



Benchmarking Foundational AI Models for the Future-Oriented Simulation of Microwave Integrated Circuit Components

Saeid Mohammadpour Jaghargh¹, Pejman Rezaei¹* and Mohammad Ali Rezaei¹

Abstract-- Owing to the rapid development of Artificial Intelligence (AI) and its growing impact on electromagnetism, this work—as a future-oriented perspective study—investigates the accuracy of several new large language models (LLMs) in the design, estimation, and simulation of monolithic microwave integrated circuit (MMIC) components. As a classical case study, a microstrip parallel-coupled line bandpass filter is designed in the X-band frequency range; following that, it is simulated using three foundational models and compared against two accurate, full-wave, conventional electromagnetic (EM) simulators—i.e., the finite element method (FEM) and the method of moments (MoM)—as well as experimental measurement results. Despite the fact that some LLMs could not satisfy the necessities and demands of EM simulations, the net results demonstrate that although LLMs could serve as useful assistants to those energy-intensive full-wave simulators, especially when integrated with them, and might stand as promising near-future candidates for EM simulations, in their present form they fail to produce physically consistent results for quantitative EM simulation; nevertheless, their high processing speed, accessibility, and growing adoption suggest that with future physics-informed training and architectural improvements, they could evolve into useful supplementary tools for the EM field.

Index Terms- Artificial intelligence (AI), electromagnetic simulation (EMS), finite element method (FEM), large language model (LLM), method of moments (MoM), microstrip bandpass filter, monolithic microwave integrated circuit (MMIC), multimodal large language model (MLLM), parallel-coupled line filter.

NOMENCLATURE

Abbreviation	Description
1 AI	Artificial Intelligence
2 DC / EC	Decoder / Encoder
3 EM	Electromagnetics
4 EMS	Electromagnetic Simulation
5 FBW	Fractional Bandwidth
6 FEM	Finite Element Method
7 GPT	Generative Pre-trained Transformer (omni)
8 GRPO	Group Relative Policy Optimization
9 LLM	Large Language Model
10 MMIC	Monolithic Microwave Integrated Circuit
11 MoM	Method of Moments
12 RAG	Retrieval-Augmented Generation
13 SFT	Supervised Fine-Tuning
14 VLM	Vision Language Models
15 VNA	Vector Network Analyzer

I. INTRODUCTION

IN recent years, artificial-intelligence-based (AI-based) large language models (LLMs) have not only revolutionized science and technology but also facilitated complex traditional mathematical approaches due to their fast, coherent, accurate, and human-like responses to various queries. Compared to conventional neural networks, LLMs—as deep learning models—contain numerous network layers and trillions

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1. Faculty of Electrical and Computer Engineering, Semnan University, Semnan, Iran.

*Corresponding author Email: prezaei@semnan.ac.ir

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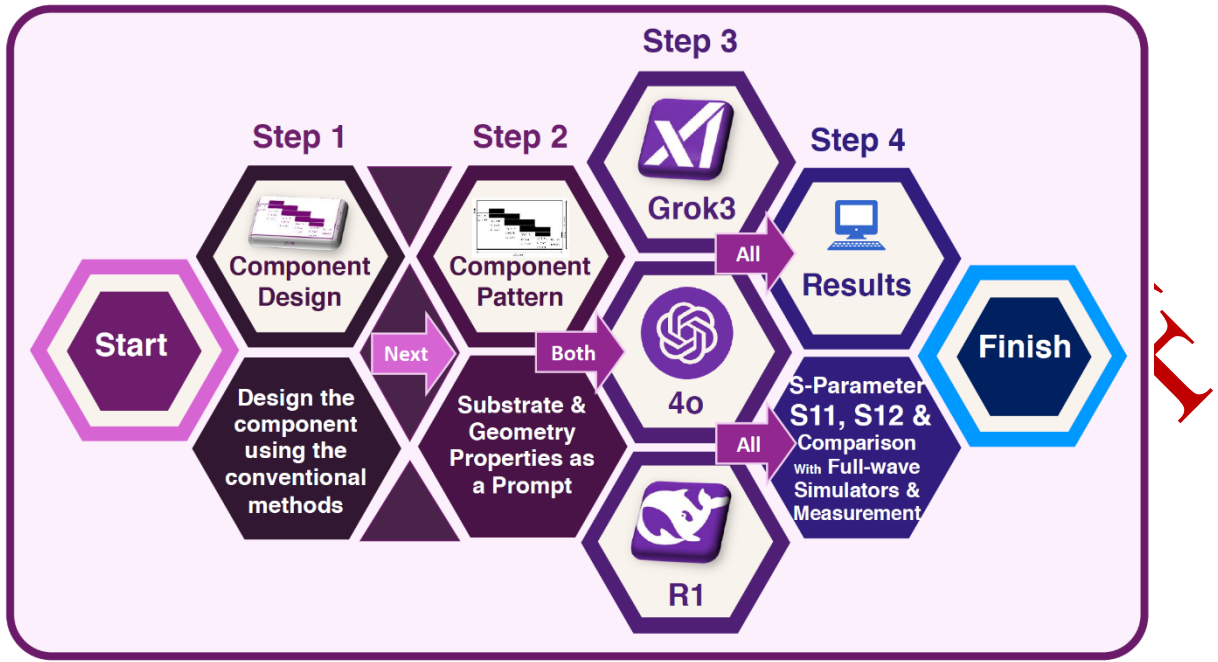


Fig. 1. A hexagon infographic for benchmarking LLMs in the simulation and design of microwave integrated circuit components.

TABLE I
Comparison of State-of-the-Art LLMs

Model	Params.	Layer	Archi. ^a	Primary Domain	Technique
GPT-4o 2024/5	1.8 Trillion	120	DC ^b only	General-purpose	Multimodal, Key-value cache
Grok3 2025/1	Tens of Billions	NA	DC only	Real-time QA	Multimodal, SFT ^d
DeepSeek R1 2025/1	671 B	61	DC only	Thinking Math/Code tasks	SFT, GRPO-based RL ^e , MoE ^g , Quantization
Gemini 2.0 Flash 2025/1	Undisclosed (Flash size)	NA	DC only	Low latency	MoE, Long-context proc.
Microsoft Copilot 2023/3	Varies: encoders to GPT-4 sizes	Varies	EC ^c only	Enterprise productivity and search	SFT, RAG pipelines ^h

^a Archi.: Architecture

^b DC: Decoder

^c EC: Encoder

^d SFT: Supervised Fine-Tuning

^e GRPO-based RL: Reinforcement Learning with GRPO

^f GRPO: Group Relative Policy Optimization

^g MoE: Mixture of Experts

^h RAG: Retrieval-Augmented Generation

of parameters, and they have been trained on enormous datasets. Therefore, they can intelligently understand natural language and respond to users' prompts in a reasonable manner. Foundational AI models, or multimodal LLMs—considered the state-of-the-art among LLMs—have been trained on massive datasets and are capable of interpreting various types of data, such as patterns, videos, and audio [1]–[2]. They tend to be defined as vision-language models (VLMs) in some references. The most cutting-edge multimodal LLMs—namely GPT-4o, DeepSeek-R1, Grok3, Gemini 2.0 Flash, and Microsoft Copilot (as a product)—are compared in Table I in terms of the number

of parameters (learnable weights), transformer layers, architectures, as well as optimization techniques. These optimization techniques include Supervised Fine-Tuning (SFT), Mixture of Experts (MoE), Group Relative Policy Optimization (GRPO)-based reinforcement learning, and Retrieval-Augmented Generation (RAG), among others. For further details, refer to [3], [4].

Recently, LLMs have been investigated across a range of areas. For example, they have been benchmarked for sentiment classification in social media [5], medical science (e.g., anesthesiology) [6], general medicine [7], and robotics (e.g., service mobile robots) [8] to evaluate their capabilities, accuracy, and effectiveness. Moreover, in some research [9], a standard approach to LLM benchmarking has been introduced, which could also represent a potential field of study in electromagnetics (EM) from a future-oriented standpoint.

To the best of the authors' knowledge, no prior study has benchmarked foundational multimodal LLMs for the direct numerical simulation of monolithic microwave integrated circuit (MMIC) components. Nevertheless, LLMs have recently been explored in broader electromagnetics contexts—such as fine-tuned models for metamaterial prediction [10], and a circuit-focused benchmark for investigating LLMs [11]. None of these works employed multimodal models in a zero-shot setting to extract full S-parameter sets from a 2D layout, nor did they systematically compare LLM outputs against full-wave simulations and measurements. The present research, therefore, represents a first step toward establishing a standardized benchmarking framework for LLMs in EM simulation.

In this study, the authors benchmark the aforementioned foundational AI models in the field of EM, specifically in the design and simulation of MMIC components. To evaluate the capabilities of these AI models, a microstrip parallel-coupled line bandpass filter is first designed using conventional methods. As is well known, microstrip technology remains a cornerstone of modern microwave engineering, enabling a wide

range of planar components such as antennas [12], [13], filters [14], [15], and advanced metamaterial circuits [16], [17].

Subsequently, a 2D image of the filter, including its physical dimensions and other necessary details, is provided to the LLMs as a prompt. Unlike 2.0 Flash and Copilot, the other multimodal LLMs are remarkably able to simulate the microstrip filter, demonstrating tremendous pattern recognition abilities. Finally, the outcomes derived from the multimodal models are compared with those obtained from two traditional, trusted numerical methods—the finite element method and method of moments—as well as measured results. Fig. 1 illustrates this process. The results of this work not only open a new window for the benchmarking and standardization of LLMs in EM but also reveal that foundational LLMs may soon surpass the traditional EM simulators.

II. MMIC COMPONENT DESIGN

Among parallel-coupled line microstrip structures—such as sensors [18], substrate integrated waveguide filters [19], optical plasmonic filters with concentric rings [20], antennas [21], [22], and metamaterials [23] – a microstrip three-pole parallel-coupled line bandpass filter, serving as a simple and conventional benchmark, has been designed. The filter is terminated with 50Ω and implemented on an *RO4003C* substrate with a height of 0.7874 mm. The substrate properties are $\epsilon_r = 3.36$, $\tan\delta = 0.0036$. As shown in Fig. 2, half-wavelength resonators are used in this type of filter. Adjacent resonators are arranged in parallel, with half of each resonator coupled to the other. There is a relatively strong coupling between each resonator and its adjacent counterpart, which makes this type of bandpass filter structure advantageous for applications requiring a broader bandwidth. The physical length of the j -th coupled line is given by:

$$l_j = \frac{\lambda_0}{4 \left(\sqrt{(\epsilon_{re})_j \cdot (\epsilon_{ro})_j} \right)^{1/2} - \Delta l_j} \quad (1)$$

where λ_0 is the free-space wavelength at the center frequency, ϵ_{re} and ϵ_{ro} are the even-mode and odd-mode effective dielectric constants, respectively. Owing to fringing fields, the length correction term Δl_j appears at the end of each resonator. Further details can be found in [24].

III. BRIEF ELECTROMAGNETIC THEORY ON HALF-WAVELENGTH MICROSTRIP FILTER

Parallel-coupled microstrip filters, also referred to as edge-coupled filters in some references, use resonators that are half-wavelength long. Parallel-coupled microstrip filters exhibit a broader bandwidth compared to end-coupled filters, due in part to stronger coupling between adjacent resonators. Based on pre-assumed parameters (e.g., substrate properties (ϵ_r , $\tan\delta$, height of substrate, etc), desired center frequency f_0 , bandwidth ω_s , and passband ripple and stopband attenuation (L_{Ar} and L_{As})), the degree (order) of the filter n can be determined. It is evident that the required filter order differs for Butterworth, Chebyshev, and elliptic function responses.

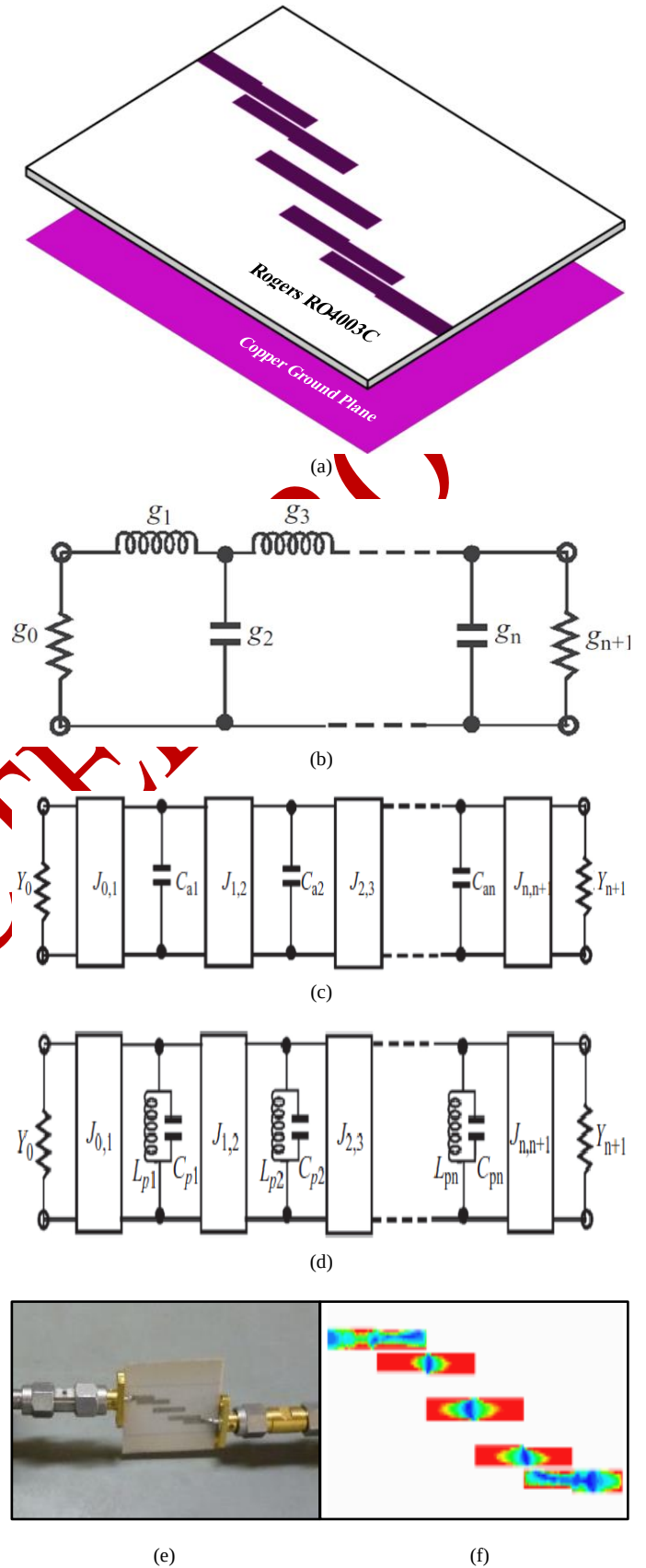


Fig. 2. (a) 3D view, (b) lowpass prototype, (c) lowpass prototype based on immittance inverters, (d) bandpass prototype based on immittance inverters, (e) fabricated prototype, and (f) electric field distribution of the proposed parallel-coupled microstrip filter at 10 GHz. The purplish regions are copper.

The elliptic function response typically presents one order less than Chebyshev filters and two orders less than Butterworth filters. Consequently, microstrip filters based on elliptic functions are simpler and require fewer resonators; however, their design procedure is more complex. In this work, as an engineering trade-off, the Chebyshev response has been selected. The minimum order of the filter is given by [25],[26]:

$$\frac{\cosh^{-1} \sqrt{\frac{10^{0.1L_{As}} - 1}{10^{0.1L_{Ar}} - 1}}}{\cosh^{-1} \omega_s} \leq n \quad (2)$$

To design a bandpass filter, the elements of its equivalent lowpass filter (g_i), shown in Fig. 2(b), are initially required to be calculated using the following equations [27]-[29]. Here, g_0 is assumed to be equal to one.

$$g_1 = \frac{2}{\sinh\left(\frac{\beta}{2n}\right)} \times \sin\left(\frac{\pi}{2n}\right) \quad (3)$$

For $i = 2, 3, \dots, n$:

$$g_i = \frac{1}{g_{i-1}} \times \frac{4 \sin\left(\frac{(2i-1)\pi}{2n}\right) \times \sin\left(\frac{(2i-3)\pi}{2n}\right)}{\sinh^2\left(\frac{\beta}{2n}\right) + \sin^2\left(\frac{(i-1)\pi}{n}\right)} \quad (4)$$

If n is odd, g_i is equal to one. Otherwise, it can be calculated using:

$$g_{n+1} = \coth^2\left(\frac{\beta}{4}\right) \quad (5)$$

where β can be defined as:

$$\beta = \ln \left[\coth \left(\frac{L_{Ar}}{17.37} \right) \right] \quad (6)$$

According to immittance inverter theory, inverters can shift the impedance or admittance range, simplifying the design of microwave implantation structures. Fig. 2(c) and 2(d) illustrate the equivalent lowpass and bandpass prototypes of Fig. 2(b), respectively. C_{pi} is equal to g_i . When transforming from a lowpass to a bandpass filter, each shunt capacitor (g_i) must be changed to a combination of a shunt capacitor and an inductor (C_{pi} and L_{pi}). Equivalently, each series inductor (g_i) should be transformed into a combination of a series capacitor and an inductor (C_{si} and L_{si}). These reactive elements can be obtained using:

$$C_{pi} = \frac{g_i}{\gamma_0} \times \frac{\Omega_c}{\omega_0 FBW} \quad (7)$$

$$L_{pi} = \frac{1}{C_{pi} \omega_0^2} \quad (8)$$

$$L_{si} = g_i \gamma_0 \times \frac{\Omega_c}{\omega_0 FBW} \quad (9)$$

$$C_{si} = \frac{1}{L_{si} \omega_0^2} \quad (10)$$

where γ_0 , Ω_c , and FBW represent the characteristic admittance (or normalized constant), the cut-off frequency, and the fractional bandwidth, respectively. As demonstrated in Fig. 2(c) and 2(d), the J -parameters remain invariable after the frequency shift and can be calculated as:

$$J_{0,1} = \sqrt{\frac{\omega_0 C_{p1} Y_0 FBW}{\Omega_c g_0 g_1}} \quad (11)$$

and for $i = 1, 2, \dots, n-1$

$$J_{i,i+1} = \frac{\omega_0 FBW}{\Omega_c} \times \sqrt{\frac{C_{pi} C_{p(i+1)}}{g_i g_{i+1}}} \quad (12)$$

$$J_{n,n+1} = \sqrt{\frac{\omega_0 C_{pn} Y_{n+1} FBW}{\Omega_c g_n g_{n+1}}} \quad (13)$$

Eventually, the design equations for a bandpass half-wavelength parallel-coupled microstrip filter are defined as:

$$\frac{J_{01}}{Y_0} = \sqrt{\frac{\pi}{2}} \times \sqrt{\frac{FBW}{g_0 g_1}} \quad (14)$$

where $J_{j,j+1}$ represents the characteristic admittance of the J -inverter, and $Y_0 = 1/Z_0$ (terminating lines characteristic admittance with $Z_0 = 50 \Omega$). Also, for $j = 1, 2, \dots, n-1$

$$\frac{J_{j,j+1}}{Y_0} = \frac{\pi}{2} \times \frac{FBW}{\sqrt{g_j g_{j+1}}} \quad (15)$$

$$\frac{J_{n,n+1}}{Y_0} = \sqrt{\frac{\pi}{2}} \times \sqrt{\frac{FBW}{g_n g_{n+1}}} \quad (16)$$

For $j = 0, 1, 2, \dots, n$, the microstrip resonator odd-mode and even-mode characteristic impedances in this kind of filter are given by:

$$[Z_{0o}]_{j,j+1} = \frac{1}{Y_0} \left(1 - \frac{J_{j,j+1}}{Y_0} + \left(\frac{J_{j,j+1}}{Y_0} \right)^2 \right) \quad (17)$$

$$[Z_{0e}]_{j,j+1} = \frac{1}{Y_0} \left(1 + \frac{J_{j,j+1}}{Y_0} + \left(\frac{J_{j,j+1}}{Y_0} \right)^2 \right) \quad (18)$$

After calculating (17) and (18), and considering the dielectric constant and the substrate height, ϵ_{re} and ϵ_{ro} can be determined, which in turn yield the width, spacing, as well as physical length of the j -th coupled line. For further information, refer to Chapter 4 of [24]. Moreover, (1) provides a well-suited estimation of the physical length. The physical dimensions of the ultimate microstrip filter are illustrated in Fig. 3.

IV. PROMPT OR QUERY ENGINEERING

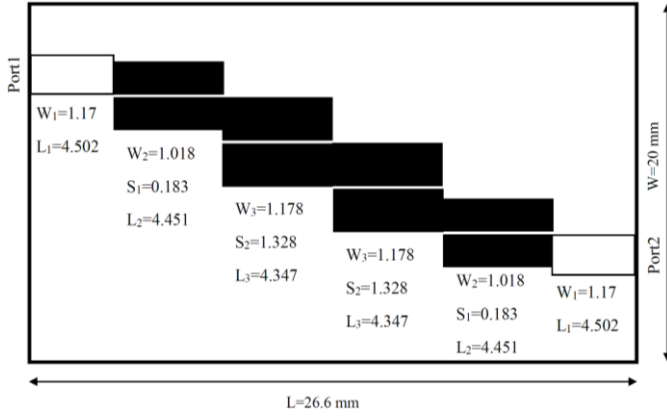


Fig. 3. The pattern used to prompt AI models, which also illustrates the proposed structure's layout. Units are in millimeters.

Having designed and specified the dimensions of the microwave component, the user provides a 2D image of the filter, as shown in Fig. 3, to the aforementioned LLMs as an appropriate prompt. W_i , S_i , and L_i represent the width, length, and spacing between the coupled lines, respectively. Besides the 2D pattern, the substrate properties and the frequency range (1 to 20 GHz) required for the analysis were also provided to the multimodal models. The S-parameter values are extracted directly from the raw, plain-text outputs of each LLM and recorded without any modification or post-processing. Fig. 1 also illustrates this procedure.

As far as energy saving is concerned, LLM inference for a single query is fast; the training and deployment of large multimodal models are themselves energy-intensive processes. As a result, any future comparison with full-wave solvers must consider the full lifecycle energy cost, not just per-query speed. At the same time, measuring the energy consumption of hardware systems with full-wave software is a very laborious task, because these systems are usually distributed in a mosaic across research centers worldwide, and most of these software applications run on powerful hardware with power-hungry CPUs, GPUs, and FPGAs.

V. COMPARISON OF AI-BASED LLM, FULL-WAVE SIMULATION, AND MEASUREMENT

Only the computer vision systems of the three AI models—GPT-4o, DeepSeek-R1, and Grok3—responded coherently to the prompts and were able to generate and simulate the S-parameters of the microstrip filters. Furthermore, the results were attained using two full-wave methods—FEM and MoM—and then compared with measured results. For the simulations, these two very accurate and reliable methods have been attempted. In the FEM, which uses volumetric techniques, the

entire computational space and domain are discretized and then meshed. Then the differential form of Maxwell's equations is solved by the simulator. Its basis is the formulation of the vector wave equation, which follows the electric field E such that:

$$\int_{\Omega} (\nabla \times E) \cdot (\nabla \times v) d\Omega - k_0^2 \int_{\Omega} (\epsilon_r E \cdot v) d\Omega = A \quad (19)$$

$$A = -jk_0 Z_0 \int_{\Gamma} v \cdot J d\Gamma \quad (20)$$

for all test functions v in the appropriate function space is satisfied [30]. The MoM, in contrast, solves the surface integral equations, requiring discretization only of the conducting and dielectric surfaces; it is particularly efficient for planar microwave structures [31]. Together, these two methods provide a trusted and well-established baseline against which LLM-generated results are compared.

As shown in Figs. 4 and 5, the full-wave simulations and measured results exhibit good agreement, while the AI-based results demonstrate consistency primarily with each other. As indicated, Fig. 4 has two sections, and the zoom-in part shows details from 8 to 12 GHz. The comparison also reveals that LLMs, with their strong pattern recognition capabilities, could accurately predict the center frequency (f_0) of the microwave component and the magnitude of insertion loss at f_0 . Nevertheless, the LLMs were unable to achieve acceptable accuracy in predicting the FBW and magnitude of S_{11} at f_0 . Although there is a negligible frequency shift between the full-wave methods and the measured results,

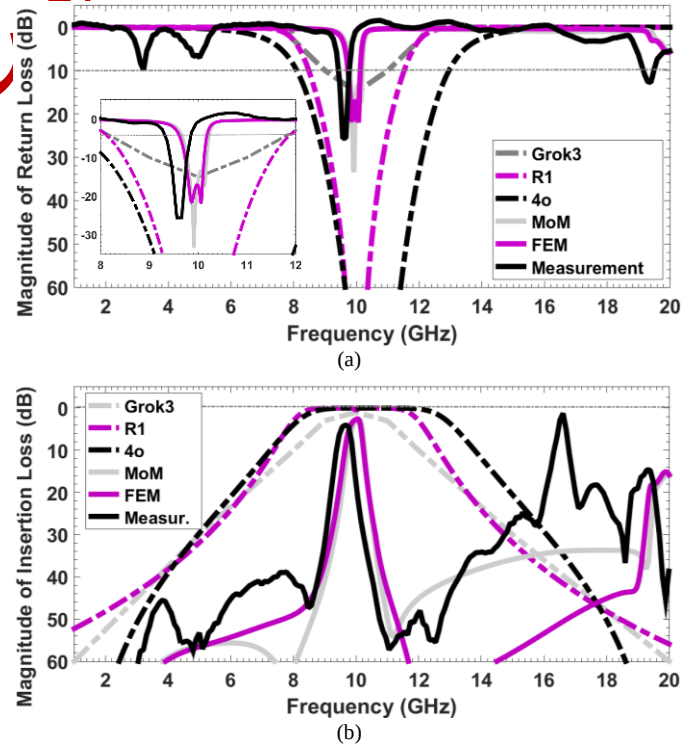


Fig. 4. Comparison of the magnitude of AI-predicted S-parameters for the proposed microstrip filter with results from full-wave simulations and measurements. (a) Return loss, displayed in two sections: the upper section shows the full frequency range, while the lower section provides a zoomed-in view of the 8-12 GHz band. (b) Insertion loss.

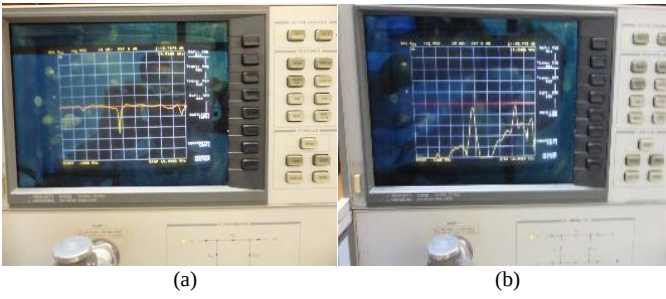


Fig. 5. Measurement results displayed on the network analyzer screen. (a) Return loss. (b) Insertion loss.

the FBW factors for them are in complete agreement. This agreement is also repeated for the Q-factor. It is worth emphasizing that the parallel-coupled microstrip bandpass filter is theoretically designed to operate at 10 GHz with approximately a 4% bandwidth. As mentioned above, Grok3 and DeepSeek-R1 can estimate f_0 with high accuracy, although GPT-4o can also intelligently predict the center frequency with a very small error. However, when it comes to predicting the FBW, Q-factor, and the magnitude of the return loss, Grok3 demonstrates the best practical performance compared with the R1 and 4o AI models. It is worth mentioning that the performance of all three AI models in estimating and simulating the MMIC component is astounding. On the one hand, these results reveal that Grok3, despite having fewer layers in its architecture, benefits from an efficient technique for estimating and simulating MMIC components from their 2D layouts; on the other hand, Flash 2.0 and Copilot did not respond to the designed prompt or query. Therefore, their responses to the queries were not reported. These results are summarized in Table II.

It should be noted that the S-parameters generated by the LLMs, in particular the S_{11} values of -104.1 dB (DeepSeek-R1) and -212.7 dB (GPT-4o), might be physically meaningless for the present conventional parallel-coupled line filter. In standard room-temperature measurements, vector network analyzers (VNAs) typically achieve a dynamic range down to about -80 dB for microstrip structures, as discussed by J. Hong in [24]. In superconducting microstrip filters, measurements can even reach -100 dB (Chapter 4 of the same reference). However, the parallel-coupled filter is a conventional design on a normal substrate, and the reference simulations (FEM/MoM) and laboratory measurements yield S_{11} in the range of -21 dB to -33 dB. As a result, the LLM outputs far exceed any physically justifiable limit for this case. These numbers surprisingly are not the result of measurement or extraction errors; they are the exact, unmodified numerical responses of the AI models and reveal a fundamental lack of physics-based reasoning in current LLMs when confronted with quantitative EM simulation tasks. To explain more, these physically impossible values should not be interpreted as LLMs' output errors (or operators' mistakes) but as direct consequences of the LLMs' physics-unaware generation process; they lack any internal mechanism to enforce passivity, reciprocity, or realistic return-loss limits, and thus they complete the prompt with statistically plausible, but physically meaningless, numbers.

TABLE II

Comparison of Results between Foundational LLMs, Full-Wave Methods, and Measurements

Model	f_0 (GHz)	FBW (%)	S_{11} at f_0 (dB)	S_{12} at f_0 (dB)	Q-factor
Grok3	10	20	-15	-1	4.17
DeepSeek-R1	10	30	-104.1 [†]	-0.5	2.5
GPT-4o	10.6	46	-212.7 [†]	-0.001 [†]	0.45
MoM	10	4	-33.5	-2.6	24.4
FEM	10	4	-21.4	-2.6	24.4
Measurement	9.7	4	-25.6	-2.9	24.15

[†]: These S-parameter values are physically unattainable for the conventional (non-superconducting) microstrip filter design presented here. They are the exact raw outputs of the LLMs and are reported solely for benchmarking transparency.

VI. CONCLUSION

To sum up, this work presented a first-of-its-kind benchmarking study of state-of-the-art foundational AI models for simulating an electromagnetic component. Initially, an MMIC component—specifically, a parallel-coupled microstrip bandpass filter—was theoretically designed, simulated, and measured as a classic benchmark for X-band applications with the assistance of EM simulators. Following this, to evaluate five cutting-edge LLMs, a 2D pattern of the benchmark electromagnetic component was presented to them for prediction and simulation purposes. Three of these AI models, considered strong multimodal or vision-language models, were able to interpret the 2D pattern, respond meaningfully to the query, and ultimately estimate the microstrip filter characteristics. Finally, the results obtained from the VLMs, full-wave simulation techniques, and measurements were compared. However, the findings demonstrated that three VLMs could predict both the center frequency and the magnitude of the insertion loss of the component to some extent. Still, their outputs also included physically unrealizable values, indicating that the models currently treat electromagnetic simulation as a pattern-matching task rather than solving Maxwell's equations. Overall, Grok3, R1, and GPT-4o exhibited the best performance in simulating the benchmark microwave component, respectively. Despite the fact that current results suggest that LLMs are not yet capable of replacing full-wave EM simulators, their pattern recognition capabilities point to a potential role as a rapid pre-screening assistant. Concrete next steps include fine-tuning these models on domain-specific S-parameter databases, incorporating physics-informed loss functions that enforce comprehensible conditions, comparing the EM parameter estimation achieved by VLMs with single AI-based optimizers, and extending the benchmark to a wider variety of MMIC components and frequency bands. Future work (or future AI assistants specifically trained in electromagnetics) on physics-based fine-tuning may narrow the accuracy gap. While the present results clearly reveal that the aforementioned LLMs are not yet ready to replace full-wave solvers, their rapid evolution and pattern-recognition strengths suggest they could gradually become useful complementary tools, provided that physics-based training becomes an integral part of their development. As a highly ambitious prediction, it is worth noting, however, that

owing to rapid advancements in deep learning-based LLMs, these models may soon surpass traditional simulation methods.

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CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AI DISCLOSURE

The authors used ChatGPT (OpenAI, San Francisco, USA) and/or DeepSeek (DeepSeek AI, Hangzhou, China) to assist in language editing and improving the clarity of the manuscript. It is emphasized that all AI-assisted outputs were reviewed and verified by the authors.

DATA AVAILABILITY STATEMENT

All data generated or analyzed during this study are included in this published article.

AUTHORS CONTRIBUTION STATEMENT

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