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Research article

Machine learning-based surrogates for eVTOL performance prediction and design optimization

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Abstract: Predicting the performance of different electric vertical take-off and landing (eVTOL) vehicle designs is paramount to vehicle manufacturers and hobbyists. These vehicles' maximum flight time (endurance) and maximum flight distance (range) depend on design and operational parameters relating to their structure, propulsion system, payload, and mission profile. In recent years, sophisticated physics-based models have been developed to estimate and optimize their aerodynamic, propulsion, and electrical performance. Integrating and simulating those models can closely estimate a vehicle's endurance and range. However, this demands advanced knowledge of different subsystems utilized and extensive computational resources limiting the wide-scale utilization of such models. This paper showcases the development and implementation of a framework to train simpler machine learning-based surrogates. The surrogate models are trained on a limited number of eVTOL performance estimates generated by physics-based models and can mimic them accurately. Forty-seven thousand eVTOL vehicle designs were simulated to generate the training data for various machine-learning models. These include several decision tree models, K-nearest neighbor models, linear regression models, and a multi-perceptron neural network model. Vehicle design and operational parameters such as propeller size, payload mass, drag coefficient, velocity, and motor and battery parameters are used as features, and vehicle endurance and range estimates are used as targets. Compared to the alternative approaches, these surrogate models are computationally very efficient and easy to understand and use. Testing on hold-out datasets shows excellent performance, with multiple models having a mean average percentage error of less than 2% in estimating vehicle endurance and range.

Keywords: eVTOL; electric aerial vehicles; UAVs; performance prediction; surrogate models; physics-based modeling; machine learning; design optimization; endurance estimation

1. Introduction

The applications for electric aerial vehicles have grown significantly in the past decade. They include military missions, search-and-rescue operations, real-time surveillance, package delivery, hazardous site inspection, etc. [1]. These vehicles can be primarily classified based on their design and application [2]. Vehicles with electric propulsion systems are popular due to their simplicity, reliability, and high efficiency. These include electric vertical take-off and landing (eVTOL) vehicles, which are promoted for short-duration flights in locations with challenging topography for landing traditional aircraft.

eVTOL vehicles have multiple rotors and use propellers, electric motors, and batteries for propulsion [3] as shown in Figure 1. In addition to other vehicle and operational parameters like vehicle mass, aerodynamic drag, payload mass, and velocity, these components influence a vehicle's endurance and range. Vehicle endurance indicates the duration a vehicle can remain airborne, while range gives the distance it can fly. Accurate estimations of these key metrics for different vehicle designs and mission profiles can help manufacturers and hobbyists choose the best combination of components that maximize performance and satisfy their missions. Several studies have explored the performance modeling of these individual subsystems as well as assembled vehicles [4, 5, 6]. Extensive knowledge of these systems, integration of high-fidelity physics-based models of these components, and extensive computational resources are needed to estimate these metrics accurately and rapidly. These factors limit the widespread utilization of prediction models and cause teams to explore experimental methods [7, 8, 9] to support vehicle design decisions. These challenges and also real-time mission replanning requirements during contingencies highlight the need for alternative approaches that can provide designers and operators with accurate and efficient vehicle performance estimation models, motivating the exploration of machine learning (ML)-based surrogates in this work.

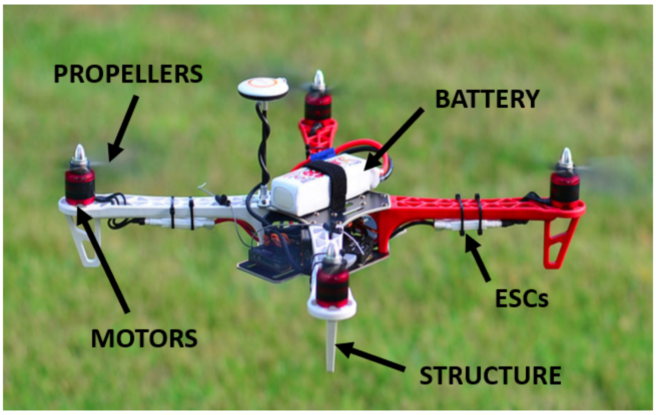

Figure 1. A multi-rotor aerial vehicle depicting the various components that affect its endurance and range performance.

Through this work, the authors aim to sidestep the high computational costs associated with physics-based models using ML-based surrogates trained on simulation data. These surrogates offer not only predictive accuracy but also significantly enhanced computational efficiency, making them ideal for real-time applications and rapid design iterations. Such lightweight prediction tools could rapidly provide valuable insights into component compatibility and facilitate the development of more efficient vehicles. They could also benefit operations teams by providing in-time insights for real-time mission replanning, ensuring eVTOL vehicles can adapt to dynamic mission requirements, component failures, and changing environmental conditions.

1.1. Literature review

The endurance and range prediction of aerial vehicles and analysis of design attributes are popular research domains. Mathematical expressions to estimate the range and endurance for a battery-powered aircraft were developed for steady-state flight in [10]. These performance metrics for a fixed-wing micro aerial vehicle (MAV) were modeled using simpler equations that considered aerodynamic and propulsive efficiency in [11]. In [12], even simpler analytical models were developed at the loss of accuracy to evaluate the benefit of dumping used and empty batteries to increase vehicle endurance. In [13], an electric rotorcraft endurance model based on momentum theory was developed and verified against experimental tests on five vehicles.

In [4], a framework was developed to estimate electric multirotor vehicle performance and design optimization while considering mission requirements. The authors highlight the challenges in making informed decisions while designing these vehicles and inaccuracies in manufacturers' data. They attempted to parametrize vehicle structural and drive component (motors, electronic speed controllers, and batteries) parameters based on available data. A single propeller airfoil shape, blade element momentum theory (BEMT), and propulsion system electrical model were utilized to estimate vehicle performance given some mission parameters. Validation of their models showed a mean absolute percentage error between reported and estimated endurance values of 5.7%. In another similar effort, a multirotor vehicle's design attributes were studied [6], where equations for modeling a vehicle were established, and MIT-developed tools XFOIL [14] and QPROP [15] were employed to estimate the combined performance of motor-propeller pairs accurately. These works emphasize the complexity of modeling the underlying physics of different vehicle components to achieve acceptable endurance and range estimates. These estimates generated for a limited number of vehicle designs and the associated data could serve to train the proposed surrogate machine-learning models. Shifting the focus to the realm of machine learning, there are a few studies that delve into its application concerning electric aerial vehicles.

Very little research has been done on machine learning techniques to predict or optimize all eVTOL design parameters for enhanced endurance or range. Using existing fixed-wing unmanned aerial vehicle (UAV) designs and performance data, surrogate machine learning models were utilized and compared to empirical models to estimate UAV design parameters and performance in [16]. The machine learning-based estimations were reported to be better than those from empirical correlations. For eVTOL vehicles, surrogate regression and semi-analytic models were developed to estimate the weight of vehicles [17]. Several works have investigated surrogate models for estimating the aerodynamic flows around and properties of aerial vehicles. In [18], a deep-learning-based surrogate model was developed to determine the aerodynamic performance characteristics of unmanned aerial vehicles. Thousands of vehicle designs were simulated to generate training data for the deep-learning models. In [19], the authors developed a methodology to utilize surrogate machine learning models to predict steady turbulent aerodynamic fields to overcome the computational limitations of physics-based aerodynamic simulations. In [20], the noise and aerodynamic performance of eVTOL vehicles were predicted using deep-learning surrogates. Additional surrogate modeling efforts in this space are related to airfoil design [21], aerodynamic performance [22], control [23, 24], machine vision [25], and altitude determination [26]. Recently, surrogate models have also been utilized for eVTOL certification [27], trajectory planning [28], and swarm formations [29].

A similar problem, although unrelated to aerial vehicles, was addressed in [30], where authors aimed to predict the performance of computer system designs. In this study, linear regression models and artificial neural networks (ANN) were tested, with two distinct training data types: simulated and historical data. Interestingly, the prediction errors were minimal (3.4%) even when the training datasets constituted only 1% of the total design space. In [31], the goal was to predict used car prices, given features such as year, make, model, and cylinder volume. Various algorithms were employed, such as multiple linear regression analysis, nearest neighbors method, and decision trees. Most of these algorithms yielded comparable performance. This machine-learning application, although different, shares a similar approach to what is achieved in this work to predict the endurance and range of eVTOL vehicles. Due to the unavailability of sufficient real vehicular performance data generated under similar test conditions to train the models, which can lead to a poor prediction performance [32], we choose to generate and utilize simulated data as described in the next section.

2. Materials and methods

As discussed in previous sections, the physics-based modeling approach is very involved, and a flow chart describing one such approach is shown in Figure 2. It shows the steps followed and inputs needed to estimate the endurance, range, and other performance metrics, like the thrust-to-weight ratio of eVTOL vehicles. This framework is utilized in this effort to generate the datasets to train the surrogate ML models. This is implemented using the ’R’ programming language. The physics-based models take in vehicle structural mass, payload mass, vehicle drag coefficient, motor parameters, propeller parameters, and others as inputs. Using datasheets and MIT-developed tools XFOIL and QPROP, the combined motor-propeller performance for different input voltages textcolorblackis determined. For a vehicle to maintain steady state flight, the total thrust T generated by the n_m number of motors of a vehicle should equal the sum of the vehicle weight W and the drag force experienced by it, as given by Eq. 2.1. Here, ρ represents air density, C_D is the coefficient of drag of the vehicle, A is the vehicle’s effective area, and V is the steady state velocity.

$$T = W + \frac{1}{2}\rho C_D A V^2 \tag{2.1}$$

Ultimately, a vehicle’s endurance, E, and range, R, for any selected throttle input, τ, are given by Eqs. 2.2 and 2.3. In these equations, C represents battery capacity, I_m is motor current, and T is the total thrust generated by the motor-propeller systems.

$$E = \frac{C}{I_m(\tau)\, n_m} \tag{2.2}$$

$$R = EV = \frac{C}{I_m(\tau)\, n_m}\sqrt{\frac{T(\tau) - W}{\frac{1}{2}\rho A C_D}} \tag{2.3}$$

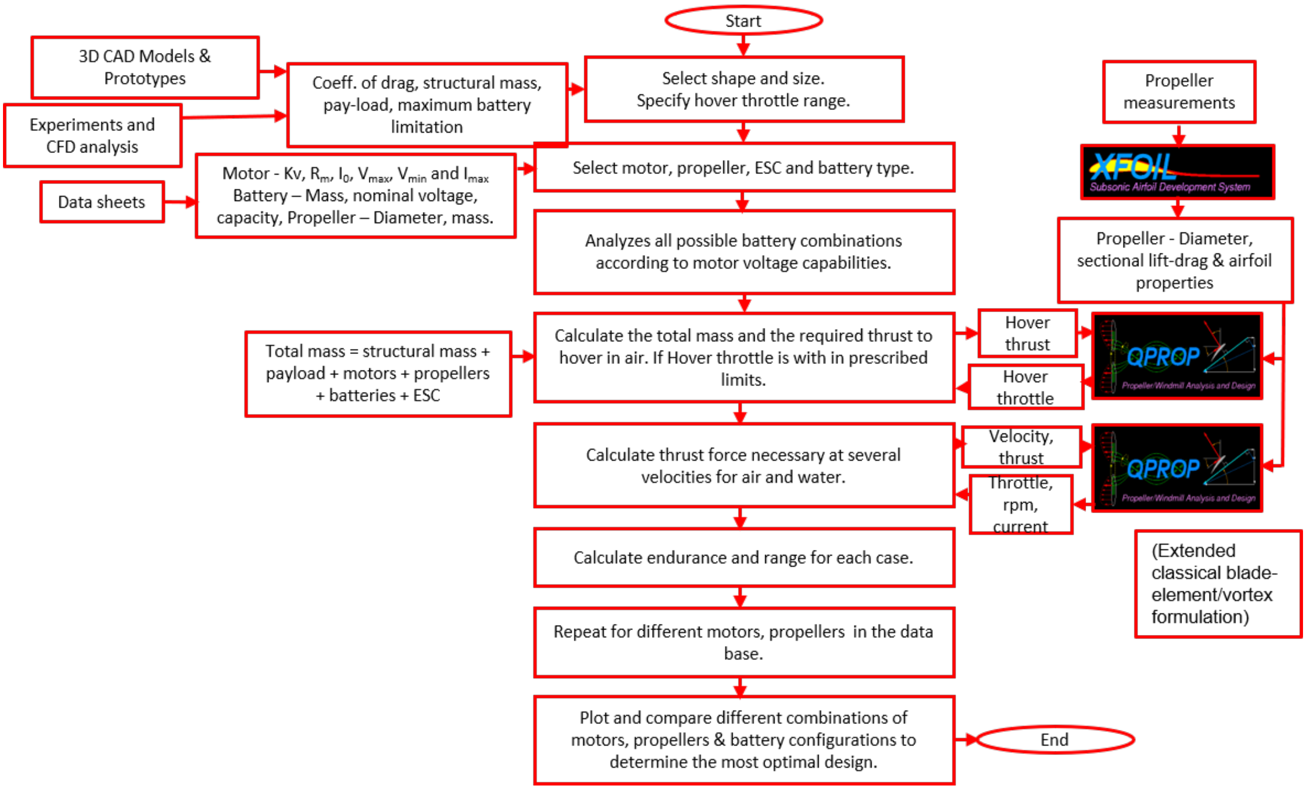

Figure 2. Flow chart showing the steps and tools used to estimate the performance of eVTOL vehicles using physics-based models. Data from these simulations is utilized to train surrogate models.

More details about the physics-based modeling descriptions and equations utilized to generate the datasets can be found in [6]. A sample design space exploration technique is utilized, and a small subset of all the possible designs and operational regimes is selected and simulated to estimate endurance and range values. The process adopted to train the ML models is illustrated in Figure 3. Different physics models (aerodynamics, motor performance, propeller performance, and battery physics) are integrated and used to generate target values. The input features and estimated values together make up the entire dataset, which is split into a training and a test dataset. The training datasets are utilized to train the models, while the test data is set aside and used to evaluate the performance and generalizability of the trained models.

2.1. Physics-model simulation and data generation

The integrated physics-based model described in [6] is run several times by varying the inputs to the model. The program runs through all the motors (69) and propellers (3) available in a database and different battery configurations. Each program run generated one CSV sheet for each of the motors for different propeller and battery-pack combinations and vehicle velocities (0 to 30 m/s). Some combinations do not generate enough lift and are eliminated. The physics model estimates the endurance and range of each feasible design and velocity. Hence, several endurance and range values are generated for each vehicle configuration. Nearly 1000 CSV sheets were generated and combined to provide over half a million instances for training and testing the ML models. Specifically, the dataset was comprised

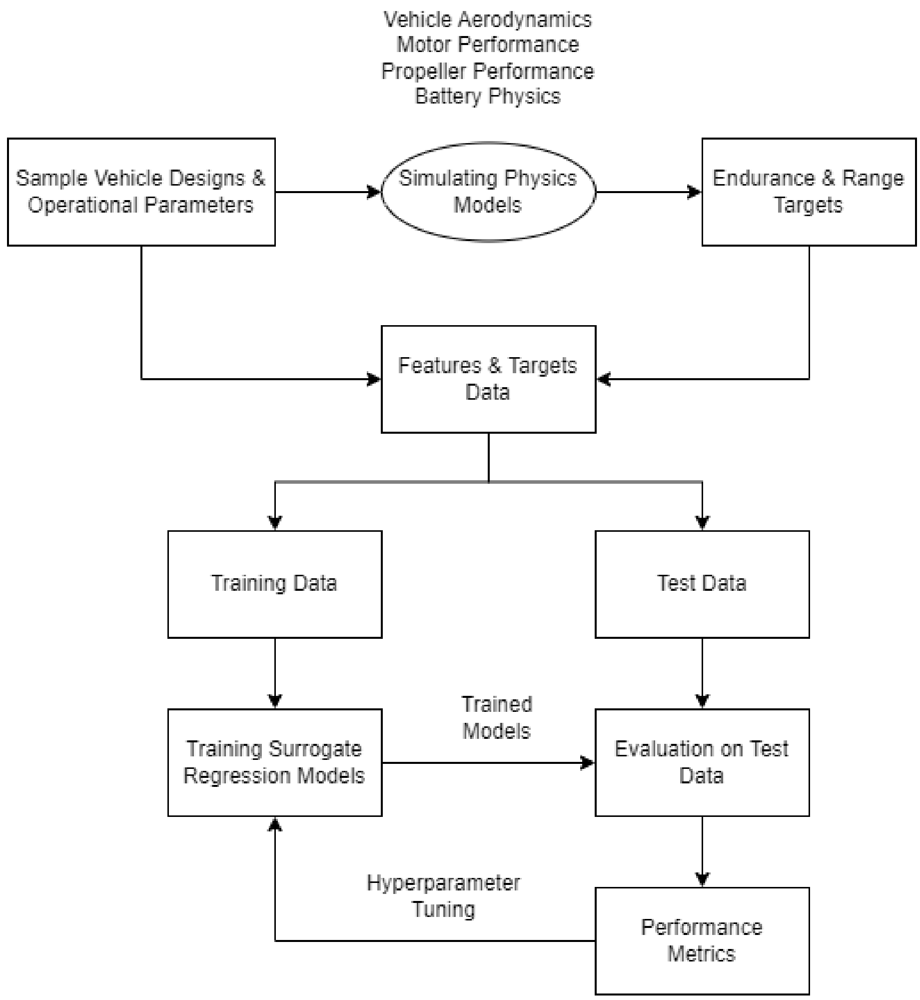

Figure 3. Flowchart showing the process utilized to generate eVTOL performance estimates data and how it is used to train, test, and optimize surrogate ML models.

of 543,085 records, out of which 380,159 (70%) were used for training and 162,926 (30%) were used for testing. The simulated data is free of outliers and erroneous or missing values. The outputs of these simulations (i.e., range and endurance estimates) were utilized as targets for prediction models.

2.2. Features selection

Features are the inputs to the ML models needed to predict the target values. Feature selection is an important step that affects the performance of the models. Here, using subject matter knowledge, some of the parameters fed to the physics models are selected as features [6]. Several variables like propeller pitch, number of cells, total battery system mass, and others are captured in other features and are removed. These features may also be beneficial when using other training datasets, which provide information that other features do not. For example, propellers (from T-motor) of three different diameters are utilized in this dataset. However, there is no variability in the propeller pitch values given a propeller diameter, making the propeller pitch values redundant. Such variables are removed, which resulted in twelve features as indicated in Table 1. The table also indicates the variable type, range of values observed, and their units.

Table 1. Names, type, range, and units of the features selected as inputs to train the surrogate ML models.

S.No	Feature	Type	Range	Units
1	Structural Mass	Real	1, 2	kg
2	Payload Mass	Real	0, 1, 2, 4	kg
3	Motor Mass	Real	18–1650	g
4	Motor Kv	Integer	50–2550	RPM/V
5	Motor Internal Resistance	Real	0.05–0.5	Ohm
6	Motor No Load Current	Real	0.05–0.5	A
7	Propeller Diameter	Integer	13, 15, 28	in
8	Battery Voltage	Real	10–58	V
9	Battery Capacity	Integer	3–99	Ah
10	Vehicle Mass	Real	2–25	kg
11	Drag Coefficient	Integer	1, 2	-
12	Velocity	Integer	0–29	m/s

2.3. Features distribution and visualization

The datasets are properly formatted to train the ML algorithms, and the different features can be visualized to observe underlying distributions and correlations between them. The distributions of values for the twelve selected features are shown in Figure 4 and can reveal any potential issues or anomalies in the data, such as unexpected gaps. Some of the distributions observed are a direct result of the selected inputs for the simulations, and others are derived from the inputs. Small eVTOL vehicle designs with either 1 kg or 2 kg frame mass are simulated carrying either no payload or with a 1, 2, or 4 kg payload. Sample drag coefficient values of 1 or 2 derived from experimental results considering vertical flight are utilized. Propeller measurements required for accurate simulations were available for the three propeller designs and are utilized. Data for 69 different motors (sold by T-motor company) was scraped from the web, and the motor parameters visualized correspond to the motors selected. Motor parameters such as motor mass, motor Kv, internal resistance, and no-load current indicate lightweight and efficient motor designs appropriate for aerial vehicles. The simulations were allowed to iterate over 0 m/s to 30 m/s velocities, and the distribution was automatically generated and indicative of the feasible mission profiles for the simulated designs. Similarly, the battery capacity and vehicle mass distributions result from iterating through different 18650 Lithium-ion battery pack combinations that resulted in flight-capable designs. Battery pack voltages were increased by adding the number of cells in series within the range suitable for the selected motors, and the number of parallel cells was increased until the vehicle weight was too large for a safe flight. The vehicle mass also includes the mass of the motors and propellers.

These visualizations also help guide the selection or extraction of features as well as the identification of appropriate models to learn the selected features.

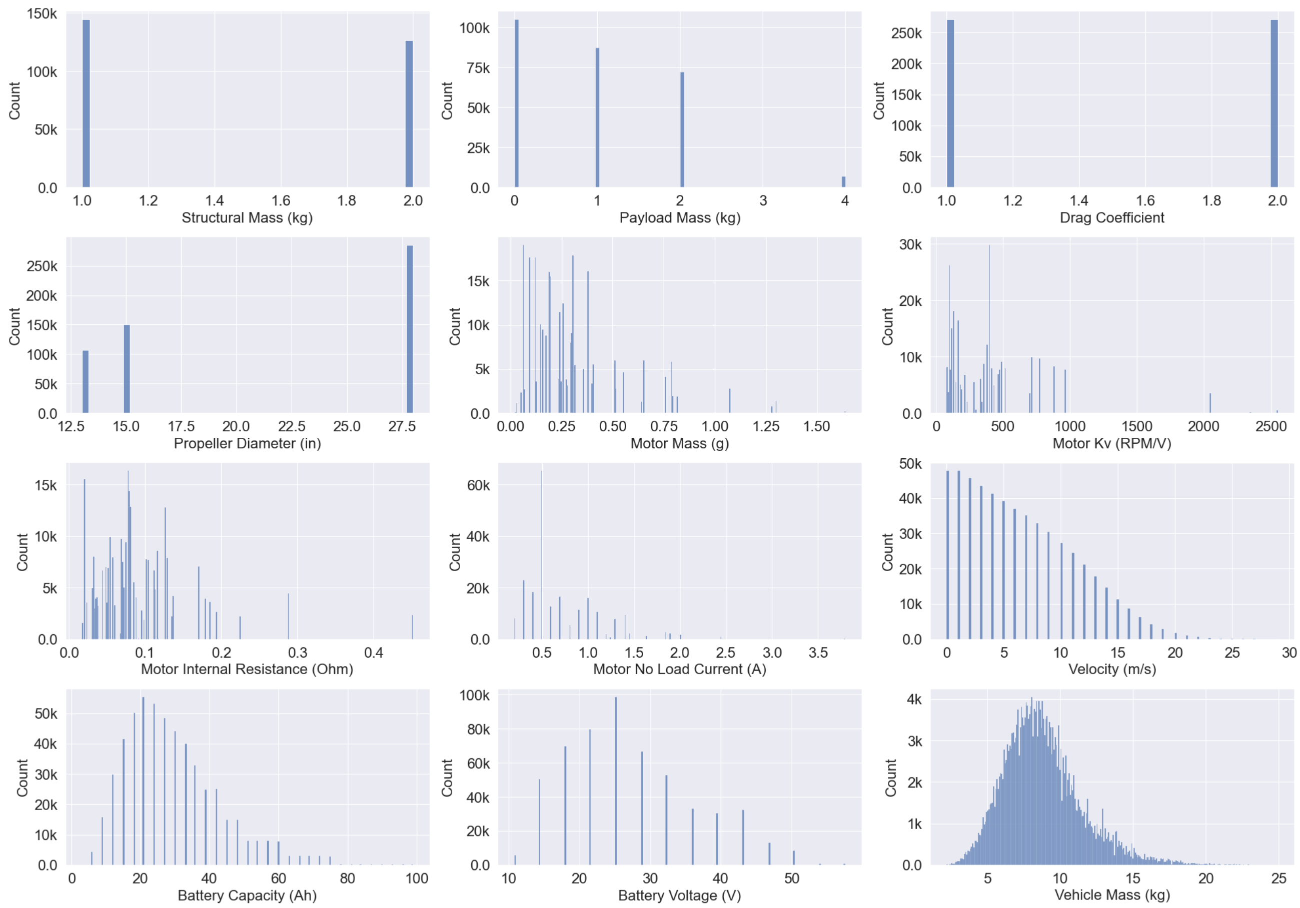

Figure 4. Frequency distribution of the twelve variables selected as features to train the surrogate ML models.

Similarly, distributions for the target variables (i.e., endurance and range) are also shown in Figure 5 and Figure 6. The endurance of the different designs ranges from about 10 minutes to a maximum of about 120 minutes. It follows a normal distribution, with the mean being around 45 minutes. The vehicle range values have a minimum of 0 Km observed during hovering flights that result in maximum endurance. The maximum range observed is 25 Km.

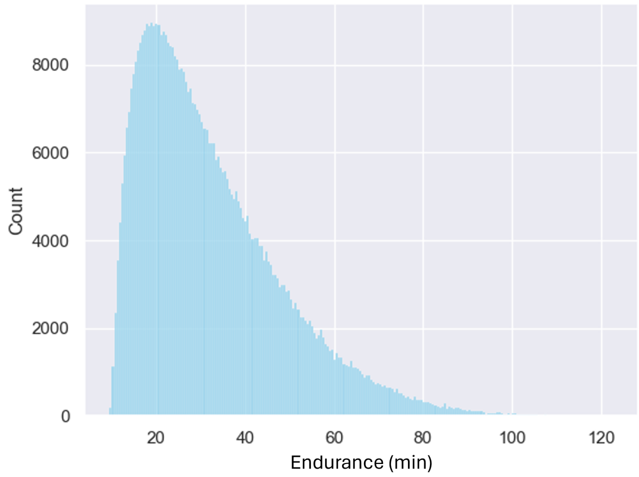

Figure 5. Frequency distribution of vehicle endurance values generated by the physics-based models in the complete dataset.

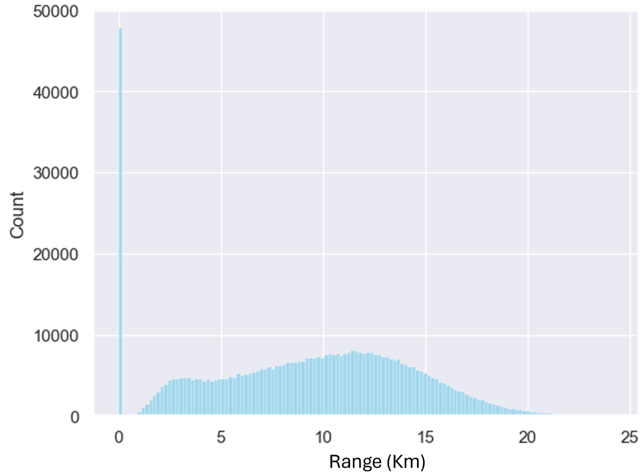

Figure 6. Frequency distribution of vehicle range values generated by the physics-based models in the complete dataset.

Figure 7 plots the maximum endurance of a vehicle (obtained for a hovering flight) against the maximum range for a vehicle. Three specific motors are highlighted. The figure shows that good vehicle designs result in both increased endurance and range estimates.

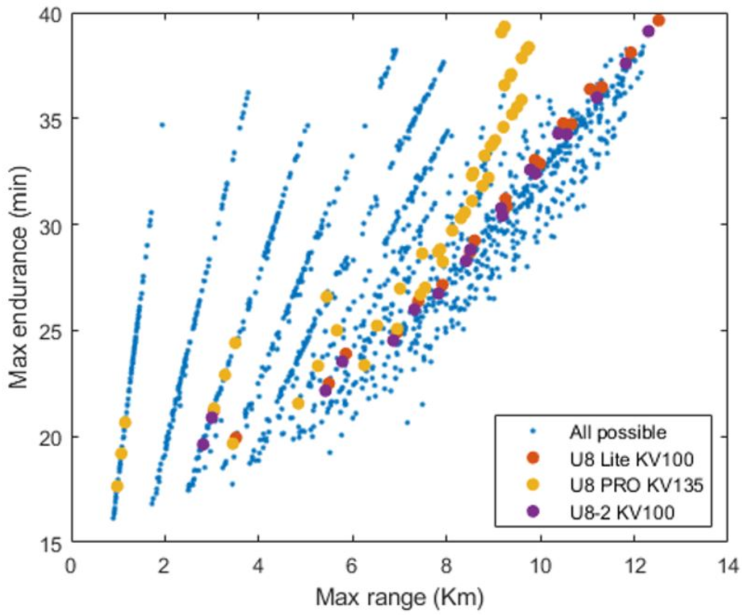

Figure 7. Maximum endurance versus maximum range values of different vehicle designs as estimated by the physics-based models. Vehicle designs corresponding to three motors are highlighted.

Figure 8 shows the endurance of different vehicle designs for fixed motor throttle setpoints using a scatter plot. In the figure, *t2wr* indicates the thrust-to-weight ratio of a vehicle design, which is another key performance metric for vehicle designs with high values indicating improved maneuverability. The marker colors indicate the Kv rating of the motors. Vehicles hover or move at lower velocities at lower throttle setpoints. This results in higher endurance values, as shown in the figure. The figure also shows the vast number of vehicle designs and missions simulated to train the surrogate models.

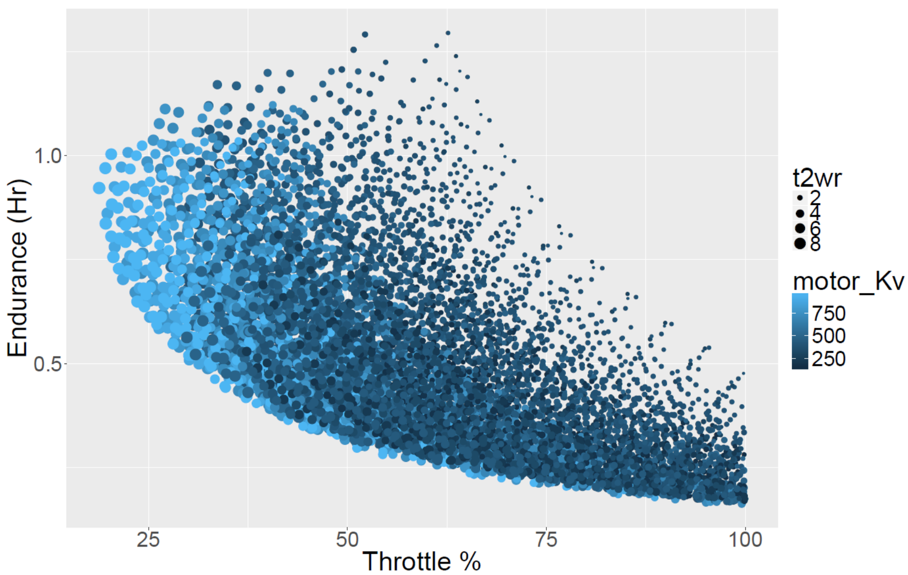

Figure 8. Physics-models' estimated endurance values of different vehicle designs for different simulated throttle set points. The color and size of the dots indicate the motor Kv rating and the thrust-to-weight ratio, respectively.

A Pearson correlation heatmap, shown in Figure 9, illustrates the inter-variable relationships present in the simulated data. It shows that vehicle range and endurance are negatively correlated. Vehicle velocity, V, correlates the strongest with the target variables. It does so directly with range and inversely with endurance, as expected. Other variables, such as battery capacity, propeller diameter, payload mass, and motor mass, have notable correlations with the target variables. The ML algorithms are expected to capture and utilize these correlations in estimating the target variables.

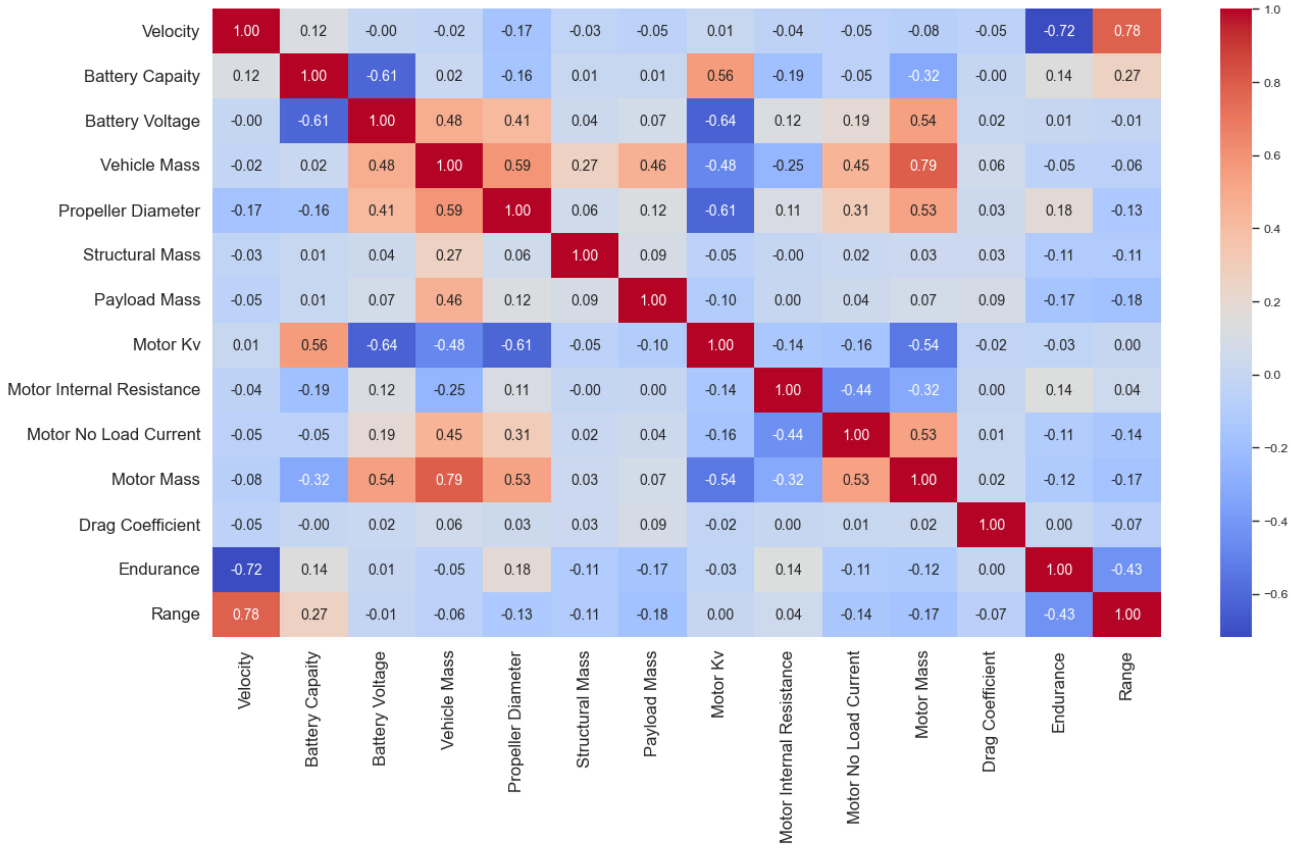

Figure 9. Heatmap showing Pearson's correlation coefficients between the 12 vehicle design features and also the physics estimated endurance and range values.

2.4. Algorithms investigated

Several ML regression models were evaluated to predict vehicle endurance and range. These included a variety of decision trees, a neural network model, and others, as indicated below. Each model exhibited different performance and computational overheads based on its underlying learning methodology.

- **Tree-based ensemble methods**:
  - **Extra trees regressor (ET)**, **random forest regressor (RF)**, **gradient boosting regressor (GB)**, **extreme gradient boosting regressor (XGBoost)**, and **light gradient boosting machine (LightGBM)**: These algorithms construct multiple decision trees on random subsets of the data and combine their predictions to improve accuracy and robustness. They can capture non-linear relationships and are less prone to overfitting compared to individual decision trees. However, they can be computationally expensive and may struggle with high-dimensional or sparse data.
    - **ET**: An ensemble learning method that utilizes ensemble learning by fitting randomized decision trees to sub-samples of the dataset. It employs averaging to enhance predictive accuracy and mitigate overfitting.
    - **RF**: Another ensemble tree-based learning method that builds multiple decision trees and

merges them to obtain a more accurate and stable prediction.

    * **GB**: A machine learning technique for regression problems, which builds a predictive model in a stage-wise fashion as other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.
    * **XGBoost**: An optimized distributed gradient boosting library designed to be highly efficient, flexible, and portable, implementing machine learning algorithms under the Gradient Boosting framework.
    * **LightGBM**: A gradient boosting framework that uses tree-based learning algorithms and is designed for distributed and efficient training, particularly on large datasets.

- **Neural networks**:
  - **Multilayer perceptron regressor (MLP)**: A feedforward artificial neural network (ANN) that learns complex patterns through multiple layers of interconnected nodes. It can model non-linear relationships and handle high-dimensional data but requires careful tuning and may be prone to overfitting or getting stuck in local minima.
- **Linear Models**:
  - **K nearest neighbors regressor (KNN)**: A non-parametric method that predicts based on the average of the nearest neighboring data points. It is simple and interpretable but can be sensitive to irrelevant features and the choice of the number of neighbors.
  - **Linear regression (LR)**: A linear model that assumes a linear relationship between input and output variables. It is computationally efficient and interpretable but may struggle with non-linear relationships and high-dimensional data.
  - **Elastic net (EN)**: A regularized linear regression technique that combines L1 (Lasso) and L2 (Ridge) regularization. It can handle multicollinearity and perform feature selection but may oversimplify non-linear relationships.

Performance metrics such as mean absolute error (MAE), root mean squared error (RMSE), R-squared (R^2), and mean absolute percentage error (MAPE) were utilized. The different ML models listed above are evaluated using the test data, and the above metrics were generated by comparing the ML predictions to the endurance and range values estimated by the physics-based models.

3. Results and discussion

This study investigated the effectiveness of ML-based surrogate models in predicting the performance metrics of eVTOL vehicles, specifically focusing on endurance and range metrics. The surrogate models are expected to offload the computational requirements and complexity of the physics-based models on the end-user's part. Python's PyCaret library [33] is used for training and hyperparameter tuning of the models. The results show that several ML models offer superior predictive performance, particularly the ET models fine-tuned through hyperparameter optimization. The results below demonstrate the models' potential as a reliable and rapid eVTOL performance evaluation and design optimization solution.

3.1. Endurance prediction results

Results for the endurance prediction models are shown in Table 2. Results show that the optimized ET model, with 100 estimators using 10-fold cross-validation and training time of 178 seconds, achieved the best performance with a MAPE of 1.2% and an R^2 value of 0.9991. The RF model placed second with a MAPE value of 1.72 % and an R^2 value of 0.9979, followed by the MLP model. In terms of mean absolute error, the GB model, for example, had an MAE of 2.69 minutes, which may be within acceptable error limits for a vehicle with greater than 30 minutes of flight time.

Figure 10 shows the predictions generated by the ET model on the test data compared to the target values. The closer the predictions are to the identity line, the better they are. Figure 11 shows the influence of different features utilized. This feature importance plot indicates that the endurance values largely depend on the vehicle's velocity in a simulation, with a variable importance score nearing 0.6. The highest influence score matches the observation from the Pearson correlation heatmap in Figure 9. The battery capacity and payload mass features hold second and third spots.

Table 2. Performance evaluation metrics for the different endurance prediction surrogate models on the test dataset.

Model	MAE	RMSE	R^2	MAPE (%)
ET	0.31	0.49	0.999	1.20
RF	0.47	0.73	0.998	1.72
MLP	0.63	0.89	0.997	2.19
XGBoost	0.95	1.28	0.994	3.17
LightGBM	1.17	1.59	0.990	4.07
KNN	1.48	2.34	0.979	4.47
GB	2.70	3.88	0.941	8.69
LR	4.89	6.67	0.826	18.03
EN	6.02	8.42	0.722	21.26

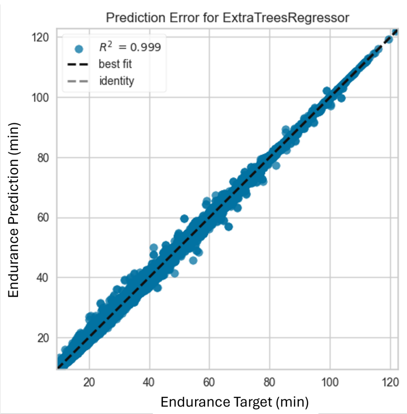

Figure 10. ET surrogate model predicted endurance values compared to the target physics-model estimated values.

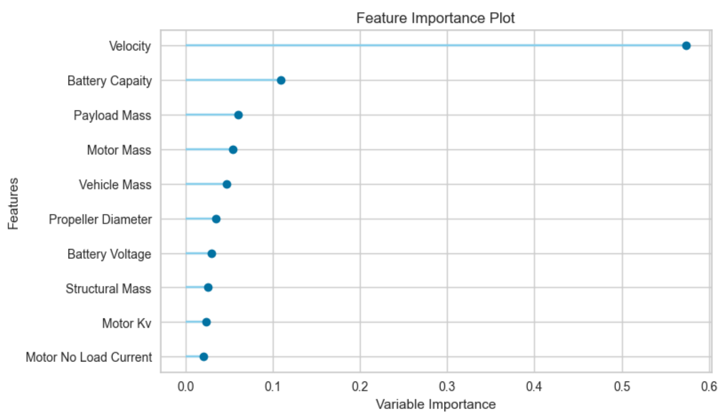

Figure 11. Feature importance values of the ET surrogate model to predict vehicle endurance.

Other tree-based models, such as the XGBoost and LightGBMs, exhibited a small increase in error rates. Their performance was a balance between computational complexity and predictive accuracy. The worst-performing models among those tested were the LR model and the EN model, which had MAPE values of 18.03% and 21.26%, respectively.

3.2. Range prediction results

Results for the different eVTOL range prediction models are depicted in 3, which show similar trends as the endurance models. The best model, the ET, with 100 estimators using 10-fold cross-validation and a training time of 141 seconds, shows a high R^2 score of 0.9995 and a MAPE value of 0.87%. This model's predictions are visually compared to the target values in Figure 12. The feature importance plot is shown in Figure 13, and it also illustrates vehicle velocity (V) as the most important feature, with a variable importance score exceeding 0.7. Again, the features, battery capacity, and vehicle payload maintained their second and third positions.

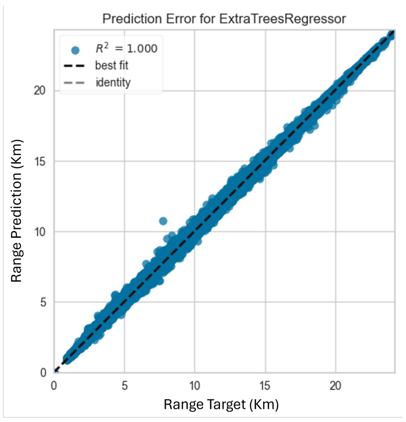

Figure 12. ET surrogate model predicted range values compared to the target physics-model estimated values.

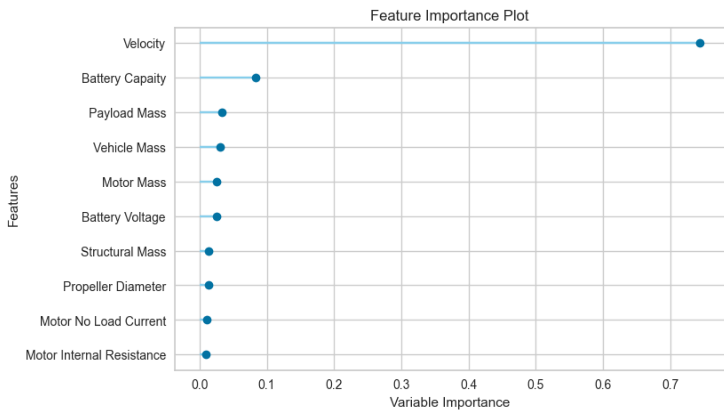

Figure 13. Feature importance values of the ET surrogate model to predict vehicle range.

The RF followed closely, after the top performer, with a R^2 score of 0.999. The K-Nearest Neighbors Regressor Model ranked 6^{th} out of the nine tested models and had an R^2 score of 0.981 and a MAPE value of 5.71%. The LR model ranked 8^{th} with a MAPE value of 0.21, followed by the EN model.

Table 3. Performance evaluation metrics for the different range prediction surrogate models on the test dataset.

Model	MAE	RMSE	R^2	MAPE (%)
ET	0.07	0.12	0.999	0.87
RF	0.10	0.16	0.999	1.27
MLP	0.20	0.27	0.997	2.60
XGBoost	0.24	0.32	0.996	3.08
LightGBM	0.33	0.43	0.992	4.07
KNN	0.50	0.69	0.981	5.71
GB	0.74	0.98	0.963	8.38
LR	1.98	2.53	0.753	21.23
EN	2.20	2.77	0.702	24.43

Overall, the tree-based models, particularly the ET, demonstrated top performance with MAPE values of 1.2% and 0.87% for endurance and range targets, respectively. The RF model followed closely, with MAPE values of 1.72% and 1.27% for the two targets. The less than 2% MAPE error for endurance and range prediction is well within acceptable error margins. The range and endurance EN models, for example, have similar MAPE values but different MAE and RMSE values. This is due to the different scales of the two target variables.

The ranking of the ML models was consistent across almost all metrics for both targets. Similarly, the feature importance rankings, shown in Figure 11 and Figure 13, for both targets using the ET are similar. In addition to the overall feature importance values, tools like Shapley values [34] or LIME [35] can be utilized to explain each prediction. These tools allow for extracting the contribution of each feature to a selected vehicle design's predicted performance, facilitating the identification and iteration of design features expected to yield the largest performance improvements.

The surrogate models offer not only predictive accuracy but also significantly enhanced computational efficiency, making them ideal for real-time applications and rapid design iterations. These lightweight models could be extremely beneficial during flight operations, especially during contingencies. They can provide instantaneous feedback on performance metrics, enabling aircraft dispatchers or autonomous controllers to make informed adjustments to flight parameters, dynamically optimizing endurance and range.

The scalability of these models ensures adaptability to various eVTOL designs and operational scenarios, making them versatile tools for a wide range of applications. These models also benefit operations teams by facilitating in-time mission replanning during contingencies. This capability ensures that eVTOL vehicles can adapt to changing mission requirements, system failures (like battery capacity drops), and environmental conditions, thereby enhancing overall mission success rates.

Ultimately, integrating such surrogate models, following thorough verification and validation steps, into eVTOL design and operational workflows promises to enhance both the development and operational phases. This integration is expected to drive advancements in eVTOL technology, optimize performance, and improve contingency management.

4. Conclusions

The results underscore the ability of ML models to learn and mimic the equations carefully crafted in physics-based models that estimate the performance of electric aerial vehicles. The ML training framework and generated insights offer a data-driven pathway to refining eVTOL designs and operational strategies.

Results generated in this work show that tree-based models like the ET and RF demonstrated excellent eVTOL prediction performance. Most of the models tested showed sufficient accuracy for viable utilization in predicting the range and endurance of these vehicles. Their MAPE values at less than 2% are well within acceptable limits, and their simplicity makes them very appealing. From the feature importance values extracted, it is clear that vehicle velocity, which depends on an eVTOL mission, influences the endurance-range tradeoff the most. In addition, battery capacity and payload mass are critical parameters affecting their performance.

In conclusion, the work has led to the successful development of simpler surrogates to physics-based models to predict the endurance and range of eVTOL vehicles. The results demonstrate that an ML model trained on a broader range of motor, propeller, vehicle, and battery parameters could be immensely useful. The end-users of such a tool extend beyond vehicle designers and manufacturers to include mission planners and operations teams seeking tools to support real-time mission replanning. Including real-time vehicle health parameters as inputs to such models could also result in onboard autonomy software that is key to their operation.

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Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

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A. Appendix: Model hyperparameters

The hyperparameters for the top models used in predicting range and endurance estimates, including RF, MLP, and ET models, are provided below. Python code to recreate similar results and train ML surrogate models is provided as a GitHub repository at https://github.com/snchimata/evtol_performance.

A.1. Range models

- RF

```
'bootstrap': True,
'ccp_alpha': 0.0,
'criterion': 'squared_error',
'max_depth': None,
'max_features': 1.0,
'max_leaf_nodes': None,
'max_samples': None,
'min_impurity_decrease': 0.0,
'min_samples_leaf': 1,
'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0,
'n_estimators': 100,
'n_jobs': -1,
'oob_score': False,
'random_state': 123,
'verbose': 0,
'warm_start': False
```

- MLP

```
'activation': 'relu',
'alpha': 0.0001,
'batch_size': 'auto',
'beta_1': 0.9,
'beta_2': 0.999,
'early_stopping': False,
'epsilon': 1e-08,
'hidden_layer_sizes': (100,),
```

```
'learning_rate': 'constant',
'learning_rate_init': 0.001,
'max_fun': 15000,
'max_iter': 500,
'momentum': 0.9,
'n_iter_no_change': 10,
'nesterovs_momentum': True,
'power_t': 0.5,
'random_state': 123,
'shuffle': True,
'solver': 'adam',
'tol': 0.0001,
'validation_fraction': 0.1,
'verbose': False,
'warm_start': False
```

- ET

```
'bootstrap': False,
'ccp_alpha': 0.0,
'criterion': 'squared_error',
'max_depth': None,
'max_features': 1.0,
'max_leaf_nodes': None,
'max_samples': None,
'min_impurity_decrease': 0.0,
'min_samples_leaf': 1,
'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0,
'n_estimators': 100,
'n_jobs': -1,
'oob_score': False,
'random_state': 123,
'verbose': 0,
'warm_start': False
```

A.2. Endurance models

- RF

```
'bootstrap': True,
'ccp_alpha': 0.0,
'criterion': 'squared_error',
'max_depth': None,
```

```
'max_features': 1.0,
'max_leaf_nodes': None,
'max_samples': None,
'min_impurity_decrease': 0.0,
'min_samples_leaf': 1,
'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0,
'n_estimators': 100,
'n_jobs': -1,
'oob_score': False,
'random_state': 123,
'verbose': 0,
'warm_start': False
```

- MLP

```
'activation': 'relu',
'alpha': 0.0001,
'batch_size': 'auto',
'beta_1': 0.9,
'beta_2': 0.999,
'early_stopping': False,
'epsilon': 1e-08,
'hidden_layer_sizes': (100,),
'learning_rate': 'constant',
'learning_rate_init': 0.001,
'max_fun': 15000,
'max_iter': 500,
'momentum': 0.9,
'n_iter_no_change': 10,
'nesterovs_momentum': True,
'power_t': 0.5,
'random_state': 123,
'shuffle': True,
'solver': 'adam',
'tol': 0.0001,
'validation_fraction': 0.1,
'verbose': False,
'warm_start': False
```

- ET

```
'bootstrap': False,
```

```
'ccp_alpha': 0.0,
'criterion': 'squared_error',
'max_depth': None,
'max_features': 1.0,
'max_leaf_nodes': None,
'max_samples': None,
'min_impurity_decrease': 0.0,
'min_samples_leaf': 1,
'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0,
'n_estimators': 100,
'n_jobs': -1,
'oob_score': False,
'random_state': 123,
'verbose': 0,
'warm_start': False
```

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