UNIVERSIDADE FEDERAL DO PARÁ
INSTITUTO DE TECNOLOGIA
BELÉM, PARÁ, BRASIL

ENGENHARIA ELÉTRICA

OTIMIZAÇÃO DE DISPOSITIVOS BASEADOS EM CRISTAIS FOTÔNICOS USANDO MÉTODOS EM MACHINE LEARNING

TRABALHO DE CONCLUSÃO DE CURSO

BANCA:

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PROF. DR. RODRIDO M. E S. DE OLIVEIRA

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CO-ORIENTADOR: PROF. DR. RONALDO DE F. ZAMPOLO
DISCENTE: LUIZ HENRIQUE P. ASSUNÇÃO

| **PALAVRAS-CHAVES:** NANOFOTÔNICA. INTELIGÊNCIA ARTIFICIAL. OTIMIZAÇÃO. MODELAGEM INVERSA |

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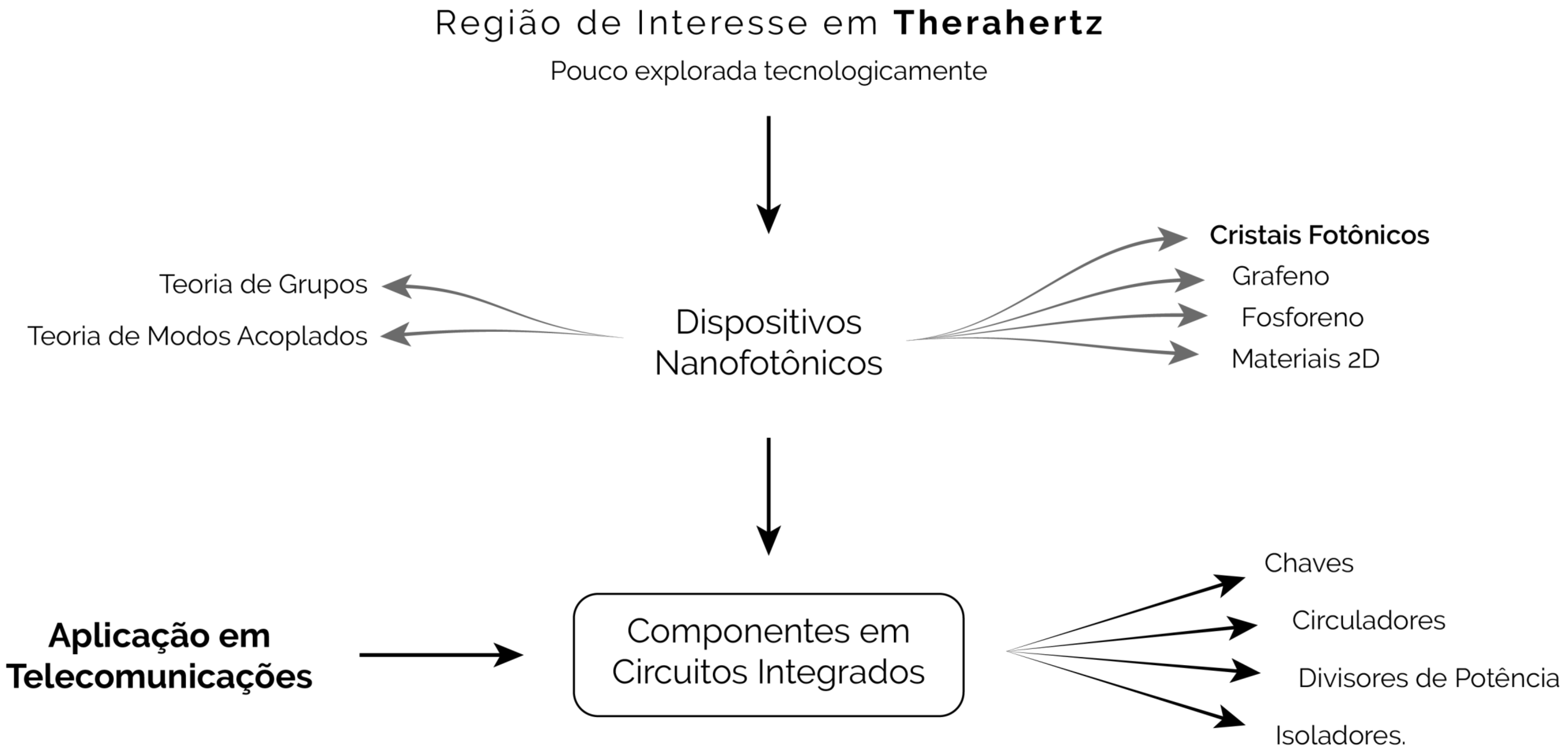
ESTRUTURA DE TÓPICOS

CAPÍTULO 1

INTRODUÇÃO

- Contexto e Motivação
- Trabalhos Relacionados


Região de Interesse em **Therahertz**
Pouco explorada tecnologicamente
Teoria de Grupos
Teoria de Modos Acoplados
Dispositivos Nanofotônicos
Cristais Fotônicos
Grafeno
Fosforeno
Materiais 2D
Aplicação em Telecomunicações
Componentes em Circuitos Integrados
Chaves
Circuladores
Divisores de Potência
Isoladores.

DISPOSITIVOS NANOFOTÔNICOS

Método dos Elementos Finitos

Simulações Eletromagnéticas

GEOMETRIA → ESPECTRO

Custo Computacional Elevado

Conforme aumenta a complexidade

Alto consumo de tempo

Problema Multivariáveis

Imprecisão humana

Método empírico

Design Direto

Recursividade intensa

Não-automatizado

OTIMIZAÇÃO POR APRENDIZADO DE MÁQUINA

Simulações Eletromagnéticas

Dados

GEOMETRIA ← ESPECTRO

Redes Neurais Profundas

Aplicam-se a problemas multivariáveis

Problemas não-lineares

Processo Automatizado

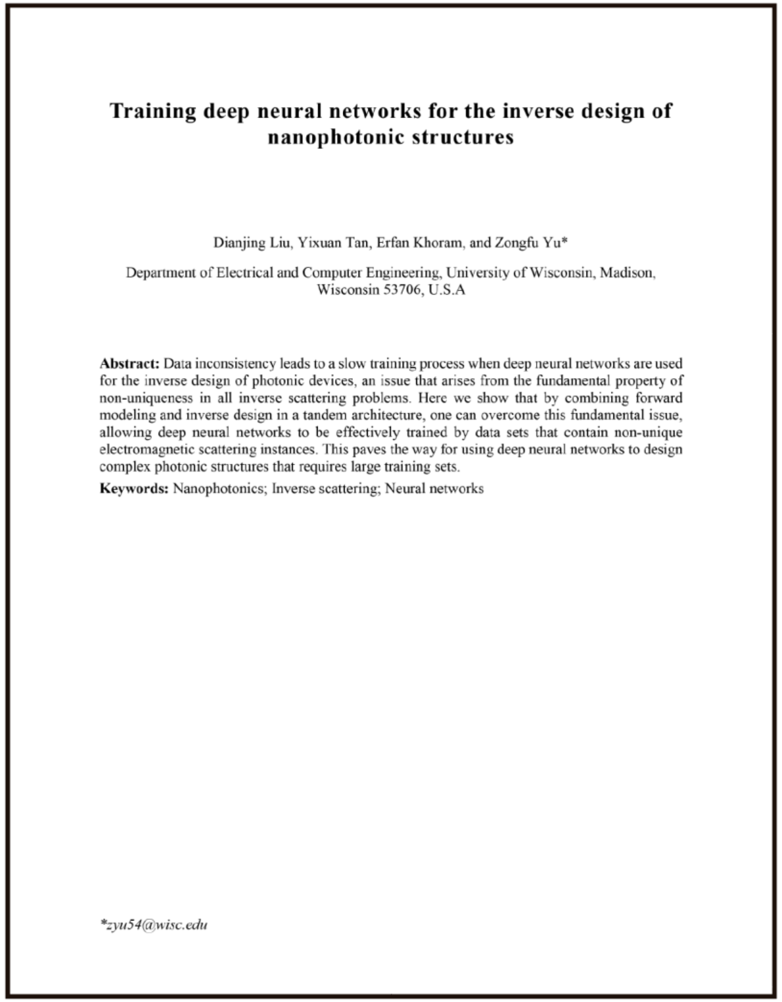
Banco de dados

Menor tempo demandado

Design Inverso

Aprender a partir dos dados

Condições desejáveis de operação



Training deep neural networks for the inverse design of nanophotonic structures

Dianjing Liu, Yixuan Tan, Erfan Khoram, and Zongfu Yu*

Department of Electrical and Computer Engineering, University of Wisconsin, Madison, Wisconsin 53706, U.S.A

Abstract: Data inconsistency leads to a slow training process when deep neural networks are used for the inverse design of photonic devices, an issue that arises from the fundamental property of non-uniqueness in all inverse scattering problems. Here we show that by combining forward modeling and inverse design in a tandem architecture, one can overcome this fundamental issue, allowing deep neural networks to be effectively trained by data sets that contain non-unique electromagnetic scattering instances. This paves the way for using deep neural networks to design complex photonic structures that requires large training sets.

Keywords: Nanophotonics; Inverse scattering; Neural networks

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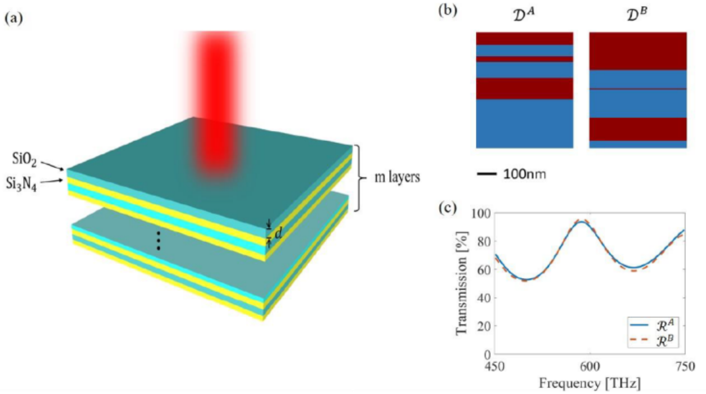
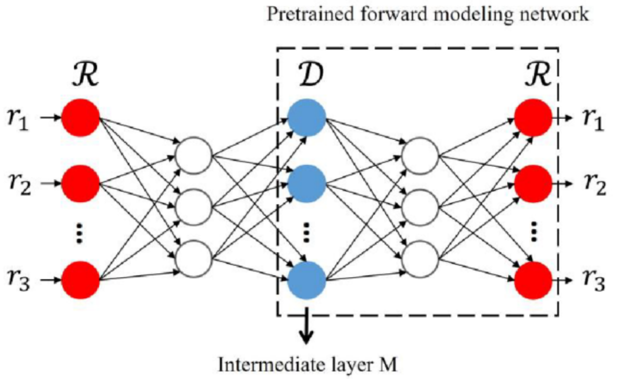
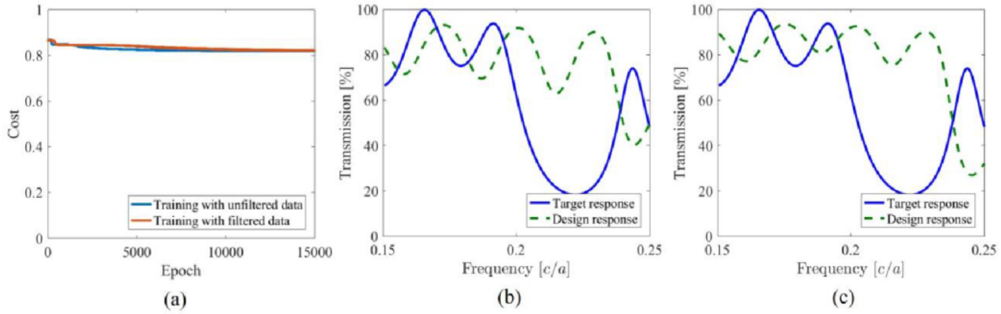
» Problema da não-unicidade da resposta eletromagnética

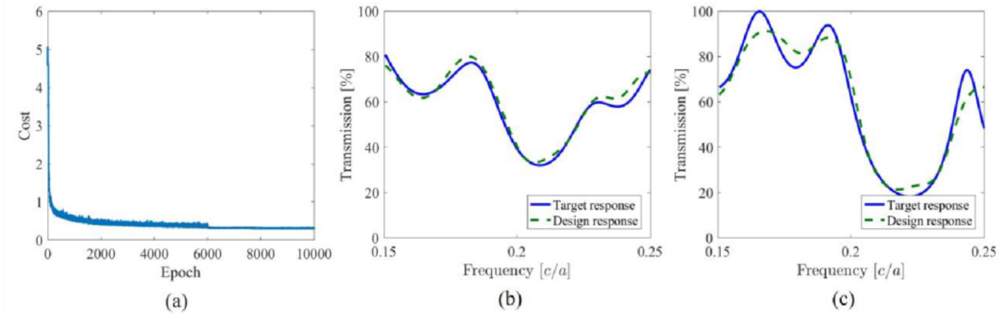


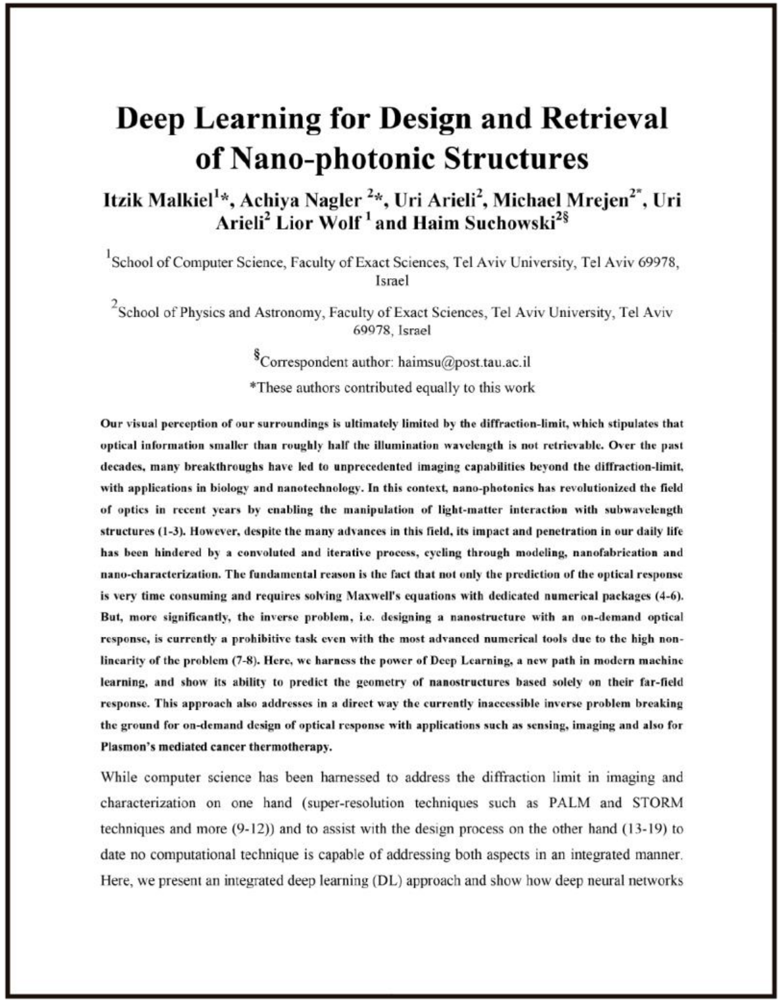


Processos separados



Modelo pré-treinado





Deep Learning for Design and Retrieval of Nano-photonic Structures

Itzik Malkiel[1]*, Achiya Nagler [2]*, Uri Arieli[2], Michael Mrejen[2*], Uri Arieli[2] Lior Wolf [1] and Haim Suchowski[2§]

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Our visual perception of our surroundings is ultimately limited by the diffraction-limit, which stipulates that optical information smaller than roughly half the illumination wavelength is not retrievable. Over the past decades, many breakthroughs have led to unprecedented imaging capabilities beyond the diffraction-limit, with applications in biology and nanotechnology. In this context, nano-photonics has revolutionized the field of optics in recent years by enabling the manipulation of light-matter interaction with subwavelength structures (1-3). However, despite the many advances in this field, its impact and penetration in our daily life has been hindered by a convoluted and iterative process, cycling through modeling, nanofabrication and nano-characterization. The fundamental reason is the fact that not only the prediction of the optical response is very time consuming and requires solving Maxwell's equations with dedicated numerical packages (4-6). But, more significantly, the inverse problem, i.e. designing a nanostructure with an on-demand optical response, is currently a prohibitive task even with the most advanced numerical tools due to the high non-linearity of the problem (7-8). Here, we harness the power of Deep Learning, a new path in modern machine learning, and show its ability to predict the geometry of nanostructures based solely on their far-field response. This approach also addresses in a direct way the currently inaccessible inverse problem breaking the ground for on-demand design of optical response with applications such as sensing, imaging and also for Plasmon's mediated cancer thermotherapy.

While computer science has been harnessed to address the diffraction limit in imaging and characterization on one hand (super-resolution techniques such as PALM and STORM techniques and more (9-12)) and to assist with the design process on the other hand (13-19) to date no computational technique is capable of addressing both aspects in an integrated manner. Here, we present an integrated deep learning (DL) approach and show how deep neural networks

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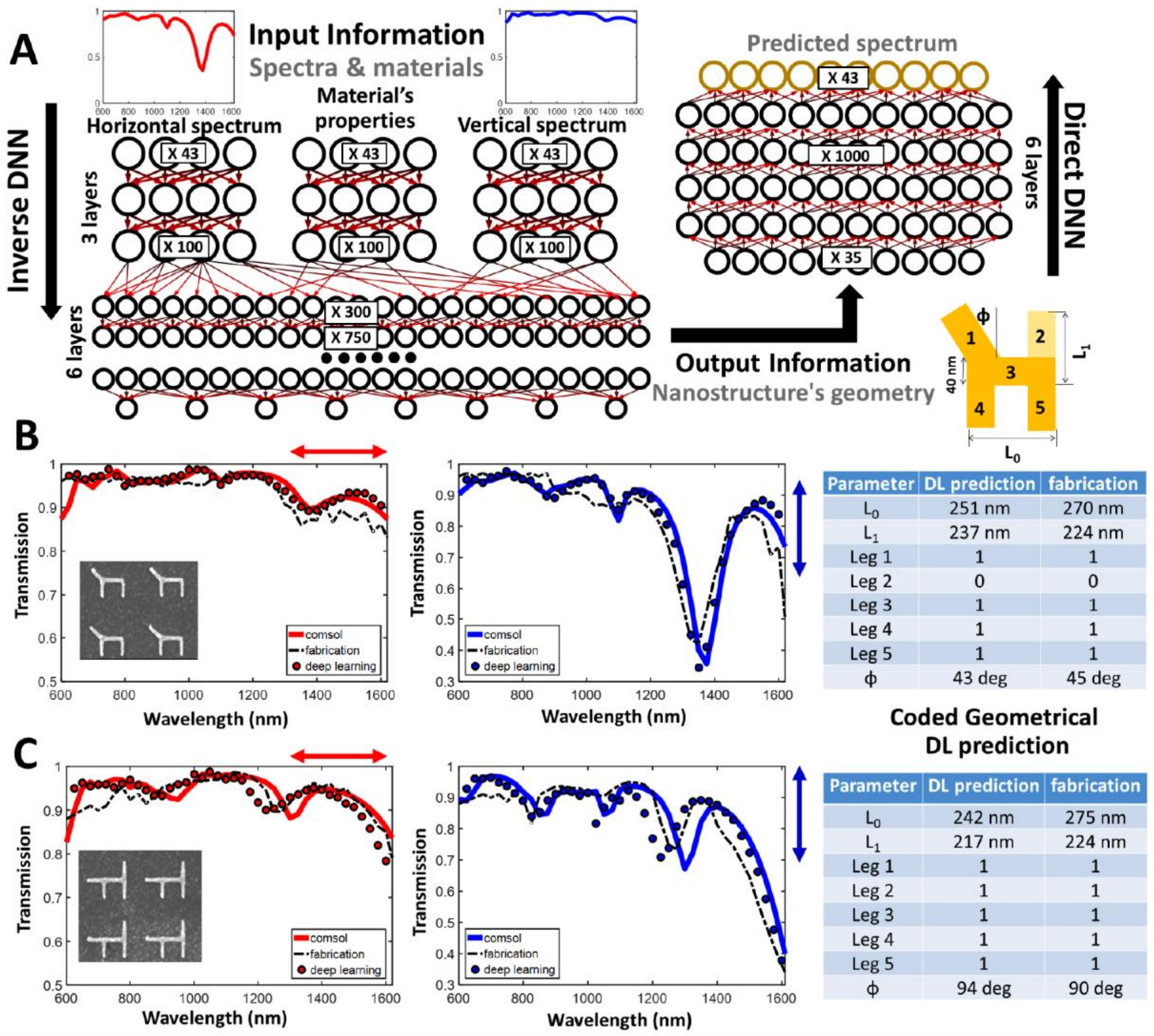
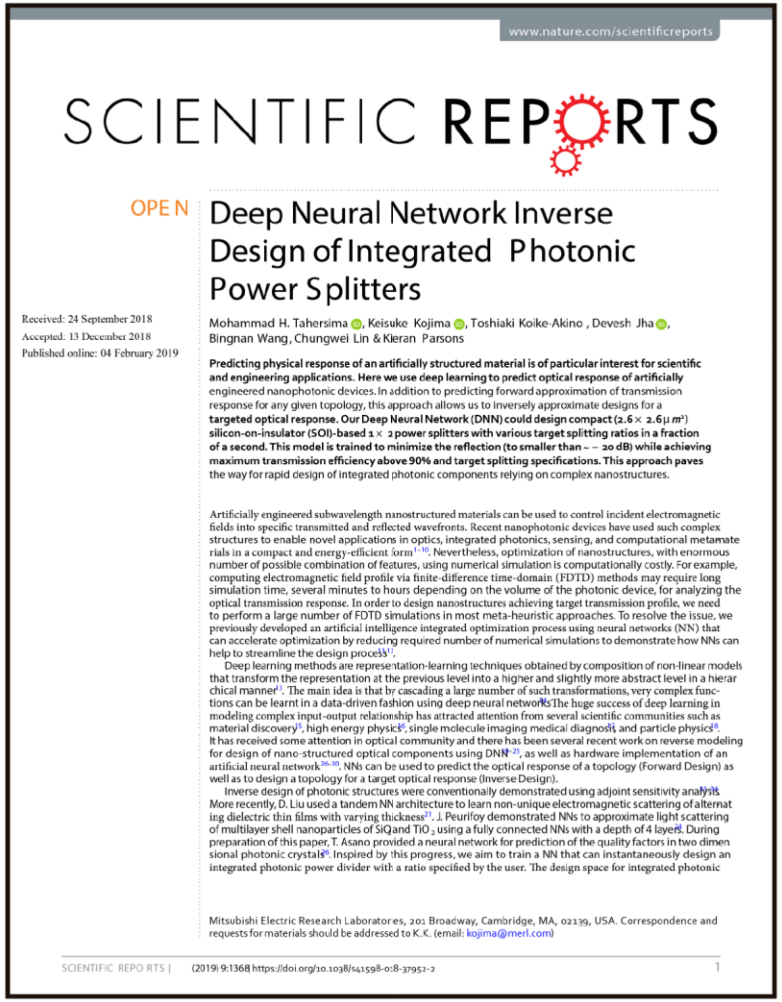


Parameter	DL prediction	fabrication
L_0	251 nm	270 nm
L_1	237 nm	224 nm
Leg 1	1	1
Leg 2	0	0
Leg 3	1	1
Leg 4	1	1
Leg 5	1	1
ϕ	43 deg	45 deg

Parameter	DL prediction	fabrication
L_0	242 nm	275 nm
L_1	217 nm	224 nm
Leg 1	1	1
Leg 2	1	1
Leg 3	1	1
Leg 4	1	1
Leg 5	1	1
ϕ	94 deg	90 deg



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OPEN

Deep Neural Network Inverse Design of Integrated Photonic Power Splitters

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Mohammad H. Tahersima, Keisuke Kojima, Toshiaki Koike-Akino, Devesh Jha, Bingnan Wang, Chungwei Lin & Kieran Parsons

Predicting physical response of an artificially structured material is of particular interest for scientific and engineering applications. Here we use deep learning to predict optical response of artificially engineered nanophotonic devices. In addition to predicting forward approximation of transmission response for any given topology, this approach allows us to inversely approximate designs for a **targeted optical response. Our Deep Neural Network (DNN) could design compact ($2.6 \times 2.6 \mu m^2$) silicon-on-insulator (SOI)-based 1×2 power splitters with various target splitting ratios in a fraction of a second. This model is trained to minimize the reflection (to smaller than ~ −20 dB) while achieving maximum transmission efficiency above 90% and target splitting specifications. This approach paves** the way for rapid design of integrated photonic components relying on complex nanostructures.

Artificially engineered subwavelength nanostructured materials can be used to control incident electromagnetic fields into specific transmitted and reflected wavefronts. Recent nanophotonic devices have used such complex structures to enable novel applications in optics, integrated photonics, sensing, and computational metamaterials in a compact and energy-efficient form[1–10]. Nevertheless, optimization of nanostructures, with enormous number of possible combination of features, using numerical simulation is computationally costly. For example, computing electromagnetic field profile via finite-difference time-domain (FDTD) methods may require long simulation time, several minutes to hours depending on the volume of the photonic device, for analyzing the optical transmission response. In order to design nanostructures achieving target transmission profile, we need to perform a large number of FDTD simulations in most meta-heuristic approaches. To resolve the issue, we previously developed an artificial intelligence integrated optimization process using neural networks (NN) that can accelerate optimization by reducing required number of numerical simulations to demonstrate how NNs can help to streamline the design process[11,12].

Deep learning methods are representation-learning techniques obtained by composition of non-linear models that transform the representation at the previous level into a higher and slightly more abstract level in a hierarchical manner[13]. The main idea is that by cascading a large number of such transformations, very complex functions can be learnt in a data-driven fashion using deep neural networks[14]. The huge success of deep learning in modeling complex input-output relationship has attracted attention from several scientific communities such as material discovery[15], high energy physics[16], single molecule imaging medical diagnosis[17] and particle physics[18]. It has received some attention in optical community and there has been several recent work on reverse modeling for design of nano-structured optical components using DNN[19–25], as well as hardware implementation of an artificial neural network[26–30]. NNs can be used to predict the optical response of a topology (Forward Design) as well as to design a topology for a target optical response (Inverse Design).

Inverse design of photonic structures were conventionally demonstrated using adjoint sensitivity analysis[31–34]. More recently, D. Liu used a tandem NN architecture to learn non-unique electromagnetic scattering of alternating dielectric thin films with varying thickness[21]. J. Peurifoy demonstrated NNs to approximate light scattering of multilayer shell nanoparticles of SiO_2 and TiO_2 using a fully connected NNs with a depth of 4 layers[24]. During preparation of this paper, T. Asano provided a neural network for prediction of the quality factors in two dimensional photonic crystals[26]. Inspired by this progress, we aim to train a NN that can instantaneously design an integrated photonic power divider with a ratio specified by the user. The design space for integrated photonic

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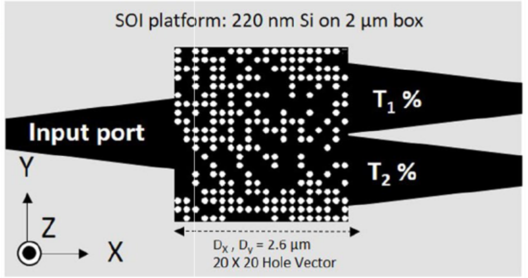
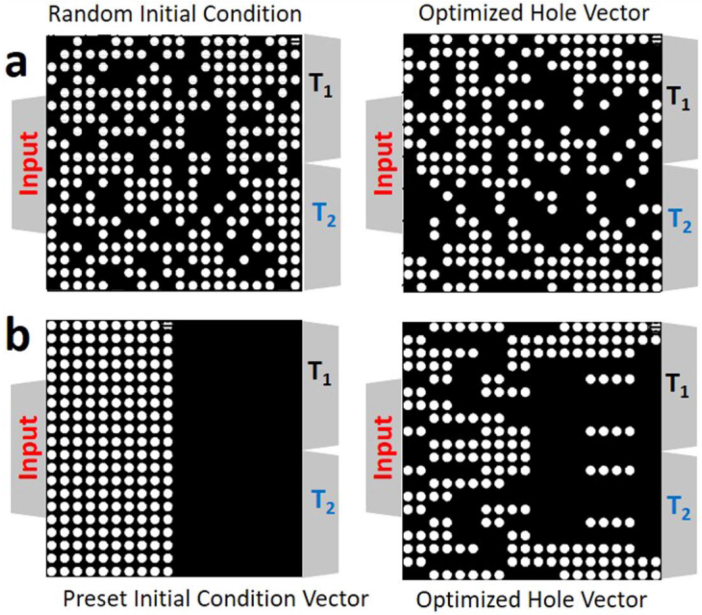
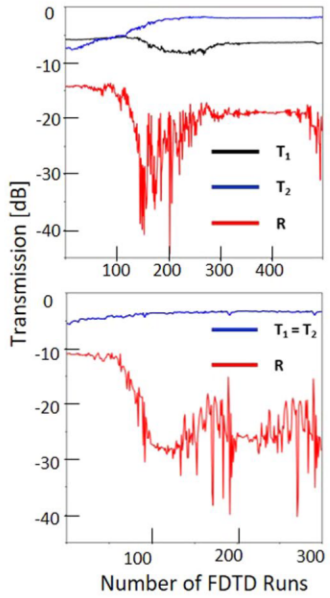
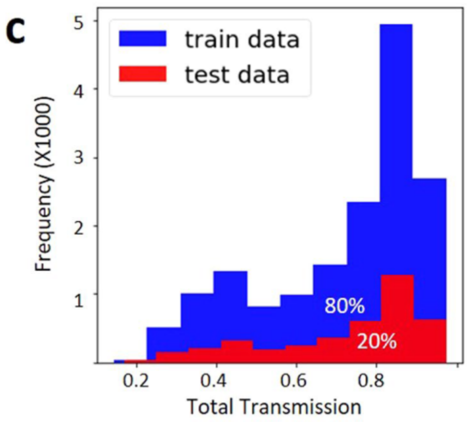
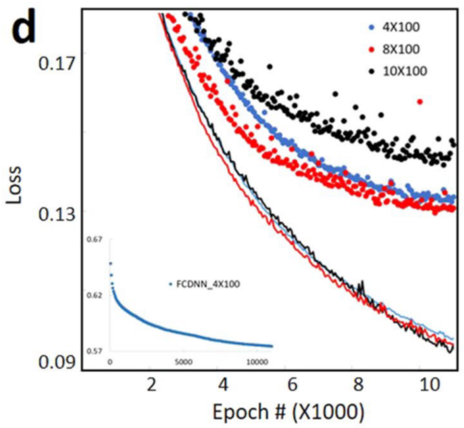


Divisor de potência 1x2
Eficiência: 90%









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Tackling Photonic Inverse Design with Machine Learning

Zhaocheng Liu,* Dayu Zhu, Lakshmi Raju, and Wenshan Cai*

Machine learning, as a study of algorithms that automate prediction and decision-making based on complex data, has become one of the most effective tools in the study of artificial intelligence. In recent years, scientific communities have been gradually merging data-driven approaches with research, enabling dramatic progress in revealing underlying mechanisms, predicting essential properties, and discovering unconventional phenomena. It is becoming an indispensable tool in the fields of, for instance, quantum physics, organic chemistry, and medical imaging. Very recently, machine learning has been adopted in the research of photonics and optics as an alternative approach to address the inverse design problem. In this report, the fast advances of machine-learning-enabled photonic design strategies in the past few years are summarized. In particular, deep learning methods, a subset of machine learning algorithms, dealing with intractable high degrees-of-freedom structure design are focused upon.

1. Overview

Over the past two or three decades, the exploration of artificially structured photonic media has represented a central theme in the optical sciences. By carefully engineering photonic structures to be comparable with or smaller than the wavelength, light behaviors, and properties like transmittance, polarization, chirality, and frequency, can be accurately manipulated in unprecedented manners. As such, artificial photonic structures are enabling tremendous applications in modern optical engineering and advanced science research, such as virtual/augmented reality,[1] sensing technologies,[2] optical system miniaturization,[3] and optical communications.[4] Nowadays, research in photonics has branched out to various fields with substantial influence in the scientific community. For example, photonic crystals[5] consist of repeating regions of distinct refractive indices, enabling allowed and forbidden spectral ranges oflight and controlling the propagation oflight inside the crystal. Plasmonics[6] studies how light gives rise to and interacts with collective excitations offree electrons at metal surfaces, manipulating light waves down to the deep subwavelength scale. By introducing spatial variations in the optical response of miniature light scatterers, metasurfaces[7,8] enable arbitrary wavefront shaping with unprecedented flexibility by producing controllable abrupt changes in the phase, amplitude, and polarization oflight waves. Apart from the enumerated cases, there are several specific disciplines of photonics, and the unique characteristics of artificial structures of photonic devices offer the possibility for extensive applications.

Analogous to the subject of macroscopic artificial structures, the design of microscopic structures remains a major topic in photonic research. Although photonic structure performance is typically straightforward to predict, through sophisticated simulation algorithms such as finite element method (FEM) and finite different time domain (FDTD), the inverse problem, designing an on-demand photonic device, is not closed-form. At the early stages of nanophotonics research, the prototypical designs were mostly based on educable guesses such as the split-ring,[9] V-shaped antenna,[8,10] and gammadions[11] to name a few. However, limited by the prior knowledge of humans and the complicated light-matter interaction mechanisms, photonic devices with unconventional functionalities and extremely high efficiencies may have never been discovered with intuitively guessed geometries. In order to address the difficulty of photonic and optical design, inverse design methodologies, such as adjoint methods[12] and evolutionary algorithms,[13] have become one of the main themes of photonics research in recent years. These algorithms have successfully been implemented for the design of various unconventional photonic devices, such as power splitters,[14] light trapping structures,[15] and dielectric nanoantennas.[16] In order to further expand the capabilities of machine-aided design approaches, and to avoid some downsides of traditional optimization (such as the local minimum problem and expensive computations), the optical community has started to look at data-driven and machine learning methods as alternative approaches to address the inverse design problem.

In the past two decades, the prevalence ofinformation technology and the advances of hardware have been greatly accelerating machine learning and data science development. As such, machine learning has become the central research theme in

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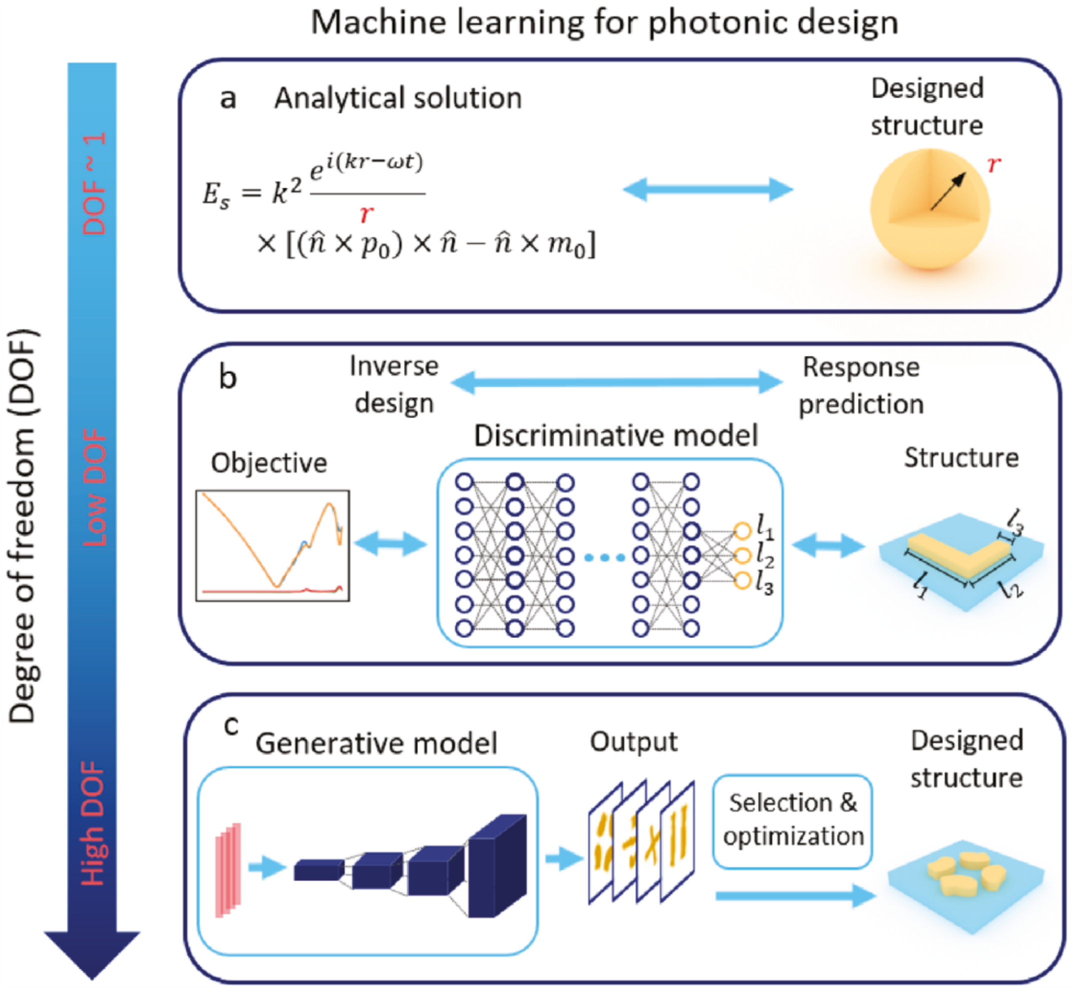
- Graus de Liberdade (DOF)
- Espaço de design



CAPÍTULO 2

REVISÃO BIBLIOGRÁFICA

- Nanofotônica
- Aprendizado de Máquina

Nanofotônica

Nanotecnologia
Fotônica

Estudo da compreensão
da luz nos materiais
em escala nanométrica

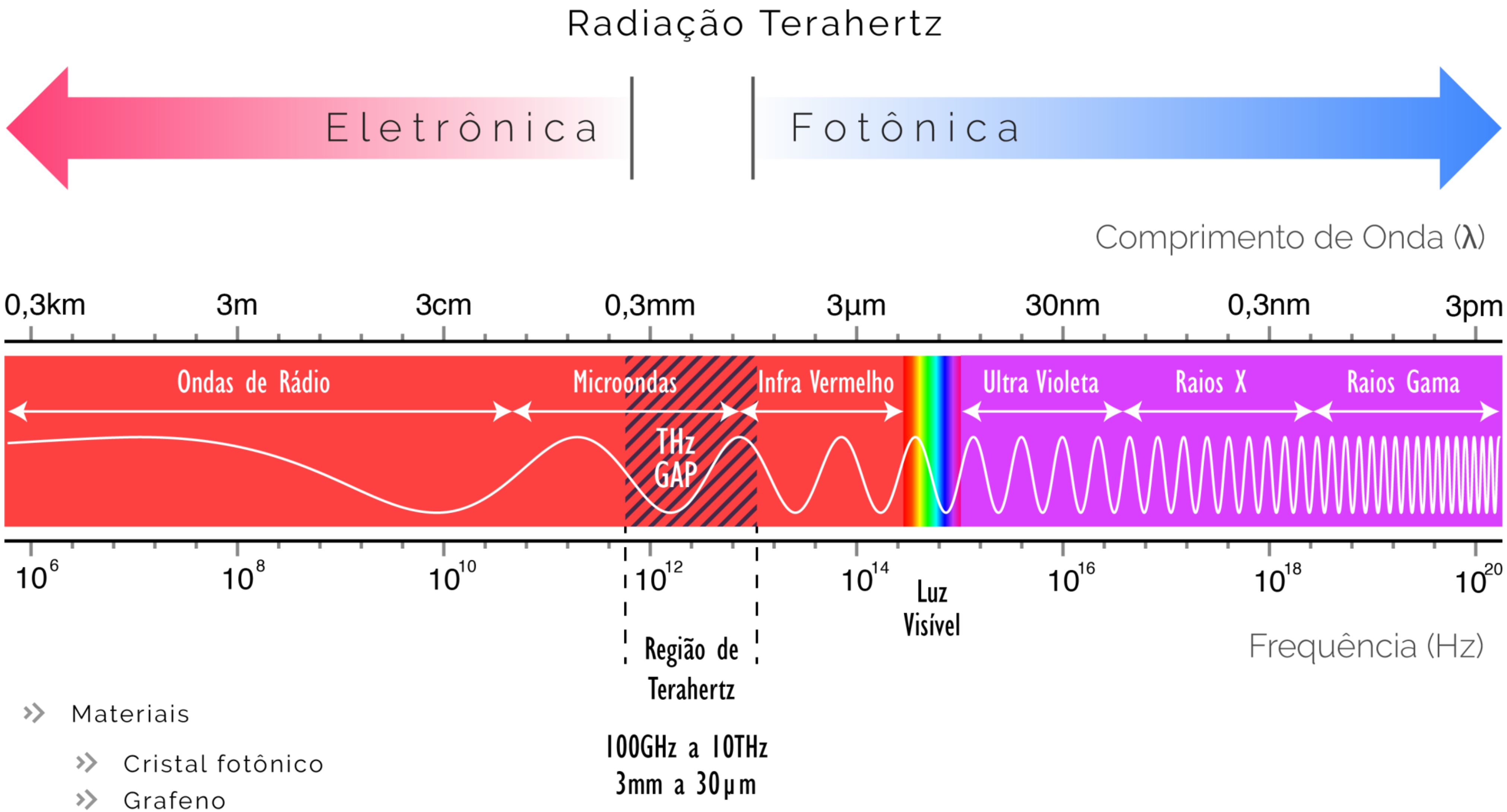
Telecomunicações
Imagens médicas
Biologia celular
Células fotovoltaicas

Radiação
Terahertz

Penetra pano e couro e
alguns milímetros na pele,
mas sem os efeitos potencialmente
prejudiciais dos raios-X

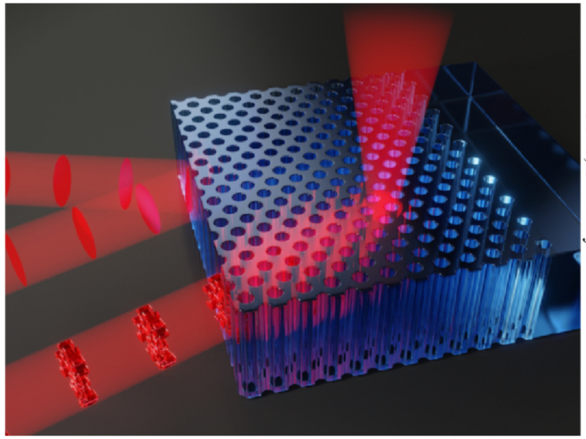
Não-ionizante
Pouco explorada
Segura em humanos
Comunicação sem fio

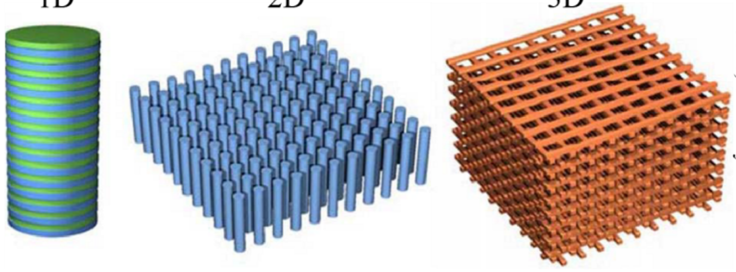
5G = 10 Gbits/s
THz = 100 Gbits/s



- Materiais
  - Cristal fotônico
  - Grafeno

Cristal Fotônico

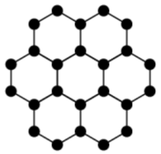

COPS, University of Twente

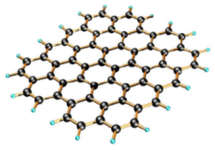


COPS, University of Twente

- Nanoestruturas projetadas para afetar o movimento dos fótons
- Constante dielétrica em 1, 2 ou 3 dimensões
- Introdução de defeitos na estrutura
- Organização em padrões periódicos

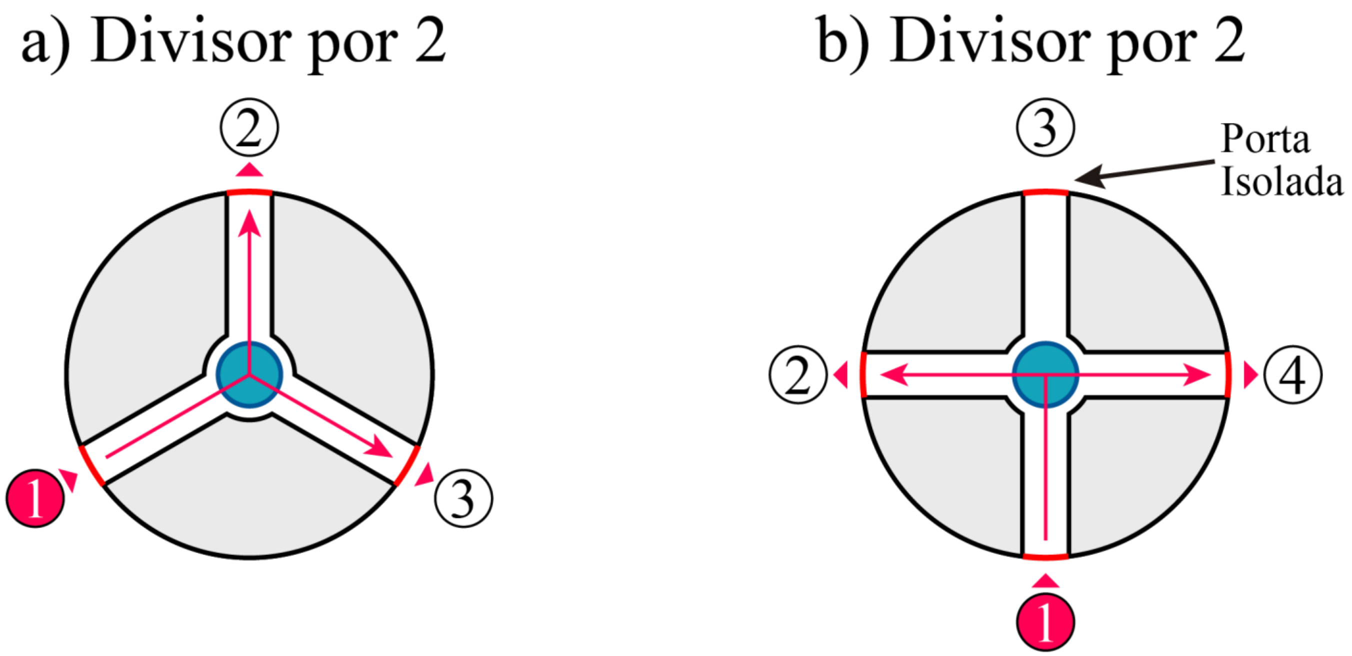
Si » Silício
GaAs » Arsenieto de Gálio



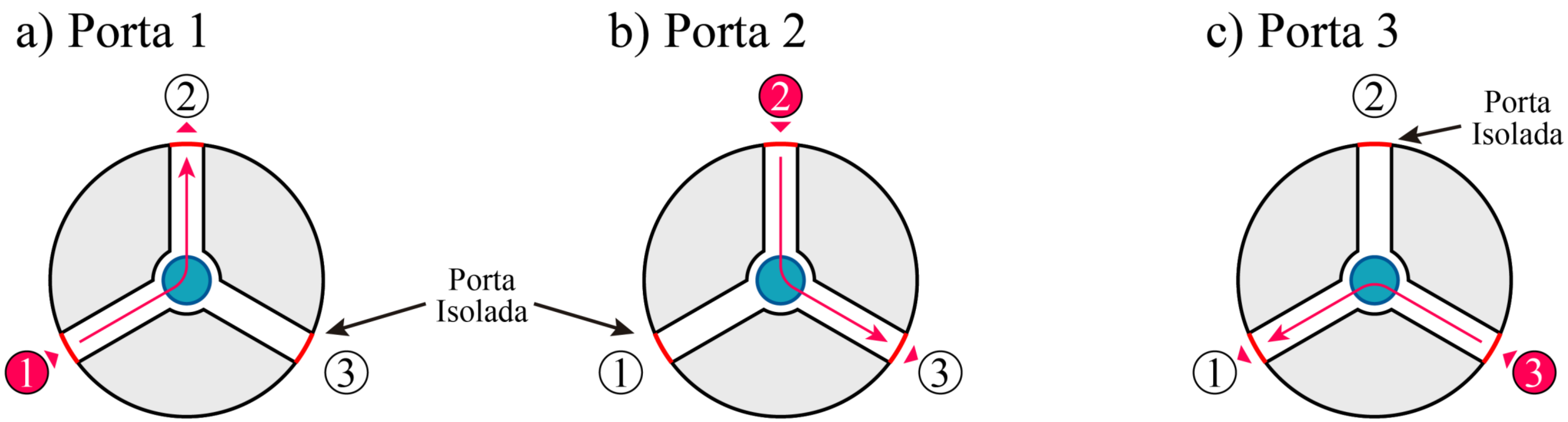


- Grafeno
  - Substância mais fina já feita (1 átomo de espessura)
  - Excelente condutividade térmica e elétrica
  - Resistência mecânica

Divisor de Potência

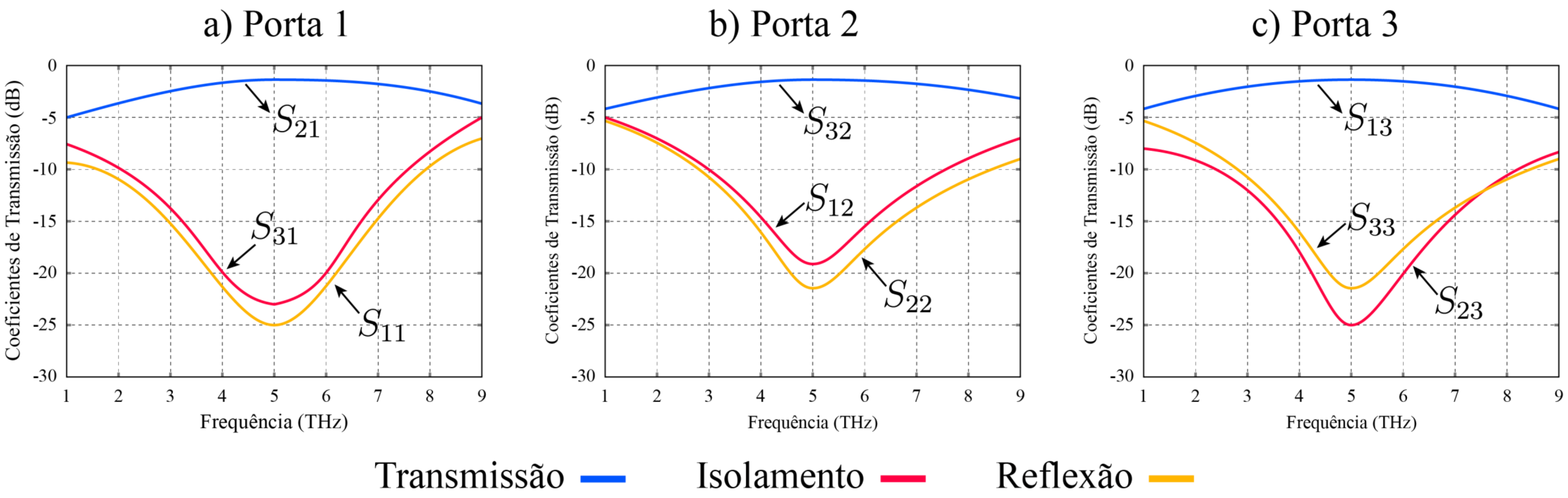


Circulador



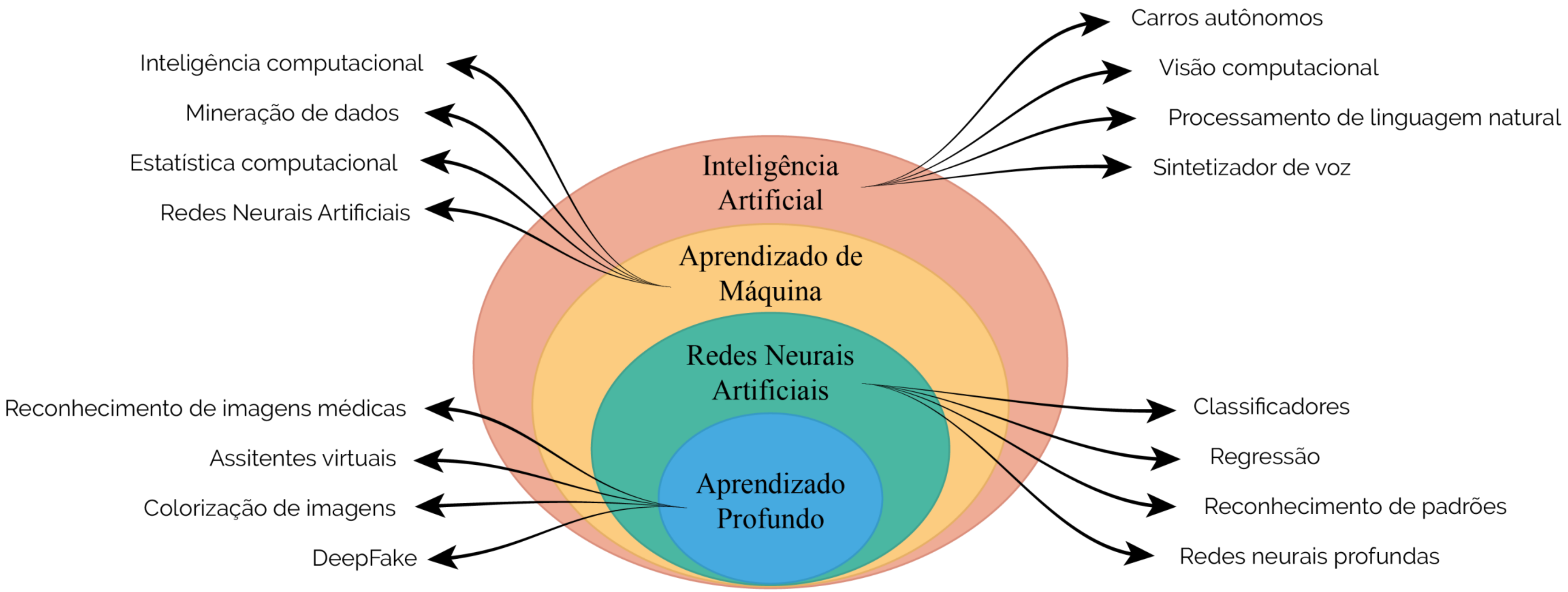
- Não-recíproco
- Proteção da fonte contra reflexão
- Circuitos emissores e receptores

Parâmetros-S

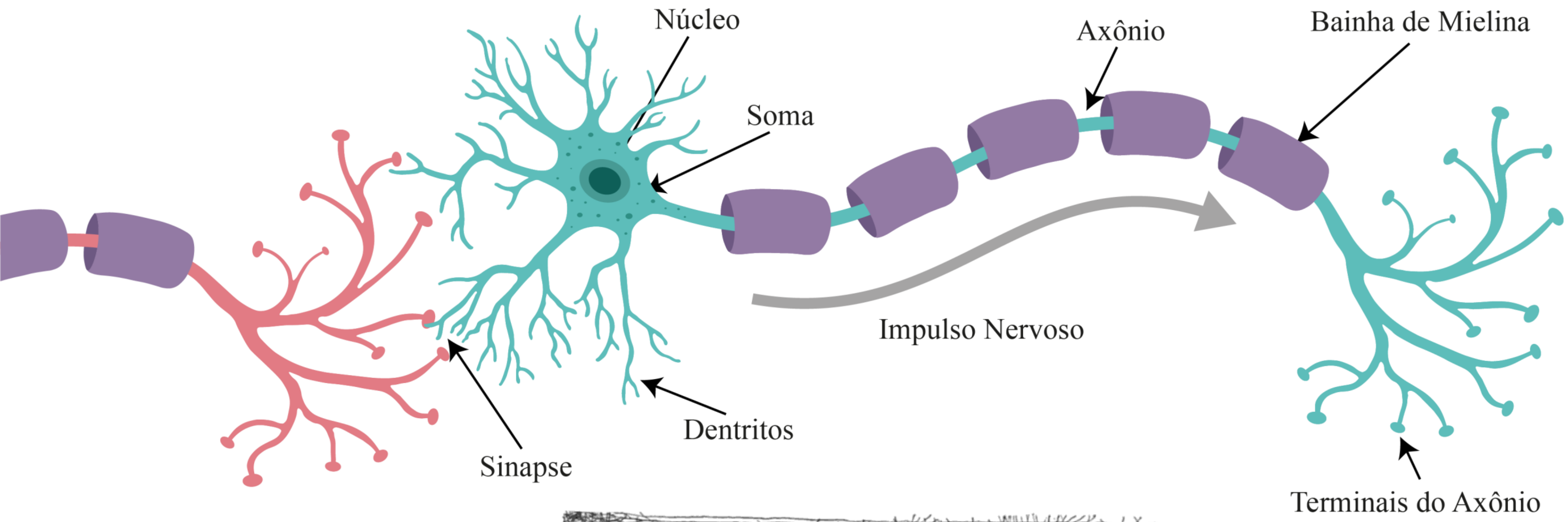


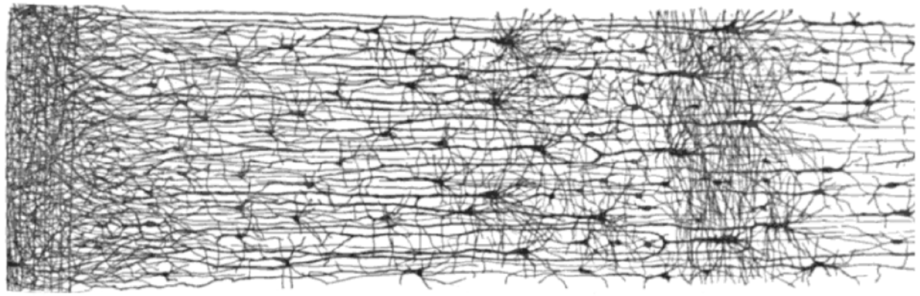
Aprendizado de Máquina

- A Inteligência Artificial é uma técnica que permite aos computadores imitar a inteligência humana.
- O Machine Learning permite que os computadores usem a experiência para aprimorar as tarefas.



Neurônio Biológico

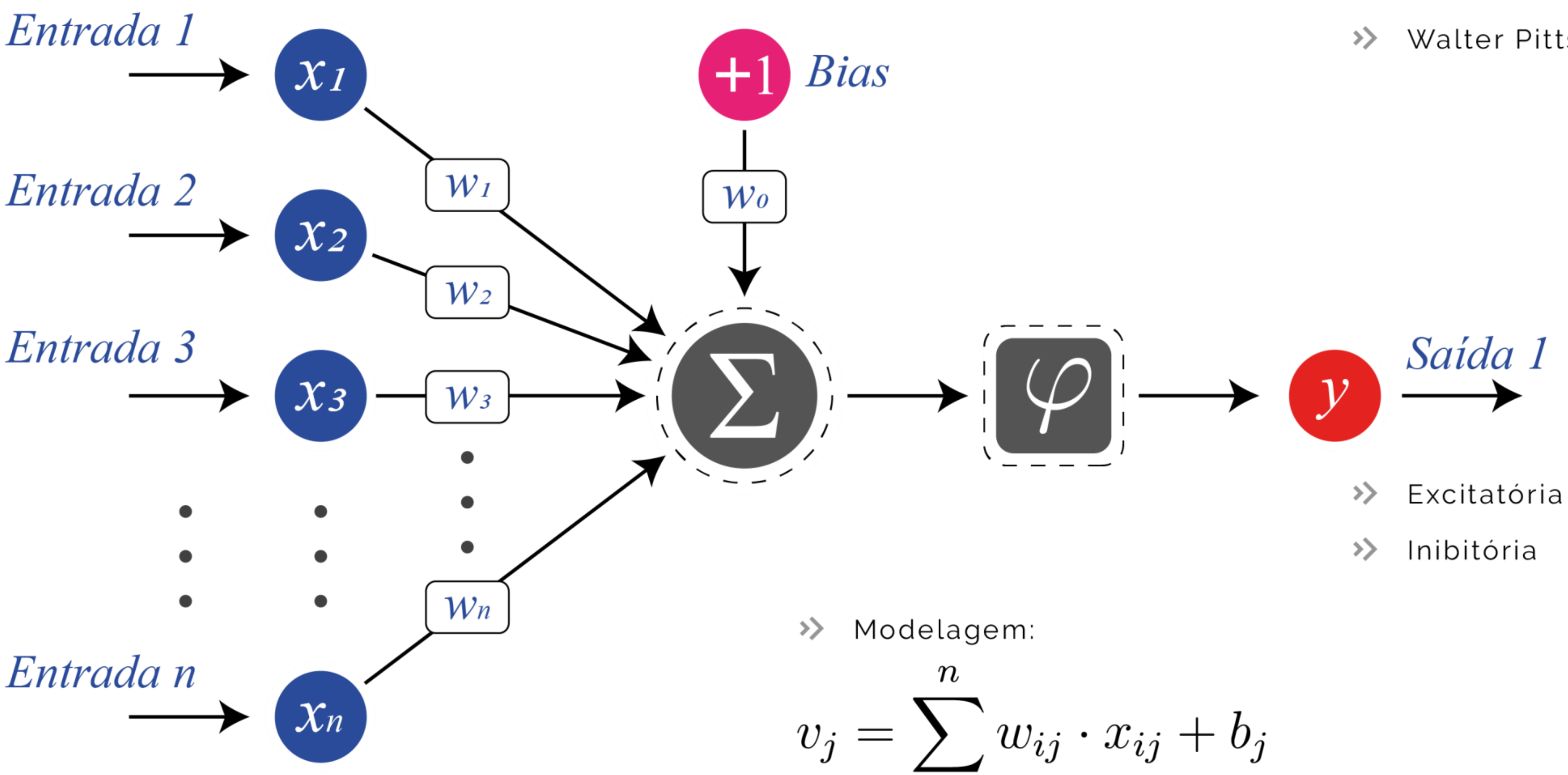




Santiago Ramon y Cajal (1899)

Neurônio Artificial

- Warren McCulloch
- Walter Pitts



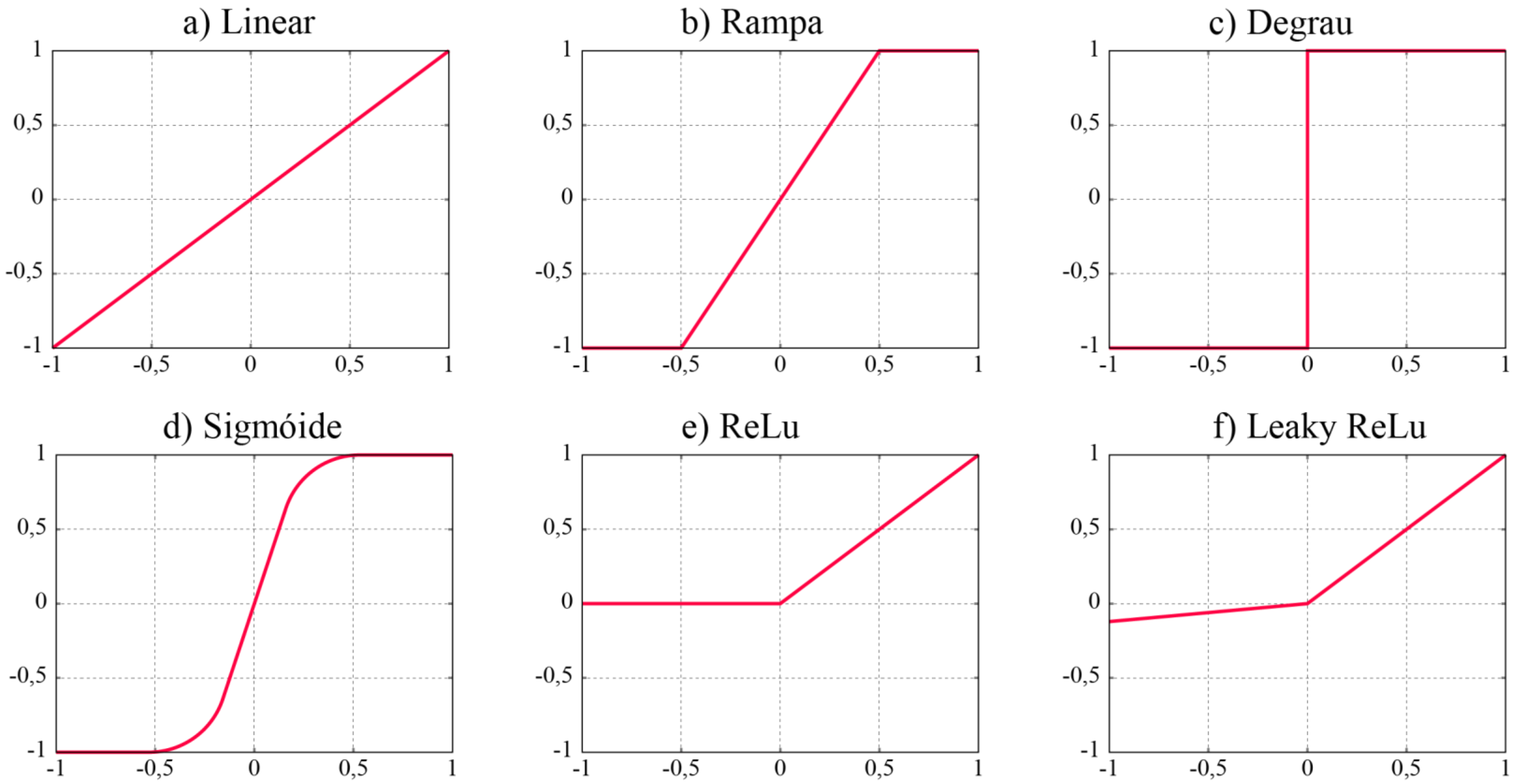
- Excitatória
- Inibitória

- Modelagem:

$$v_j = \sum_{i=1}^{n} w_{ij} \cdot x_{ij} + b_j$$

$$y_j = \varphi(v_j)$$

Função de Ativação



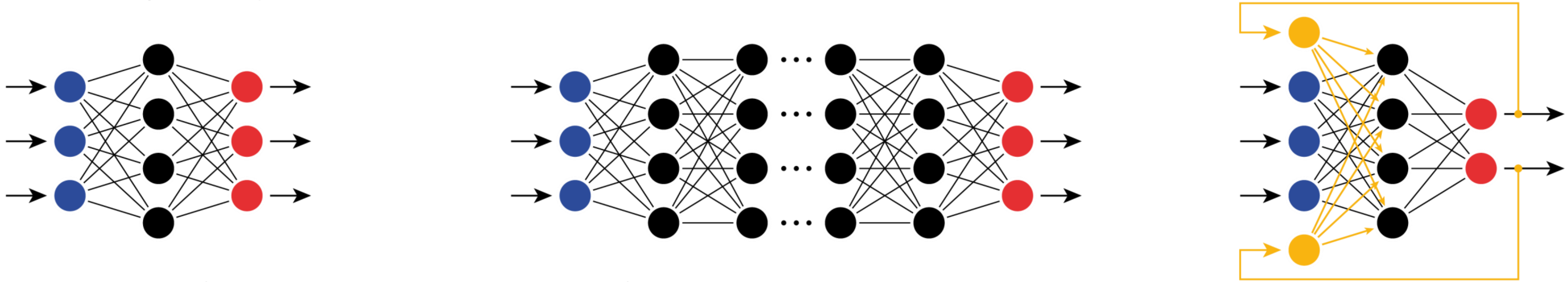
- Saída contínua
- Saída limitada
- Estados binários

- Probabilidade de classes
- Saída retificada
- Estados binários

Arquitetura de Rede

Rede Multilayer Perceptron

Rede Neural Profunda



Rede Feedforward

- Fluxo unidirecional
- Mapeamento funcional

Como variáveis de entrada afetam variáveis de saída

Rede Recorrente

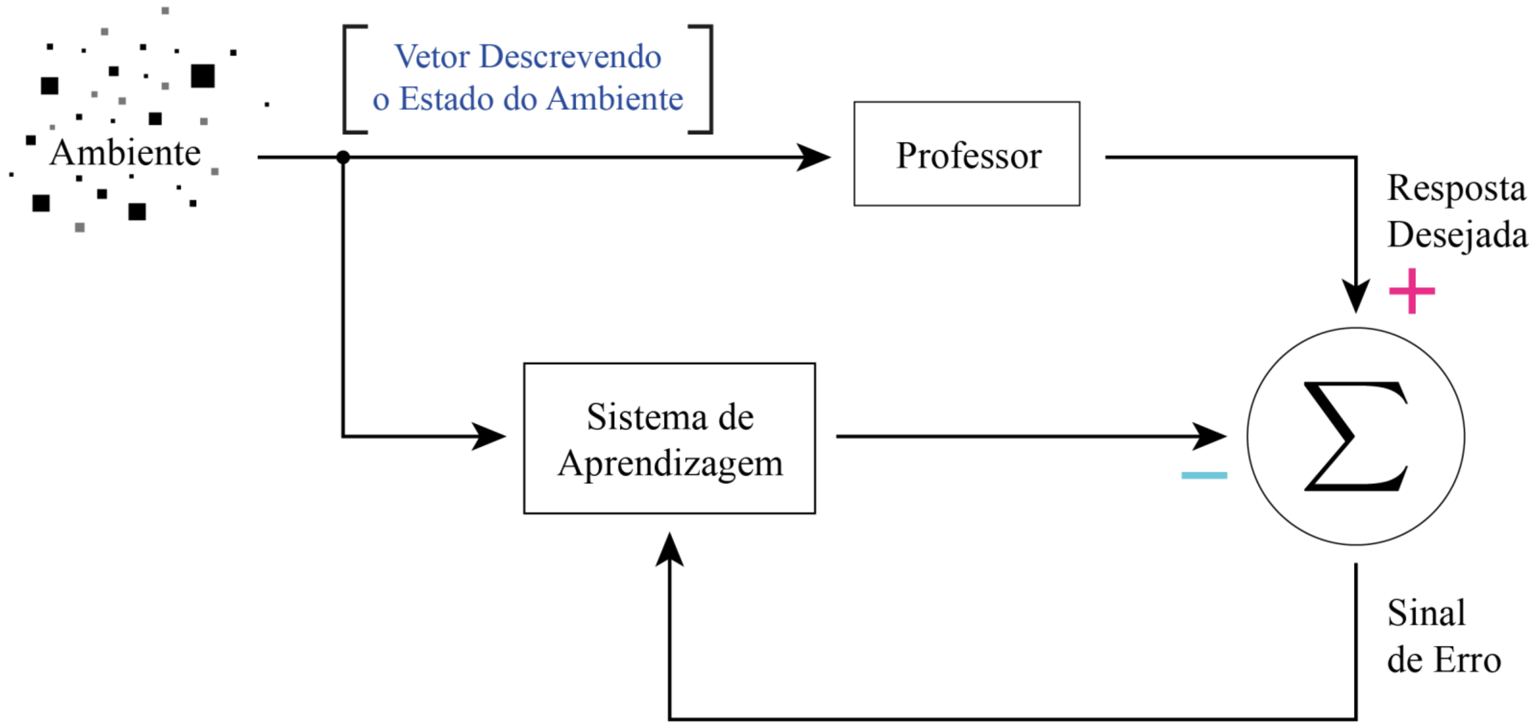
- Realimentação
- Memória

Sistema de autocompletar do mecanismo de pesquisa do Google

● Camada de Entrada ● Camada Intermediária ● Camada de Saída ● Entrada Recorrente

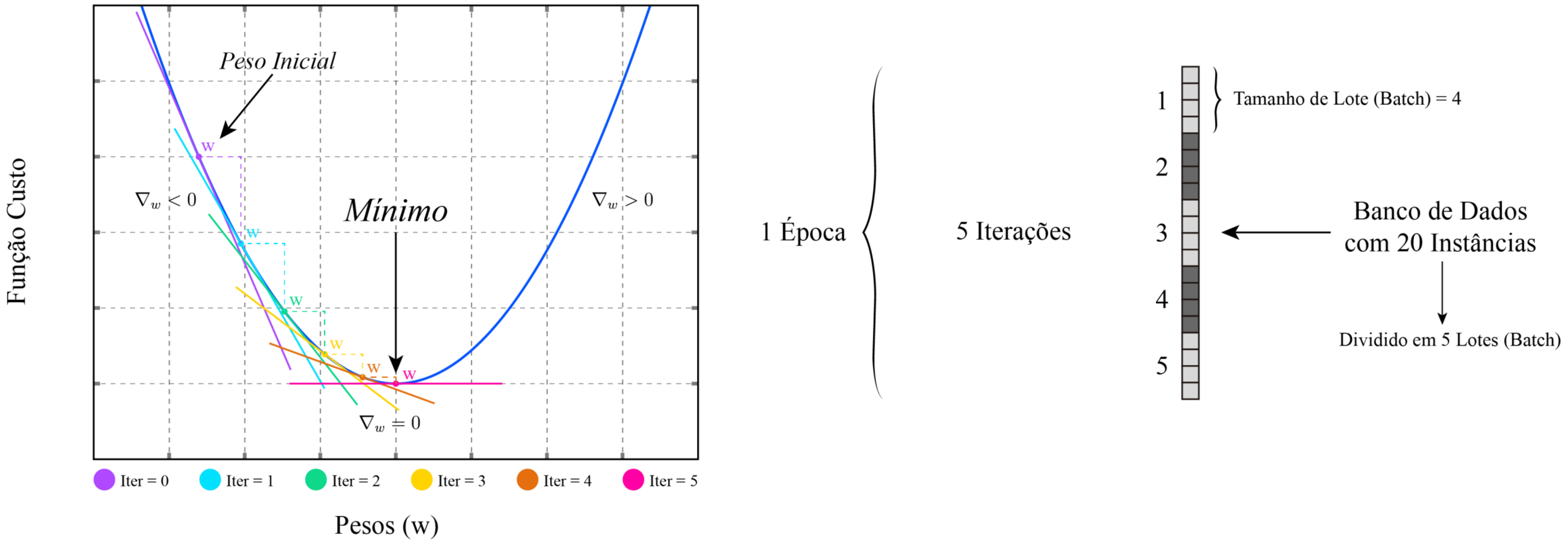
Algoritmos e Processos de Aprendizagem

- Aprendizado supervisionado



- Aprendizado não-supervisionado
  - Não há professor
  - Somente as entradas são fornecidas
- Aprendizado por reforço
  - Atingir um objetivo
  - Sistema de recompensa

Algoritmos e Processos de Aprendizagem



Algoritmo Backpropagation

- Passo para frente (forward pass)
- Passo para trás (backward pass)

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

$$\frac{\partial E(y_i,\hat{y}_i)}{\partial w_{ij}} = \frac{\partial E(y_i,\hat{y}_i)}{\partial \hat{y}}\frac{\partial \hat{y}}{\partial v_j}\frac{\partial v_j}{\partial w_{ij}}$$

$$\frac{\partial E(y_i,\hat{y}_i)}{\partial w_{ij}} = -(y_i - \hat{y}_i)\,\varphi'(v_j)\frac{\partial v_j}{\partial w_{ij}}$$

$$\frac{\partial v_j}{\partial w_{ij}} = \frac{\partial(x_1 w_1 + x_2 w_2 + \cdots + x_{nj} w_{nj})}{\partial w_i} = x_{nj}$$

$$\frac{\partial E(y_i,\hat{y}_i)}{\partial w_{ij}} = -(y_i - \hat{y}_i)\,\varphi'(v_j)x_i$$

Taxa de aprendizagem

Novo peso sináptico

$$w_{ij}^{+} = w_{ij} - \eta\frac{\partial E(y_i,\hat{y}_i)}{\partial w_{ij}}$$

Cálculo do erro

Peso sináptico atual

$\eta \uparrow$ Passos de convergência grande

$\eta \downarrow$ Passos de convergência pequeno

Valor padrão:

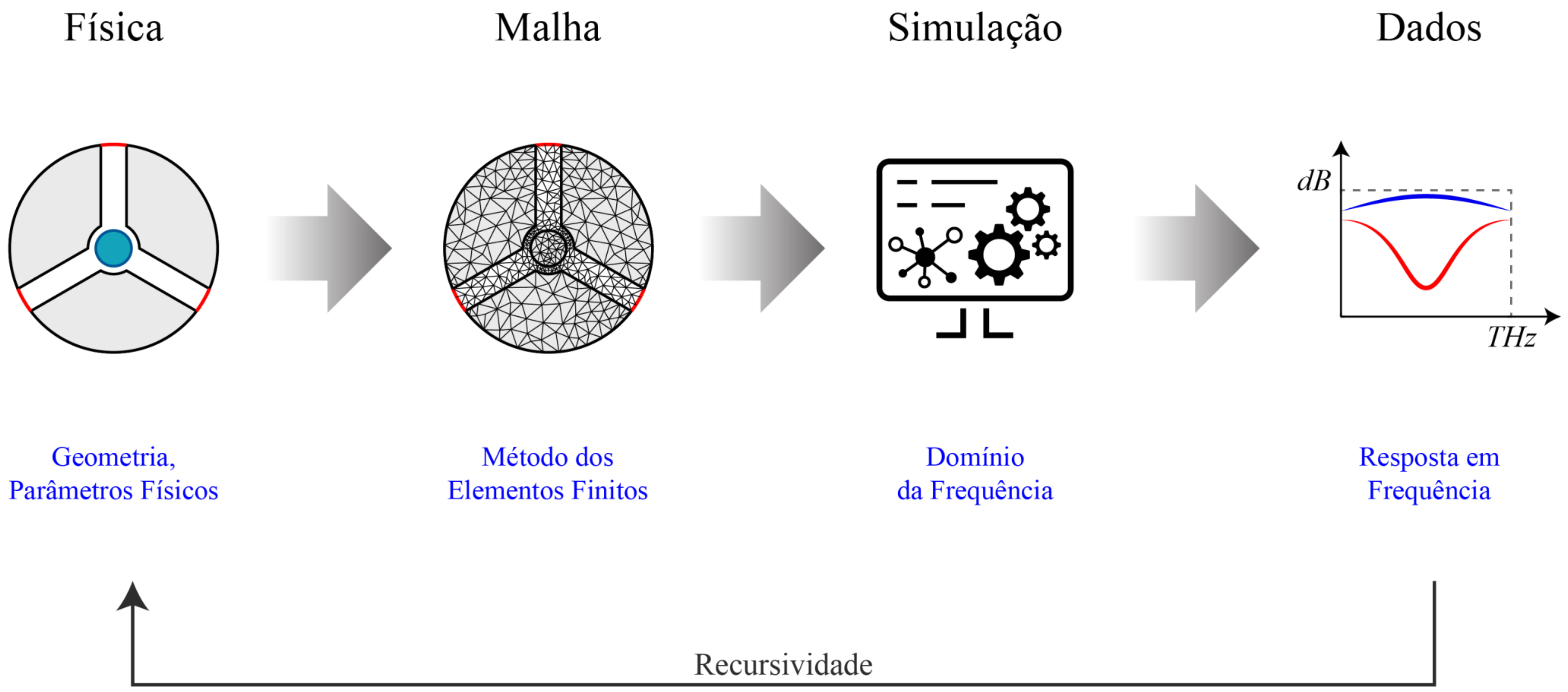
0,1

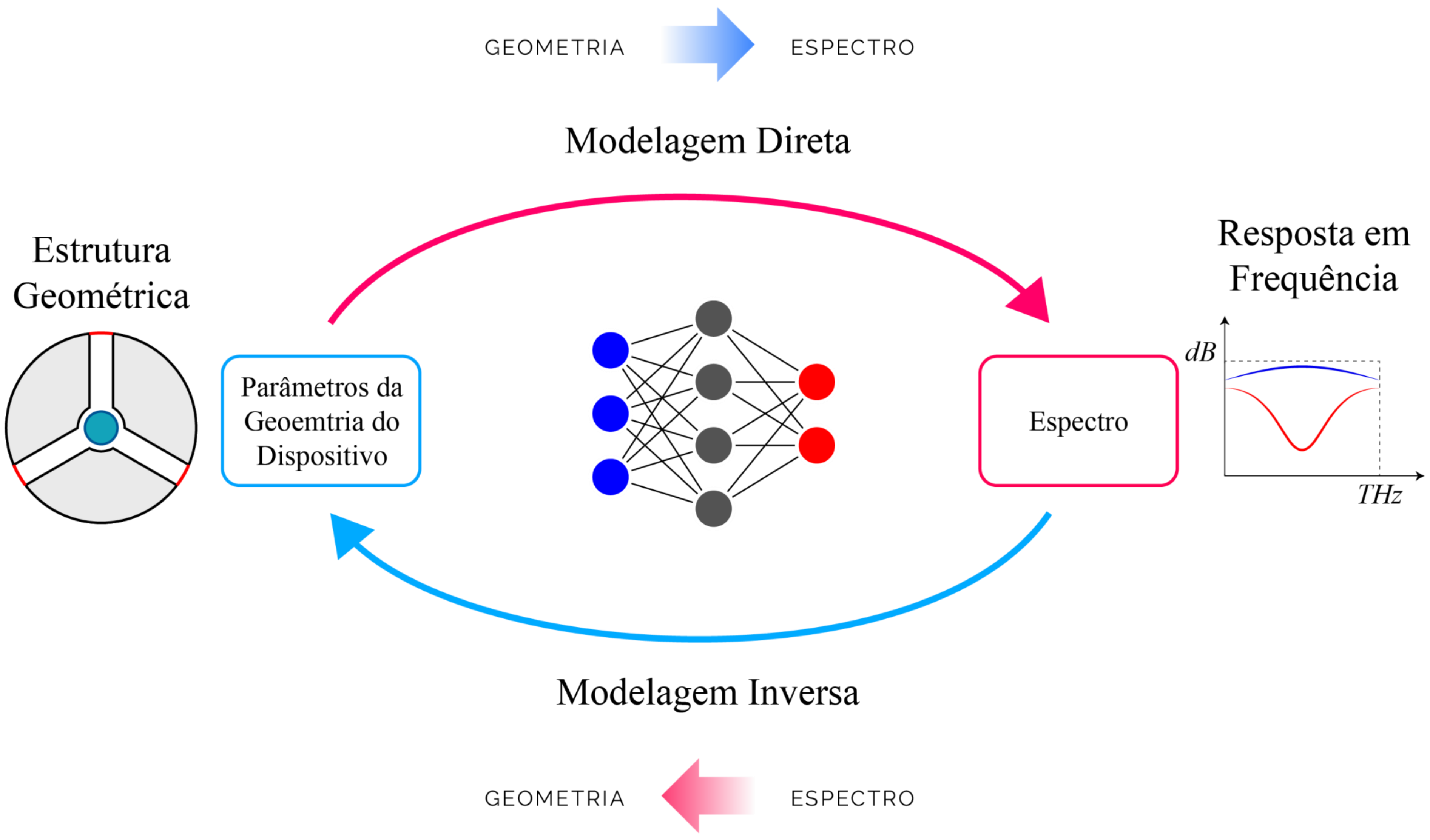
CAPÍTULO 3

MÉTODO PROPOSTO

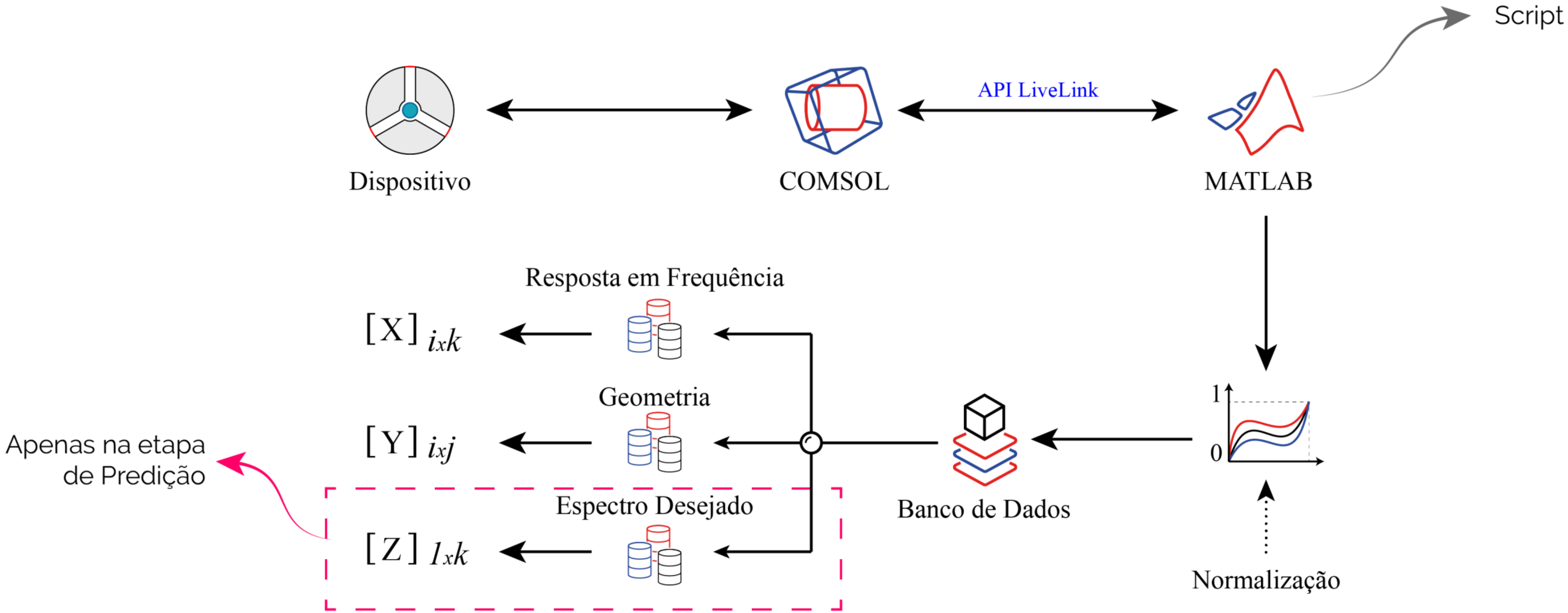
- Descrição do Problema
- Otimização por Aprendizado Profundo
- Aplicação em Circulador

DESCRIÇÃO DO PROBLEMA

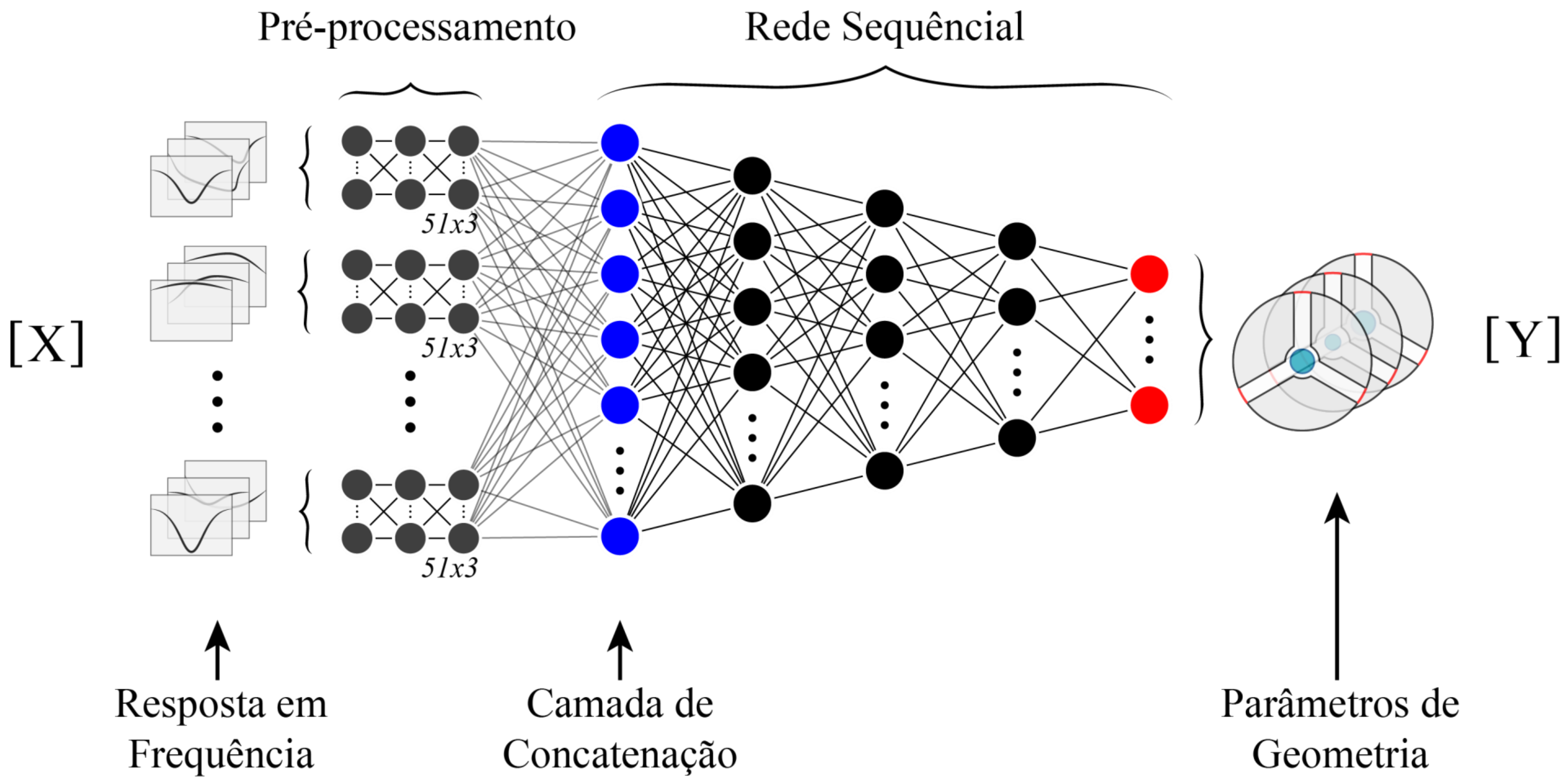



GEOMETRIA
ESPECTRO
Modelagem Direta
Estrutura Geométrica
Parâmetros da Geoemtria do Dispositivo
Espectro
Resposta em Frequência
dB
THz
Modelagem Inversa
GEOMETRIA
ESPECTRO

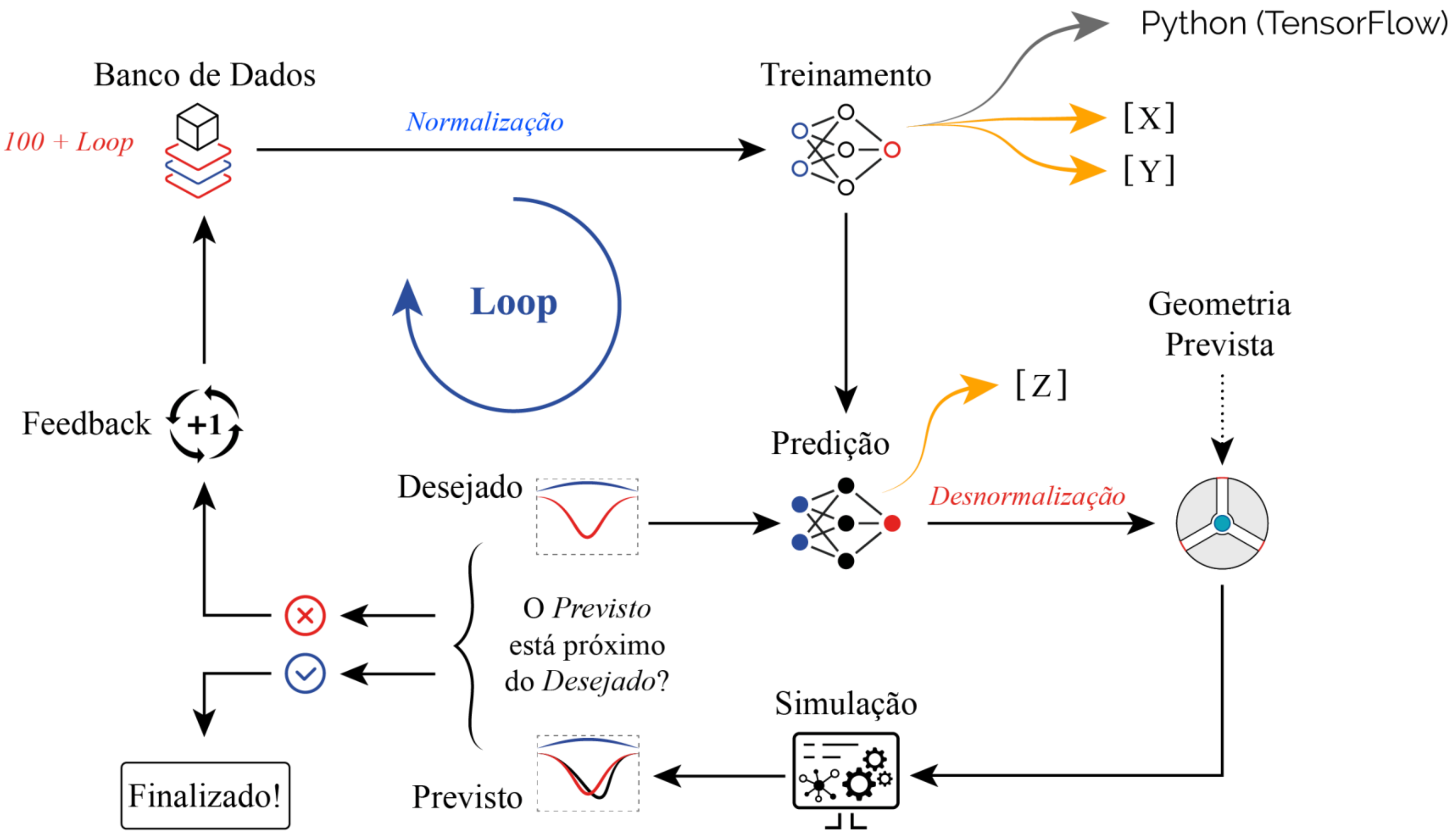
Construção do Banco de Dados



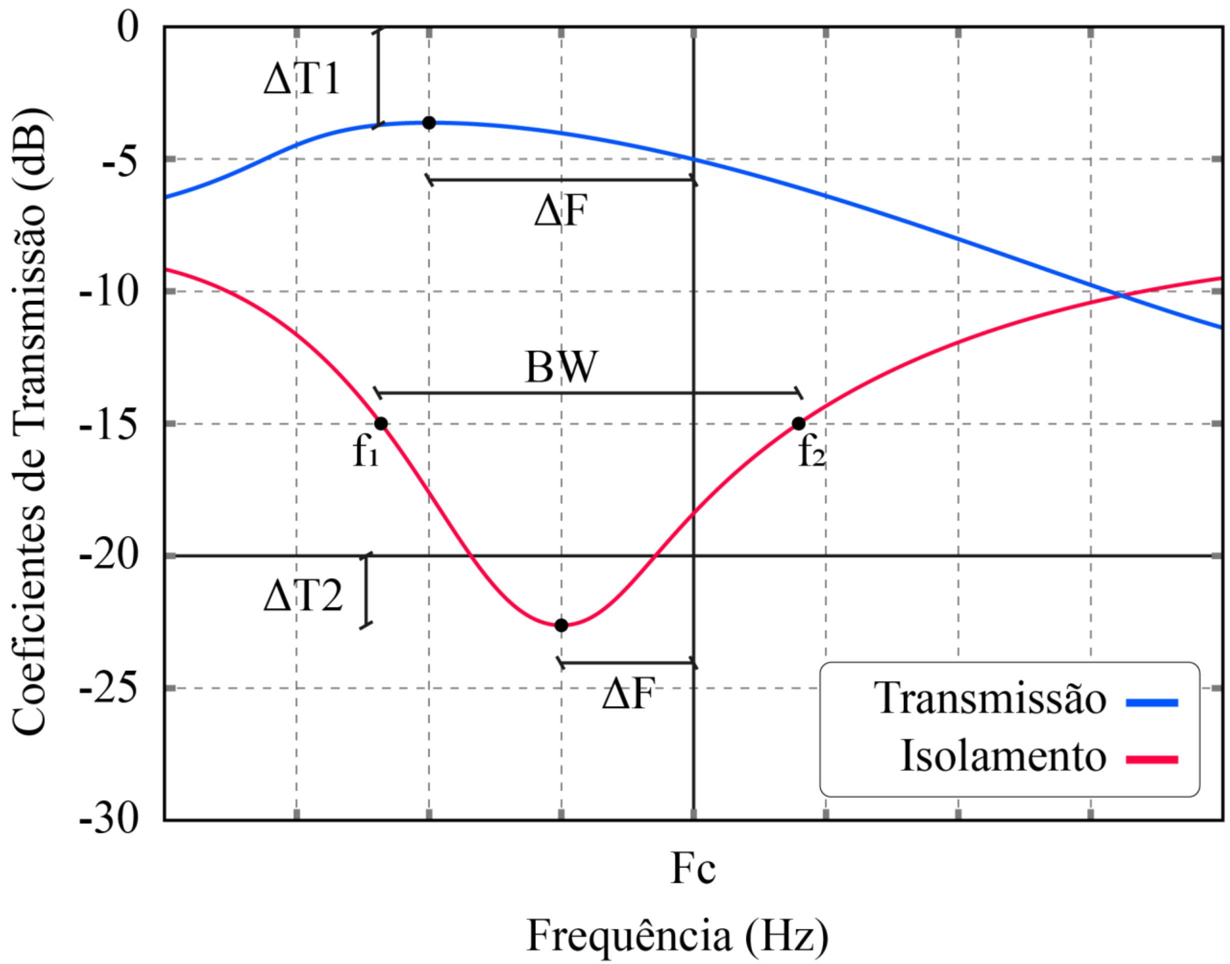
Construção do Banco de Dados



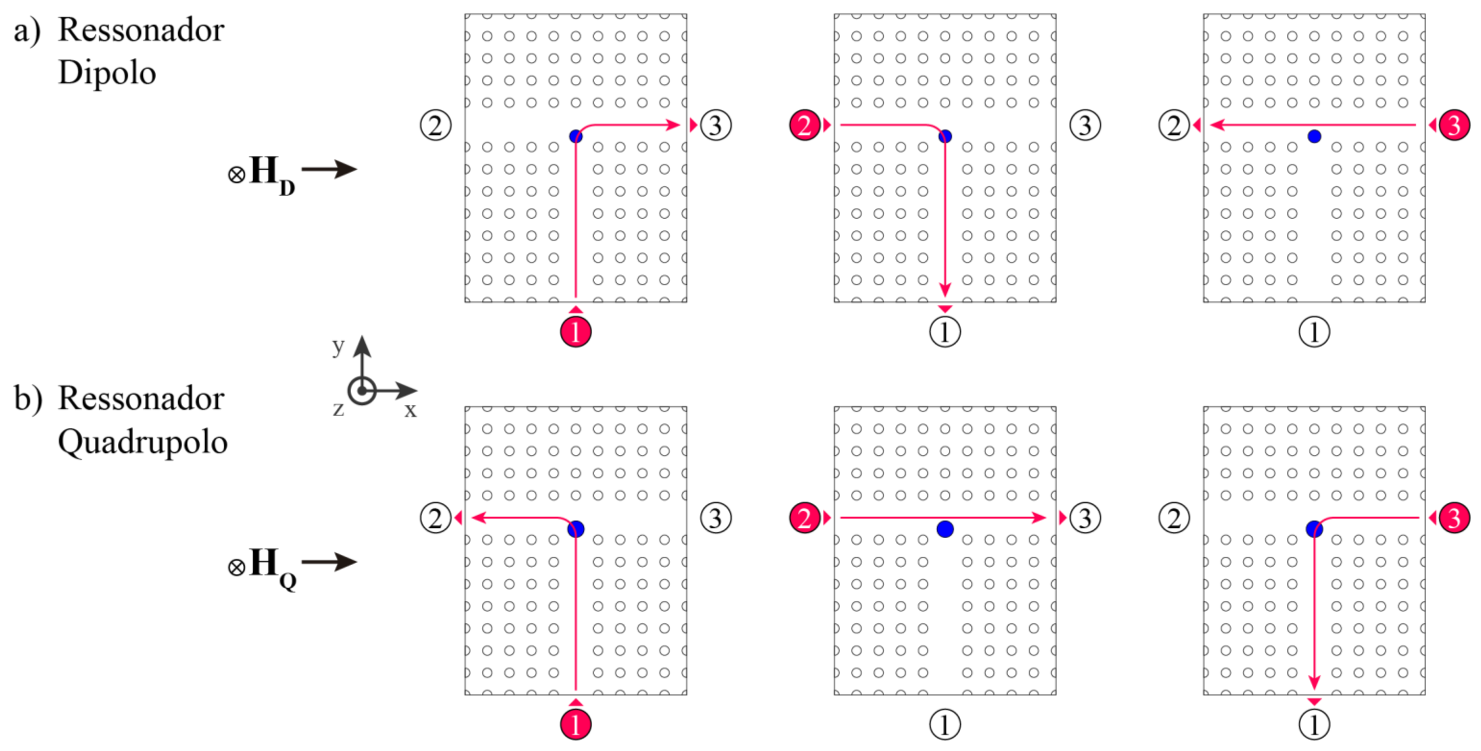
Construção do Banco de Dados

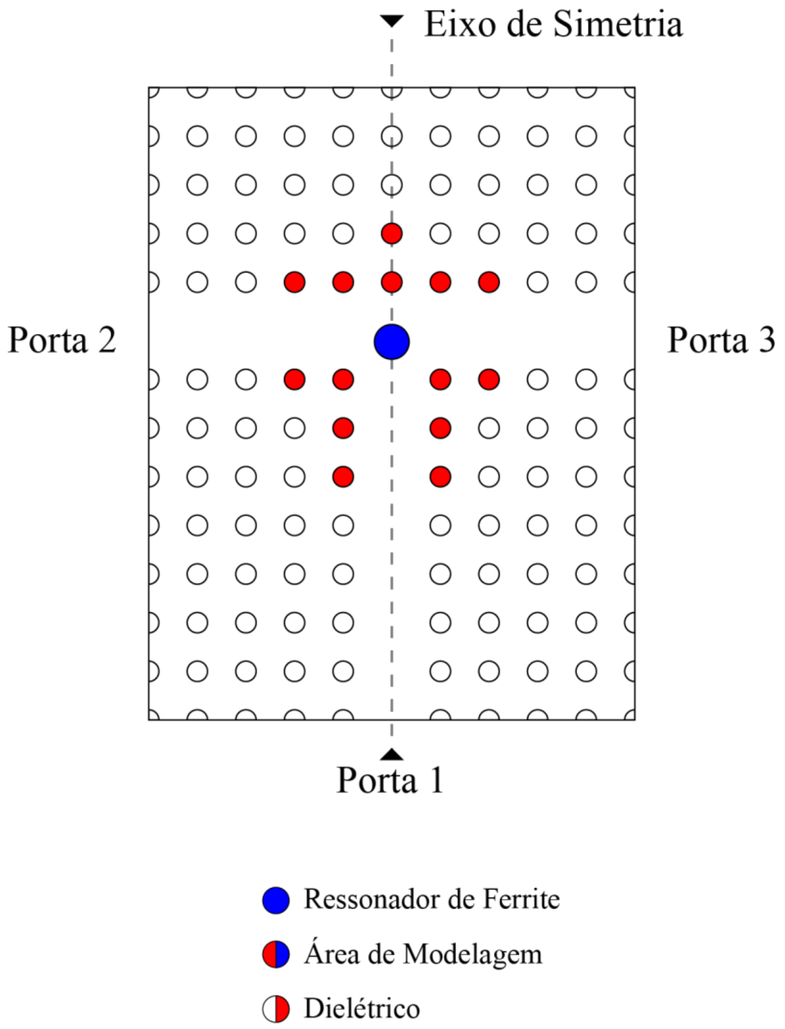


Fatores de Qualidade



Circulador Baseado em Cristal Fotônico





Arquitetura de Rede

- Entrada 459
- Saída 24

3 X 3 X 51 = 459

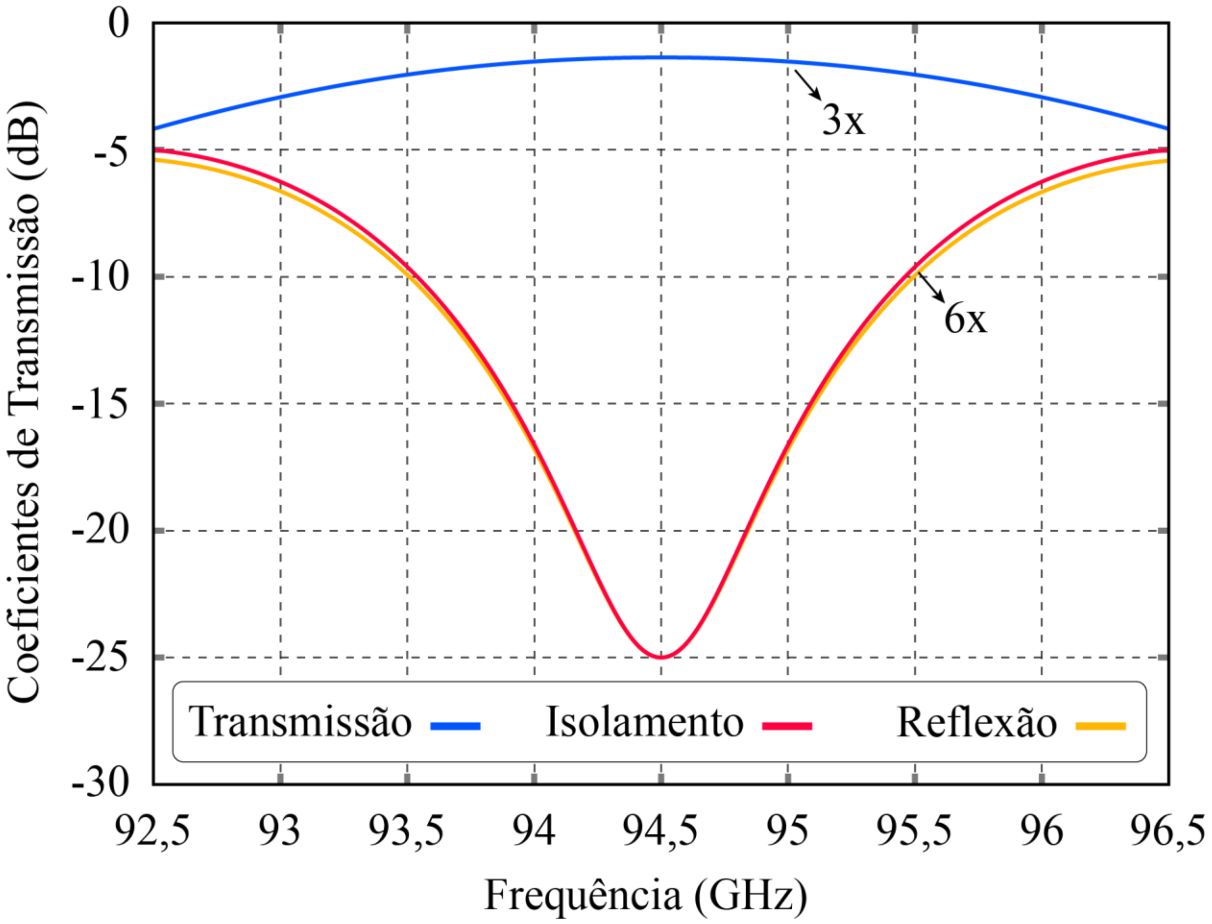
- Rede 1 ⟶ 459 - 200 - 24
- Rede 2 ⟶ 459 - 200 - 100 - 24
- **Rede 3** ⟶ 459 - 300 - 200 - 100 - 24

- Rede 4 ⟶ (51) || x9 -> 459 - 300 - 200 - 100 - 24
- **Rede 5** ⟶ (51 - 51 - 51) || x9 -> 459 - 200 - 100 - 24
- Rede 6 ⟶ (51 - 51 - 51 - 51 - 51 - 51) || x9 -> 459 - 300 - 200 - 100 - 24

- Performance

Rede	Erro (Dipolo)	Erro (Quadrupolo)
1	3,6307e-2	4,3351e-2
2	2,8347e-2	3,7666e-2
3	2,6205e-2	3,5608e-2
4	2,5085e-2	3,3075e-2
5	**2,4539e-2**	**3,2202e-2**
6	2,5934e-2	3,3595e-2

Operação Ideal



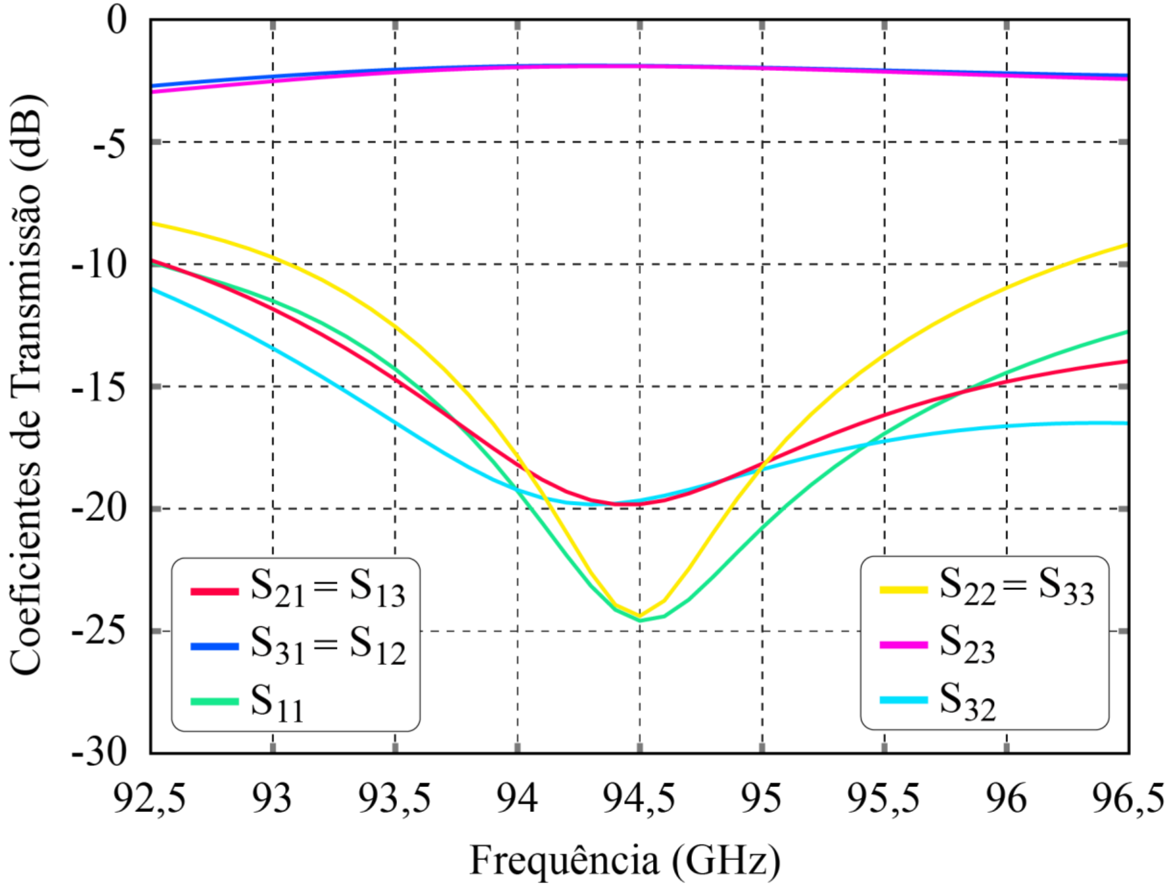
CAPÍTULO 4

RESULTADOS

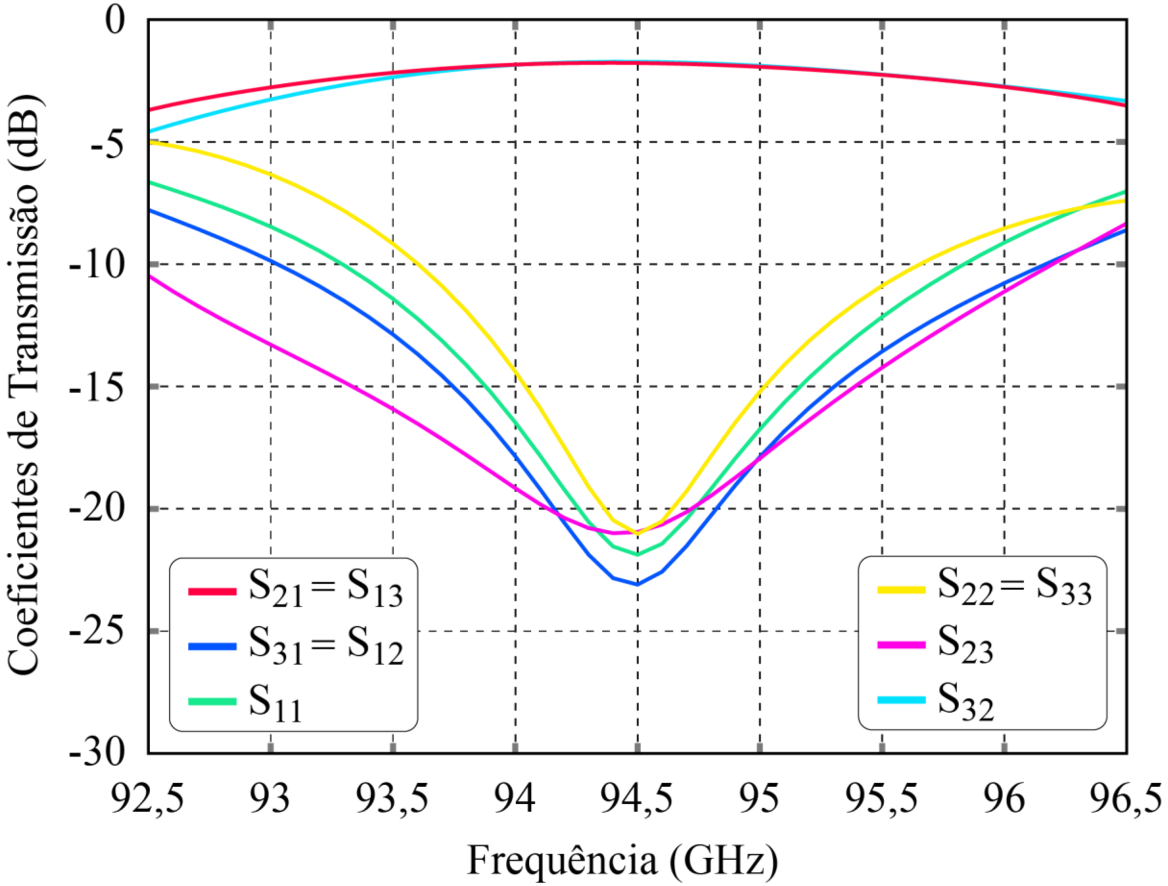
- Circulador

Resposta em Frequência

Dipolo

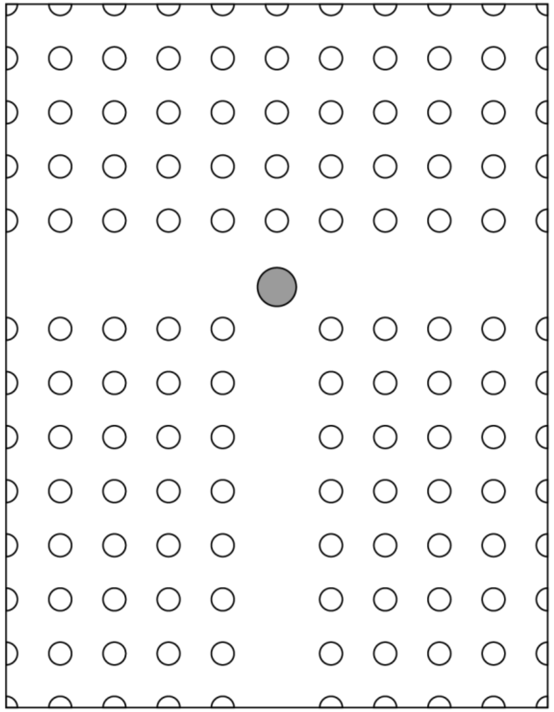


Quadrupolo

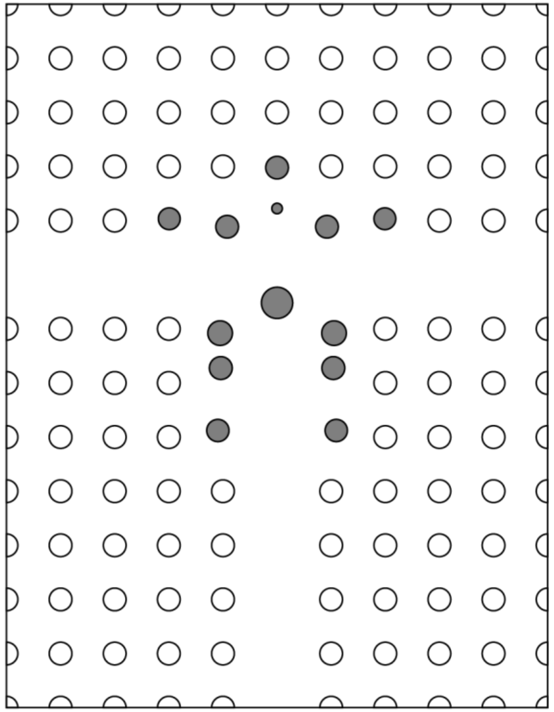


Geometria Otimizada

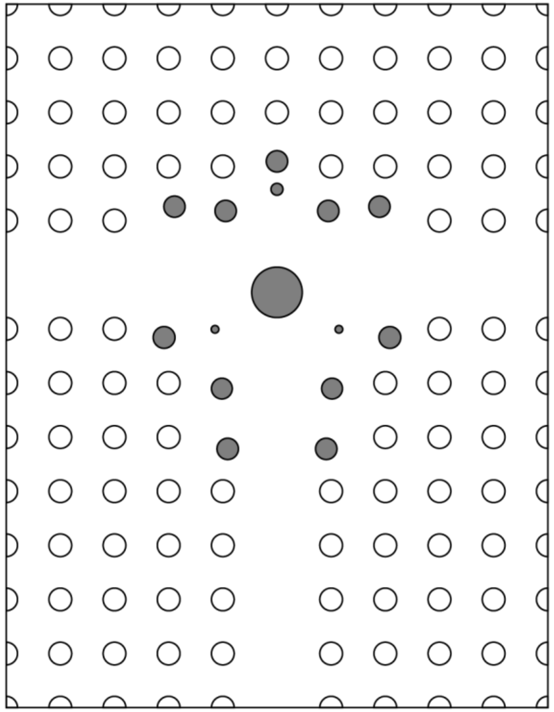
» Geometria Base



» Dipolo



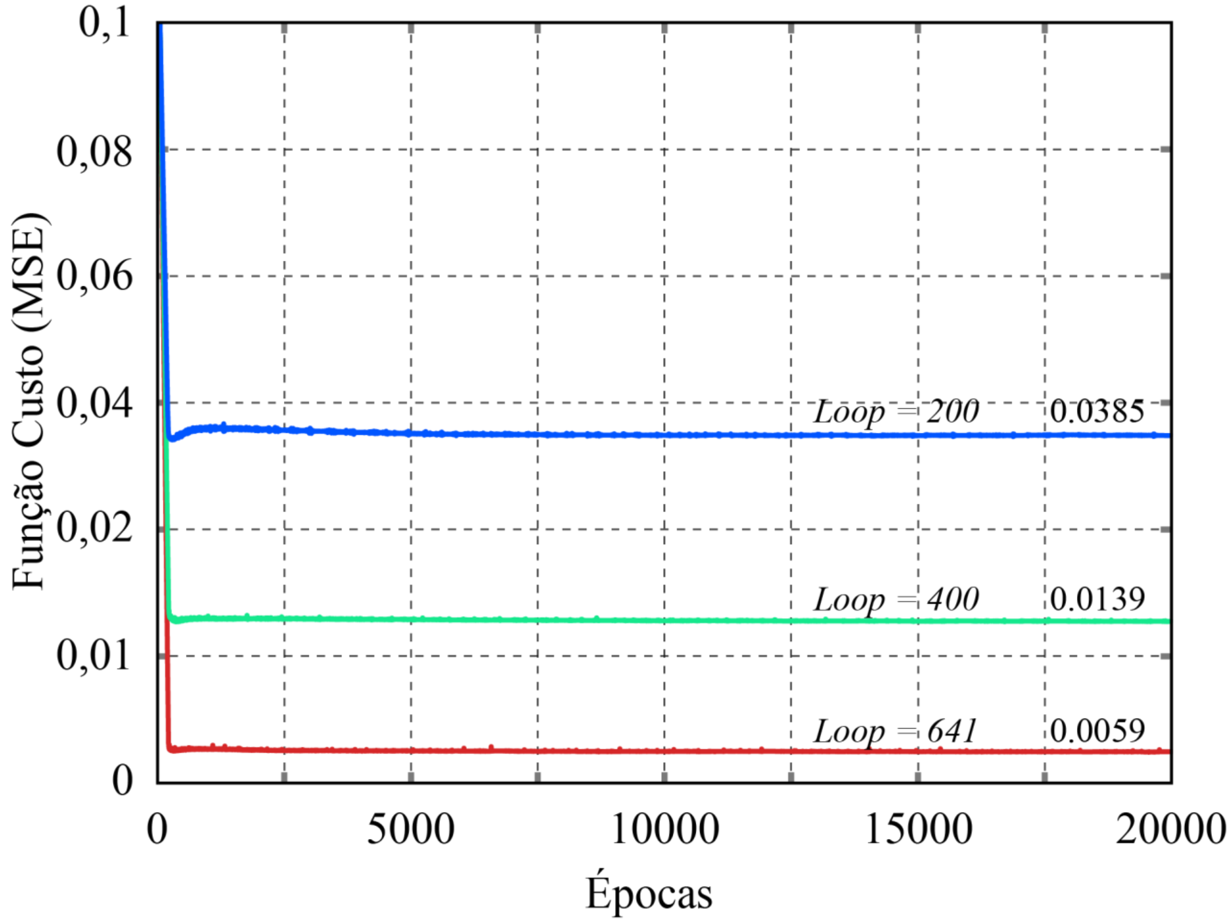
» Quadrupolo



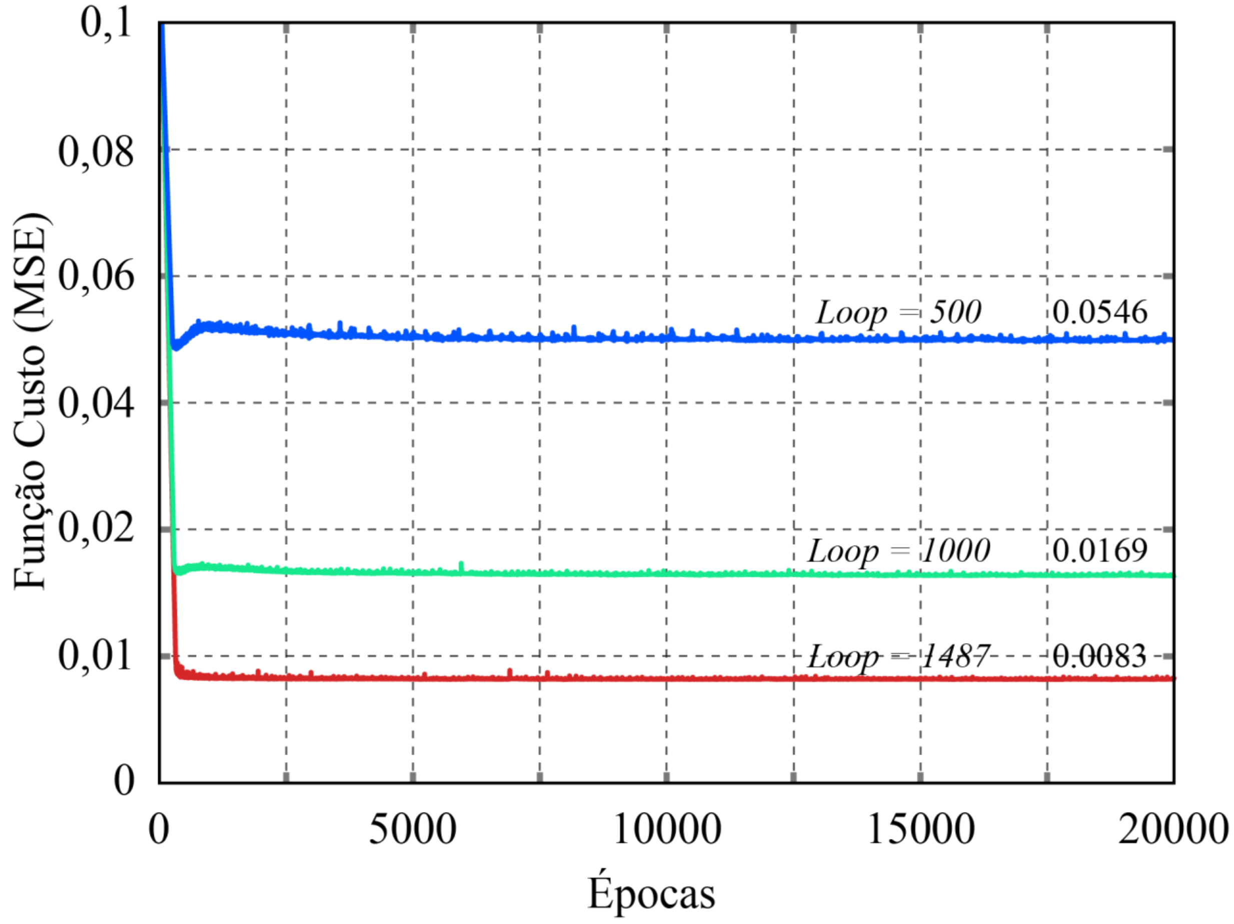
Geometria Otimizada

Performance - Rede Neural

Dipolo



Quadrupolo



Performance - Fatores de Qualidade

Dipolo

Fatores	Valor Ideal	Valor Otimizado	Erro (MSE)
ΔF_{11}	94,5 GHz	94,5 GHz	0
ΔF_{21}	94,5 GHz	94,5 GHz	0
ΔF_{31}	94,5 GHz	94,5 GHz	0
ΔF_{12}	94,5 GHz	94,5 GHz	0
ΔF_{22}	94,5 GHz	94,5 GHz	0
ΔF_{32}	94,5 GHz	94,3 GHz	0,04
ΔF_{13}	94,5 GHz	94,4 GHz	0,01
ΔF_{23}	94,5 GHz	94,5 GHz	0
ΔF_{33}	94,5 GHz	94,5 GHz	0
$\Delta T1_{21}$	-1 dB	-1,7 dB	0,49
$\Delta T1_{32}$	-1 dB	-1,7 dB	0,49
$\Delta T1_{13}$	-1 dB	-1,7 dB	0,49
$\Delta T2_{11}$	≤ -20 dB	-24,9 dB	0
$\Delta T2_{31}$	≤ -20 dB	-19,98 dB	0,04
$\Delta T2_{12}$	≤ -20 dB	-24,85 dB	0
$\Delta T2_{22}$	≤ -20 dB	-20,1 dB	0
$\Delta T2_{23}$	≤ -20 dB	-20,1 dB	0
$\Delta T2_{33}$	≤ -20 dB	-24,85 dB	0
BW	- -	1,5 GHz	- -

Quadrupolo

Fatores	Valor Ideal	Valor Otimizado	Erro (MSE)
ΔF_{11}	94,5 GHz	94,5 GHz	0
ΔF_{21}	94,5 GHz	94,4 GHz	0,01
ΔF_{31}	94,5 GHz	94,5 GHz	0
ΔF_{12}	94,5 GHz	94,5 GHz	0
ΔF_{22}	94,5 GHz	94,5 GHz	0
ΔF_{32}	94,5 GHz	94,4 GHz	0,01
ΔF_{13}	94,5 GHz	94,4 GHz	0,01
ΔF_{23}	94,5 GHz	94,4 GHz	0,01
ΔF_{33}	94,5 GHz	94,5 GHz	0
$\Delta T1_{21}$	-1 dB	-1,76 dB	0,57
$\Delta T1_{32}$	-1 dB	-1,72 dB	0,51
$\Delta T1_{13}$	-1 dB	-1,76 dB	0,57
$\Delta T2_{11}$	≤ -20 dB	-21,87 dB	0
$\Delta T2_{31}$	≤ -20 dB	-23,09 dB	0
$\Delta T2_{12}$	≤ -20 dB	-23,09 dB	0
$\Delta T2_{22}$	≤ -20 dB	-20,97 dB	0
$\Delta T2_{23}$	≤ -20 dB	-20,99 dB	0
$\Delta T2_{33}$	≤ -20 dB	-21,02 dB	0
BW	- -	0,9 GHz	- -

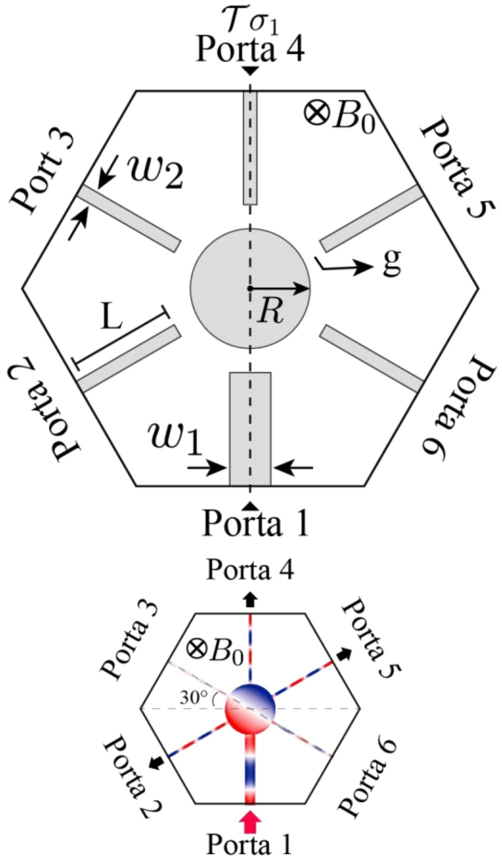
APÊNDICE

APLICAÇÃO EM DIVISOR DE POTÊNCIA

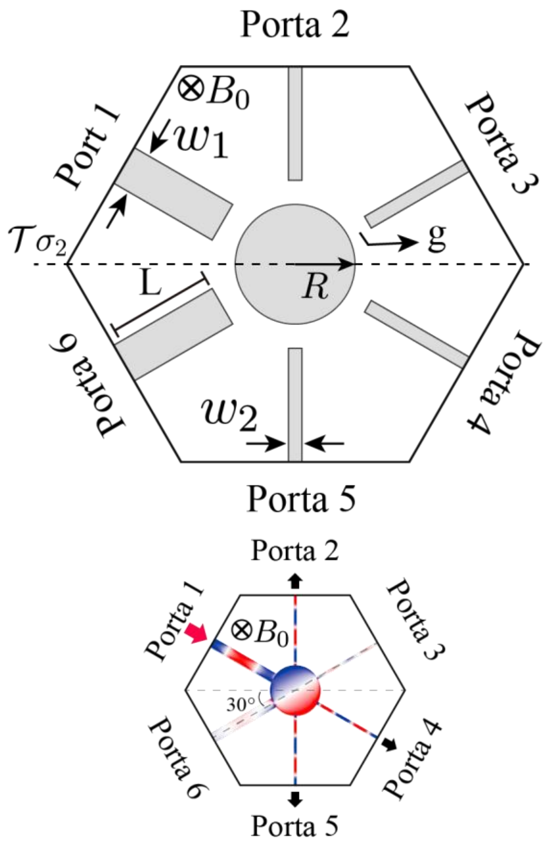
- Dispositivos
- Resultados Parciais

- Divisor de potência baseado em grafeno

a) Simetria Vertical



b) Simetria Horizontal



Arquitetura de Rede

- Entrada 306
- Saída 19

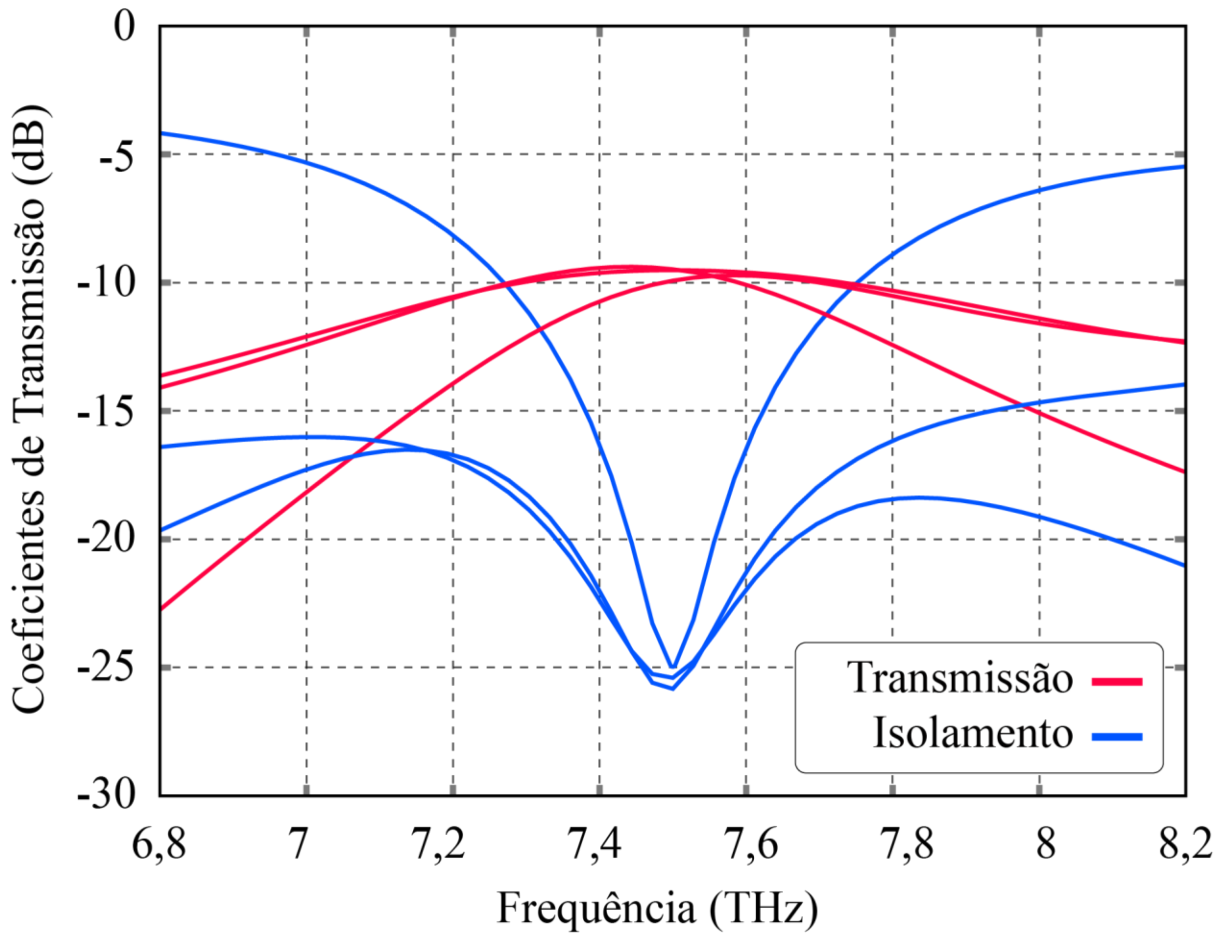
- Rede 1 ⟶ 306 - 150 - 19
- Rede 2 ⟶ 306 - 200 - 100 - 19
- **Rede 3** ⟶ 306 - 150 - 100 - 50 - 19

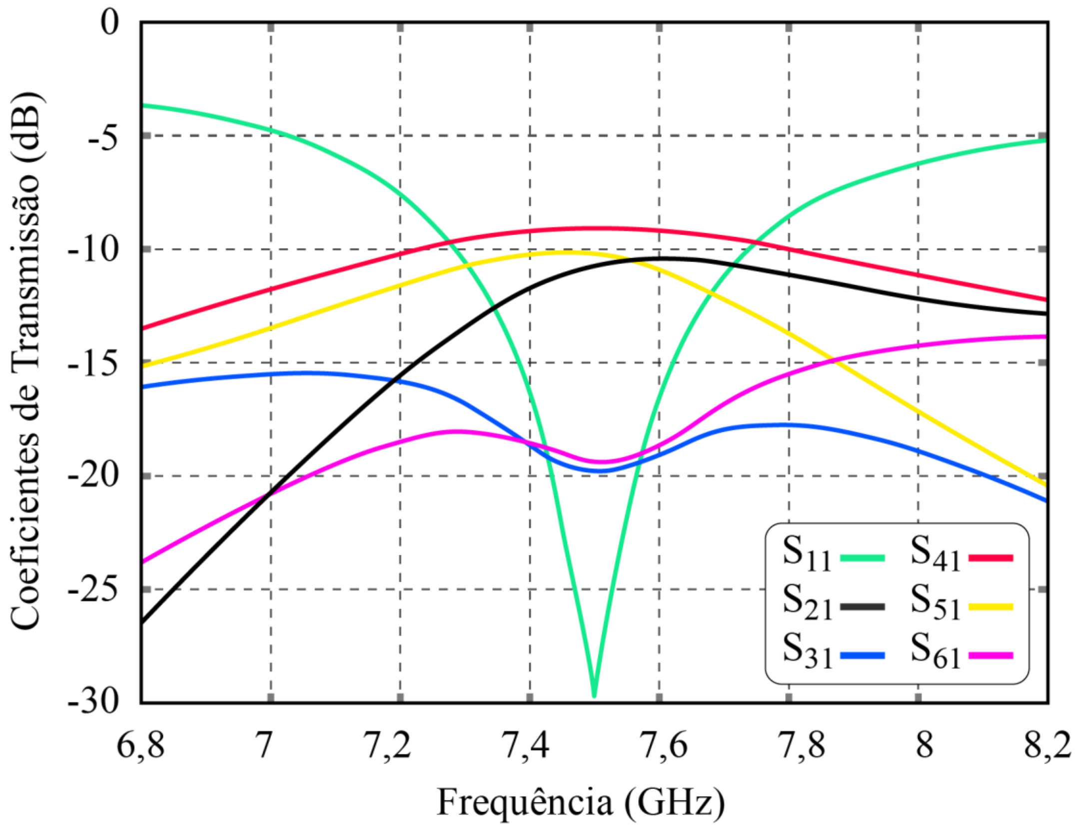
- Rede 4 ⟶ (51) || x6 -> 306 - 150 - 100 - 50 - 19
- **Rede 5** ⟶ (51 - 51 - 51) || x6 -> 306 - 150 - 100 - 50 - 19
- Rede 6 ⟶ (51 - 51 - 51 - 51 - 51 - 51) || x6 -> 306 - 150 - 100 - 50 - 19

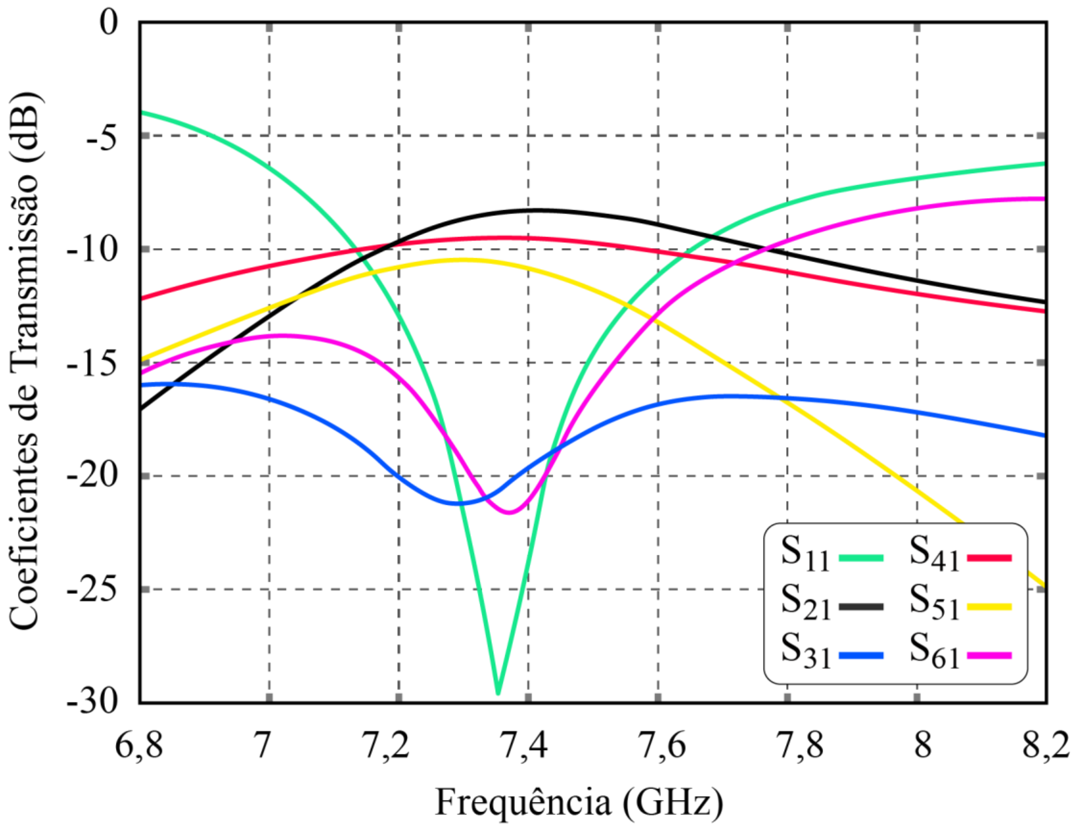
- Performance

Rede	Erro (Divisor Vertical)	Erro (Divisor Horizontal)
1	3,5325e-2	5,4233e-2
2	3,1709e-2	4,8093e-2
3	2,6919e-2	3,7429e-2
4	2,6228e-2	4,1021e-2
5	**2,3523e-2**	**3,6947e-2**
6	2,6551e-2	3,0931e-2

Operação Ideal




0
-5
-10
-15
-20
-25
-30
Coeficientes de Transmissão (dB)
6,8
7
7,2
7,4
7,6
7,8
8
8,2
Frequência (GHz)
S_{11}
S_{21}
S_{31}
S_{41}
S_{51}
S_{61}


0
-5
-10
-15
-20
-25
-30
Coeficientes de Transmissão (dB)
6,8
7
7,2
7,4
7,6
7,8
8
8,2
Frequência (GHz)
S_{11}
S_{21}
S_{31}
S_{41}
S_{51}
S_{61}

CAPÍTULO 5

CONSIDERAÇÕES FINAIS

- Conclusão
- Sugestões para Trabalhos Futuros
- Trabalhos Desenvolvidos

» Circulador baseado em Cristal Fotônico

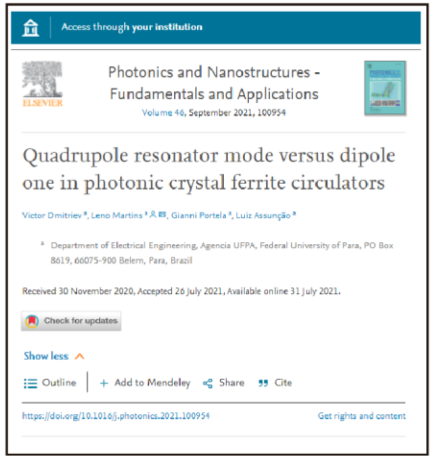
- Circulador Dipolo → 3 semanas
- Circulador Quadrupolo → 5 semanas

» Método promissor para o design de nanoestruturas baseadas em **Cristais Fotônicos**.

» Método pode ser aplicado ao design de estruturas, independentemente da escala.

» O uso de APIs facilitam muito na integração e automatização de processos.

- Uso de **redes neuriais convolucionais** para o design inverso.
- Implementação de modelos **generativos** e **discriminativos** em conjunto (**GANs**) para o design inverso.
- Averiguar as implicações do **problema da não-unicidade** da resposta eletromagnética.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Photonics and Nanostructures - Fundamentals and Applications
Volume 46, September 2021, 100954

Quadrupole resonator mode versus dipole one in photonic crystal ferrite circulators

Victor Dmitriev [a], Leno Martins [a], Gianni Portela [a], Luiz Assunção [a]

[a] Department of Electrical Engineering, Agencia UFPA, Federal University of Para, PO Box 8619, 66075-900 Belem, Para, Brazil

Received 30 November 2020, Accepted 26 July 2021, Available online 31 July 2021.

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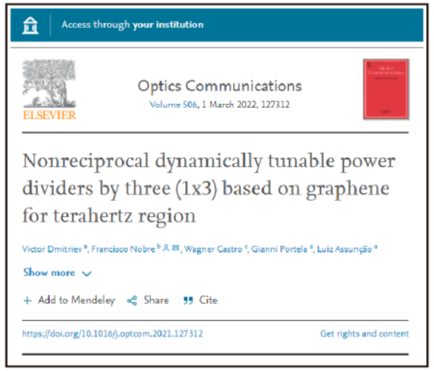
[1] V. Dmitriev, G. Portela, L. Martins and L. Assunção. *“Quadrupole resonator mode versus dipole one in photonic crystal ferrite circulators”*. Photonics and Nanostructures - Fundamentals and Applications, 2021.

DOI: https://doi.org/10.1016/j.photonics.2021.100954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Optics Communications
Volume 506, 1 March 2022, 127312

Nonreciprocal dynamically tunable power dividers by three (1x3) based on graphene for terahertz region

Victor Dmitriev [a], Francisco Nobre [b], Wagner Castro [c], Gianni Portela [a], Luiz Assunção [a]

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[2] V. Dmitriev, F. Nobre, W. Castro, G. Portela and L. Assunção. *“Nonreciprocal Dynamically Tunable Power Dividers By Three (1x3) Based on Graphene for Terahertz Region”*. Optics Communications, 2021.

DOI: https://doi.org/10.1016/j.optcom.2021.127312

VICTOR DMITRIEV
LUIZ H. P. ASSUNÇÃO

OBRIGADO!

REFERÊNCIAS

- [1] V. Dmitriev, G. Portela, L. Martins and L. Assunção. *"Quadrupole resonator mode versus dipole one in photonic crystal ferrite circulators"*. Photonics and Nanostructures - Fundamentals and Applications, 2021.
- [2] V. Dmitriev, F. Nobre, W. Castro, G. Portela and L. Assunção. *"Nonreciprocal Dynamically Tunable Power Dividers By Three (1x3) Based on Graphene for Terahertz Region"*. Optics Communications, 2021.

AGRADECIMENTOS

ITEC INSTITUTO DE TECNOLOGIA UFPA
FEEB Faculdade de Engenharias Elétrica e Biomédica | UFPA
NanoTribo
CNPq Conselho Nacional de Desenvolvimento Científico e Tecnológico
PROPESP Pró-Reitoria de Pesquisa e Pós-Graduação | UFPA

FIM