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(Research Paper)

Surrogate Modeling Based on Deep Learning for the Trajectory of a Launch Vehicle

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Abstract

Purpose: In recent years, the analysis and design of systems through computer-based simulations have attracted considerable attention from researchers focused on predicting system performance. Such engineering analyses depend on the execution of costly and complex computer codes. Approximate methods have been extensively utilized to alleviate the computational burden of engineering analyses, and the advancement of modeling techniques allows for rapid, cost-effective, and accurate evaluations of engineering systems. This paper aims to explore the potential of deep learning models as an alternative approach for modeling the trajectory of a launch vehicle.

Design/methodology/approach: To enable analyses such as design optimization, reliability assessment, and others, there is a necessity for a simplified model that can efficiently represent the detailed and expensive product model. These simplified

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predictive models are also known as surrogate models. This approach employs experimental data to train neural networks and assesses its predictive accuracy against the Response Surface Method (RSM).

Findings: The results demonstrated that the use of deep learning significantly enhances prediction accuracy and provides the capability to estimate performance under various conditions. Consequently, at the comparison point for the total mass of the launch vehicle, the simulation code produced a value of 108,500 kg using the deep learning method, while the total mass with the RSM technique was 108,556.6 kg, indicating that the accuracy of the deep learning model is superior.

Practical implications: The deep learning model can identify complex nonlinear relationships among input variables, leading to more robust predictions. This advantage arises from the flexibility of deep neural networks, which adeptly learn intricate patterns within the training data. This model significantly decreases the time needed for predictions compared to traditional modeling techniques, which often require extensive iterative processes and parameter tuning. This reduction in computational load is vital for real-time aerospace applications, where swift decision-making is essential.

Originality/value: This paper analyzes the effectiveness of deep learning models in flight trajectory modeling, specifically concerning the two-stage launch vehicle Kosmos 3M, aiming to reduce total mass while improving computational efficiency and accuracy in predictive modeling for optimal flight path design.

Keywords: Surrogate model, Deep learning, Trajectory of a launch vehicle, Response Surface Method (RSM)

1. Introduction

Modeling and analyzing the trajectory of launch vehicles presents a significant challenge in aerospace engineering. The complexity of flight dynamics, combined with pronounced environmental influences, necessitates the use of rapid and reliable models for predicting launch vehicle behavior. Surrogate models have emerged as effective tools that reduce analysis time and costs across various sectors, including mechanical, aerospace, and chemical engineering. These models support diverse applications, such as component design optimization, experimental data analysis, and the prediction of complex system behaviors. This study proposes a novel deep learning-based approach for modeling flight trajectories and compares its performance with that of the Response Surface Method (RSM).

1.1 Literature Review

Surrogate models play a critical role in optimizing and simulating complex systems, effectively addressing the computational time and cost associated with intricate simulations. Recent research illustrates the proficiency of surrogate models in supporting nested optimization, sensitivity analysis, and parameter optimization (Wang et al., 2022, Xu & Zhang, 2024, Shao et al., 2025). Furthermore, developments in deep learning and artificial neural networks have made these tools appealing alternatives for surrogate modeling (Liu et al., 2024). Their capacity to process vast datasets and learn intricate patterns often enables neural networks to surpass traditional modeling methods in specific predictive tasks. Numerous studies advocate that adopting these techniques enhances both accuracy and efficiency compared to classical approaches (Alizadeh et al., 2020).

In the field of flight dynamics, research indicates that deep learning models can effectively replicate the complex and nonlinear behaviors characteristic of flight systems. Notably, prior studies have highlighted the potential of convolutional neural networks (CNNs) in accurately predicting the dynamics of launch vehicles (Silvestre et al., 2024). Conversely, while the Response Surface Method (RSM) remains a well-established technique for modeling and forecasting system behaviors, its effectiveness may wane when confronted with nonlinear and complex system dynamics (Myers & Montgomery, 2016; Jensen, 2017). Surrogate models generally fall into two categories: data-driven and analytical models. Data-driven models, such as deep learning algorithms, leverage extensive datasets to accurately identify intricate patterns (see Table 1).

Table 1. Surrogate modeling techniques and their classification into analytical and data-driven categories

Classification	Techniques	Description	Reference
Analytical Models	Response Surface Method (RSM)	This technique is used to identify the relationship between inputs and outputs of a system, exhibiting good performance in linear modeling.	Myers & Montgomery (2016)
	Polynomial Chaos Expansion	These models are applied in uncertainty problems and are useful for predicting outputs affected by random inputs.	Narula. (2022)
Data-Driven Models	Neural Networks	Especially deep neural networks (DNNs) are used for their ability to recognize complex patterns in data.	Shao et al. (2025)
	Decision Tree Models	These models are utilized in predicting and classifying data, responding effectively to complex issues.	Friedman (2001)

Surrogate models are applied across various engineering fields. Table 2 illustrates the applications of surrogate models across three different engineering domains, providing relevant examples for each field.

Table 2. Applications of surrogate models in engineering

Engineering Domain	Description	Example
Mechanical Engineering	Surrogate models are employed to predict the behavior of materials under various loads and to gather information from dynamic simulations. These techniques assist engineers in optimizing materials and structures.	Utilization of deep learning-based models to predict operational conditions in internal combustion engines (Wang et al, 2022).
Aerospace Engineering	This field is significantly influenced by surrogate models, which can predict the behavior of flying vehicles and optimize their designs.	Use of neural networks to predict outcomes of complex simulations in aircraft design (Xu & Zhang, 2024). Proposed a new synthetic meta-model methodology for liquid propellant engine's cooling system optimization (Alimohammadi et al., 2021a).

Engineering Domain	Description	Example
		Suggested a new framework for liquid rocket engine cooling systems with sensitivity analysis based on RSM (Alimohammadi et al., 2021b). conducted multi-disciplinary design optimization (MDO) utilizing RSM, genetic algorithms (GA), and simulating annealing methods (Lam, 2020).
Chemical Engineering	Surrogate models are utilized in the optimization of chemical processes and in predicting reaction behaviors. These methods can assist chemical engineers in reactor design and material processing.	Application of response surface models for predicting and optimizing parameters in chemical processes (Box & Draper., 1987).

Therefore, considering the literature review and conducted research, as well as the existing complexities in trajectory modeling and the need for high precision, this study examines the utilization of deep learning models and compares them with traditional methods such as RSM.

2. The main elements of the subject

2.1 Surrogate models

Surrogate models are employed as quick estimators of system behavior. These models have gained considerable recognition for their ability to reduce computational complexity. One of the main advantages of these models is their use in multi-objective optimization, as noted in recent literature (Zhu et al., 2019). Surrogate models act as effective tools in the simulation and optimization of complex systems across various fields. They aid researchers and engineers in predicting system parameters and behaviors at minimal cost and time. Recent studies, including one published by Hasib et al., (2024), emphasize that advancements in machine learning and artificial intelligence have greatly enhanced the accuracy and speed of these models.

2.1.2 Construction of surrogate models

The construction of surrogate models involves the following stages:

a) Data Acquisition: This stage includes conducting preliminary simulations (running baseline simulations to collect necessary data) and/or gathering experimental data (utilizing real-world and empirical data to provide the foundation for model development). For example, Kriging typically requires a set of data points that includes prior simulation outcomes (Qian et al., 2020).

b) Variable Selection: Sensitivity analysis can help identify key variables that significantly influence output. This technique is applied not only based on past experiences but also through statistical and empirical methods to optimize this process. The output of this stage is a list of important variables that should be included in the model (Juan et al., 2022).

c) Modeling Technique Selection: In this stage, various modeling techniques are chosen based on the type and complexity of the data and the goals of the model:

- Regression Models: Widely used for predicting linear and nonlinear relationships. For instance, linear regression could be targeted for modeling material distribution in manufacturing processes.
- Tree-Based Models: These models excel in complex issues due to their high resolution (Kim & Choi, 2022).
- Neural Networks: These models are gaining traction due to their ability to recognize complex patterns and nonlinear relationships in data (He et al., 2016).
- Kriging: Known for its high accuracy in parametric spaces, this approach is used for designing and optimizing complex systems.

d) Model Training: This stage generally involves using learning algorithms to determine the optimal parameters for the model. Optimization algorithms like NSGA-II are also utilized to find optimal points in design (Deb et al., 2002).

e) Model Validation: This stage necessitates comparing the model's results with independent data. Key identification criteria include correlation coefficients and RMSE (Root Mean Square Error) (Kleijnen, 2018).

2.1.2 Types of Surrogate Models

Surrogate models can be categorized into the following types:

a) Linear Models: These models are generally suitable for simple, linear systems and are easy to implement.

b) Nonlinear Models: Including neural networks and decision trees, these are applicable for simulating more complex systems.

c) Bayesian Models: These provide a means for modeling uncertainty. This type of model is particularly useful in designs and simulations facing high uncertainty (Andrews & Baguley, 2017).

The following table presents a comparison of various types of surrogate models, highlighting the advantages and disadvantages of each model based on the latest academic papers and recent research, as shown in Table 3.

Table 3. Comparison of types of surrogate models

Surrogate Model	Advantages	Disadvantages	Reference
Regression Models	Simple implementation and interpretation	Limitations in modeling nonlinear relationships	Jang et al. (2022)
	Accurately relates to linear data	Low accuracy in complex issues	Zhu et al.(2019)
Tree-Based Models	High resolution and ability to model complex relationships Clear and understandable conclusions Can leverage non-specific data	Overfitting in non-sample data Requires appropriate parameter and input variable tuning	Kim & Choi (2022) Breiman et al., (1984)
Neural Networks	Ability to identify complex patterns in data	Requires a larger volume of training data	He et al.(2016)
	Adaptability and learning from new data Performs optimally in nonlinear and large-scale problems	Determining an appropriate network structure can be complex	Sharma et al., (2025)
Kriging	High accuracy in predictions and uncertainty modeling	Sensitivity to the selection of initial data points	Qian et al., (2020)
	Highly effective in parametric design and optimization Capability in multivariate analysis	Higher computational time compared to other models	Han (2016)

- Regression Models: Recent studies show that regression models continue to be widely used in many simple to moderate applications. However, in complex scenarios, especially in engineering and data science, satisfaction with the results may be limited.
- Tree-Based Models: These models have garnered significant attention in industrial and commercial applications due to their high resolution, as they can uncover complex relationships and deliver easily interpretable results.
- Neural Networks: With recent advancements in deep learning, these models are rapidly evolving and excelling on large, complex datasets. However, they encounter challenges due to the necessity for vast amounts of data and considerable computational time.
- Kriging: Kriging is recognized as one of the most sophisticated predictive methods, particularly beneficial in uncertain conditions. It is crucial to note that optimal performance requires careful design and a substantial number of initial data points.

The choice of an appropriate surrogate model hinges on the nature of the data, the specific problem being addressed, and the unique requirements of the project. In scenarios involving complex and nonlinear data, neural networks and tree-based models may be more suitable. In contrast, for issues that involve uncertainty and demand precision, Kriging may be preferred. As a result, surrogate models are essential in expediting design and optimization processes, and with recent advancements in data mining and machine learning, their usage is increasing. These models are acknowledged as tools for managing costs and time in large and complex projects.

2.2 Deep learning-based surrogate model

Recent advancements in deep learning, particularly over the past few years, have significantly influenced surrogate modeling. Innovative techniques such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have demonstrated remarkable effectiveness in identifying complex, non-linear patterns in data . (Hasib et al., 2024, Sharma et al., 2025, Wu et al., 2017).

- Deep Neural Networks (DNN): These networks comprise multiple layers of neurons that aid in modeling intricate patterns. This architecture is especially beneficial for tasks requiring precise and repetitive predictions, such as dynamic simulations.
- Convolutional Neural Networks (CNN): These networks excel at processing image data and assist in feature and pattern recognition within images. In surrogate modeling, CNNs can be utilized to simulate the spatial and temporal behaviors of systems.
- Recurrent Neural Networks (RNN): Due to their ability to process sequential data, RNNs are effective for problems involving time-stamped and sequential data, such as fluid dynamics simulations. These networks can retain information over time, potentially enabling more accurate simulations.
- Hybrid Models: Combining various deep learning models can be advantageous. This strategy may involve integrating CNNs with RNNs or other models to harness the strengths of each.

Deep learning models are acknowledged as powerful tools for enhancing the efficiency and accuracy of system modeling. For example:

- Deep Neural Networks: These networks feature multiple layers and specific characteristics that improve their pattern recognition and learning capabilities, leading to greater accuracy in system simulations.
- Hybrid Models: Employing combinations of different models, such as merging CNNs and RNNs, can boost performance and prediction accuracy.

This trend empowers researchers to create models that require less input data while also yielding superior results.

2.2.1 Challenges and limitations in deep learning

This section outlines the primary challenges associated with using deep learning for surrogate modeling:

- Requirement for High-Quality Training Data: Adequate and high-quality training data are essential for effective model training. The lack of suitable data can result in insufficient model enhancements.

- Extended Training Times: Training deep models is frequently time-intensive and requires substantial computational resources. This can hinder swift research and conclusions in complex matters.
- Generalization Challenges: A major issue in deep learning is the capacity to generalize models to new and unfamiliar conditions. This can result in prediction instability.

Through a review and analysis of the literature, existing research gaps and the advanced capabilities of deep learning in this field can be identified and addressed. This includes highlighting challenges faced by researchers, such as the necessity for sufficient training datasets and training duration.

3. Research methodology

The following flowchart illustrates the primary stages of the research methodology (see Fig. 1):

3.1 Problem Definition: The first step involves identifying the main problem that can be addressed using precise and efficient models, such as deep learning.

3.2 Receiving Requirements and Mathematical Modeling of the System: At this stage, all system requirements for modeling are identified, and accurate mathematical modeling is conducted to describe the system and significant data points.

3.3 Data Collection: All data with the required characteristics for modeling and prediction are gathered.

3.4 Selection of Surrogate Model: Utilizing deep learning methods: In this phase, various surrogate models, including Deep Neural Networks (DNN), are evaluated based on the collected data. The most suitable model is selected based on the characteristics of the data and system requirements, thus initiating the training and evaluation process.

3.5 Data Preprocessing: During this step, the data is reviewed and normalized. Additionally, dependent features are removed to prevent potential issues in later stages.

3.6 Data Splitting: The data is divided into two sets: training data and test data.

3.7 Training the Deep Learning Model: The model is trained using the training data, and its accuracy is assessed.

3.8 Comparison of Model Results: The results obtained from the RSM model and the deep learning model are compared, and their performances are evaluated against specified metrics, such as Mean Squared Error (MSE).

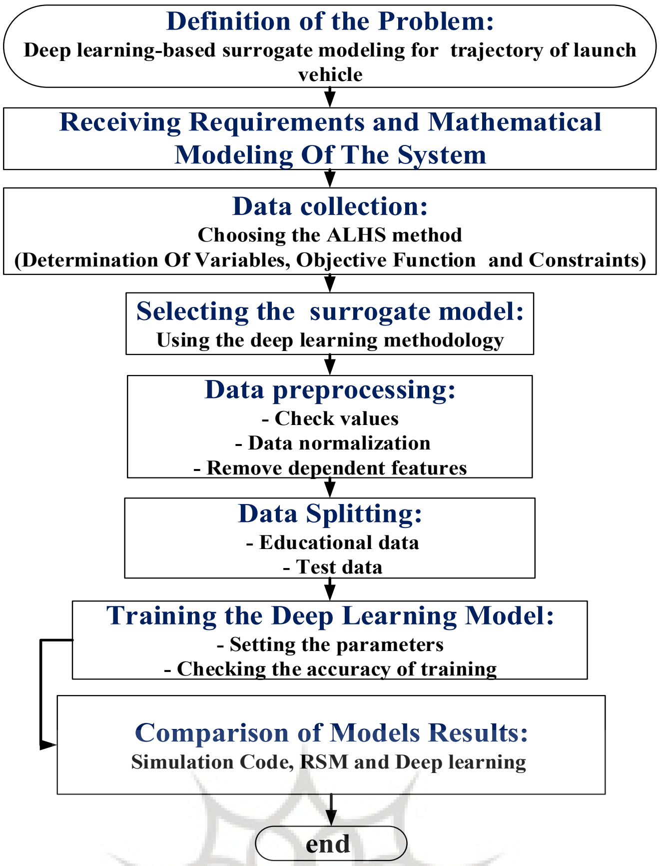

Fig. 1. Research methodology steps

The application of deep learning models as a novel and alternative method for modeling the flight trajectory of launch vehicles can greatly improve prediction accuracy and decrease analysis time. Comparing this approach with Response Surface Methodology (RSM) can yield new insights for future analyses and optimizations.

4. Case study

4.1 Design and implementation of deep learning models for launch vehicle trajectory

4.1.1 Problem definition: launch vehicles, due to their mobility and high dynamic complexities, require precise and efficient models to predict their flight paths. Modeling the flight trajectory utilizing deep learning can be proposed as an effective solution for predicting these paths. In this study, we aim to develop a trajectory model that not only achieves high accuracy but also consumes less computational time.

4.1.2 Receiving Requirements and Mathematical Modeling of the System: The two-stage Kosmos 3M launch vehicle, powered by liquid propellant, is designed to place a 1200 kg payload into a circular orbit at 750 km above the Earth's surface. The objective is to minimize the launch mass at the moment of launch. The orbital inclination is 50.6° latitude, and the launch vehicle is launched at sea level (Mirshams et al., 2015).

4.1.3 Data Collection: For data collection, the design of experiments and Advanced Latin Hypercube Sampling (ALHS) techniques were employed. This method enables us to define the input variables accurately, specify the objective function, and outline the necessary constraints. The input variables are presented in Table 4, and the objective function is detailed in Table 5.

Table 4. Input variables for design

Variables Name	Symbol	Units	Lower bound	Upper bound
Burn time of stage one	tb1	sec	126	133
Burn time of stage two	tb2	sec	326	333
Dry structure mass of stage one	ms1	kg	5000	5400
Dry structure mass of stage two	ms2	kg	1200	1500
Propellant mass of stage one	mp1	kg	82200	83000
Propellant mass of stage two	mp2	kg	18000	18800
Thrust of stage one	thr1	N	1480000	1490000
Thrust of stage two	thr2	N	158000	164000
Diameter of stage one	Dref	m	2.1	2.8
Trajectory angle coefficient (1)	aa	-	0.00	0.00
Trajectory angle coefficient (2)	bb	-	0.00	0.00
Vertical flight time	vertical_time	sec	6.00	6.60

Table 5. Objective Function

Response	Name	Nominal value	Symbol	Units
R1	Total Mass first stage	1.088E+05	Mo1	kg

4.1.4 Selection of surrogate model (utilization of deep learning method):

At this stage, various surrogate models, including Deep Neural Networks (DNN), are evaluated based on the collected data. The most suitable model is selected based on the characteristics of the data and the requirements of the system, after which the training and evaluation process commences, which is presented in Figure 2.

4.1.5 Data preprocessing: Before initiating the training, the data undergo preprocessing, which includes:

- Value Examination: Identifying and removing missing and outlier values.
- Data Normalization: This process utilizes the mean and standard deviation of the variables to ensure that the variables are on a comparable scale, thereby aiding in the training process.
- Removal of Dependent Features: Identifying influential features and eliminating unnecessary ones to improve model performance.

4.1.6 Data splitting: The data is divided into two main subsets**:**

- Training data: Used for training the model.
- Test data: Utilized to evaluate the accuracy and performance of the model post-training.

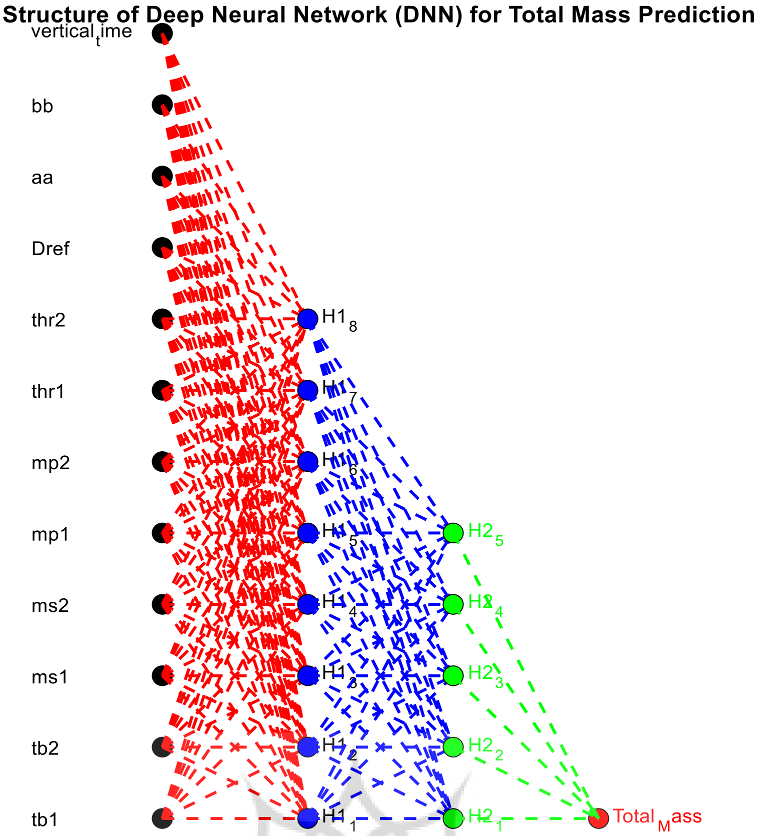

Fig. 2. Structure of Deep Neural Network(DNN) for total mass prediction

4.1.7 Training the deep learning model

In this stage, the parameter settings and the calculation of regression coefficients using the least squares method are conducted. Predictions are made with the model, and finally, the accuracy of the model is assessed. The accuracy of the model for predicting actual values in the case study is illustrated in Figure 3.

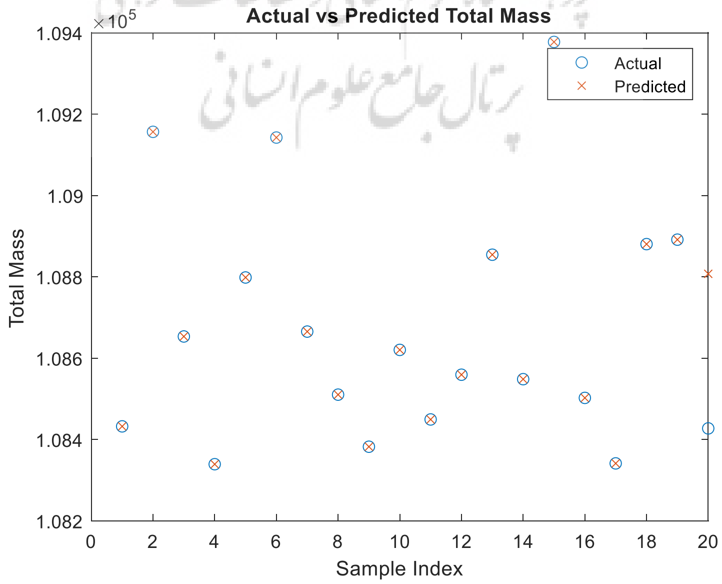

Fig. 3. Model accuracy for predicting actual total mass

4.1.8 Comparison of the results of the models:

To evaluate the accuracy of the deep learning model in predicting data, an introduction to the Response Surface Methodology (RSM) technique will first be presented.

4.2 Surrogate model based on Design of Experiments (RSM Method)

4.2.1 Selection of Variables and Objective Function: In order to construct a surrogate model, the variables, objective function, and design constraints must be specified. In this study, 12 design variables, one objective function, and 13 constraints were established.

4.2.2 Design of Experiments**:** Following the definition of the problem and selection of variables, the objective function, and their levels, the next step is the design of experiments. The experimental design involves the following steps in this research:

- Selection of Experimental Design: In this study, the Response Surface Methodology (RSM) was chosen as the experimental design using Design Expert software.
- Conducting Experiments: Advanced Latin Hypercube Sampling (ALHS) was utilized to conduct experiments for the surrogate models, with a total of 100 experimental runs planned.

4.2.3 Data Analysis: The statistical methods employed in the experimental design include hypothesis testing, plotting graphs, analysis of variance (ANOVA), and regression analysis. The output data from MATLAB was subsequently imported into Design Expert software. After several steps, the software computed various response surface scenarios and proposed the most suitable condition based on Adjusted R^2 and R^2 values. In this case, the software suggested a linear model.

4.2.4 Response Surface Equation (Predictive Model): Based on the 12 input variables, the following equation was derived to predict the flight trajectory behaviour of the system according to the specified levels of each variable. This equation consists of two parts: a constant term and the coefficients of the variables in a linear format.

Total Mass first stage = + 9237.8359 + 0.292069 * tb1 + 0.746752 * tb2 + 1.03710 * ms1 + 0.977958 * ms2 + 0.986009 * mp1 + 1.00371*mp2-0.00207*thr1 + 0.00110*thr2 + 23.7795 * Dref-1.21094E+06 * aa-2.28200E+06bb+17.88953*vertical_time

5. Discussion

The research conducted on the application of surrogate modeling in various engineering domains has yielded significant insights and underscores the evolving role of advanced computational techniques in aerospace engineering. This study employs two surrogate modeling approaches to develop a predictive model for the flight trajectory simulation code concerning the total mass of the first stage of the Kosmos 3M launch vehicle. The first method utilized is the traditional Response Surface Methodology (RSM), while the second approach leverages deep learning-based surrogate modeling. This section compares the results obtained from the deep learning model and the traditional RSM approach, elucidating the strengths and weaknesses of both methodologies.

5.1 Performance comparison

To model the flight trajectory simulation computer code using a surrogate model approach based on Response Surface Methodology (RSM), the following process was carried out. Utilizing experimental design methods and Advanced Latin Hypercube Sampling (ALHS), 100 tests were planned, which were executed in MATLAB considering the flight path design functions. The variables defined for the flight trajectory design in MATLAB are presented in Table 4. The number of input variables for the launch vehicle flight trajectory design in each test is 12.

For variance analysis and regression decomposition, the output data from MATLAB was entered into the Design Expert software. After performing several steps, the software calculated various response surface states, as shown in Table 6, and proposed the most suitable state based on Adjusted R^2 and R^2. As observed, the software suggests the Linear state for this problem.

Table 6. Various response surface states

Source	Sequential p-value	Adjusted R^2	Predicted R^2
Linear	< 0.0001	0.9884	0.9875
2FI	0.8288	0.9855	0.9292
Quadratic	0.6543	0.9883	0.7180
Cubic		Aliased	

The response surface equation, which represents the Total Mass of the first stage, is based on the 12 input variables from Table 4, which is used to predict the system's behaviour in relation to the specified levels of each variable. As indicated in the table, this equation comprises two parts: a constant term and the coefficients of the variables in the linear state.

The process of constructing the predictive model using a deep learning approach involves several key stages, including data collection, preprocessing, and model training. The accuracy of the deep learning model in predicting the total mass of the first stage of the Kosmos 3M launch vehicle is significantly higher than that of the RSM model, as demonstrated in Table 7. While RSM serves as a reliable baseline, it primarily relies on linear relationships and may struggle with the inherent complexities of launch vehicle dynamics. In contrast, the deep learning model has the capacity to identify complex nonlinear relationships among input variables, resulting in more robust predictions. This advantage stems from the flexibility of deep neural networks, which effectively learn complex patterns within the training data.

Table 7. Comparison of deep learning model, RSM, and simulation code

Variables Name	value	Simulation Code	RSM Total Mass	Deep learning
Burn time of stage one	128	108500	108556.6	108500
Burn time of stage two	328			
Dry structure mass of stage one	5250			
Dry structure mass of stage two	1250			
Propellant mass of stage one	82000			
Propellant mass of stage two	18800			
Thrust of stage one	1480000			
Thrust of stage two	162000			
Diameter of stage one	2.3			
Trajectory angle coefficient (1)	0.0023			
Trajectory angle coefficient (2)	0.0008			
Vertical flight time	6.5			

5.2 Model robustness and computation efficiency

Additionally, the computational efficiency of the deep learning model is noteworthy. This model significantly reduces the time required for predictions compared to traditional modeling techniques, which typically necessitate extensive iterative processes and parameter tuning. This reduction in computational load is crucial for real-time aerospace applications, where rapid decision-making is imperative. Consequently, these features position deep learning as a transformative tool in trajectory optimization and planning.

5.3 Limitations and future directions

Despite these promising results, certain limitations of the deep learning model must be acknowledged. Its dependence on the quality and quantity of input data raises concerns regarding its generalizability. Existing deficiencies within the training dataset may lead to issues such as overfitting or underfitting, necessitating robust data collection strategies. Therefore, future research should focus on expanding the dataset to encompass a wider array of launch conditions and additional parameters that could influence trajectory predictions.

5.4 Integration of techniques

An intriguing consideration for future studies is the integration of deep learning with traditional methods such as RSM. Hybrid approaches can capitalize on the strengths of both techniques, potentially enhancing overall accuracy while maintaining computational efficiency. Such strategic integrations may lead to the development of a more comprehensive framework for trajectory analysis, ultimately resulting in improved designs and operational strategies in launch vehicle systems. The comparison point for the design of the flight trajectory of the launch vehicle case study is illustrated in Figure 4.

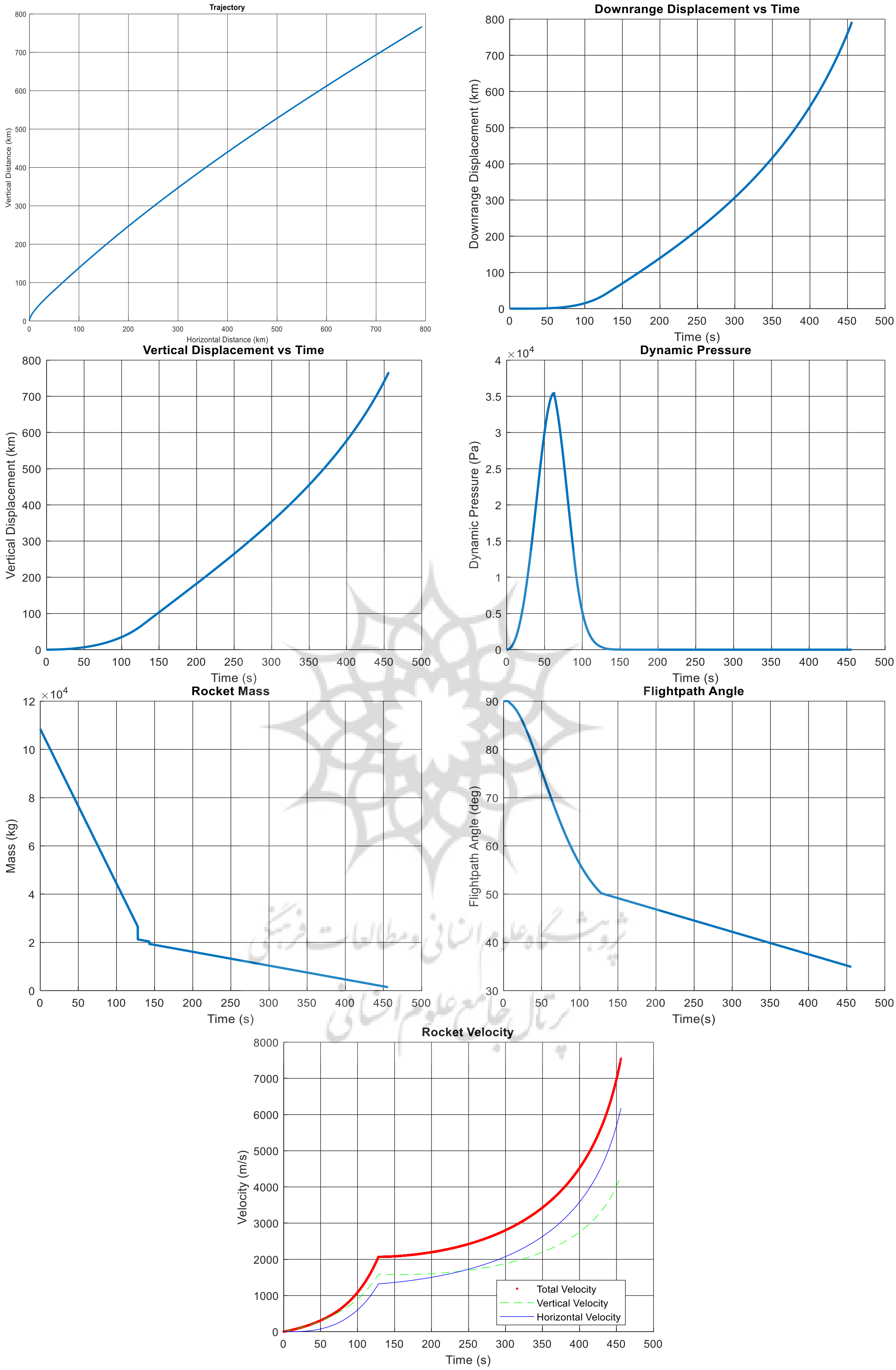

Fig. 4. Comparison point for predictive models in designing the flight trajectory of the launch vehicle

6. Conclusions

This study was conducted for the conceptual design phase of the flight trajectory of a two-stage launch vehicle, focusing on the selection of suitable subsystems and the optimization of the flight trajectory profile to meet mission requirements. In recent years, there has been a growing emphasis on computer simulations. However, these simulations can be computationally intensive. Therefore, to save computation time and facilitate design analysis, there is a need for a simplified model that can provide an efficient representation of the accurate and costly product model. Such simplified predictive models are also referred to as surrogate models. Surrogate models are created with a mathematical description based on corresponding input-output datasets derived from the precise simulation model.

In this paper, we investigated the effectiveness of deep learning models in flight trajectory modeling, specifically in relation to the two-stage launch vehicle Kosmos 3M, with the aim of reducing total mass while enhancing computational efficiency and accuracy in predictive modeling for optimal flight path design. Our methodology included thorough requirements gathering, data collection via Advanced Adaptive Latin Hypercube Sampling (ALHS), and meticulous preprocessing of input variables, which provided a solid foundation for model training. The following conclusion has been drawn from the analysis and discussion mentioned above.

a) The RSM surrogate model was constructed using experimental design methods and Advanced Latin Hypercube Sampling (ALHS), and it was validated through ANOVA with a 95% confidence level, resulting in the confirmation of a linear model for the proposed flight trajectory.

b) Evaluating various surrogate modeling approaches led to the development and training of a Deep Neural Network (DNN) which demonstrated significant capability in accurately predicting the total mass during ascent. A comparative analysis between our deep learning model and the traditional Response Surface Methodology (RSM) revealed notable advantages of the DNN in terms of predictive performance and robustness. Nonetheless, RSM continues to provide valuable benchmarks for research comparisons.

c) The findings of this research emphasize the potential of deep learning techniques to enhance accuracy in modeling the flight trajectories of launch vehicles while also paving the way for future advancements in aerospace design optimization. By integrating deep learning methodologies within the trajectory prediction framework, we expect substantial improvements in the modeling of complex aerospace systems, ultimately leading to increased efficiency in aerospace operations.

d) In our assessments, the deep learning approach yielded a benchmark total mass value of 108,500 kg for the launch vehicle, compared to the total mass derived from the RSM method, which amounted to 108,556.6 kg. This discrepancy highlights the superior accuracy of the deep learning model relative to the RSM approach. The insights gained from this study can serve as a valuable resource for future research endeavors aimed at leveraging machine learning techniques in the field of aerospace engineering.

e) The accuracy of these predictive models can be utilized for subsequent design phases where six degrees of freedom dynamic equations are taken into consideration. Additionally, this approach can be applied to multi-stage launch vehicles in the conceptual design phase.

6.1 Future research recommendations

In the concluding section of the paper, suggestions for future research are presented. These recommendations include:

- Development of Hybrid Techniques: The use of hybrid techniques that combine traditional models with deep learning could lead to improvements in performance and prediction accuracy.
- Optimization of Algorithms: Focusing on optimizing deep learning algorithms to reduce training time and enhance efficiency under various conditions is proposed as an important goal for future research.
- Improvement of Generalization: Investigating techniques that can enhance the generalization capabilities of deep learning models.

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