

Article

Feature Purification Using Extreme Learning Machine for RIS-ISAC Channel Estimation

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Abstract

Integrated sensing and communication (ISAC) technology enables the joint integration of communication and sensing functions through the efficient utilization of spectrum/energy resources. By further incorporating with the reconfigurable intelligent surfaces (RISs), the wireless propagation environment of ISAC systems can be dynamically controlled, thereby enhancing the overall sensing and communication (SAC) performance. In this context, accurate channel estimation is a fundamental prerequisite for the efficient operation of the RIS-assisted ISAC systems. However, the strong coupling between SAC signals from direct and reflected channel links, as well as severe noise interference, limits the SAC channel estimation accuracy. This paper proposes a novel two-stage channel estimation scheme for RIS-assisted ISAC systems, where the direct and reflected SAC channels are respectively estimated in the first and second stages. To mitigate the negative effects of noise interference in each estimation stage, an extreme learning machine-based feature purification module is precisely designed, improving the quality of received SAC signals and generating purified channel features. Then, the dedicated deep neural network adopts the purified channel features to estimate SAC channels. Simulation results demonstrate that, under different signal-to-noise ratio conditions and channel dimensions, the proposed scheme achieves superior estimation accuracy and strong robustness compared to the benchmark methods.

Keywords: channel estimation; extreme learning machine (ELM); feature purification; integrated sensing and communication (ISAC); reconfigurable intelligent surfaces (RISs)



Academic Editor: Pablo García Triviño

Received: 30 May 2026

Revised: 1 July 2026

Accepted: 13 July 2026

Published: 15 July 2026

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1. Introduction

Future wireless communication systems are evolving toward higher frequency bands, large-scale deployment, and higher levels of intelligence. The traditional communication approaches, which rely on boosting the transmit power and employing the complex signal processing techniques, are progressively approaching their performance limits [1–3]. In this context, reconfigurable intelligent surfaces (RISs) have attracted significant attention as a novel programmable paradigm for controlling the wireless propagation environments [4,5]. RIS is composed of a large number of low-cost passive reflecting elements. Hence, it can independently adjust the phase and amplitude parameters of the incident signals, thereby enabling flexible reconfiguration of the propagation channel. Compared to the conventional

active or large-scale antenna arrays, RIS possesses various advantages, such as low energy consumption, simple hardware implementation, and flexible deployment [6]. By intelligently manipulating signal propagation paths, RIS can effectively mitigate blockage and multipath fading, while significantly enhancing system coverage and spectrum utilization efficiency [7]. Building upon conventional passive RIS, recent studies have further extended RIS architectures to more advanced paradigms, such as simultaneously transmitting and reflecting RIS (STAR-RIS). It provides additional spatial degrees of freedom for wireless transmission optimization [8]. The developments of the STAR-RIS further highlight the increasing importance of efficient signal processing and accurate channel estimation for the RIS-enabled wireless systems.

As wireless networks advance toward the 6G era, the scarcity of spectrum resources and the growing demands for multifunctional integration have become increasingly pronounced [9,10]. In response, integrated sensing and communication (ISAC) has emerged as another promising paradigm. By sharing hardware platforms and spectrum resources within a unified system framework, ISAC enables the deep integration of sensing and communication (SAC) functionalities, thereby significantly improving resource utilization efficiency and reducing system overhead [11–13]. Compared to the conventional architecture in which communication and radar systems operate independently, ISAC is capable of providing high-precision target detection [14], localization [15], and tracking [16] while maintaining reliable communication performance. To further enhance these sensing capabilities, recent studies have investigated advanced beamforming and signal processing techniques for extended target sensing, demonstrating significant improvements in sensing accuracy and robustness. A predictive error ellipse-based beamforming scheme was investigated in [17] to optimize the sensing accuracy under practical ISAC scenarios. The work in [18] demonstrates that intelligent signal processing plays a key role in enhancing ISAC performance and expanding its application potential. The dual functionalities of ISAC make it highly promising for a wide range of applications, including the intelligent transportation, autonomous driving, and industrial Internet of Things scenarios [19,20].

However, in ISAC systems, the sharing of spectrum and hardware resources inevitably leads to the mutual interference between SAC signals. By reconfiguring the wireless propagation environment, RIS can not only enhance the communication quality and sensing accuracy, but its passive nature also contributes to reducing the overall energy consumption of ISAC systems. As a result, the integration of RIS has become a key enabling technology for ISAC systems [21–23]. In recent years, most studies on RIS-assisted ISAC systems have primarily focused on the waveform design, resource allocation, and interference mitigation. Nevertheless, the performance gains achieved by these approaches critically rely on the availability of accurate channel state information (CSI) [24–26]. Since acquiring accurate CSI from the received signals is a fundamental prerequisite for the ISAC-RIS system designs, it is essential to address the practical channel estimation problems. Despite its importance, channel estimation in RIS-ISAC systems faces several significant challenges [27]. First, compared to the conventional systems with only direct channel links, the ISAC systems assisted by the RIS possess both the direct and reflected SAC channel links. These substantially increase the channel dimensionality and the number of CSI parameters, thereby leading to a higher estimation complexity. Second, since RIS is typically composed of passive elements without signal processing ability, it is difficult to directly obtain channel information at the RIS side, limiting the applicability of traditional pilot-based estimation methods. Furthermore, in ISAC scenarios, the mutual interference between SAC signals further exacerbates the uncertainty in channel estimation.

To acquire accurate CSI for RIS-assisted ISAC systems, extensive efforts have been devoted to channel estimation techniques. Conventional channel estimation methods,

such as least squares (LSs) and minimum mean square error estimators, have the advantages of low computational complexity and easy implementation. Previous studies [27,28] have emphasized that the conventional mathematical optimization techniques can achieve satisfactory estimation performance, while their computational complexity increases significantly with the growing dimensions of RIS-assisted systems, especially in large-scale scenarios. Moreover, the complicated propagation characteristics introduced by RIS further increase the difficulty of constructing accurate analytical models. Data-driven approaches, on the other hand, can efficiently address highly complex optimization problems, including those that are difficult to model analytically. By constructing various neural network (NN) models, these methods establish nonlinear mappings between the received signals and channel responses, thereby achieving high estimation accuracy with acceptable training overhead. Representative studies employ deep neural networks (DNNs) to establish the nonlinear mappings between the received signals and SAC channels, thereby achieving higher estimation accuracy than the conventional model-based approaches. For instance, in [29], two DNN architectures were respectively designed to estimate channels from the reflected SAC links for RIS-assisted ISAC systems. In [30], a conditional generative adversarial network is introduced, where conditional information guides the generator to produce channel samples that are closer to the true distribution, demonstrating superior accuracy and robustness. However, the above works only concentrate on the reflected SAC channel estimation. Then, in [31], a convolutional neural network (CNN)-based channel estimation method was proposed for an uplink ISAC-RIS system, where the direct SAC channels, reflected communication channel, and reflected sensing channel are respectively estimated in three stages. By controlling the on/off states of the RIS and the base station, the channel estimation process is divided into multiple stages, which effectively reduces the overall estimation complexity caused by the coupling of sensing and communication channels. To reduce the training overhead, an extreme learning machine-based channel estimation was investigated in [32] for a multi-user ISAC-RIS system, achieving satisfactory estimation accuracy.

The LS estimator is commonly adopted as a baseline method due to its simplicity in implementation. However, its limitations become increasingly pronounced in complex RIS-assisted ISAC systems. On the one hand, the LS estimator is highly sensitive to the noise interference, and its performance degrades significantly under low signal-to-noise ratio (SNR) conditions. On the other hand, the reliance of LS estimation on the linear assumptions makes it difficult to capture the inherent nonlinear characteristics of the ISAC-RIS system, which may lead to estimation bias. Moreover, as the number of RIS elements increases, the pilot overhead grows substantially, making it challenging to meet practical deployment requirements. Therefore, it is critical to design an efficient, robust, and generalizable channel estimation method for the RIS-assisted ISAC systems. Although existing deep-learning-based RIS-ISAC channel estimation methods have achieved encouraging performance, several limitations remain. First, most existing studies focus only on reflected channels or require multiple estimation stages, without jointly considering both direct and reflected sensing/communication channels in a unified framework. Second, existing ELM-based methods mainly employ ELM as the channel estimator itself, while its capability for feature purification and noise suppression has not been explored. Finally, existing methods generally adopt a single estimation network, without considering the distinct characteristics of direct and reflected channels. To address the above challenges in the existing literature, this paper proposes a novel two-stage channel estimation scheme for a RIS-assisted ISAC system. The direct SAC channels are estimated in the first stage, whereas the reflected SAC channel estimation problems are solved in the second one. Note that, for each estimation stage, an ELM-based feature purification module is introduced to suppress

noise interference from the received signals and extract informative channel features. The purified features are then input into the dedicated DNN for the SAC channel estimation, improving estimation accuracy. The main contributions of this work can be summarized as follows:

1. A two-stage estimation framework is proposed to tackle the coupling issue of the SAC channels. By controlling the on/off states of the RIS, the overall estimation problem is decomposed into two subproblems, enabling separate estimation of the direct and reflected SAC channels. Compared with existing multi-stage or reflected-channel-oriented methods, the proposed framework enables more accurate and robust estimation of all required channels.
2. In each estimation stage, an ELM-based feature purification module is precisely devised to mitigate the negative effect of noise interference. Different from the existing ELM-based channel estimation methods that directly employ ELM as the estimator, the proposed ELM module is dedicated to purifying the channel features. It extracts key channel features from the received noisy signals and enhances signal quality, thereby improving system robustness under noisy conditions. Moreover, by adopting the purified channel features, two distinct DNN models are respectively designed for the direct and reflected channel estimation, accommodating the different characteristics of direct and reflected channels.
3. Extensive simulations are conducted to evaluate the performance of the proposed method. Numerical results demonstrate that, compared to the benchmark methods, the proposed scheme achieves significant performance improvements in both estimation accuracy and stability.

2. System Model

Consider a RIS-assisted ISAC system model in Figure 1. It consists of a full-duplex (FD) ISAC base station (BS), sensing target, downlink user equipment (UE), and RIS. The ISAC BS is equipped with M transmit antennas and one receive antenna, enabling it to simultaneously sense the target and communicate with the single-antenna downlink UE.

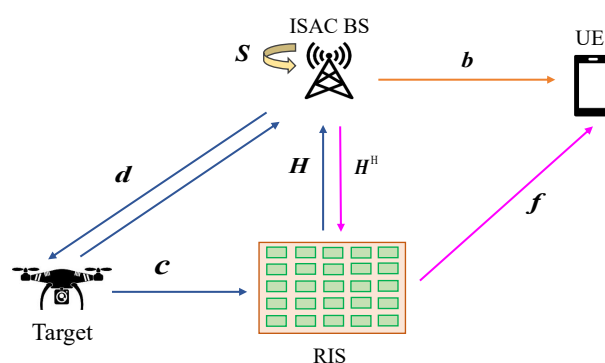


Figure 1. RIS-assisted ISAC system model.

The RIS composed of L passive reflecting elements is deployed to assist the ISAC system. It is worth noting that the placement of the RIS has a significant impact on system performance. Therefore, in this paper, the RIS is assumed to be deployed near the ISAC BS to achieve better performance [31]. In the target sensing procedure, the ISAC BS transmits signals toward the target via two paths: the direct BS–target–BS link and the reflected BS–target–RIS–BS link. The sensing channel coefficients of the BS–target–BS, BS–target–RIS, and RIS–BS links are denoted by $\mathbf{d} \in \mathbb{C}^{M \times 1}$, $\mathbf{c} \in \mathbb{C}^{M \times L}$, and $\mathbf{H} \in \mathbb{C}^{1 \times L}$, respectively. For downlink communication, the ISAC BS transmits signals to the downlink UE through both the direct BS–UE link and the reflected BS–RIS–UE link, where $\mathbf{b} \in \mathbb{C}^{M \times 1}$

and $\mathbf{f} \in \mathbb{C}^{L \times 1}$ represent the communication channel coefficients of the BS–UE and RIS–UE links, respectively. Due to the adoption of full-duplex operation, the BS experiences self-interference (SI) while receiving uplink signals. Accordingly, the SI channel at the ISAC BS is denoted by $\mathbf{S} \in \mathbb{C}^{M \times 1}$. In addition, let $\mathcal{N}_a^b = \{a, a+1, \dots, b\}$ denote the set of integers from a to b , where $a < b$.

In Figure 2, a pilot transmission protocol is designed for estimating the SAC channels in the RIS-assisted ISAC system. For the proposed two-stage channel estimation method, let S_l denote the number of frames in the l -th estimation stage, where $l \in \mathcal{N}_1^2$. The duration of this stage spans from the $(C^{S_{l-1}} + 1)$ -th subframe to the C^{S_l} -th subframe, with $C^{S_0} = 0$, and each subframe consists of P^{S_l} time slots. The ISAC BS transmits pilot sequences within the $(C^{S_l} - C^{S_{l-1}})$ subframes. Specifically, in the c -th subframe, $c \in \mathcal{N}_{C^{S_{l-1}+1}}^{C^{S_l}}$, the pilot signal vector used at the p -th time slot, $p \in \mathcal{N}_1^{P^{S_l}}$, is denoted as $\mathbf{x}_p^{S_l} \in \mathbb{C}^{M \times 1}$. Accordingly, the pilot signal matrix within this subframe is given by $\mathbf{X}^{S_l} = [\mathbf{x}_1^{S_l}, \mathbf{x}_2^{S_l}, \dots, \mathbf{x}_{P^{S_l}}^{S_l}] \in \mathbb{C}^{M \times P^{S_l}}$. In addition, the RIS phase shift vector corresponding to the c -th subframe is denoted as $\mathbf{v}_c^{S_l} \in \mathbb{C}^{1 \times L}$, which remains constant within each subframe. Based on the above pilot transmission protocol, the received signals at the ISAC BS and the downlink UE at the p -th time slot of the c -th subframe are denoted by $y_{c,p}^{S_l}$ and $r_{c,p}^{S_l}$, respectively expressed as

$$y_{c,p}^{S_l} = (\mathbf{d}^H + \mathbf{H} \text{diag}\{\mathbf{v}_c^{S_l}\} \mathbf{c}^H) \mathbf{x}_p^{S_l} + \mathbf{S}^H \mathbf{x}_p^{S_l} + n_{c,p}^{S_l}, \quad (1)$$

$$r_{c,p}^{S_l} = (\mathbf{b}^H + \mathbf{f}^H \text{diag}\{(\mathbf{v}_c^{S_l})^H\} \mathbf{H}^H) \mathbf{x}_p^{S_l} + w_{c,p}^{S_l}. \quad (2)$$

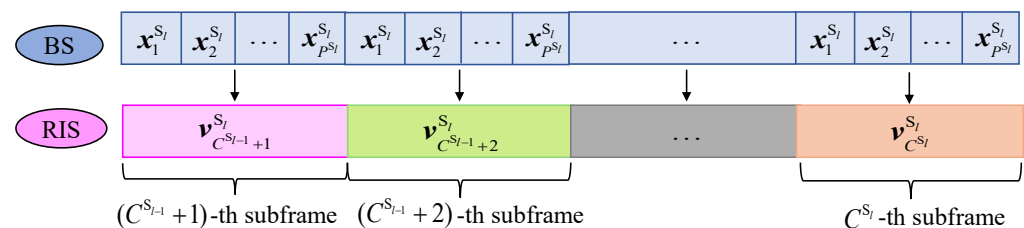


Figure 2. Pilot transmission protocol.

Here, $\mathbf{v}_c^{S_l} = [\beta_c e^{j\varphi_{c,1}}, \beta_c e^{j\varphi_{c,2}}, \dots, \beta_c e^{j\varphi_{c,L}}]$, where the amplitude and phase shift of the l -th RIS element are denoted by $\beta_c \in [0, 1]$ and $\varphi_{c,l} \in [0, 2\pi)$, respectively, with $l \in \mathcal{N}_1^L$. The additive Gaussian noise terms $n_{c,p}^{S_l}$ and $w_{c,p}^{S_l}$ follow zero-mean complex Gaussian distributions with variances σ^2 and ζ^2 , respectively. It is worth noting that the propagation environment between the transmit and receive antennas at the ISAC BS typically varies slowly [33,34]. Therefore, the SI channel $\mathbf{S}$ can be pre-estimated at the ISAC BS using the LS method, and the residual self-interference can be eliminated prior to channel estimation [33]. From (1) and (2), we have $\mathbf{H} \text{diag}\{\mathbf{v}_c^{S_l}\} = \mathbf{v}_c^{S_l} \text{diag}\{\mathbf{H}\}$ and $\text{diag}\{\mathbf{v}_c^{S_l}\} \mathbf{f} = \text{diag}\{\mathbf{f}\} \mathbf{v}_c^{S_l}$. Thus, the equivalent reflected channels for the BS–target–RIS–BS link and the BS–RIS–UE link can be defined as $\mathbf{A} = \mathbf{c} \text{diag}\{\mathbf{H}^H\}$ and $\mathbf{G} = \mathbf{H} \text{diag}\{\mathbf{f}\}$. Accordingly, (1) and (2) are further rewritten as

$$y_{c,p}^{S_l} = (\mathbf{d}^H + \mathbf{v}_c^{S_l} \mathbf{A}^H) \mathbf{x}_p^{S_l} + n_{c,p}^{S_l}, \quad (3)$$

$$r_{c,p}^{S_l} = (\mathbf{b}^H + (\mathbf{v}_c^{S_l})^H \mathbf{G}^H) \mathbf{x}_p^{S_l} + w_{c,p}^{S_l}. \quad (4)$$

It should be emphasized that the SAC channel estimation problem becomes highly challenging, due to the mutual interference among SAC signals. Therefore, the pilot transmission protocol designed in Figure 2 aims to estimate the sensing channels $\mathbf{d}$ and $\mathbf{A}$ at the ISAC BS, as well as the communication channels $\mathbf{b}$ and $\mathbf{G}$ at the downlink UE.

3. Proposed Two-Stage Channel Estimation Scheme

3.1. Design of Two-Stage Estimation

To simplify the channel estimation problem, a two-stage estimation method is proposed to sequentially estimate the direct and reflected channels. By controlling the on/off states of the RIS, the direct SAC channels $\mathbf{d}$ and $\mathbf{b}$ are estimated in stage S_1 , while the reflected sensing channel $\mathbf{A}$ and the downlink reflected communication channel $\mathbf{G}$ are estimated in stage S_2 .

From the 1st to the C^{S_1} -th subframe, the direct SAC channels $\mathbf{d}$ and $\mathbf{b}$ are estimated in S_1 . During this stage, all RIS elements remain turned off. Based on the pilot transmission protocol, the signals received by the ISAC BS and the downlink UE in the c -th subframe are denoted as $\mathbf{y}_c^{S_1} \in 1 \times P^{S_1}$ and $\mathbf{r}_c^{S_1} \in 1 \times P^{S_1}$, respectively expressed as

$$\mathbf{y}_c^{S_1} = \mathbf{d}^H \mathbf{X}^{S_1} + \mathbf{n}_c^{S_1}, \quad c \in \mathcal{N}_1^{C^{S_1}}, \quad (5)$$

$$\mathbf{r}_c^{S_1} = \mathbf{b}^H \mathbf{X}^{S_1} + \mathbf{w}_c^{S_1}, \quad c \in \mathcal{N}_1^{C^{S_1}}, \quad (6)$$

where $\mathbf{n}_c^{S_1} = [n_{c,1}^{S_1}, n_{c,2}^{S_1}, \dots, n_{c,P^{S_1}}^{S_1}] \in 1 \times P^{S_1}$ and $\mathbf{w}_c^{S_1} = [w_{c,1}^{S_1}, w_{c,2}^{S_1}, \dots, w_{c,P^{S_1}}^{S_1}] \in 1 \times P^{S_1}$ denote the noise vectors. To avoid mutual interference between SAC signals and improve estimation accuracy, the pilot matrix $\mathbf{X}^{S_1}$ is required to satisfy orthogonality conditions. Since the columns of a discrete Fourier transform (DFT) matrix have constant modulus and are mutually orthogonal, they can ensure interference-free training. Therefore, a DFT matrix $\mathbf{O}$ is adopted, where its (u, v) -th element is given by $\mathbf{O}_{(u,v)} = \frac{1}{\sqrt{M}} e^{j \frac{2\pi}{P^{S_1}} uv}$. Considering the pilot overhead, let $P^{S_1} = 2M$ [35]. Hence, the pilot matrix $\mathbf{X}^{S_1}$ at the BS is constructed by selecting the first M columns of the DFT matrix $\mathbf{O}$.

In S_2 , to estimate the reflected SAC channels $\mathbf{A}$ and $\mathbf{G}$, all RIS elements are transformed to the on state from the $(C^{S_1} + 1)$ -th to the C^{S_2} -th subframe. The ISAC BS and the downlink UE receive signals in the c -th subframe accordingly, which are respectively given by

$$\mathbf{y}_c^{S_2} = (\mathbf{d}^H + \mathbf{v}_c^{S_2} \mathbf{A}^H) \mathbf{X}^{S_2} + \mathbf{n}_c^{S_2}, \quad c \in \mathcal{N}_{C^{S_1}+1}^{C^{S_2}}, \quad (7)$$

$$\mathbf{r}_c^{S_2} = (\mathbf{b}^H + (\mathbf{v}_c^{S_2})^H \mathbf{G}^H) \mathbf{X}^{S_2} + \mathbf{w}_c^{S_2}, \quad c \in \mathcal{N}_{C^{S_1}+1}^{C^{S_2}}, \quad (8)$$

The pilot signal matrix $\mathbf{X}^{S_2}$ is designed as an $M \times P^{S_2}$ DFT matrix in S_2 , where the (u, v) -th element is given by $\mathbf{X}_{(u,v)}^{S_2} = 1/\sqrt{M} e^{j \frac{2\pi}{P^{S_2}} uv}$. To satisfy the system requirement of low pilot overhead, P^{S_2} is set to M . In addition, the DFT matrix is employed to construct the RIS phase shift matrix $\mathbf{V}^{S_2} = \left[(\mathbf{v}_{C^{S_1}+1}^{S_2})^T, (\mathbf{v}_{C^{S_1}+2}^{S_2})^T, \dots, (\mathbf{v}_{C^{S_2}}^{S_2})^T \right]^T \in (C^{S_2} - C^{S_1}) \times L$, with the condition $C^{S_2} - C^{S_1} \geq L$ [31].

3.2. Design of Input–Output Pairs

In the channel estimation process, the receiver can typically only access noisy observations. Although directly performing estimation based on the raw received signals

can achieve acceptable performance to some extent, it is often susceptible to degradation caused by noise and interference. To address this issue, the proposed method divides the overall channel estimation procedure into two independent modules. The first module, referred to as the feature purification module, aims to extract informative features from the received noisy signals to enhance the quality of the input data. The second module, namely the channel estimation module, leverages the high-quality outputs provided by the feature purification stage to accurately reconstruct the channel. As a result, the proposed approach improves estimation accuracy and robustness under complex noise conditions. In the following, the input–output pair design for the feature purification module and channel estimation module are introduced.

3.2.1. Input–Output Pair Design for Feature Purification Module

The feature purification module takes noisy received signals as input, performs denoising processing, and generates purified signal representations. While preserving essential channel characteristics, it effectively suppresses noise interference, thereby providing more stable and reliable inputs for subsequent channel estimation. Based on the signals received at the ISAC BS and the downlink UE, the input–output mapping of the feature purification module are further constructed for the two estimation stages.

In Stage S_1 : The direct sensing channel $\mathbf{d}$ is estimated at the ISAC BS, while the downlink UE estimates the direct communication channel $\mathbf{b}$. For the proposed method, the input of the feature purification module at the ISAC BS, denoted by $\mathbf{R}_{BS}^{S_1}$, is directly constructed from the received signal $\mathbf{y}_c^{S_1}$ in (5). Similarly, the input of the feature purification module at the downlink UE, $\mathbf{R}_{UE}^{S_1}$, is formed based on the received signal $\mathbf{r}_c^{S_1}$ in (6), expressed as

$$\mathbf{R}_{BS}^{S_1} = \left[\Re\{\mathbf{y}_1^{S_1}, \mathbf{y}_2^{S_1}, \dots, \mathbf{y}_{C_{S_1}}^{S_1}\}, \Im\{\mathbf{y}_1^{S_1}, \mathbf{y}_2^{S_1}, \dots, \mathbf{y}_{C_{S_1}}^{S_1}\} \right]^T, \quad (9)$$

$$\mathbf{R}_{UE}^{S_1} = \left[\Re\{\mathbf{r}_1^{S_1}, \mathbf{r}_2^{S_1}, \dots, \mathbf{r}_{C_{S_1}}^{S_1}\}, \Im\{\mathbf{r}_1^{S_1}, \mathbf{r}_2^{S_1}, \dots, \mathbf{r}_{C_{S_1}}^{S_1}\} \right]^T, \quad (10)$$

Here, $\Re\{\cdot\}$ and $\Im\{\cdot\}$ denote the real and imaginary parts of a complex vector, respectively. By constructing the corresponding outputs to approximate the ideal signals, the feature purification process aims to learn the mapping from noisy received signals to noise-free counterparts. Specifically, based on (5) and (6), the noiseless components $\mathbf{d}^H \mathbf{X}^{S_1}$ and $\mathbf{b}^H \mathbf{X}^{S_1}$ are extracted as targets. Accordingly, the desired outputs of the feature purification module at the ISAC BS $\mathbf{H}_{BS}^{S_1}$ and the downlink UE $\mathbf{H}_{UE}^{S_1}$ are given by

$$\mathbf{H}_{BS}^{S_1} = \left[\Re\{\mathbf{d}^H \mathbf{X}^{S_1}\}, \Im\{\mathbf{d}^H \mathbf{X}^{S_1}\} \right]^T, \quad (11)$$

$$\mathbf{H}_{UE}^{S_1} = \left[\Re\{\mathbf{b}^H \mathbf{X}^{S_1}\}, \Im\{\mathbf{b}^H \mathbf{X}^{S_1}\} \right]^T, \quad (12)$$

In Stage S_2 : The reflected sensing channel $\mathbf{A}$ is estimated at the ISAC BS, while the downlink UE estimates the reflected communication channel $\mathbf{G}$. The design of the input–output pairs in this stage differs from that in Stage S_1 . For the proposed method, the input at the ISAC BS, $\mathbf{R}_{BS}^{S_2}$, is constructed using the obtained direct sensing channel $\hat{\mathbf{d}}$ in Stage S_1 together with the received signal $\mathbf{y}_c^{S_2}$ in (7). First estimating the direct channel in S_1 can have a relatively reliable and noise-resilient estimation. Based on this result, the influence of the direct-link component on the received signal can be effectively mitigated in S_2 , thereby reducing the solution space of the reflected channel and improving the overall stability of channel estimation. Similarly, the input at the downlink UE, $\mathbf{R}_{UE}^{S_2}$, is constructed

from the estimated direct communication channel $\hat{\mathbf{b}}$ in S_1 and the received signal $\mathbf{r}_c^{S_2}$ in (8). Then, $\mathbf{R}_{BS}^{S_2}$ and $\mathbf{R}_{UE}^{S_2}$ are respectively given by

$$\mathbf{R}_{BS}^{S_2} = \left[\Re\{\mathbf{y}_{C^{S_1+1}}^{S_2}, \mathbf{y}_{C^{S_1+2}}^{S_2}, \dots, \mathbf{y}_{C^{S_2}}^{S_2}, \hat{\mathbf{d}}^T\}, \Im\{\mathbf{y}_{C^{S_1+1}}^{S_2}, \mathbf{y}_{C^{S_1+2}}^{S_2}, \dots, \mathbf{y}_{C^{S_2}}^{S_2}, \hat{\mathbf{d}}^T\} \right]^T, \quad (13)$$

$$\mathbf{R}_{UE}^{S_2} = \left[\Re\{\mathbf{r}_{C^{S_1+1}}^{S_2}, \mathbf{r}_{C^{S_1+2}}^{S_2}, \dots, \mathbf{r}_{C^{S_2}}^{S_2}, \hat{\mathbf{b}}^T\}, \Im\{\mathbf{r}_{C^{S_1+1}}^{S_2}, \mathbf{r}_{C^{S_1+2}}^{S_2}, \dots, \mathbf{r}_{C^{S_2}}^{S_2}, \hat{\mathbf{b}}^T\} \right]^T. \quad (14)$$

Similarly, by extracting the terms $(\mathbf{d}^H \mathbf{X}^{S_2} + \mathbf{v}_c^{S_2} \mathbf{A}^H \mathbf{X}^{S_2})$ from (7) and $(\mathbf{b}^H \mathbf{X}^{S_2} + (\mathbf{v}_c^{S_2})^H \mathbf{G}^H \mathbf{X}^{S_2})$ from (8), the ideal signal representations can be constructed. Accordingly, in the second stage, the desired outputs of the feature purification module at the ISAC BS and UE are given by

$$\mathbf{H}_{BS}^{S_2} = \left[\Re\{\mathbf{d}^H \mathbf{X}^{S_2} + \mathbf{v}_c^{S_2} \mathbf{A}^H \mathbf{X}^{S_2}\}, \Im\{\mathbf{d}^H \mathbf{X}^{S_2} + \mathbf{v}_c^{S_2} \mathbf{A}^H \mathbf{X}^{S_2}\} \right]^T, \quad (15)$$

$$\mathbf{H}_{UE}^{S_2} = \left[\Re\{\mathbf{b}^H \mathbf{X}^{S_2} + (\mathbf{v}_c^{S_2})^H \mathbf{G}^H \mathbf{X}^{S_2}\}, \Im\{\mathbf{b}^H \mathbf{X}^{S_2} + (\mathbf{v}_c^{S_2})^H \mathbf{G}^H \mathbf{X}^{S_2}\} \right]^T. \quad (16)$$

3.2.2. Input–Output Pair Design for Channel Estimation Module

Based on the above input–output pair design of the feature purification module, the channel estimation module takes the purified received signals $\bar{\mathbf{y}}_c^{S_l}$ and $\bar{\mathbf{r}}_c^{S_l}$ at the ISAC BS and the downlink UE as inputs, respectively. The corresponding outputs of the channel estimation module are directly determined by the true channel parameters.

In Stage S_1 : The purified received signals at the ISAC BS and UE, $\bar{\mathbf{y}}_c^{S_1}$ and $\bar{\mathbf{r}}_c^{S_1}$, are used to construct the inputs of the channel estimation module for the SAC links, respectively given by

$$\bar{\mathbf{R}}_{BS}^{S_1} = \left[\Re\{\bar{\mathbf{y}}_1^{S_1}, \bar{\mathbf{y}}_2^{S_1}, \dots, \bar{\mathbf{y}}_{C^{S_1}}^{S_1}\}, \Im\{\bar{\mathbf{y}}_1^{S_1}, \bar{\mathbf{y}}_2^{S_1}, \dots, \bar{\mathbf{y}}_{C^{S_1}}^{S_1}\} \right]^T, \quad (17)$$

$$\bar{\mathbf{R}}_{UE}^{S_1} = \left[\Re\{\bar{\mathbf{r}}_1^{S_1}, \bar{\mathbf{r}}_2^{S_1}, \dots, \bar{\mathbf{r}}_{C^{S_1}}^{S_1}\}, \Im\{\bar{\mathbf{r}}_1^{S_1}, \bar{\mathbf{r}}_2^{S_1}, \dots, \bar{\mathbf{r}}_{C^{S_1}}^{S_1}\} \right]^T, \quad (18)$$

At the ISAC BS, the output of the channel estimation module, $\bar{\mathbf{H}}_{BS}^{S_1}$, is constructed based on the true direct sensing channel $\mathbf{d}$. As for the downlink UE, the output of the channel estimation module, $\bar{\mathbf{H}}_{UE}^{S_1}$, is generated from the true downlink direct communication channel $\mathbf{b}$. Hence, $\bar{\mathbf{H}}_{BS}^{S_1}$ and $\bar{\mathbf{H}}_{UE}^{S_1}$ are respectively denoted by

$$\bar{\mathbf{H}}_{BS}^{S_1} = \left[\Re\{\mathbf{d}^T\}, \Im\{\mathbf{d}^T\} \right]^T, \quad (19)$$

$$\bar{\mathbf{H}}_{UE}^{S_1} = \left[\Re\{\mathbf{b}^T\}, \Im\{\mathbf{b}^T\} \right]^T. \quad (20)$$

In Stage S_2 : The input of the channel estimation module at the ISAC base station, denoted by $\bar{\mathbf{R}}_{BS}^{S_2}$, is constructed from the purified received signals $\bar{\mathbf{y}}_c^{S_2}$ and the estimated direct sensing channel $\hat{\mathbf{d}}$ in S_1 . Similarly, using the processed received signals $\bar{\mathbf{r}}_c^{S_2}$ and the obtained downlink direct communication channel $\hat{\mathbf{b}}$ in S_1 , the input of the channel

estimation module at UE is formed as $\bar{\mathbf{R}}_{\text{UE}}^{S_2}$. The corresponding expressions of $\bar{\mathbf{R}}_{\text{BS}}^{S_2}$ and $\bar{\mathbf{R}}_{\text{UE}}^{S_2}$ are respectively given by

$$\bar{\mathbf{R}}_{\text{BS}}^{S_2} = \left[\Re\{\bar{\mathbf{y}}_{\text{CS}_1+1}^{S_2}, \bar{\mathbf{y}}_{\text{CS}_1+2}^{S_2}, \dots, \bar{\mathbf{y}}_{\text{CS}_2}^{S_2}, \hat{\mathbf{d}}^T\}, \Im\{\bar{\mathbf{y}}_{\text{CS}_1+1}^{S_2}, \bar{\mathbf{y}}_{\text{CS}_1+2}^{S_2}, \dots, \bar{\mathbf{y}}_{\text{CS}_2}^{S_2}, \hat{\mathbf{d}}^T\} \right]^T, \quad (21)$$

$$\bar{\mathbf{R}}_{\text{UE}}^{S_2} = \left[\Re\{\bar{\mathbf{r}}_{\text{CS}_1+1}^{S_2}, \bar{\mathbf{r}}_{\text{CS}_1+2}^{S_2}, \dots, \bar{\mathbf{r}}_{\text{CS}_2}^{S_2}, \hat{\mathbf{b}}^T\}, \Im\{\bar{\mathbf{r}}_{\text{CS}_1+1}^{S_2}, \bar{\mathbf{r}}_{\text{CS}_1+2}^{S_2}, \dots, \bar{\mathbf{r}}_{\text{CS}_2}^{S_2}, \hat{\mathbf{b}}^T\} \right]^T. \quad (22)$$

At the ISAC BS, the corresponding output of the channel estimation module, $\bar{\mathbf{H}}_{\text{BS}}^{S_2}$, is determined by the ground-truth sensing channel $\mathbf{A}$. At the downlink UE, the output of the channel estimation module, $\bar{\mathbf{H}}_{\text{UE}}^{S_2}$, corresponds to the true downlink reflected communication channel $\mathbf{G}$. Here, $\bar{\mathbf{H}}_{\text{BS}}^{S_2}$ and $\bar{\mathbf{H}}_{\text{UE}}^{S_2}$ are respectively expressed as

$$\bar{\mathbf{H}}_{\text{BS}}^{S_2} = [\Re\{\text{vec}[\mathbf{A}]\}, \Im\{\text{vec}[\mathbf{A}]\}]^T, \quad (23)$$

$$\bar{\mathbf{H}}_{\text{UE}}^{S_2} = [\Re\{\text{vec}[\mathbf{G}]\}, \Im\{\text{vec}[\mathbf{G}]\}]^T. \quad (24)$$

3.3. Training Dataset Generation

To construct a complete training dataset containing $V \times Q$ samples, we first generate V groups of original signal samples based on the received signals. Then, synthetic additive white Gaussian noise is added to the original channels to create $Q - 1$ noisy replicas for each original sample. The noise level is controlled by $\text{SNR}_{ch} = P_{ch}/\sigma_{ch}^2$, where P_{ch} and σ_{ch}^2 denote the channel power and the variance of the additive noise, respectively [29]. This data augmentation strategy not only improves the robustness of the model but also enhances its generalization capability, thereby improving channel estimation performance. Taking the feature purification module as an example, based on the designed input-output pairs, the training dataset at the ISAC BS can be expressed as

$$\left(r_{\text{BS}}^{S_l}, h_{\text{BS}}^{S_l} \right) = \left\{ \left(\mathbf{R}_{\text{BS}}^{S_l}(1, 1), \mathbf{H}_{\text{BS}}^{S_l}(1) \right), \left(\mathbf{R}_{\text{BS}}^{S_l}(1, 2), \mathbf{H}_{\text{BS}}^{S_l}(1) \right), \dots, \left(\mathbf{R}_{\text{BS}}^{S_l}(1, Q), \mathbf{H}_{\text{BS}}^{S_l}(1) \right), \right. \\ \left. \left(\mathbf{R}_{\text{BS}}^{S_l}(2, 1), \mathbf{H}_{\text{BS}}^{S_l}(2) \right), \dots, \left(\mathbf{R}_{\text{BS}}^{S_l}(V, Q), \mathbf{H}_{\text{BS}}^{S_l}(V) \right) \right\}, \quad l \in \mathcal{N}_1^2. \quad (25)$$

Here, $\left(\mathbf{R}_{\text{BS}}^{S_l}(v, q), \mathbf{H}_{\text{BS}}^{S_l}(v) \right)$ represents the (v, q) -th, $v \in \mathcal{N}_1^V$ and $q \in \mathcal{N}_1^Q$ training sample. Similarly, the same procedure is applied to construct the training dataset at the downlink UE, denoted by $\left(r_{\text{UE}}^{S_l}, h_{\text{UE}}^{S_l} \right)$. The total number of training samples N_{tr} is set to $VQ = 10^4$, where $V = 10^3$ and $Q = 10$. The channel SNR is configured as $\text{SNR}_{ch} = 30$ dB. Moreover, 90% of the dataset is used for training, and the remaining 10% is reserved for testing.

4. NN Framework Design for Proposed Estimation Method

The proposed NN framework is designed according to the characteristics of the channel estimation problems in the RIS-ISAC system. The received pilot signals are inevitably interfered with by the noise, while the propagation characteristics of the direct and reflected channels are significantly different. Hence, it may lead to the insufficient feature extraction and unsatisfactory estimation accuracy when directly employing a single DNN to estimate all SAC channels. To address this issue, the proposed NN framework adopts a channel feature enhancement strategy. Specifically, an ELM network is first introduced to suppress noise and purify the received signal features. The purified features are subsequently fed into dedicated neural network estimators for channel estimation. Moreover, different neural network architectures are adopted for the two estimation stages according to the

characteristics of the corresponding channels. This design enables each NN to focus on learning the channel-specific features, thereby improving estimation accuracy and robustness. In the following, the NN framework design for the proposed estimation method is provided in detail.

4.1. ELM-Based Feature Purification Framework

The ELM is a single hidden-layer feedforward neural network (FNN) composed of an input layer, a hidden layer, and an output layer. Unlike traditional neural networks that rely on iterative gradient descent to update parameters, ELM randomly initializes the input weights and hidden-layer biases, and then analytically determines the output weights. Hence, it can reduce the computational complexity and significantly improve the training efficiency [36]. To build the ELM-based feature purification framework, the ELM network model with N_ζ input neurons, N_h hidden neurons, and N_γ output neurons is adopted. Then, the output matrix of the hidden layer $\mathbf{U} \in \mathbb{R}^{N_{tr} \times N_h}$ can be expressed as

$$\mathbf{U} = \begin{bmatrix} f(\omega_1 \mathbf{R}(1, 1) + b_1) & \dots & f(\omega_{N_h} \mathbf{R}(1, 1) + b_{N_h}) \\ \vdots & \ddots & \vdots \\ f(\omega_1 \mathbf{R}(N_{tr}, N_\zeta) + b_1) & \dots & f(\omega_{N_h} \mathbf{R}(N_{tr}, N_\zeta) + b_{N_h}) \end{bmatrix}, \quad (26)$$

where $\omega_h = [\omega_{h,1}, \omega_{h,2}, \dots, \omega_{h,N_\zeta}]^T \in \mathbb{C}^{N_\zeta \times 1}$ denote the input weight vector connecting the h -th hidden neuron and the N_ζ input neurons. The bias and activation function of the h -th hidden neuron are denoted by b_h and $f(\cdot)$, respectively. Furthermore, define $\theta_h = [\theta_{h,1}, \theta_{h,2}, \dots, \theta_{h,N_\gamma}]^T \in \mathbb{C}^{N_\gamma \times 1}$ as the output weight vector between the h -th hidden neuron and the N_γ output neurons. By stacking the output vectors $\mathbf{H}(v)$, the output data matrix can be constructed as $\mathbf{Y} = [\mathbf{H}(1), \mathbf{H}(2), \dots, \mathbf{H}(N_{tr})]^T \in \mathbb{C}^{N_{tr} \times N_\gamma}$. Through randomly initializing the input weights and biases, the output weight matrix of the hidden layer can be determined as $\Theta_{\text{ELM}} = [\theta_1, \theta_2, \dots, \theta_{N_h}]^T \in \mathbb{R}^{N_h \times N_\gamma}$. Thus, the ELM model can be expressed as

$$\mathbf{Y} = \mathbf{U} \Theta_{\text{ELM}}. \quad (27)$$

In the ELM framework, when the activation function $f(\cdot)$ is infinitely differentiable, the parameters ω and b in the hidden-layer output matrix $\mathbf{U}$ are randomly initialized and remain fixed. In this case, the formulation in (27) becomes an equivalent linear system. Then, the ELM model only needs to determine the output weight matrix Θ by solving the following least-squares problem:

$$\hat{\Theta}_{\text{ELM}} = \min_{\Theta} \|\mathbf{U} \Theta_{\text{ELM}} - \mathbf{Y}\|_2. \quad (28)$$

By solving the least-squares problem, the optimal weight matrix can be obtained as

$$\hat{\Theta}_{\text{ELM}} = \mathbf{U}^+ \mathbf{Y}, \quad (29)$$

where $\mathbf{U}^+$ denotes the Moore–Penrose pseudoinverse of $\mathbf{U}$.

Based on the above training process, the proposed ELM-based channel estimation framework exhibits the following three advantages. First, with fixed hidden-layer parameters, the linear relationship in (27) always holds, allowing the output weights to be directly computed via matrix operations. Compared with traditional gradient-based learning methods, ELM significantly accelerates training effectively and reduces computational complexity [36]. Second, since no iterative weight updates are required, ELM avoids issues such as local minima and sensitivity to the hyperparameters, improving training stability and reliability. Finally, ELM demonstrates strong generalization capability. The

unique network structure of ELM enables it to adapt to varying channel conditions under different SNR levels, making the method highly robust and practically valuable. Based on the above concepts, two ELM-based feature purification frameworks are developed, which are respectively named as the Direct ELM (D-ELM) framework and Reflected ELM (R-ELM) framework. The D-ELM framework is utilized to extract the informative direct channel features in the first direct channel estimation stage, whereas the R-ELM framework is adopted to purify the reflected channel features in the second one.

4.2. Channel Estimation Framework

To address the distinct estimation requirements of the direct and reflected channels in the two estimation stages, two NN channel estimation frameworks are designed, respectively namely Direct Estimation (D-EST) framework and Reflected Estimation (R-EST) framework. Each NN framework consists of a feature purification module based on ELM (i.e., D-ELM/R-ELM module) and a channel estimation module based on DNN. Here, the DNN-based channel estimation module adopted in S_1 is referred to as Direct DNN (D-DNN), while that adopted in S_2 is named as Reflected DNN (R-DNN).

In stage S_1 , which focuses on direct channel estimation, the proposed D-EST framework involves two networks, including the D-ELM network in the feature purification module and D-DNN in the channel estimation module. Here, the hidden layer of the D-ELM network contains $N_h = 200$ neurons with the Sigmoid activation function. Since the direct channel typically has relatively low dimensionality and a simple structure, the D-DNN network is built by a fully connected FNN. It consists of an input layer, two fully connected layers (FFL), and an output layer, where each FFL contains 200 neurons and uses the Tanh activation function.

In stage S_2 , which aims at reflected channel estimation, the proposed R-EST framework is constructed by two networks, including the R-ELM network in the feature purification module and R-DNN in the channel estimation module. The reflected SAC channels exhibit higher dimensionality and more complex structural characteristics. Therefore, the proposed R-EST framework enhances the feature purification module accordingly. Specifically, the hidden layer size of the R-ELM network is increased to $N_h = 900$ neurons, and the Sigmoid activation function is adopted to improve feature extraction capability. Then, the R-DNN network is built by the CNN architecture to effectively capture the complex mapping between the input–output pairs in S_2 . It consists of an input layer, two hidden layers, and an output layer. The first hidden layer is a convolutional layer (CL) equipped with 132 filters of Kernel size 4, using the Tanh activation function. This hidden layer is followed by a flattening operation. The second hidden layer is a fully connected layer containing 900 neurons with a linear activation function. During NN training, the Adam optimizer is used to update the CNN parameters, with a learning rate of 2×10^{-4} . A mini-batch training strategy is adopted to reduce the sample correlation, where each batch contains 200 samples. In addition, a stopping mechanism is introduced to prevent overfitting. The detailed architectures of the proposed D-EST and R-EST networks are summarized in Tables 1 and 2.

Table 1. Architecture of D-EST network.

Model	Layers	Size	Activation Function
D-ELM	Input	$2MP^{S_1}$	-
	FFL	200	Sigmoid
	Output	$2MP^{S_1}$	-
D-DNN	Input	$2MP^{S_1}$	-
	FFL	200	Tanh
	FFL	200	Tanh
	Output	$2MP^{S_1}$	-

Table 2. Architecture of R-EST network.

Model	Layers	Size	Kernel	Activation Function
R-ELM	Input	$2P^{S_2}(C^{S_2} - C^{S_1})$	-	-
	FFL	900	-	Sigmoid
	Output	$2P^{S_2}(C^{S_2} - C^{S_1})$	-	-
R-DNN	Input	$2P^{S_2}(C^{S_2} - C^{S_1})$	-	-
	CL	132	4	Tanh
	FFL	900	-	Linear
	Output	2ML	-	-

4.3. Offline Training

To ensure the stability of the proposed framework, the feature purification module (i.e., D-ELM/R-ELM) and channel estimation module (i.e., D-DNN/R-DNN) are trained separately. For the feature purification module, the NN input $\mathbf{R}(v, q)$ is first normalized as $\tilde{\mathbf{R}}(v, q)$. Then, we train the proposed ELM-based purification network to obtain a well-trained feature purification model. The normalization process can be given by

$$\tilde{\mathbf{R}}(v, q) = g_{std}(\mathbf{R}(v, q)) = \frac{\mathbf{R}(v, q) - \mathbb{E}\{\mathbf{R}(v, q)\}}{\mathbb{D}\{\mathbf{R}(v, q)\}}, \quad v \in \mathcal{N}_1^V, \quad q \in \mathcal{N}_1^Q, \quad (30)$$

where $g_{std}(\cdot)$ denotes the standardization operator, and $\mathbb{E}\{\mathbf{R}(v, q)\}$ and $\mathbb{D}\{\mathbf{R}(v, q)\}$ represent the mean and standard deviation of the NN input, respectively.

For the channel estimation module, data preprocessing and network training are conducted in a similar manner. Specifically, the preprocessing includes input normalization and output scaling. The input $\tilde{\mathbf{R}}(v, q)$ is normalized according to (30), while the output $\bar{\mathbf{H}}(v)$ is scaled by a factor β . Then, the preprocessed samples $(\tilde{\mathbf{R}}(v, q), \hat{\mathbf{H}}(v))$ are utilized to train the proposed DNN-based channel estimation network, resulting in a well-trained estimation network. During NN training, the output of the DNN-based estimator can be approximated as

$$\hat{\mathbf{H}}(v) \approx f(\tilde{\mathbf{R}}(v, q), \hat{\mathbf{H}}(v); \boldsymbol{\Theta}_{\text{DNN}}), \quad (31)$$

where $f(\cdot; \boldsymbol{\Theta}_{\text{DNN}})$ denotes the DNN mapping function, and $\boldsymbol{\Theta}_{\text{DNN}}$ represents all hyperparameters of the estimation network. To optimize the network performance, the proposed DNN updates the parameters by minimizing the mean squared error of the loss function, which can be expressed as

$$\mathcal{F} = \frac{1}{VQ} \sum_{v \in \mathcal{N}_1^V, q \in \mathcal{N}_1^Q} \left(f(\tilde{\mathbf{R}}(v, q); \boldsymbol{\Theta}_{\text{DNN}}) - \hat{\mathbf{H}}(v) \right)^2. \quad (32)$$

4.4. Online Testing

During the testing phase, the noisy received signals are first preprocessed in the same manner as in the training stage. Then, the standardized input $\tilde{\mathbf{R}}(v, q)$ together with the initialized parameters $\{\omega, b\}$ are substituted into (26) to compute the hidden-layer output matrix $\tilde{\mathbf{U}}$. Subsequently, the optimized output weight matrix $\hat{\boldsymbol{\Theta}}_{\text{ELM}}$ is applied, which is obtained from (29). The output of the trained ELM-based purification network is given by $\tilde{\mathbf{Y}}$, which represents the purified received signal.

$$\tilde{\mathbf{Y}} = \tilde{\mathbf{U}}\hat{\boldsymbol{\Theta}}_{\text{ELM}}. \quad (33)$$

Next, the SAC channel estimation is performed. The purified signal is standardized according to (30) to obtain the normalized sample $\hat{\mathbf{R}}(v, q)$, which is then fed into the trained DNN-based estimation network to produce the following output:

$$\hat{\mathbf{H}}(v) = f\left(\hat{\mathbf{R}}(v, q); \hat{\Theta}_{\text{DNN}}\right). \quad (34)$$

Here, $\hat{\Theta}_{\text{DNN}}$ denotes the trained hyperparameters of the DNN-based estimation network (i.e., D-DNN/R-DNN). Finally, the NN output is rescaled by β^{-1} and subjected to simple postprocessing to obtain the estimated direct SAC channels $\{\hat{\mathbf{d}}, \hat{\mathbf{b}}\}$ and the reflected SAC channels $\{\hat{\mathbf{A}}, \hat{\mathbf{G}}\}$. The overall estimation framework is summarized in Figure 3. As can be seen, Figure 3 illustrates the overall architecture of the proposed two-stage channel estimation framework. Since the received pilot signals are inevitably interfered with by the noise, the ELM modules (i.e., D-ELM and R-ELM) are first employed to suppress noise and extract informative feature representations. The purified channel features are then fed into dedicated NN estimators for channel estimation. Furthermore, different NNs (i.e., D-DNN and R-DNN) are adopted for the two stages according to the characteristics of the corresponding channels, thereby improving both learning efficiency and estimation accuracy.

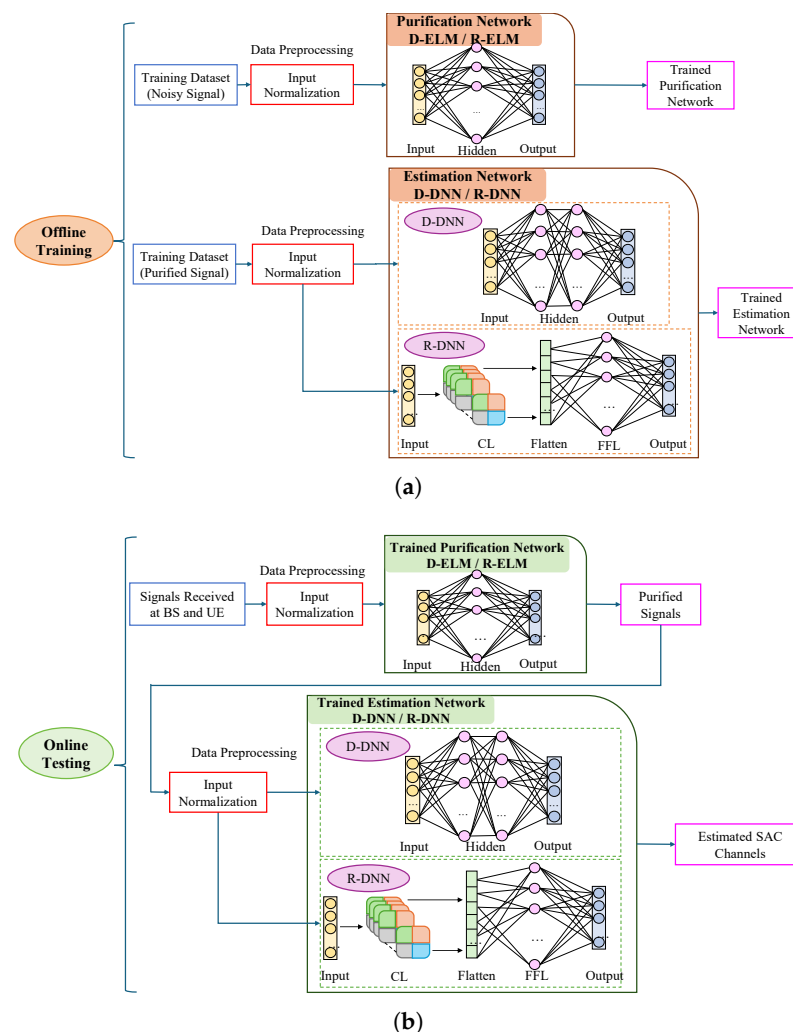


Figure 3. The proposed estimation framework: (a) offline training, (b) online testing.

5. Simulation Results

5.1. Simulation Setup

In the simulation experiments, unless otherwise specified, the number of BS antennas M is set to 6, the number of RIS elements L is 30, and $C^{S_1} = 1$, $C^{S_2} = L + 1$. Referring to [31], the sensing channel of the BS–target–RIS link is modeled as

$$\mathbf{c} = \alpha_1 \mathbf{a}(\vartheta_{\text{BT}}) \mathbf{a}(\vartheta_{\text{TR}})^H, \quad (35)$$

where α_1 denotes the complex gain of the BS–target–RIS link, and its phase is uniformly distributed over $[0, 2\pi)$ with constant amplitude $|\alpha_1| = 1$ [32]. For an $\bar{M}$ -element array, the steering vector $\mathbf{a}(\bar{\vartheta})$ associated with the angle of arrival $\bar{\vartheta}$ is defined as

$$\mathbf{a}(\bar{\vartheta}) = \left[1, e^{j\frac{2\pi\bar{d}}{\lambda}\sin(\bar{\vartheta})}, \dots, e^{j\frac{2\pi\bar{d}}{\lambda}(\bar{M}-1)\sin(\bar{\vartheta})} \right]^T, \quad (36)$$

where $\bar{d}$ and λ denote the element spacing and signal wavelength, respectively. Accordingly, by substituting $\bar{\vartheta} = \vartheta_{\text{BT}}$, $\bar{d} = d_{\text{B}}$ and $\bar{M} = M$ into (36), $\mathbf{a}(\vartheta_{\text{BT}})$ is derived, while $\mathbf{a}(\vartheta_{\text{TR}})$ is obtained by setting $\bar{\vartheta} = \vartheta_{\text{TR}}$, $\bar{d} = d_{\text{R}}$ and $\bar{M} = L$. Here, ϑ_{BT} represents the angle from the BS to the target, and ϑ_{TR} denotes the angle from the target to the RIS. In general, the ISAC BS antenna spacing d_{B} and the RIS element spacing d_{R} are both set to $\lambda/2$. Similarly, the BS–target–BS link can be modeled as $\mathbf{d} = \alpha_2 \mathbf{a}(\vartheta_{\text{BT}})$, where α_2 is the reflection coefficient of this link and follows the same distribution as α_1 .

The communication channels are modeled as Rician fading according to [32]. Then, the channel $\mathbf{H}$ of the RIS–BS link is expressed as

$$\mathbf{H} = \sqrt{\frac{K_{\text{RB}}}{K_{\text{RB}} + 1}} \mathbf{H}_{\text{LoS}} + \sqrt{\frac{1}{K_{\text{RB}} + 1}} \mathbf{H}_{\text{NLoS}}, \quad (37)$$

where the Rician factor K_{RB} is set to 10, $\mathbf{H}_{\text{LoS}}$ and $\mathbf{H}_{\text{NLoS}}$ denote the line-of-sight (LoS) and non-line-of-sight (NLoS) components of $\mathbf{H}$, respectively. According to (36), $\mathbf{H}_{\text{LoS}}$ is defined as $\mathbf{a}(\vartheta_{\text{RB}})^H$, where ϑ_{RB} is the angle from the RIS to the BS. Other communication channels, such as $\mathbf{b}$ and $\mathbf{f}$, can be modeled similarly, with their Rician factors also set to 10. In Table 3, the path loss of each link is obtained by setting the distances and path loss exponents of the SAC channels. Specifically, the path loss at distance d_n can be given by $\zeta_n = \zeta_0 (d_n/d_0)^{-\beta_n}$ with $n \in \mathcal{N}_1^5$, where β_n denotes the path loss exponent, and $\zeta_0 = -30$ dBm represents the path loss at the reference distance $d_0 = 1$ m. Finally, according to [32], the transmit power of the ISAC BS P_{B} is set to 20 dBm.

Table 3. Path loss of SAC channels.

Channel Link	Distance	Path Loss Exponent
RIS–BS link	$d_1 = 2$ m	$\beta_1 = 2$
BS–target–BS link	$d_2 = 140$ m	$\beta_2 = 3.5$
BS–target–RIS link	$d_3 = 140$ m	$\beta_3 = 2.3$
BS–UE link	$d_4 = 50$ m	$\beta_4 = 3$
RIS–UE link	$d_5 = 50$ m	$\beta_5 = 2.2$

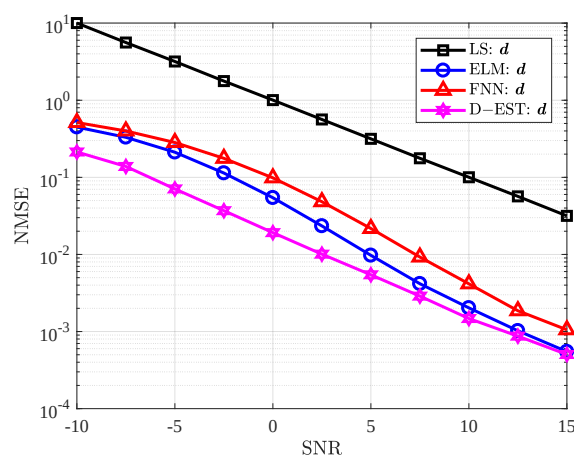
The hyperparameters adopted in this work were determined through preliminary experiments on a validation dataset by following common practices in deep learning. Specifically, the hidden-layer sizes of the D-ELM and R-ELM modules were selected based on the sensitivity analysis presented in Section 5.4.3. For the DNN-based estimators, the numbers of convolutional filters and the learning rate were chosen from several commonly

used candidate values to achieve stable convergence and satisfactory estimation performance while maintaining moderate computational complexity. Once determined, these hyperparameters were fixed for all subsequent simulations to ensure a fair comparison.

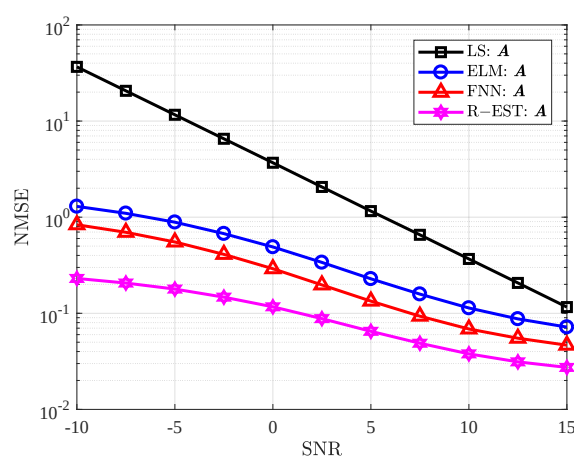
5.2. NMSE Performance Under Different SNRs

Figures 4 and 5 illustrate the NMSE performance for both SAC channel estimation at the ISAC BS and downlink UE under different SNR conditions. During the offline training phase, the SNR is set to [15, 20] dB with a step size of 5 dB, while in the online testing phase, the SNR ranges from [−10, 20] dB with a step size of 2.5 dB. The LS-based method in [32], as well as two traditional learning models, namely FNN and ELM, are adopted as benchmark schemes. The normalized mean square error (NMSE) is used as the performance metric, defined as

$$\text{NMSE} = \mathbb{E} \left\{ \frac{\| \text{Estimated} - \text{True} \|_F^2}{\| \text{True} \|_F^2} \right\} \quad (38)$$



(a)



(b)

Figure 4. NMSE versus SNR for channel estimation at the ISAC BS: (a) direct sensing channel d , (b) reflected sensing channel A .

The FNN consists of two hidden layers, each containing 256 neurons, and its hyperparameter settings are consistent with those in [32]. The ELM adopts a single hidden layer structure with 256 neurons and uses the Sigmoid activation function. Simulation results show that, as the SNR increases, the impact of noise gradually diminishes, and the estimation performance of the LS baseline, as well as the traditional FNN and ELM methods,

improves accordingly. However, compared with these benchmark schemes, the proposed method demonstrates superior performance. This improvement is mainly attributed to the feature purification module based on ELM, which effectively extracts salient features and significantly enhances signal quality, thereby enabling the subsequent channel estimation network to achieve more accurate results using the purified feature data.

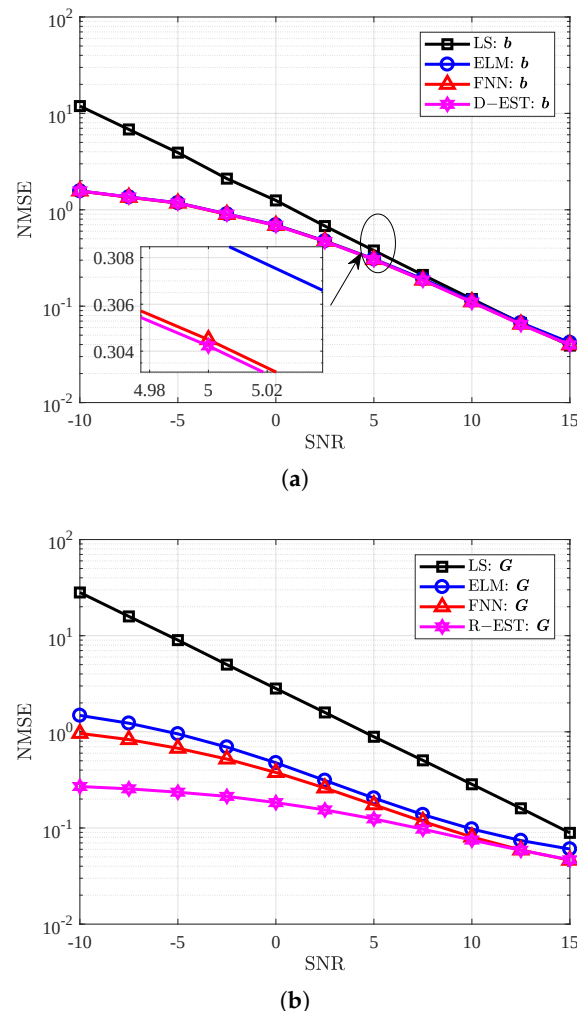


Figure 5. NMSE versus SNR for channel estimation at the downlink UE: (a) direct communication channel b , (b) reflected communication channel G .

More specifically, in the direct channel estimation task, the proposed D-EST method exhibits clear advantages. When estimating the direct sensing channel d , compared with the LS baseline, a gain of approximately 12 dB can be achieved at $\text{NMSE} = 10^{-1}$. For the downlink direct communication channel b , the proposed method achieves performance comparable to that of the FNN-based approach. It is worth noting that, due to the more complex structure of the communication channel, the performance improvement is less pronounced than that of the sensing channel. For reflected channel estimation, the proposed R-EST method is further introduced to estimate the reflected sensing channel A and the downlink reflected communication channel G . The proposed approach consistently outperforms the LS baseline across the entire SNR range in terms of NMSE, with particularly significant gains observed in the low-SNR region. For instance, at $\text{NMSE} = 10^{-1}$, compared with the LS method, R-EST achieves an SNR gain of approximately 14 dB for estimating the reflected sensing channel A , and about a 7.5 dB improvement for the reflected communication channel G . It is worth emphasizing that reflected channel estimation is inherently more challenging due to the cascaded channel structure. Nevertheless, the proposed R-EST

method maintains superior performance over all SNR conditions, demonstrating its effectiveness in handling complex cascaded channel estimation problems. In addition to the NMSE performance, the proposed method also performs well outside the SNR range used during training, further indicating its strong generalization capability.

5.3. NMSE Performance Under Different Channel Dimensions

5.3.1. NMSE Performance Under Different M

Figures 6 and 7 analyze the impact of increasing the number of antennas M on the NMSE performance at the ISAC BS and downlink UE. The SNR values in the offline training and online testing phases are fixed at 0 dB and 10 dB, respectively, while the number of the RIS elements is set to $L = 30$. Figures 6a and 7a present the NMSE performance of the proposed D-EST method for direct SAC channel estimation. It can be observed that, under different SNR conditions, the proposed method achieves significant performance improvement over the LS baseline when estimating the direct sensing channel $\mathbf{d}$, as evidenced by a continuous decrease in NMSE. This advantage becomes more pronounced as the antenna scale increases. For the downlink direct communication channel $\mathbf{b}$, at SNR = 0 dB, the proposed D-EST method outperforms the LS baseline, while at SNR = 10 dB, the performance of the two methods is comparable. Moreover, as M increases, the NMSE performance of the proposed method remains relatively stable. This stability is mainly attributed to the feature purification module, which enhances the quality of the received signal and further improves the robustness of the subsequent channel estimation stage in large-scale scenarios.

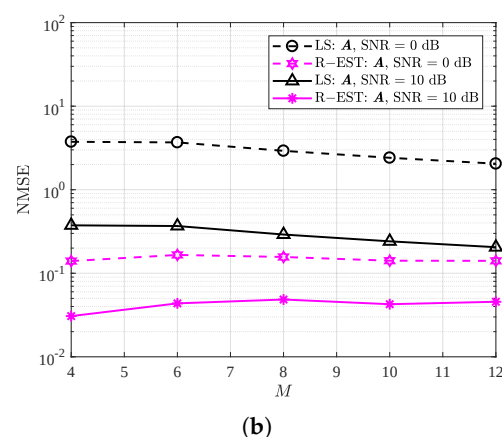
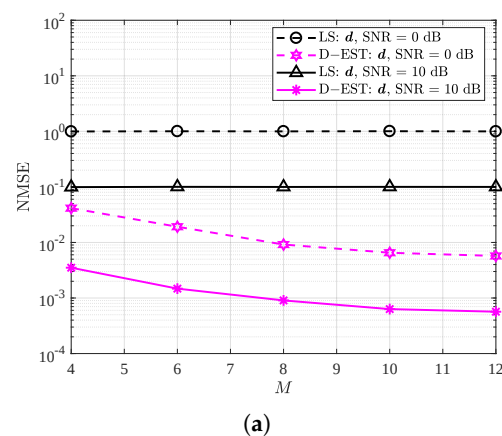


Figure 6. NMSE versus M for channel estimation at the ISAC BS: (a) direct sensing channel $\mathbf{d}$, (b) reflected sensing channel $\mathbf{A}$.

Figures 6b and 7b evaluate the estimation performance of the reflected SAC channels. For both the reflected sensing channel $\mathbf{A}$ and the downlink reflected communication channel

$\mathbf{G}$, the proposed R-EST method consistently outperforms the LS baseline across different antenna configurations. Notably, for the estimation of $\mathbf{A}$, the proposed method exhibits robustness with respect to variations in M , indicating that it can effectively suppress noise and improve estimation accuracy as the channel dimension increases. For the estimation of $\mathbf{G}$, at SNR = 0 dB, the performance of the proposed method further improves with increasing M , reflecting its strong generalization capability in large-scale systems. However, at SNR = 10 dB, the NMSE of the proposed method shows a gradual increasing trend as the antenna scale grows, which may be attributed to the more complex correlation structure in high-dimensional channels. Although the NMSE slightly degrades at high SNR, the proposed method still maintains a clear performance advantage over the LS baseline. This demonstrates that the feature purification module effectively enhances channel estimation performance across different SNR conditions, fully validating its efficiency and reliability in noise suppression and accurate channel estimation.

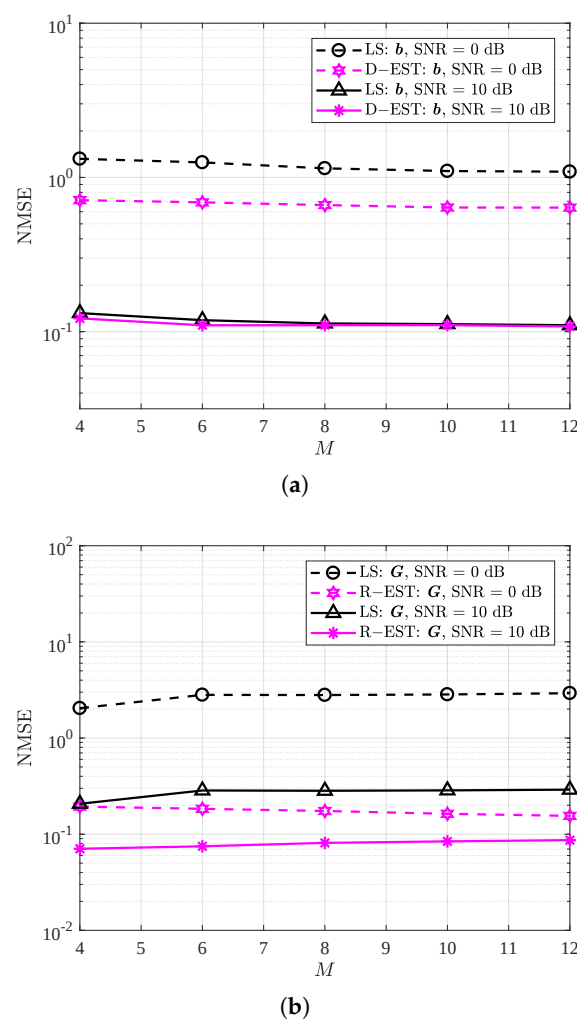


Figure 7. NMSE versus M for channel estimation at the downlink UE: (a) direct communication channel $\mathbf{b}$, (b) reflected communication channel $\mathbf{G}$.

5.3.2. NMSE Performance Under Different L

Figures 8 and 9 illustrate the performance of the proposed R-EST method for reflected SAC channel estimation when the number of RIS reflecting elements L varies under the same SNR conditions. For estimating the reflected sensing channel $\mathbf{A}$, the proposed method consistently outperforms the LS baseline across different values of L and SNR settings. Moreover, at SNR = 0 dB, the method demonstrates strong robustness to variations in

L . At $\text{SNR} = 10$ dB, however, as L increases, the NMSE performance shows a slight degradation, which may be attributed to the increased complexity of high-dimensional feature mapping in the RIS-assisted channel. For the downlink reflected communication channel $\mathbf{G}$, at $\text{SNR} = 0$ dB, the proposed method achieves significant performance gains compared to the LS baseline. Notably, as the number of RIS elements increases, the NMSE remains relatively stable, indicating that the proposed method possesses strong noise resilience in low-SNR environments and can effectively mitigate noise interference while maintaining high estimation accuracy. On the other hand, at $\text{SNR} = 10$ dB, the proposed R-EST method still demonstrates superior performance. Overall, the simulation results verify that the proposed approach is capable of handling complex correlation structures and high-dimensional channel conditions. Furthermore, it exhibits strong stability across different RIS element scales, highlighting its effectiveness and robustness in large-scale RIS-assisted systems.

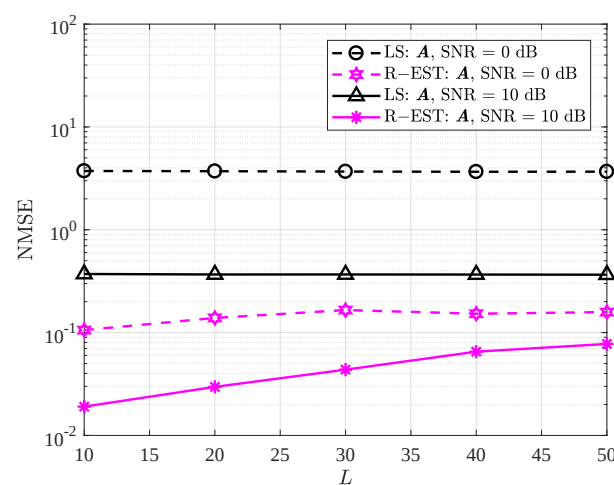


Figure 8. NMSE versus L for reflected sensing channel estimation at the ISAC BS.

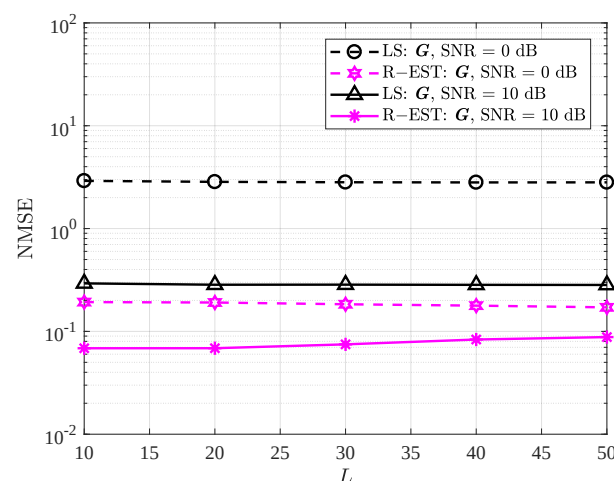


Figure 9. NMSE versus L for reflected communication channel estimation at the downlink UE.

5.4. Ablation Study

5.4.1. Effectiveness of the ELM-Based Feature Purification Network

To further validate the effectiveness of the proposed ELM-based feature purification module, an ablation study is conducted by removing the D-ELM and R-ELM modules while keeping the channel estimation networks (i.e., D-DNN and R-DNN modules) unchanged. Specifically, the received signals are directly fed into the D-DNN and R-DNN modules

without any feature purification. Figure 10 illustrates the NMSE performance under different SNR conditions. Compared with the estimator without feature purification (i.e., the curves named as D-DNN/R-DNN only), the proposed method (i.e., D-EST/R-EST) consistently achieves lower NMSE over the entire SNR range. The performance improvement is particularly significant in the low-SNR region, where the received signals suffer from severe noise interference. This lies in the fact that the proposed ELM module effectively suppresses noise and extracts informative channel features before channel estimation. Consequently, the subsequent D-DNN/R-DNN modules operate on higher-quality feature representations, leading to more accurate channel estimation. As the SNR increases, the performance gap between the two methods gradually decreases since the influence of noise becomes weaker. Nevertheless, the proposed method still maintains superior estimation accuracy, demonstrating that the ELM-based feature purification not only improves noise robustness but also enhances the representation capability of the estimation framework.

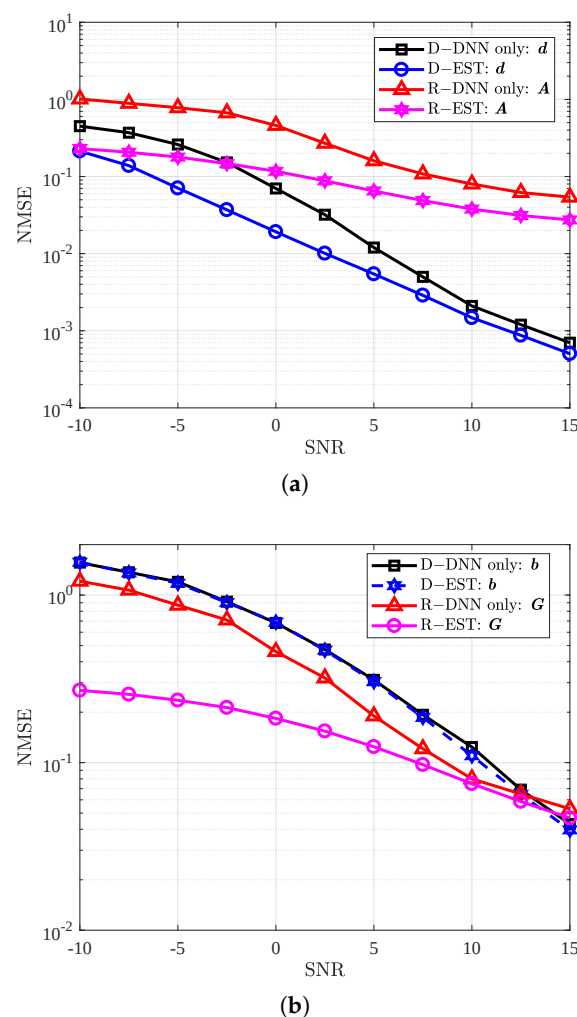
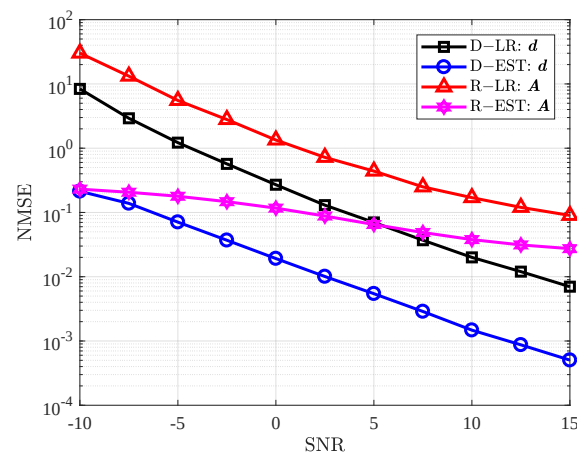


Figure 10. Ablation study for the effectiveness of the D-ELM/R-ELM modules: (a) NMSE performance at the ISAC BS, (b) NMSE performance at the downlink UE.

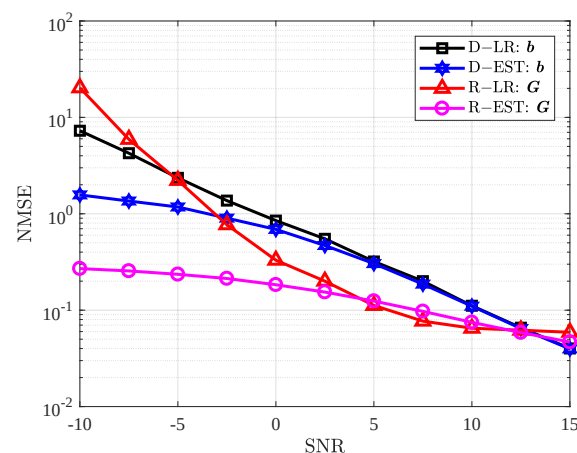
5.4.2. Effectiveness of the Channel Estimation Network

To further investigate whether the performance improvement is solely contributed by the feature purification module, another ablation experiment is conducted by replacing the proposed D-DNN/R-DNN module with a lightweight linear regression (LR) estimator while preserving the D-ELM/R-ELM module (i.e., the curves named as D-LR and R-LR). The comparison results are presented in Figure 11. It can be observed that introducing the

ELM purification module significantly improves the estimation performance compared with directly applying a lightweight LR estimator. Moreover, the proposed D-EST/R-EST estimator, which consists of the D-ELM/R-ELM and D-DNN/R-DNN modules, still achieves the best NMSE performance under all the SNR conditions. This observation indicates that the performance improvement of the proposed framework is not attributed to a single component. Instead, the ELM-based feature purification and the subsequent deep neural network cooperate to achieve superior channel estimation performance. The purification module mainly suppresses noise and extracts informative features, whereas the DNN/CNN estimator effectively learns the nonlinear mapping from purified features to channel coefficients.



(a)



(b)

Figure 11. Ablation study for the effectiveness of the D-DNN/R-DNN modules: (a) NMSE performance at the ISAC BS, (b) NMSE performance at the downlink UE.

5.4.3. Sensitivity Analysis of the Hidden-Layer Size

Since the hidden-layer size directly affects the representation capability of the ELM network, a sensitivity analysis is conducted to evaluate its influence on the channel estimation performance. Different hidden-layer sizes are considered for both the D-ELM and R-ELM modules. The SNR is fixed to 10 dB while keeping all other simulation parameters unchanged. Figure 12 presents the NMSE performance under different hidden-layer sizes of the D-ELM and R-ELM modules. When the number of hidden neurons increases from 100 to 200, the estimation performance is continuously improved due to the enhanced nonlinear feature representation capability. However, further increasing the hidden-layer size beyond 200 only yields marginal performance improvement while introducing ad-

ditional computational complexity. Similar observations can be obtained for the R-ELM module. Increasing the hidden-layer size initially improves the estimation accuracy since the reflected channels exhibit higher dimensionality and more complicated correlation structures. Nevertheless, when the number of hidden neurons exceeds 900, the NMSE performance becomes nearly saturated. Therefore, considering both estimation accuracy and computational complexity, the hidden-layer sizes of 200 and 900 are adopted for the D-ELM and R-ELM modules, respectively.

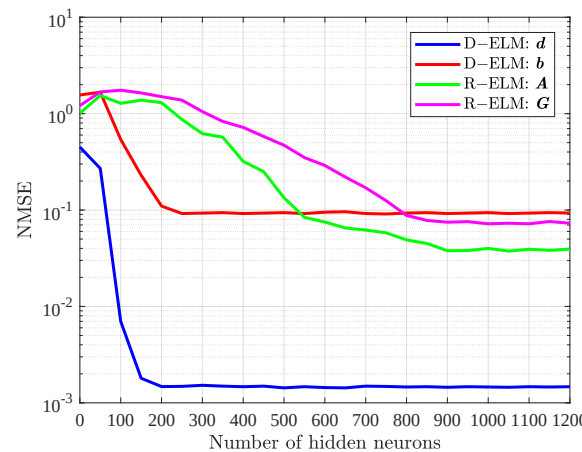


Figure 12. Sensitivity analysis of the hidden-layer size for the D-ELM and R-ELM modules.

5.5. Discussion on Practical Deployment

It should be noted that the simulation setup in this paper is based on several commonly adopted assumptions to facilitate algorithm verification, including ideal self-interference cancellation, predefined RIS on/off control, known pilot sequences, and channel-model-based offline training. The practical deployment of the proposed method is discussed in the following.

First, the residual self-interference may still exist after cancellation for practical full-duplex ISAC systems. Such residual interference further interferes with the received pilots and degrades the channel estimation accuracy. Thanks to the proposed ELM-based feature purification module before channel estimation, partial residual interference can be regarded as structured interference and be suppressed during the feature purification procedure. Therefore, the proposed approach is expected to exhibit certain robustness against imperfect self-interference cancellation, although additional retraining using residual-SI datasets may be required for severe interference conditions.

Second, the proposed two-stage estimation framework assumes accurate RIS on/off switching. In practical implementations, switching delay and hardware imperfections may introduce slight deviations from the ideal RIS states. Since the proposed estimator learns the mapping between the received signals and SAC channels in a data-driven manner, such impairments can be incorporated into the offline training dataset, allowing the neural network to adapt to practical RIS control errors.

Third, the proposed method assumes predefined pilot sequences and channel-model-based offline training. When the pilots are interfered with, synchronization errors occur, or channel model is mismatched, the distribution of received signals may deviate from the training samples, leading to the degradation of the channel estimation performance. Although some performance degradation is expected under severe distribution mismatch, the proposed framework can be continuously updated using newly collected channel samples through offline retraining or transfer learning, thereby maintaining satisfactory estimation performance under practical deployment.

Finally, the simulations are conducted under a representative RIS-assisted ISAC scenario to verify the effectiveness of the proposed framework. In practical wireless systems, different propagation environments, channel models, and path loss conditions may be encountered. Since the proposed method is data-driven, its NN parameters can be retrained using datasets generated under the corresponding system settings without modifying the overall two-stage estimation framework. Therefore, the proposed architecture is not limited to the specific simulation configuration considered in this work and can be readily extended to more general RIS-assisted ISAC scenarios.

6. Conclusions

This paper addresses the channel estimation problem in RIS-assisted ISAC systems and proposes a two-stage channel estimation method based on ELM-driven feature purification. By controlling the on/off states of the RIS, the direct and reflected channels are estimated separately in two stages, and the corresponding D-EST and R-EST networks are designed to construct the overall estimation framework. For each estimation stage, a feature purification module is introduced prior to channel estimation to effectively mitigate the noise interference in complex channel environments. This module is employed to extract features from the received signals, thereby enhancing signal quality. The purified features are then utilized as inputs to the channel estimation module, which accurately estimate the channel parameters. Simulation results demonstrate that, under various SNR conditions and channel dimensions, the proposed method significantly outperforms benchmark schemes in terms of NMSE performance, while exhibiting strong generalization capability. This makes it an effective solution for improving estimation accuracy and robustness in the RIS-assisted ISAC systems. Future work will extend the proposed framework to more practical RIS-assisted ISAC systems involving multiple users, multiple sensing targets, cooperative multi-RIS deployments, and dynamic wireless environments.

Author Contributions: Conceptualization, G.L. and Y.L.; methodology, G.L. and Y.L.; software, G.L.; validation, G.L. and Y.L.; formal analysis, G.L. and Y.L.; investigation, G.L. and Z.Z.; resources, Y.L.; data curation, G.L. and Z.Z.; writing—original draft preparation, G.L.; writing—review and editing, Y.L. and G.L.; visualization, G.L.; supervision, Y.L.; project administration, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to the ongoing development and maintenance of the research code and simulation platform.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ISAC	Integrated Sensing and Communication
RIS	Reconfigurable Intelligent Surface
SAC	Sensing and Communication
ELM	Extreme Learning Machine
CSI	Channel State Information
NN	Neural Network
DNN	Deep Neural Network
CNN	Convolutional Neural Network
LSs	Least Squares

SNR	Signal-to-Noise Ratio
FD	Full-Duplex
BS	Base Station
UE	User Equipment
SI	Self-Interference
DFT	Discrete Fourier Transform
FNN	Feedforward Neural Network
NMSE	Normalized Mean Square Error

References

1. Aman, W.; Illi, E.; Al-Kuwari, S.; Qaraqe, M. Integrating Communication, Sensing and Security: Progress and Prospects of PLS in ISAC Systems. *IEEE Commun. Surv. Tutor.* **2026**, *28*, 6318–6353. <https://doi.org/10.1109/COMST.2026.3691091>.
2. Dai, Q.; Zeng, Y.; Wang, H.; You, C.; Zhou, C.; Cheng, H.; Xu, X.; Jin, S.; Lee, S., A.; Eldar, Y.C.; et al. A Tutorial on MIMO-OFDM ISAC: From Far-Field to Near-Field. *IEEE Commun. Surv. Tutor.* **2026**, *28*, 4319–4358. <https://doi.org/10.1109/COMST.2025.3650568>.
3. He, B.; Chen, Z.; Luo, J.; Liu, C.; Wang, S.; Park, J.; Wang, F.; Quek, T.Q.S. Toward Secure Semantic Transmission in the Era of GenAI: A Diffusion-Based Framework. *IEEE Commun. Mag.* **2026**, *64*, 110–117. <https://doi.org/10.1109/MCOM.001.2500553>.
4. Zhao, Y.; Jian, M.; Yuan, Y. RIS-Enabled UAV Communications and Sensing: Opportunities, Challenges, and Key Technologies. *IEEE Trans. Cognit. Commun. Netw.* **2026**, *12*, 5451–5472. <https://doi.org/10.1109/TCCN.2026.3657121>.
5. Premanand, R.; Vishwakarma, N.; Jose, J.; Singh, R.; Madhukumar, A.S. RIS for 6G THz Networks: Advances in Modeling, Hardware, Signal Processing, and Standardization. *IEEE Commun. Surv. Tutor.* **2026**, *28*, 6018–6056. <https://doi.org/10.1109/COMST.2026.3687119>.
6. Luo, J.; Qu, Z.; He, B.; Wang, S.; Taricco, G.; Yuen, C. Covert Pilot Spoofing Attack via Active Reconfigurable Intelligent Surface. *IEEE Trans. Wireless Commun.* **2026**, *25*, 9467–9482. <https://doi.org/10.1109/TWC.2025.3643349>.
7. Luo, J.; Wang, S.; He, B.; Zhu, Y. Large-Scale Aerial Reconfigurable Intelligent Surface-Aided Robust Anti-Jamming Transmission. *IEEE Trans. Commun.* **2026**, *74*, 8342–8357. <https://doi.org/10.1109/TCOMM.2026.3690386>.
8. Liu, X.; Wang, H.; Zheng, K.; Chi, K. Throughput Maximization of IoT Transmission in STAR-RIS-Aided Symbiotic Radio Networks. *IEEE Internet Things J.* **2026**, *13*, 3371–3388. <https://doi.org/10.1109/JIOT.2025.3633393>.
9. Qaisar, M.U.F.; Yuan, W.; Günlü, O.; Riihonen, T.; Cui, Y.; Zhang, L.; Gonzalez-Prelcic, N.; Renzo, M.D.; Han, Z. The Role of ISAC in 6G Networks: Enabling Next-Generation Wireless Systems. *IEEE Trans. Netw. Sci. Eng.* **2026**, *13*, 7825–7861. <https://doi.org/10.1109/TNSE.2026.3666665>.
10. Liu, Y.; He, B.; Wang, F. Security-aware Semantic-driven ISAC via Paired Adversarial Residual Networks. *IEEE Trans. Veh. Technol.* **2026**, Early access. <https://doi.org/10.1109/TVT.2026.3671883>.
11. Han, K.; Meng, K.; Wang, X.; Masouros, C. Network-Level ISAC Design: State-of-the-Art, Challenges, and Opportunities. *IEEE J. Select. Top. Electromagn. Antenn. Propag.* **2025**, *1*, 65–83. <https://doi.org/10.1109/JSTEAP.2025.3603139>.
12. Mura, S.; Tagliaferri, D.; Mizmizi, M.; Spagnolini, U.; Petropulu, A. Optimized Waveform Design for OFDM-Based ISAC Systems Under Limited Resource Occupancy. *IEEE Trans. Wireless Commun.* **2025**, *24*, 5241–5254. <https://doi.org/10.1109/TWC.2025.3546475>.
13. Wei, Z.; Piao, J.; Yuan, X.; Wu, H.; Zhang, J.A.; Feng, Z.; Wang, L.; Zhang, P. Waveform Design for MIMO-OFDM Integrated Sensing and Communication System: An Information Theoretical Approach. *IEEE Trans. Commun.* **2024**, *72*, 496–509. <https://doi.org/10.1109/TCOMM.2023.3317258>.
14. Galappaththige, D.; Zargari, S.; Tellambura, C.; Li, G.Y. Near-Field ISAC: Beamforming for Multi-Target Detection. *IEEE Wirel. Commun. Lett.* **2024**, *13*, 1938–1942. <https://doi.org/10.1109/LWC.2024.3397081>.
15. Zhang, Z.; Ren, H.; Pan, C.; Hong, S.; Wang, D.; Wang, J.; You, X. Target Localization in Cooperative ISAC Systems: A Scheme Based on 5G NR OFDM Signals. *IEEE Trans. Commun.* **2025**, *73*, 3562–3578. <https://doi.org/10.1109/TCOMM.2024.3486981>.
16. Wang, L.; Abanto-Leon, L.F. Resource Allocation for ISAC Networks with Application to Target Tracking. In Proceedings of the 2024 IEEE Globecom Workshops (GC Wkshps), Cape Town, South Africa, 8–12 December 2024; pp. 1–6. <https://doi.org/10.1109/GCWkshp64532.2024.11101625>.
17. Zhou, S.; Xiang, L.; Wang, Y.; Yang, K.; Wong, K.K.; Chae, C. Extended Target Adaptive Beamforming for ISAC: A Perspective of Predictive Error Ellipse. *IEEE Trans. Wireless Commun.* **2026**, *25*, 10604–10617. <https://doi.org/10.1109/TWC.2026.3652714>.
18. Wang, Y.; Xiang, L.; Wei, Z.; Wang, C.; Zhang, X.; Yang, K. TF-Diffusion: A Diffusion-Based Time-Frequency Framework for Bistatic ISAC Signal Enhancement. *IEEE Trans. Cogn. Commun. Netw.* **2026**, *12*, 9162–9175. <https://doi.org/10.1109/TCCN.2026.3705806>.
19. He, B.; Wang, F.; Cheng, J. Joint Secure Transceiver Design for Integrated Sensing and Communication. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 13377–13393. <https://doi.org/10.1109/TWC.2024.3400849>.

20. Liu, F.; Mu, J.; Xu, W.; Miao, J.; Bazzi, W.; Mumtaz, S. Toward Secure and Energy-Efficient ISAC in Low-Altitude IoT: A Game-Theoretic DRL Framework With Adaptive Sensing. *IEEE Internet Things J.* **2025**, *12*, 53202–53214. <https://doi.org/10.1109/JIOT.2025.3617537>.
21. Li, Y.; Khan, F.; Ahmed, M.; Soofi, A.A.; Khan, W.U.; Sheemar, C.K.; Asif, M.; Han, Z. RIS-Based Physical Layer Security for Integrated Sensing and Communication: A Comprehensive Survey. *IEEE Internet Things J.* **2025**, *12*, 32444–32468. <https://doi.org/10.1109/JIOT.2025.3567553>.
22. Magbool, A.; Kumar, V.; Wu, Q.; Di Renzo, M.; Flanagan, M.F. A Survey on Integrated Sensing and Communication With Intelligent Metasurfaces: Trends, Challenges, and Opportunities. *IEEE Open J. Commun. Soc.* **2025**, *6*, 7270–7318. <https://doi.org/10.1109/OJCOMS.2025.3594049>.
23. Zhang, J.A.; Wu, K.; Renzo, M.D.; Cui, T. RIS-Enabled Integrated Sensing and Communications: From Theory to Practice. *Proc. IEEE* **2026**, Early access. <https://doi.org/10.1109/JPROC.2026.3678371>.
24. Chen, J.; Wu, K.; Niu, J.; Li, Y.; Xu, P.; Andrew Zhang, J. Spectral and Energy Efficient Waveform Design for RIS-Assisted ISAC. *IEEE Trans. Commun.* **2025**, *73*, 158–172. <https://doi.org/10.1109/TCOMM.2024.3435030>.
25. Zhong, K.; Hu, J.; Liu, J.; An, D.; Pan, C.; Teh, K.C.; Yu, X.; Li, H. P²C²M: Parallel Product Complex Circle Manifold for RIS-Aided ISAC Waveform Design. *IEEE Trans. Cognit. Commun. Netw.* **2024**, *10*, 1441–1451. <https://doi.org/10.1109/TCCN.2024.3375501>.
26. Wu, Z.; Li, X.; Cai, Y.; Yuan, W. Joint Trajectory and Resource Allocation Design for RIS-Assisted UAV-Enabled ISAC Systems. *IEEE Wireless Commun. Lett.* **2024**, *13*, 1384–1388. <https://doi.org/10.1109/LWC.2024.3370989>.
27. Luong, N.C.; Huynh-The, T.; Vu, T.; Van Le, D.; Nguyen, H.T.; Hai, N.D.; Nguyen, G.; Anh, N.D.D.; Niyato, D.; Kim, D.I.; et al. Advanced Learning Algorithms for Integrated Sensing and Communication (ISAC) Systems in 6G and Beyond: A Comprehensive Survey. *IEEE Commun. Surv. Tutor.* **2026**, *28*, 2572–2611. <https://doi.org/10.1109/COMST.2025.3584333>.
28. Miuccio, L.; Panno, D.; Riolo, S. A DNN-based estimate of the PRACH traffic load for massive IoT scenarios in 5G networks and beyond. *Comput. Netw.* **2021**, *201*, 108608. <https://doi.org/10.1016/j.comnet.2021.108608>.
29. Liu, Y.; Al-Nahhal, I.; Dobre, O.A.; Wang, F. Deep-Learning-Based Channel Estimation for IRS-Assisted ISAC System. In Proceedings of the 2022 IEEE Global Communications Conference (GLOBECOM), Rio de Janeiro, Brazil, 4–8 December 2022; pp. 4220–4225. <https://doi.org/10.1109/GLOBECOM48099.2022.10001672>.
30. Faisal, A.; Al-Nahhal, I.; Lee, K.; Dobre, O.A.; Shin, H. Conditional Generative Adversarial Networks for Channel Estimation in RIS-Assisted ISAC Systems. *IEEE Trans. Commun.* **2025**, *73*, 7828–7841. <https://doi.org/10.1109/TCOMM.2025.3541047>.
31. Liu, Y.; Al-Nahhal, I.; Dobre, O.A.; Wang, F. Deep-Learning Channel Estimation for IRS-Assisted Integrated Sensing and Communication System. *IEEE Trans. Veh. Technol.* **2023**, *72*, 6181–6193. <https://doi.org/10.1109/TVT.2022.3231727>.
32. Liu, Y.; Al-Nahhal, I.; Dobre, O.A.; Wang, F.; Shin, H. Extreme Learning Machine-Based Channel Estimation in IRS-Assisted Multi-User ISAC System. *IEEE Trans. Commun.* **2023**, *71*, 6993–7007. <https://doi.org/10.1109/TCOMM.2023.3308150>.
33. Masmoudi, A.; Le-Ngoc, T. A Maximum-Likelihood Channel Estimator for Self-Interference Cancellation in Full-Duplex Systems. *IEEE Trans. Veh. Technol.* **2016**, *65*, 5122–5132. <https://doi.org/10.1109/TVT.2015.2461006>.
34. Elsayed, M.; El-Banna, A.A.A.; Dobre, O.A.; Shiu, W.; Wang, P. Hybrid-Layers Neural Network Architectures for Modeling the Self-Interference in Full-Duplex Systems. *IEEE Trans. Veh. Technol.* **2022**, *71*, 6291–6307. <https://doi.org/10.1109/TVT.2022.3159535>.
35. Ma, J.; Zhang, S.; Li, H.; Gao, F.; Jin, S. Sparse Bayesian Learning for the Time-Varying Massive MIMO Channels: Acquisition and Tracking. *IEEE Trans. Commun.* **2019**, *67*, 1925–1938. <https://doi.org/10.1109/TCOMM.2018.2855197>.
36. Huang, G.; Zhu, Q.; Siew, C. Extreme learning machine: Theory and applications. *Neurocomputing* **2005**, *70*, 489–501. <https://doi.org/10.1016/j.neucom.2005.12.126>.

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