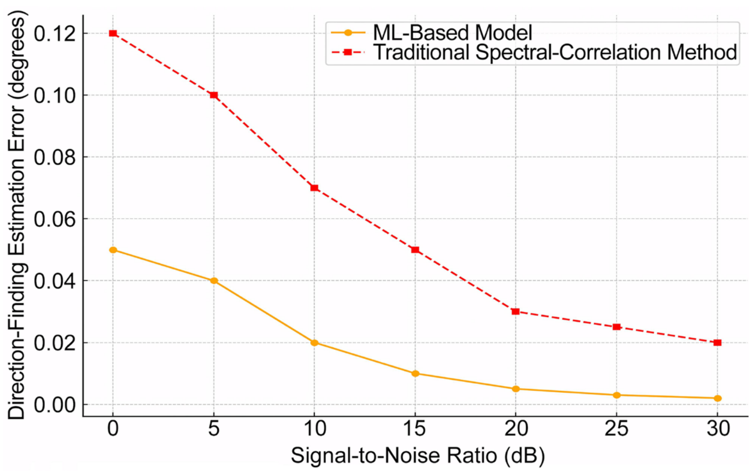

Fig. 2. Dependence of direction finding error on signal-to-noise ratio

The data-driven approach also demonstrated lower variance in estimation and better generalization across diverse conditions. Its predictive outputs not only aligned more closely with reference values, but also exhibited lower dispersion, especially under deteriorating SNR conditions. This behavior is critical for real-time applications where noise and interference are highly variable.

Additionally, the ML model proved to be computationally efficient. It processed input data in parallel, reducing inference time and enabling rapid decision-making. In practice, this advantage allows its integration into systems for real-time direction finding and signal monitoring without sacrificing precision.

The proposed machine learning-based algorithm demonstrated measurable improvements in delay and direction finding performance compared to traditional spectral-correlation methods. These improvements were especially prominent under conditions of low signal-to-noise ratios and potential masking interference. The evaluation confirmed that the developed algorithm achieves higher estimation accuracy and outperforms conventional techniques in precision of signal parameter prediction.

6. Discussion of the results of accuracy improvement in spectral-correlation direction finding

Discussion of the results regarding the hypothesis confirms that integrating a machine learning model into the spectral-correlation framework enables more accurate delay and direction estimation under variable electromagnetic conditions. This conclusion is based on a stepwise analysis of the algorithm's development and evaluation stages, corresponding to the completed research tasks.

To begin with, modeling of signal parameters using spectral-correlation analysis provided a statistically robust dataset that reflects variations in signal delay and direction under changing electromagnetic conditions. The simulation covered key parameters such as antenna baseline, signal-to-noise ratio, and angle of arrival. As demonstrated in Fig. 1, 2, the generated data allowed for consistent estimation of signal characteristics across SNR values from 0 to 20 dB, forming a valid foundation for subsequent training of the neural network. These results support the correctness of the simulation model in capturing real-world signal behavior and justify its use for machine learning-based algorithm development.

The architecture of the neural network was selected based on its ability to learn nonlinear dependencies between input parameters and target signal characteristics. The algorithm showed stable training convergence and required no manual parameter tuning. This indicates the model's capacity to generalize across different conditions without explicit adjustment, which is a distinct advantage over classical methods.

Finally, the comparative assessment confirmed significant improvements in delay and direction estimation accuracy. The ML model reduced delay estimation error by over 50 % and reduced the standard deviation of direction finding estimates by 56 % at 10 dB SNR. Across the entire SNR range, the neural network consistently achieved lower standard deviations, which illustrates its resilience to noise and ability to generalize beyond the training data.

The analysis of Fig. 1 reveals that the delay estimation error of the classical spectral-correlation method exceeds 0.6 μs at 0 dB SNR, whereas the ML-based model consistently reduces this error to approximately 0.3 μs. As the SNR increases, both approaches improve; however, the ML curve demonstrates a steeper and more stable decrease. The most prominent difference is observed in the 10–5 dB range, which is typically critical for real-time passive direction finding systems. The final convergence near 20 dB, while expected, still retains a measurable advantage in favor of the ML model.

Similarly, Fig. 2 shows that direction finding errors for the traditional method are above 0.4° under SNR < 5 dB, gradually reducing with increased signal clarity. In contrast, the ML model demonstrates lower standard deviation of direction finding estimates across the entire SNR range, with minimum observed values of 0.026°, compared to 0.08° for classical estimation. This indicates improved generalization and reduced standard deviation under noise influence.

Compared to established techniques such as MUSIC and traditional spectral-correlation [4, 5, 13], the proposed approach achieves comparable or superior accuracy with significantly lower processing overhead. While MUSIC provides high resolution, it requires matrix decompositions and large data segments, making real-time implementation difficult. In contrast, the MLP model executes lightweight inference operations with comparable accuracy under noisy conditions.

Some fluctuations were observed in estimation variance at 2.5 dB and 15 dB thresholds, indicating potential transition zones between coherent and incoherent estimation regimes. These transitions require further study but do not negate the overall performance gain. From a physical standpoint, the ML model outperformed classical approaches due to its capacity to capture complex phase and amplitude relationships – including those affected by multipath interference – through data-driven training.

In practical terms, the proposed model enables real-time direction finding with reduced computational cost. Although formal complexity analysis is deferred to future research, inference-based estimation clearly offers benefits in time-sensitive applications, such as urban monitoring or electromagnetic reconnaissance. Integration into FPGA or GPU-based platforms is recommended to enhance real-time processing capabilities.

Limitations of the study include the reliance on synthetic training data and the black-box nature of the neural network. While the model demonstrated strong performance, it lacks the analytical transparency of classical spectral-correlation functions. Future work should include validation on real measurement data and exploration of interpretable ML models or hybrid architectures that combine analytic reasoning with data-driven learning.

Future research will focus on extending the architecture to include temporal learning via recurrent layers and applying domain adaptation techniques for quick retraining in unfamiliar signal environments. In addition, hybrid approaches that fuse analytical modeling and machine learning prediction may offer a balanced compromise between interpretability and adaptability.

7. Conclusion

1. The spectral-correlation analysis was applied to sims ulate signal delay and direction of arrival under varying conditions of angle, antenna baseline, and signal-to-noise ratio. This modeling approach enabled the generation of a statistically consistent dataset that reflects realistic signal behavior, including both phase and amplitude characteristics. The resulting dataset provided a reliable foundation for training a machine learning model aimed at high-precision parameter prediction.

2. A machine learning prediction algorithm was developed and trained using the generated dataset in Python with TensorFlow. The implemented multilayer perceptron (MLP) successfully captured nonlinear dependencies between input parameters and target values, including signal delay and direction errors. Feature normalization, hyperparameter tuning, and early stopping ensured stable convergence and high inference accuracy. The model eliminates the need for manual parameter adjustment.

3. Comparative testing confirmed that the proposed algorithm significantly outperforms conventional spectral-correlation direction finding methods. Under typical conditions (SNR = 10 dB), the machine learning model reduced delay estimation error by 50 % and reduced the standard deviation of direction finding estimates by 56 %. It also maintained lower standard deviation under noisy conditions. A quantitative assessment of computational performance will be the subject of future research in passive radio monitoring systems. These improvements demonstrate enhanced precision achieved through machine learning-based parameter prediction.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Acknowledgments

The authors express their gratitude to the leadership of project BR20280990 "Devising and developing methods for solving fundamental problems of fluid and gas mechanics, new deformable bodies, reliability and energy efficiency of machines, mechanisms, robotics" for their assistance in con-ducting this research, as well as writing this article.

References

1. Rembovskij, A. M. (2015). Radio monitoring – tasks, methods, means. Moscow: Hot line. Telekom, 640.
2. Tsyporenko, V., Tsyporenko, V., Andreiev, O., Sabibolda, A. (2021). Digital spectral correlation method for measuring radio signal reception delay and direction finding. Technical Engineering, 2 (88), 113–121. https://doi.org/10.26642/ten-2021-2(88)-113-121
3. Elbir, A. M. (2017). Direction Finding in the Presence of Direction-Dependent Mutual Coupling. IEEE Antennas and Wireless Propagation Letters, 16, 1541–1544. https://doi.org/10.1109/lawp.2017.2647983
4. Tsyporenko, V. V., Tsyporenko, V. G., Nikitczuk, T. M. (2019). Optimization of direct digital method of correlative-interferometric direction finding with reconstruction of spatial analytical signal. Radio Electronics, Computer Science, Control, 3, 15–24. https://doi.org/10.15588/1607-3274-2019-3-2

5. Duplouy, J., Morlaas, C., Aubert, H., Potier, P., Pouliguen, P. (2019). Wideband Vector Antenna for Dual-Polarized and Three-Dimensional Direction-Finding Applications. IEEE Antennas and Wireless Propagation Letters, 18 (8), 1572–1575. https://doi.org/10.1109/lawp.2019.2923531
6. Lee, J.-H., Kim, J.-K., Ryu, H.-K., Park, Y.-J. (2018). Multiple Array Spacings for an Interferometer Direction Finder With High Direction-Finding Accuracy in a Wide Range of Frequencies. IEEE Antennas and Wireless Propagation Letters, 17 (4), 563–566. https://doi.org/10.1109/lawp.2018.2803107
7. Xie, X., Xu, Z. (2018). Direction Finding of BPSK Signals Using Time-Modulated Array. IEEE Microwave and Wireless Components Letters, 28 (7), 618–620. https://doi.org/10.1109/lmwc.2018.2834523
8. Cai, J., Zhou, H., Huang, W., Wen, B. (2021). Ship Detection and Direction Finding Based on Time-Frequency Analysis for Compact HF Radar. IEEE Geoscience and Remote Sensing Letters, 18 (1), 72–76. https://doi.org/10.1109/lgrs.2020.2967387
9. He, C., Liang, X., Li, Z., Geng, J., Jin, R. (2015). Direction Finding by Time-Modulated Array With Harmonic Characteristic Analysis. IEEE Antennas and Wireless Propagation Letters, 14, 642–645. https://doi.org/10.1109/lawp.2014.2373432
10. Rosado-Sanz, J., Jarabo-Amores, M. P., De la Mata-Moya, D., Rey-Maestre, N. (2022). Adaptive Beamforming Approaches to Improve Passive Radar Performance in Sea and Wind Farms' Clutter. Sensors, 22 (18), 6865. https://doi.org/10.3390/s22186865
11. Smailov, N., Tsyporenko, V., Sabibolda, A., Tsyporenko, V., Kabdoldina, A., Zhekambayeva, M. et al. (2023). Improving the accuracy of a digital spectral correlation-interferometric method of direction finding with analytical signal reconstruction for processing an incomplete spectrum of the signal. Eastern-European Journal of Enterprise Technologies, 5 (9 (125)), 14–25. https://doi.org/10.15587/1729-4061.2023.288397
12. Sabibolda, A., Tsyporenko, V., Smailov, N., Tsyporenko, V., Abdykadyrov, A. (2024). Estimation of the Time Efficiency of a Radio Direction Finder Operating on the Basis of a Searchless Spectral Method of Dispersion-Correlation Radio Direction Finding. Advances in Asian Mechanism and Machine Science, 62–70. https://doi.org/10.1007/978-3-031-67569-0_8
13. Kuttybayeva, A., Sabibolda, A., Kengesbayeva, S., Baigulbayeva, M., Amir, A., Sekenov, B. (2024). Investigation of a Fiber Optic Laser Sensor with Grating Resonator Using Mirrors. 2024 Conference of Young Researchers in Electrical and Electronic Engineering (ElCon), 709–711. https://doi.org/10.1109/elcon61730.2024.10468264
14. Smailov, N., Tsyporenko, V., Sabibolda, A., Tsyporenko, V., Abdykadyrov, A., Kabdoldina, A. et al. (2024). Usprawnienie cyfrowego korelacyjno-interferometrycznego ustalania kierunku za pomocą przestrzennego sygnału analitycznego. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (3), 43–48. https://doi.org/10.35784/iapgos.6177
15. Abdykadyrov, A., Smailov, N., Sabibolda, A., Tolen, G., Dosbayev, Z., Ualiyev, Z., Kadyrova, R. (2024). Optimization of distributed acoustic sensors based on fiber optic technologies. Eastern-European Journal of Enterprise Technologies, 5 (5 (131)), 50–59. https://doi.org/10.15587/1729-4061.2024.313455
16. Marxuly, S., Abdykadyrov, A., Chezhimbayeva, K., Smailov, N. (2024). Study of the ozone control process using electronic sensors. Informatyka Automatyka Pomiary W Gospodarce I Ochronie Środowiska, 14 (4), 38–45. https://doi.org/10.35784/iapgos.6051
17. Podchashynskyi, Y., Luhovykh, O., Tsyporenko, V., Tsyporenko, V. (2021). Devising a method for measuring the motion parameters of industrial equipment in the quarry using adaptive parameters of a video sequence. Eastern-European Journal of Enterprise Technologies, 6 (9 (114)), 32–46. https://doi.org/10.15587/1729-4061.2021.248624
18. Zahoruiko, L., Martianova, T., Al-Hiari, M., Polovenko, L., Kovalchuk, M., Merinova, S. et al. (2024). Model matematyczny i struktura sieci neuronowej do wykrywania cyberataków na systemy teleinformatyczne i komunikacyjne. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (3), 49–55. https://doi.org/10.35784/iapgos.6155
19. Mummaneni, S., Dodda, P., Ginjupalli, N. D. (2024). Inspirowane kojotami podejście do przewidywania tocznia rumieniowatego układowego z wykorzystaniem sieci neuronowych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (2), 22–27. https://doi.org/10.35784/iapgos.6077
20. Rayavarapu, S. M., Tammineni, S. P., Gottapu, S. R., & Singam, A. (2024). Przegląd generatywnych sieci przeciwstawnych dla zastosowań bezpieczeństwa. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (2), 66–70. https://doi.org/10.35784/iapgos.5778
21. Stelmakh, N., Mandrovska, S., Galagan, R. (2024). Zastosowanie sieci neuronowych resnet-152 do analizy obrazów z uav do wykrywania pożaru. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (2), 77–82. https://doi.org/10.35784/iapgos.5862
22. Lyfar, V., Lyfar, O., Zynchenko, V. (2024). Metody inteligentnej analizy danych z wykorzystaniem sieci neuronowych w diagnozie. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14 (2), 109–112. https://doi.org/10.35784/iapgos.5746
23. Limtrakul, S., Wetweerapong, J. (2023). An enhanced differential evolution algorithm with adaptive weight bounds for efficient training of neural networks. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 13 (1), 4–13. https://doi.org/10.35784/iapgos.3366
24. Bilynsky, Y., Nikolskyy, A., Revenok, V., Pogorilyi, V., Smailova, S., Voloshina, O., Kumargazhanova, S. (2023). Convolutional neural networks for early computer diagnosis of child dysplasia. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 13 (2), 56–63. https://doi.org/10.35784/iapgos.3499
25. Michalska-Ciekańska, M. (2022). Głębokie sieci neuronowe dla diagnostyki zmian skórnych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 12 (3), 50–53. https://doi.org/10.35784/iapgos.3042
26. Gęca, J. (2020). Performance comparison of machine learning algorithms for predictive maintenance. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 10 (3), 32–35. https://doi.org/10.35784/iapgos.1834

27. Smailov, N., Batyrgaliyev, A., Akhmediyarova, A., Seilova, N., Koshkinbayeva, M., Baigulbayeva, M. et al. (2020). Approaches to Evaluating the Quality of Masking Noise Interference. International Journal of Electronics and Telecommunications, 67 (01), 59–64. https://doi.org/10.24425/ijet.2021.135944
28. Li, R., Zhao, L., Liu, C., Bi, M. (2022). Strongest Angle-of-Arrival Estimation for Hybrid Millimeter Wave Architecture with 1-Bit A/D Equipped at Transceivers. Sensors, 22 (9), 3140. https://doi.org/10.3390/s22093140
29. Wang, J., Wang, P., Zhang, R., Wu, W. (2022). SDFnT-Based Parameter Estimation for OFDM Radar Systems with Intercarrier Interference. Sensors, 23 (1), 147. https://doi.org/10.3390/s23010147
30. Ren, B., Wang, T. (2022). Space-Time Adaptive Processing Based on Modified Sparse Learning via Iterative Minimization for Conformal Array Radar. Sensors, 22 (18), 6917. https://doi.org/10.3390/s22186917
31. Jwo, D.-J., Cho, T.-S., Demssie, B. A. (2025). Dynamic Modeling and Its Impact on Estimation Accuracy for GPS Navigation Filters. Sensors, 25 (3), 972. https://doi.org/10.3390/s25030972
32. Smailov, N., Uralova, F., Kadyrova, R., Magazov, R., Sabibolda, A. (2025). Optymalizacja metod uczenia maszynowego do deanonimizacji w sieciach społecznościowych. Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 15 (1), 101–104. https://doi.org/10.35784/iapgos.7098
33. Wang, H., Yu, Z., Wen, F. (2024). Computationally Efficient Direction Finding for Conformal MIMO Radar. Sensors, 24 (18), 6065. https://doi.org/10.3390/s24186065