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Transformer-Based Neural Network Metamodel for Nearly Orthogonal Sampling in Conceptual Design of Multistage Space Launch Vehicles

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ABSTRACT- This study introduces an innovative methodology for the efficient conceptual design of complex, multidisciplinary systems that involve computationally intensive analyses and a vast array of design variables. A novel nearly-orthogonal sampling strategy with superior space-filling characteristics is employed to extract maximal insights into system behaviour using a significantly reduced number of trial designs. The sampled dataset serves as input for a metamodel constructed using advanced artificial neural networks, augmented by Transformer Networks to enhance the metamodel's capacity for capturing intricate dependencies and complex interactions within the data. Furthermore, a stage-wise interconnection of discrete neural networks is proposed for trajectory metamodeling, effectively mitigating the dimensionality challenges inherent in traditional neural architectures. The optimization process integrates a hybrid approach, leveraging a Genetic Algorithm for global optimization in tandem with Sequential Quadratic Programming for localized refinement utilizing exact disciplinary analyses. The efficacy of the proposed methodology is demonstrated through its application to the conceptual design optimization of a multistage solid-fuelled space launch vehicle. The results reveal exceptional accuracy in approximating highly nonlinear functions, a substantial reduction in overall computational time, and significant minimization of the reliance on exhaustive disciplinary analyses, underscoring the transformative potential of this approach.

KEYWORDS- Transformer Network, Space launch vehicle, Neural Network, Nearly-orthogonal sampling, Trajectory planning.

I. INTRODUCTION

Design and analysis are intrinsically interdependent processes. The design paradigm must facilitate the desired analytical rigor while deriving comprehensive insights from a limited set of simulation iterations [1-3]. Conducting an exhaustive experimental design over highly complex simulation models encompassing multidimensional input spaces is computationally prohibitive. Despite the exponential advancements in computational power, the exorbitant cost associated with high-fidelity engineering analyses and simulations often impedes their applicability in critical areas such as design optimization and reliability analysis. Thus, a paradigm shift towards a more rapid, intelligent design optimization framework becomes imperative to circumvent these challenges.

Statistical approximation methodologies, including Design of Experiments (DoE) and Response Surface Methodology (RSM), have long been utilized to mitigate the computational burden of complex systems analyses. However, these conventional methods often lack the capacity to effectively handle intricate nonlinearities and high-dimensional dependencies. In the realm of design optimization for complex aerospace systems, such as multistage space launch vehicles, the integration of advanced neural network architectures plays a pivotal role in enhancing computational efficiency and robustness. [4] demonstrated the efficacy of leveraging neural network approximations within Deep MPC to handle high-dimensional control problems in robotic manipulators, providing valuable insights into robust and adaptive planning under model uncertainties. Inspired by this work, the proposed transformer-based neural network metamodel leverages similar principles of neural network-driven approximations to address the challenges of nearly orthogonal sampling and efficient trajectory metamodeling in conceptual design optimization. This adaptation not only ensures computational efficiency but also enables the metamodel to capture intricate dependencies across design variables, aligning with the robust methodologies. To address these limitations, this work leverages Transformer Networks—a state-of-the-art deep learning architecture

known for its unparalleled capability in modeling long-range dependencies and capturing complex interrelationships within large datasets [5]. By integrating Transformer Networks into the conceptual design framework, this study aims to establish a robust, scalable approach to optimizing multidisciplinary systems [6].
The proposed methodology encompasses a nearly-orthogonal sampling strategy with enhanced space-filling properties, facilitating the extraction of maximal information from the design space. The integration of advanced robotics and machine learning methodologies has significantly transformed the landscape of aerospace systems, particularly in addressing complex and dynamic challenges. [7] proposed an innovative framework for autonomous multi-robot servicing to extend spacecraft operations, demonstrating the efficacy of decentralized adaptive control in high-uncertainty environments. Building on this foundational work, the proposed transformer-based neural network metamodel draws inspiration from similar principles of adaptability and scalability to optimize the conceptual design of multistage space launch vehicles. By employing nearly orthogonal sampling techniques and robust neural network architectures, this approach aligns with the vision of intelligent aerospace systems capable of efficiently addressing high-dimensional design and operational challenges. The sampled data serves as input for a metamodel based on Transformer-augmented neural networks, which excel in approximating highly nonlinear, multidimensional functions [8]. To further combat the curse of dimensionality, a stage-wise interconnection of these networks is proposed for trajectory metamodeling, ensuring computational efficiency without compromising precision.

Figure 1: Conceptual Design of Multistage Space Launch Vehicles

The application of this methodology is demonstrated in the conceptual design optimization of a solid-fuelled space launch vehicle (SLV) tailored for low Earth orbit (LEO) missions. [9] proposed an adaptive robotic control framework for detumbling non-rigid satellites, demonstrating the importance of real-time adaptability in addressing uncertainties and intricate dynamic behaviours. Inspired by their emphasis on adaptive modelling, the proposed transformer-based neural network metamodel adopts a similar philosophy to optimize the conceptual design of multistage space launch vehicles. The framework integrates a hybrid optimization strategy—employing Genetic Algorithms (GA) for global optimization and Sequential Quadratic Programming (SQP) for localized refinement [10]. This hybrid approach, augmented by the Transformer-based metamodel, ensures rapid convergence to an optimal solution, significantly reducing computational time and reliance on exhaustive disciplinary analyses.
Conceptual design serves as the cornerstone of the overall design process, locking in nearly 80% of a vehicle's lifecycle cost. The decisions made at this stage exert a profound influence on the final product's quality and cost-effectiveness, emphasizing the need for robust, interdisciplinary collaboration. The proposed methodology effectively integrates diverse analytical domains, including aerodynamics, structural dynamics, propulsion systems, trajectory optimization, and thermal analysis, into a cohesive framework. By leveraging advanced computational intelligence, this study underscores the transformative potential of integrating Transformer Networks into the design optimization of complex aerospace systems.

II. METHODOLOGY

A. Nearly-orthogonal sampling

Design of Experiments (DoE) provides a systematic approach for exploring the trade space of the design envelope efficiently, eliminating the need for excessive and redundant simulation cases. These tools enable the designer to achieve a comprehensive understanding of the overall design through minimal computational effort. Typically, Response Surface Methodology (RSM) is employed to construct simplified surrogate models of the design space, enabling optimization algorithms to rapidly converge on optimal solutions. However, RSM is often inadequate for highly complex systems with a vast number of design variables due to its limited scalability and approximation capacity.
An orthogonal array (OA), a fractional factorial matrix, has been widely utilized to ensure a balanced exploration of the interaction effects among design variables. Orthogonal designs maintain independence between regression model coefficients, thereby enhancing analytical accuracy. Recently, advancements in multidisciplinary optimization have introduced methodologies that integrate the Taguchi method, fuzzy logic, and neural networks for comprehensive system analysis. Such approaches are instrumental in addressing complex aerospace design problems, including propulsion system performance, weight estimation, and emission analysis. However, these conventional methodologies face limitations in capturing intricate nonlinear interactions and high-dimensional correlations within the design space.
To overcome these challenges, this study introduces a Transformer Network-based metamodeling framework. Transformers, renowned for their superior ability to capture long-range dependencies and complex relationships, are employed to construct a metamodel capable of approximating highly nonlinear, multidimensional functions with exceptional accuracy. By integrating Transformer Networks with orthogonal sampling, the proposed methodology ensures a more robust exploration of the design space while maintaining computational efficiency.
A superior space-filling design is characterized by the uniform scattering of design points across the experimental region, minimizing voided or un-sampled areas. Latin Hypercube Sampling (LHS), a variant of quota sampling,

offers an effective solution for improving space-filling properties. Although Taguchi designs exhibit compactness, their poor space-filling capabilities limit their applicability to complex systems like SLV design. Conversely, Latin Hypercube designs provide better space-filling characteristics but remain computationally intensive for high-dimensional problems.

The incorporation of Transformer Networks into the space-filling sampling process significantly mitigates these limitations. The Transformers not only enhance the representational capacity of the metamodel but also optimize the distribution of design points across the space. This ensures a comprehensive and efficient exploration of the design space, paving the way for more accurate and scalable solutions to the multidisciplinary challenges of SLV conceptual design based on [11] we can get

$$Q_2 = (\mathrm{n})^k - \frac{1}{n}\sum_{d=1}^{n} \prod_{i=1}^{k} (5 - u_{di}^2) \quad (1)$$

The structural mass encompasses a comprehensive aggregation of components, including the mass of the motor cylinder (m_{cyi}), motor dome ends, forward and aft skirts $(m_{\mathrm{cll11}}, m_{\mathrm{cll22i}})$,, aft attachment $(m_{\mathrm{in,cl1i}}, m_{\mathrm{in,c2i}})$, fore and aft insulation liners $(m_{\mathrm{in,cl1i}}, m_{\mathrm{in,c2i}})$, $(m_{\mathrm{noz,ini}})$, and cylindrical section insulation liner Additional elements include the nozzle expansion cone, nozzle spherical head $(m_{\mathrm{noz,shi}})$, nozzle insulation, and ignitor (m_{igi}). Furthermore, the structural mass accounts for the thrust vector control mechanism (m_{TVCi}), cabling (m_{cabi}), and attachment components (m_{api}) as-

$$\begin{aligned} m_{\mathrm{c}} &= \frac{\pi\lambda_e^2 D^3 f f_{\mathrm{p}} p_{\mathrm{c}}}{8(\lambda_e^2-1)\sigma\cos\theta_2}\left[\frac{\lambda_e^2 D^2-(\lambda_e^2-1)d^2}{\lambda_e^2 D^2} - \frac{1+(\lambda_e^2-1)\sin^2\theta_2}{m_q}\right] \\ & D^2\rho_q\delta_q\frac{l_{q1}+l_{q2}}{D} \\ m_{j2} &= 3\pi f f_p p_c d^3\rho/\sigma \\ m_{\mathrm{inc1}} &= \frac{1}{4}\rho_{\mathrm{in}}\pi D^2 R_a t_K \end{aligned} \quad (2)$$

Here, f denotes the factor of safety, while f_p represents the ratio of peak pressure to working chamber pressure. The parameter η_{vi} corresponds to the volumetric loading fraction [12], and σ is the ultimate tensile strength of the material. ρ signifies the material density, and δ denotes the material thickness. θ_2 is the aft dome half-included angle, and S represents the submerged coefficient of the nozzle. The lengths of the forward and aft skirts are indicated by l_{q1} and l_{q2} , respectively.

The parameter R_a refers to the rate of ablation of the insulation material, while ϵ_{in} is the heat transfer coefficient of the insulation material [13-15]. The specific heat capacities of the insulation and cylindrical section are represented by c_{in} and c_{cy} , respectively. The heat transfer coefficient from the combustion gas to the insulation is expressed as α_{gi} .Additionally, $\theta_P = \frac{(T_g - T_{cy})}{(T_g - T)}$ defines the temperature ratio parameter, where T_g denotes the temperature of the combustion gas, and T_{cy} is the allowable temperature of the motor.

B. Global Optimization using Transfomer Network

To derive a polynomial formulation of the Optimal Power Flow (OPF) problem, the procedure is carried out in three systematic steps. Initially, the problem is expressed in the domain of complex numbers. Subsequently, this formulation is translated into a real-number representation. Finally, the real-number formulation is utilized to establish a polynomial representation of the OPF.

Let $\mathbf{a}^H$ and $\mathbf{A}^H$ denote the conjugate transpose of a complex vector $\mathbf{a}$ and a complex matrix $\mathbf{A}$, respectively. From [16], it can be inferred that there exist finite index sets $\mathcal{I}$ and $\mathcal{J}$, Hermitian matrices $(\mathbf{A}_k)_{k\in\mathcal{G}}$ of size nnn, complex matrices $(\mathbf{B}_i)_{i\in\mathcal{I}}$ and $(\mathbf{C}_i)_{i\in\mathcal{J}}$ of size n, and complex scalars $(b_i)_{i\in\mathcal{I}}$ and $(b_i)_{i\in\mathcal{J}}$, such that the OPF can be expressed in the following form:

$$\min_{\mathbf{v}\in\mathbb{C}^n} \sum_{k\in\mathcal{G}} c_{k2}(\mathbf{v}^{\mathrm{H}}A_k\mathbf{v})^2 + c_{k1}\mathbf{v}^{\mathrm{H}}A_k\mathbf{v} + c_{k0} \quad (3)$$

subject to

$$\begin{aligned} &\forall i \in \mathcal{I}, \quad \mathbf{v}^{\mathrm{H}}B_i\mathbf{v} \leqslant b_i, \\ &\forall i \in \mathcal{J}, \quad |\mathbf{v}^{\mathrm{H}}C_i\mathbf{v}| \leqslant c_i. \end{aligned} \quad (4)$$

The formulations outlined in above equations are not employed further in this work due to the existence of infinitely many global solutions. Specifically, the formulation from which these subsequent formulations are derived, exhibits invariance under the transformation of variables $\mathbf{v}e^{j\theta}$, where $\theta \in \mathbb{R}$. Such solutions complicate the convergence process, as optimization problems with multiple global solutions are inherently more difficult to solve compared to those with a unique solution [17-20]. To address this issue, we adopt a specific approach to eliminate the invariance by arbitrarily fixing the aerospace device energy phase at bus nnn to zero. This constraint is implemented while ensuring that the minimum gas magnitude condition $v_n^{min} \geq 0$ is satisfied. This adjustment can be operationalized by substituting the voltage constraint in [21] with the updated condition [22]. This approach ensures the optimization problem transitions from having a non-isolated solution set to a more tractable, uniquely defined solution space, facilitating the application of the moment-sum-of-squares methodology as:

$$\hat{e}_{ij}^{\ell+1} = O_e^{\ell} \parallel_{k=1}^{H} (\widehat{w}_{ij}^{k,\ell}) \quad (5)$$

where $Q^{k,\ell}, K^{k,\ell}, V^{k,\ell}, E^{k,\ell}$ denotes the number of attention head. For numerical stability, the outputs resulting from the exponentiation of terms within the soft-max function are clamped to a bounded range of [0, N]. This ensures that the values remain within a manageable scale, mitigating issues associated with extreme values that could lead to instability during computations [23-27]. The processed outputs, $\hat{h}_i^{\ell+1}$ and $\hat{e}_{ij}^{\ell+1}$, are subsequently fed into separate Feed Forward Networks (FFNs). These networks are architected with residual connections to preserve gradient flow and are flanked by normalization layers to ensure consistent scaling and improved convergence. The overall operation can be described as follows:

$$W_{ij}^{\ell+1} = (\widehat{w}_{ij}^{\ell+1} + \widehat{w}_{ij}^{\ell+1}) \quad (6)$$

III. EXPERIMENT RESULTS

The efficacy of the trained NNs was rigorously evaluated through 1000 random exact analyses, with results depicted in Fig. 2. The evaluations demonstrate the exceptional approximation capabilities of the proposed neural networks. Notably, a slightly higher dispersion in the final velocity indicates that velocity, as a state variable, is the most sensitive parameter. This nonlinearity presents challenges for accurate approximation with limited sample sizes. However, the proposed stage-wise interconnection of NNs significantly reduces velocity dispersion compared to standalone NN [28].

The importance of the proposed Nearly Orthogonal Latin Hypercube (NOLH) sampling for NN training is highlighted by comparing it with conventional Latin Hypercube Sampling (LHS). For this comparison, 2000 samples generated using standard LHS were utilized to train a NN, focusing on the first-stage velocity. Testing with 1000 random samples revealed that NOLH outperformed LHS in terms of approximation accuracy. The comparative results, as shown in Fig. 3, underscores the superiority of the proposed sampling approach.

For optimization, the PyTorch, incorporating real-coded GA with standard operators such as fitness scaling, tournament selection, crossover, and mutation, was employed. The population size was set to 200, with a maximum of 100 generations. Optimization was conducted using exact analyses and subsequently compared with metamodel-driven optimization. Tables 3 and 4 present the comparative number of exact function evaluations, demonstrating that trajectory metamodels drastically reduce the computational burden while maintaining optimal solution accuracy.

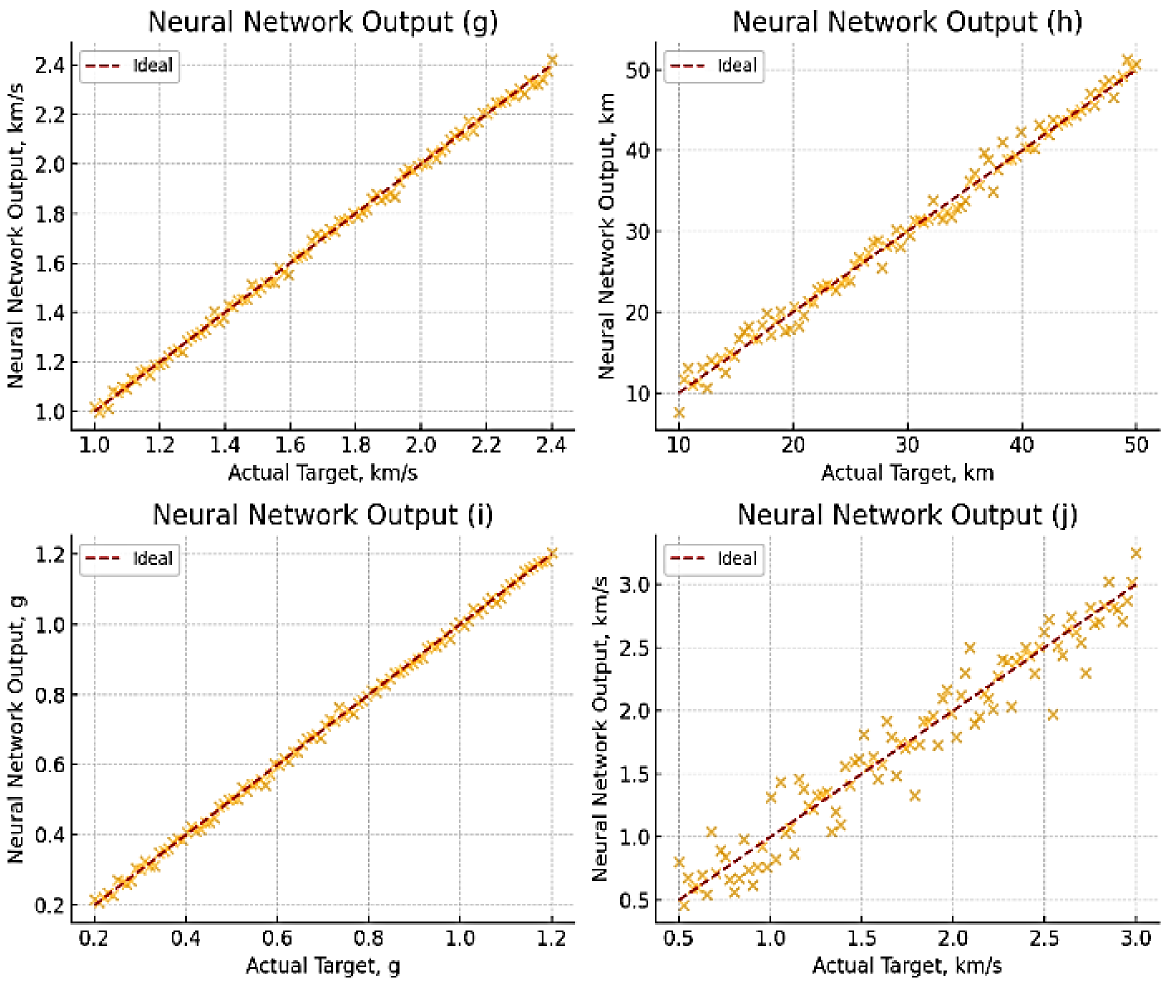

Figure 2: Approximation capability of Transformer Neural Network

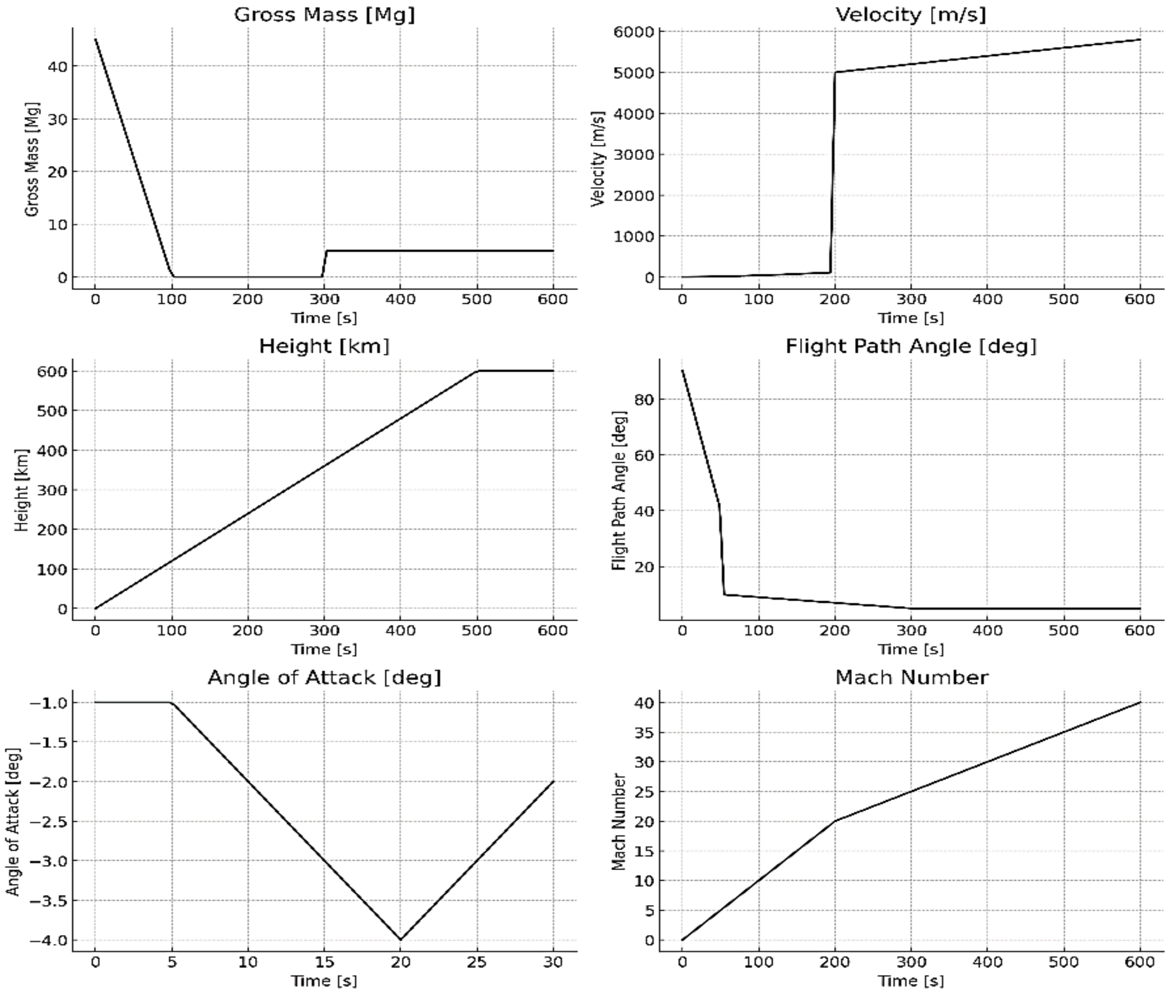

Figure 3: Optimal trajectory for different parameters

IV. CONCLUSION

This study introduces a transformative approach to conceptual design optimization for multistage space launch vehicles (SLVs) by leveraging space-filling techniques and nearly-orthogonal Latin hypercube designs for generating training data. The incorporation of Transformer Networks, with their superior ability to model intricate dependencies and nonlinear interactions, has resulted in highly efficient and accurate metamodels. These metamodels were utilized to approximate complex trajectory analyses, significantly reducing computational cost while maintaining high fidelity. The optimization framework integrates Genetic Algorithms (GA) to efficiently evolve designs toward achieving near-minimal launch mass of SLVs [29-33]. By replacing exhaustive trajectory simulations with Transformer-driven neural network metamodels, the methodology accelerates the global search for optimal solutions. Sequential Quadratic Programming (SQP) further refines the design by determining the local minimum, ensuring convergence to an optimal solution with precision.

The resulting conceptual design is inherently multidisciplinary, encompassing major dimensions, configurations of SLVs, star grain profile optimizations, and propulsion parameters. The inclusion of Transformer Networks enables the design methodology to effectively address the curse of dimensionality associated with complex systems involving a vast array of design variables [34]. This innovation underscores the robustness and scalability of the proposed framework, establishing it as a rapid and efficient tool for optimizing intricate aerospace systems.

In summary, the proposed methodology demonstrates a paradigm shift in design optimization by integrating cutting-edge machine learning architectures with advanced sampling techniques, offering a versatile and computationally efficient solution for conceptualizing complex aerospace systems.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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