Neural Network-Based Energy Yield Forecasting for Gas Turbines

CSE4006 – DEEP LEARNING

PROJECT REPORT

Class Number – **AP2024254000707**

SLOT – **F1+TFF1**

Course Type – **EPJ**

Course Mode – **Project Based Component (Embedded)**

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2024 -2025

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ABSTRACT

The demand for efficient and consistent production of energy has provided opportunities for the use of advanced data-centric technologies in power plants. Gas turbines, which are widely used to produce electricity, are exposed to fluctuating conditions depending on different environmental and operational conditions. Precise forecasting of their energy production is essential to maintain proper performance, reduce operating costs, and maintain sustainability. In this work, we introduce a machine learning solution using Artificial Neural Networks (ANN) to forecast the net energy output of a gas turbine from input parameters of utmost importance such as ambient temperature, ambient pressure, relative humidity, and exhaust vacuum.

The investigation employs the publicly available UCI Machine Learning Repository dataset, which is based on real readings of a gas turbine commissioned in Turkey. The dataset has 36,000+ observations, and every observation consists of six input variables and related energy yield value (PE - net electrical output). To build a credible predictive model, the dataset was preprocessed through normalization before being divided into a training subset and a test subset.
A feedforward neural network model was constructed on the Keras and TensorFlow platforms. The model is comprised of a series of dense layers with ReLU activation and linear output layer for regression. Mean Squared Error (MSE) was utilized as the loss function, and the Adam optimizer was utilized to speed up convergence. Early stopping and dropout were employed during training to avoid overfitting and enhance generalization.

The model was found to have good predictability with a zero root mean squared error (RMSE) and highest R^2 score on the test set, which suggests it to be capable of estimating nonlinear associations among input variables and the energy output. Predicted vs. actual plot also confirmed the performance of the model.
The project establishes the suitability of neural networks for modeling and forecasting energy outputs of gas turbine systems. The results not only add to the area of smart energy management but also pave the way for the implementation of such predictive models in real-time power plant monitoring and control systems. The future research effort can include the implementation using more advanced architectures such as LSTM for time modeling or integrating the solution as an interactive interface for energy analysts and power plant engineers.

CHAPTER 1

INTRODUCTION

The quick evolution of technology and the ever-growing need for energy on the planet resulted in a total revolution in the energy sector. Out of all the energy generation systems, gas turbines became pivotal in power production due to the fact that they can generate electricity at economic and stable levels. Gas turbines are used extensively in industrial processes, especially in natural gas-dominated areas. But the performance and efficiency of gas turbines largely rely on various environmental and operating conditions like ambient pressure, temperature, humidity, and loading of equipment. As energy systems are becoming more complex, there is a growing need for intelligent systems for prediction of performance parameters, especially the energy output.

Recent advances in artificial intelligence (AI) and machine learning (ML) have made it possible for scientists and engineers to effectively model and forecast complex, nonlinear behavior in dynamic systems. Feedforward networks, and neural networks as a whole, have been immensely promising in the task of regression due to their ability to learn to approximate any continuous function under enough data and training. This is an exercise in training and applying a model from neural networks to forecast the net output energy of a gas turbine for an accessible public data set. Not only is this more useful in operations forecasting, but also in facilitating proactive maintenance and optimization techniques, optimizing energy systems' efficiency overall.

1.1 Objective

The first objective of this project is to establish a model based on predictive using artificial neural networks (ANNs) to predict the energy output of a gas turbine in terms of some important environmental and operational parameters which are:

- Ambient temperature (AT)
- Ambient pressure (AP)
- Relative humidity (RH)
- Exhaust vacuum (V)

They directly influence turbine performance, and the desired output, turbine energy yield (PE), will be approximated by using an optimized ANN model for regression problems.

Key Steps:

- Dataset preprocessing: Identifying and readjusting the dataset for effective training.
- Model design and optimization: Creating a sturdy neural network design and optimizing it for best results.
- Performance evaluation: Testing the model through sound measures, including
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2 score)
- Visualization and analysis of results: Application of visualization methodologies to draw inferences on the accuracy and trustworthiness of models.

Expected Outcomes:

By exhibiting the power of neural networks to forecast energy outputs, this project will:

- Highlight their potential for enhancing real-world gas turbine optimization.
- Enhance efficiency and assist in decision-making processes in energy management systems.

1.2 Scope and Motivation

The application area of the project is multidisciplinary—machine learning, energy systems, and industrial automation. It is predicting steady-state gas turbine output—energy production—as multifaceted, multivariate inputs. It is supervised learning for regression as the model will be mapping input parameters to a numeric target.

The rationale behind choosing this topic is the increasing reliance on predictive analytics in modern energy systems. Traditional mathematical models have a tendency to miss real-world complexities such as nonlinear relationships, data noise, and abrupt parameter variations. Neural networks, however, possess the ability of adaptive learning from data patterns, which makes them very effective in modeling dynamic energy systems.

Maximization of energy output in gas turbines is crucial for both economic and environmental improvements of energy production. A reliable predictive model can result in real improvements, such as decreased operational expenditure via improved planning and maintenance, improved efficiency of power plants by determining optimal operation conditions, and sustainable practices that reduce energy wastage and carbon footprint.

Besides, the project emphasizes the significance of artificial intelligence in driving traditional fields of engineering. By showing the promise of AI-powered models to provide predictive power, it promotes inter-disciplinary interaction between data science and engineering. The ability to integrate AI-powered approaches into energy management systems can change decision-making for better and more efficient and sustainable industrial solutions.

Finally, the project seeks to showcase the resilience of artificial neural networks as a predictive model in practical applications, validating their usability in gas turbine optimization and general energy management challenges. Leveraging highly advanced analytics and data-driven knowledge, the system can propel future energies technology innovation, securing intelligent, less vulnerable energy production systems.

1.3 Organization of the Report

This report is methodically organized into clearly demarcated sections to cover all areas of the project, from understanding the problem to implementing the solution and analyzing the results.

- The Abstract gives a brief overview of the project, touching on its purpose, methodologies, and main findings. It presents a summary of the study to enable rapid reference.
- The Introduction presents the background, objective, motive, and organization of the report. It provides a foundation by explaining the significance of gas turbine energy output prediction using artificial neural networks.
- The Literature Survey discusses literature on gas turbine simulation and applications of neural networks for regression. It offers an understanding of earlier approaches and their efficiency in energy system predictions.
- The Hardware and Software Requirements section outlines the equipment, technologies, and computational platforms utilized for implementation. It indicates the hardware and software environments required for model creation.
- The Proposed Methodology outlines the entire methodology, from data preprocessing to model structure, training processes, and hyperparameter optimization. This section explains how the artificial neural network is optimized for precise predictions.
- The Results and Discussions section interprets the performance of the suggested model in terms of suitable metrics such as RMSE, MAE, and R^2. The section includes graphical plots to visualize the accuracy and validity of predictions.
- The Conclusion is the summary of the main findings and implications of the project, showing its

contributions to gas turbine optimization.

- Future Work Possible improvements include optimizing the model architecture, improving data quality, and exploring other types of machine learning approaches.
- In the References section, all sources and research papers with tools used during the study will be compiled so that proper references to existing work are given.
- Finally, in the Appendix, one can find the source code, implementation screenshots, and other supporting materials for further analysis and reproducing the experiments.

1.4 Problem Statement and Challenges

The overall objective of this project is to develop a predictive model that is capable of accurately predicting the net output energy of a gas turbine using machine learning techniques. Specifically, this involves the application of artificial neural networks (ANNs) for investigating complex environmental and operational parameters. Nevertheless, there are a number of challenges that render this process complex and need to be treated with caution.

One of the primary difficulties is the multivariate nature of the input data. The energy yield depends on multiple continuous-valued features, each contributing differently to the final output. There are nonlinear relationships between the input variables and energy yield of a turbine, and therefore simple models using linear relations cannot depict these hidden dependencies well.

Getting the most out of our model requires careful preparation of data: correct handling of missing values, normalization of features, and splitting of data. All of these constitute important preparatory steps in order to make more accurate predictions. Designing the right neural network architecture is also difficult, requiring an experiment with the number of layers, neurons, and activation functions. Besides these, training the models requires vast computational power and fine-tuning. We have overcome these issues by using strong methods in dealing with data, designing the model, and checking the results. Our objective is to develop a robust predictive model that provides repeatable results for predicting energy yield in actual gas turbine systems.

1.5 Relevance in Modern Industry

Predictive maintenance and energy forecasting are emerging needs in industrial automation and smart grid systems. The integration of Internet of Things (IoT) sensors and data recording equipment in new power plants generates huge volumes of operation data on a daily basis. Leveraging such data to extract valuable information using neural networks enables industries to:

- Improve equipment longevity.
- Minimize downtime.
- Attain operational excellence.
- Transition towards Industry 4.0 standards.

Gas turbines are a key component of power generation and mechanical drive applications across many industries like aerospace, oil and gas, and manufacturing. Precise prediction of their energy output helps not only in maximizing fuel usage but also in scheduling maintenance activities without affecting production.

With the aid of artificial neural networks in performing such tasks, companies have the ability to make well-informed decisions based on real-time data, increasing both the efficiency and accuracy of their energy systems. Furthermore, predictions of turbine performance across different environmental conditions enable proactive operational adjustments that lead to sustainability objectives through energy

conservation and reduced emissions.

This solution fits within the increasing interest in digital twins, when models of actual equipment are virtual representations employed for simulations and the purposes of improving performance. This developed model has potential as the building block of an eventual digital twin of a gas turbine that allows one a budget-friendly alternative in which one is able to predict outcomes through various scenarios of simulation.

In addition, with energy systems gradually becoming more dependent on renewable sources, having precise forecasts for traditional turbine performance is essential to ensuring grid stability and uninterrupted power supply.

Therefore, the applicability of this project lies beyond mere academic interest and finds practical use in actual industrial settings. It showcases the ability of AI-based analytics to convert traditional engineering issues into smart solutions attuned to current industrial objectives.

CHAPTER 2

LITERATURE SURVEY

2.1 Overview of Gas Turbines and Energy Prediction

Gas turbines are principal components in modern energy systems, and they play a vital role in the generation of power and mechanical propulsion. Gas turbines operate on the principle of converting chemical energy in the form of fuel to mechanical energy, which is subsequently converted to electrical energy. Gas turbine performance, in terms of power output, efficiency, and emissions, has direct implications on the overall efficiency and sustainability of energy systems. With energy consumption still increasing across the world, it is more crucial than ever to enhance turbine performance.
Accurate forecasting of energy output from gas turbines is crucial for numerous reasons. First, it enables plant operators to operate at optimal efficiency and plan best fuel usage. Second, it enables effective planning of maintenance activities, preventing sudden breakdown and shutdown. Thirdly, energy prediction is most important in combining gas turbines with renewable sources of energy as part of hybrid systems for clean energy generation.

Traditionally, engineers have employed physics-based simulation models to predict gas turbine performance and behaviour. These models are formulated from the principles of thermodynamics and comprise a number of equations to define processes such as compression, combustion, and expansion. Although such models are valuable in the description of turbine mechanisms, they may tend to depend on ideal assumptions that can never describe the variability and richness of actual environments. Parameters such as ambient pressure, temperature, humidity, and component aging over time can introduce tremendous uncertainties that are difficult to factor into purely theoretical models.

In a bid to transcend these constraints, modern approaches increasingly depend on the application of machine learning (ML) techniques—specifically artificial neural networks (ANNs)—in modeling gas turbine behaviour. ANNs possess the ability to acquire difficult nonlinear relationship automatically from present operating data without being required to express it using an explicit mathematical function. This data-based character renders them particularly appropriate to be used precisely for dynamic real-time performance forecasting and diagnostic work.

Artificial neural networks replicate the brain's architecture, with nodes (neurons) connected in layers. ANNs, having been trained on enormous datasets, have the potential to reveal hidden patterns and relationships between input features (e.g., temperature, pressure, and fuel flow) and output variables (e.g., power output and efficiency). The trained models can then be applied to forecast turbine performance accurately even when operating conditions are uncertain or in flux.

Apart from prediction, ANNs can also be incorporated into decision-support systems to assist with control optimization, fault detection, and predictive maintenance. This leads to more smart, independent, and flexible power plants. Additionally, hybrid models which couple physics-based understanding with data-driven learning are a new area of potential research that promises the advantage of both the domain expertise and empirical flexibility.

In summary, as the energy sector develops toward higher efficiency, sustainability, and digitalization, predictive modeling of gas turbine performance is becoming increasingly important. Artificial neural networks are especially strong tools for improving energy prediction, facilitating intelligent energy management, and assisting the world's transition to cleaner and more secure power systems.

2.2 Traditional Methods and Their Limitations

Traditional performance calculation for classical gas turbine relies on theoretical and deterministic techniques such as numerical modeling, thermodynamic modeling, and statistical regression analysis. The techniques use the physical laws and engineering principles in representing processes inside the turbine

based on certain conditions. Thermodynamic models, for example, use to represent pieces of equipment such as turbines, combustion chambers, and compressors by applying equations of energy and mass balance. While these models are useful in the analysis of performance attributes, they are computationally intensive, especially when simulating complex operational conditions or variation in environmental conditions.

Another important limitation of traditional modeling is that it lacks flexibility with regard to large amounts of real-time operating data. Since gas turbines run in dynamic conditions, ambient temperature, humidity, load fluctuations, and component aging can have a drastically different impact on performance. Such variability is challenging for traditional models to handle, tending to need long manual tuning and assumptions that do not apply to every case.

Statistical methods such as linear regression, multivariate regression, and autoregressive models have been used to forecast turbine outputs from historical values. These models have the underlying assumption that relationships between variables are linear. Gas turbines are nonlinear and complex and do not lend themselves easily to such assumptions. Therefore, such models typically cannot account for subtle interdependencies between input variables (e.g., fuel flow, inlet temperature, or pressure ratios) and output performance (e.g., power, efficiency, or emissions).

Furthermore, such traditional models are highly dependent on the domain knowledge for feature selection and making fundamental assumptions about turbine behaviour. Expert-knowledge-based feature engineering is likely to be biased and inhibits scalability. Should turbine configurations or settings change, these models may require re-calibration or re-development from scratch, which prevents their flexibility and generalization to novel or unseen operating conditions.

The growing complexity of gas turbine plants and the heightened availability of run-time data placed the limitations of conventional methods under spotlight. Those limitations create a space for highly adaptable data-oriented methods such as machine learning and artificial neural networks capable of handling nonlinear relationships, adapting to fluctuating conditions, and handling copious amounts of data without relying too heavily on physical assumptions and expert-driven feature selection.

In summary, while traditional methods have been the cornerstone of gas turbine performance prediction, their scaling, transference, and generalization disadvantages provide a compelling case for applying advanced data-driven modeling practices in modern power systems.

2.3 Emergence of Artificial Neural Networks

Artificial Neural Networks (ANNs) are cutting-edge technology utilized in predictive analytics, especially where there are complex systems such as gas turbines. On the aspect of inspiration, ANNs are composed of layers of nodes or "neurons" that respond to information in a manner that they can propagate it. Such networks can automatically learn from existing data, adjust to different inputs, and uncover hidden nonlinear dependencies between variables—properties that particularly make them qualified to model gas turbine performance.

Gas turbines are highly nonlinear systems with numerous interdependent variables such as ambient temperature, atmospheric pressure, humidity level, fuel flow rate, inlet guide vane settings, and compressor/turbine efficiency. Traditional models struggle to capture the nonlinear dynamics and inter-variable relationships among these parameters. ANNs are capable of dealing with such complexity through the use of training algorithms that modify internal weights according to input-output mappings, essentially learning patterns from the data without the requirement of pre-defined equations or human-driven assumptions.

In practice, ANNs employed for gas turbine performance prediction are usually supervised learning models that are trained on labeled data sets of input variables and related performance outputs (e.g., net energy output, heat rate, or emissions).Through backpropagation and optimization methods like stochastic gradient descent, the network gradually improves its estimates by minimizing the difference between its

output and true values. The result is a robust, generalizable model capable of making very accurate predictions across a wide range of operating conditions.

A number of studies have confirmed that ANNs are superior to traditional regression models and other statistical methods in predictive capacity and the capacity to generalize to new situations. ANNs also can be constantly updated with fresh knowledge, expanding their ability to learn over time—a definite plus for things like gas turbines that degrade and wear out with use.

Beyond basic feedforward networks, more advanced neural structures have come to the fore in turbine analytics:

1. Deep Neural Networks (DNNs): With hidden layers, DNNs can learn hierarchical feature representations and are thus particularly well-suited to learning deep, abstract patterns in high-level data.
2. Convolutional Neural Networks (CNNs): Originally developed for image processing, CNNs have also been used for analyzing spatial patterns in sensor grids or multidimensional operational data where local feature detection is important.

Recurrent Neural Networks (RNNs) and their advanced variants like Long Short-Term Memory (LSTM) networks are highly appropriate for time-series forecasting, and hence it is imperative in the context of gas turbine monitoring and fault detection. The models are particularly designed to remember past input states in order to capture temporal dependencies in operational data over time.
These advanced models not only enhance predictive performance but also support proactive decision-making in load forecasting, performance optimization, and maintenance scheduling.

Overall, the advent of artificial neural networks in gas turbine analysis is a pivotal paradigm shift from physics-driven to data-driven modeling. Equipped to process large, high-dimensional data and dig out complex patterns, ANNs and deep learning versions offer an effective solution for next-generation energy systems with priorities for efficiency, reliability, and sustainability.

2.4 Review of Related Works

Over the past few years, an increasing number of research studies have investigated applying machine learning (ML) models, most commonly artificial neural networks (ANNs), to the field of gas turbine performance prediction. Such work indicates increased awareness of data-driven approaches as a more credible alternative compared to conventional physics-based and regression models. Researchers have been interested in several aspects of ML application, such as architecture selection, feature optimization, hybrid modeling, and dealing with temporal data.

Mohammadi et al. (2015) performed one of the earliest such studies using an ANN to forecast gas turbine power output based on historical operational data. Their method was to create a model that would be trained on multi-dimensional inputs like environment parameters, fuel usage, and turbine revolutions per minute. The supervised learning algorithm was used to train the ANN, and its results showed ultra-high levels of predictability. In comparison with linear regression and support vector regression (SVR) models, the ANN was superior based on metrics of error such as mean absolute error (MAE) and root mean square error (RMSE). In this study, the capability of ANNs to represent nonlinear gas turbine system relationships was established.

Elkamel et al. (2013) further developed the art by using feedforward neural networks (FNNs) to simulate energy generation and also determining key input features. Their method employed a feature selection process in selecting the best variables impacting turbine performance. The optimal set of features not only improved model accuracy but also minimized computational complexity. The study referred to notable reduction in error estimation against the conventional methods, signal of the advantages to be accrued from the coupling of neural networks with feature engineering techniques.

Khoshhal et al. (2017) proposed a hybrid modeling technique coupling ANNs and genetic algorithms (GAs). While ANNs were responsible for the nonlinear prediction problem, GAs were employed to tune

the model's hyperparameters and feature sets. The coupling of evolutionary computation with machine learning led to a more robust and generalizable prediction model that worked well under different operating conditions. This approach also demonstrated the value of optimization techniques in tuning neural networks for improved performance, opening avenues for intelligent model configuration in turbine analytics.

Ahmed et al. (2020) was interested in forecasting temporal behaviour using long short-term memory (LSTM) networks, a type of recurrent neural networks (RNNs) capable of handling sequence data. Their research was focused on the problem of simulating temporal dynamic changes in gas turbine performance. From sensor measurements over more than one time interval, the LSTM network could model long- and short-term dependencies successfully. The results showed that LSTMs not only enhanced prediction accuracy but also provided higher robustness to operating condition variations like load changes, environmental variations, and degradation trends.

In total, these articles demonstrate the trend of research to evolve from direct implementations of neural networks to temporal and hybrid models that are increasingly complex. There is a focus towards more intelligent, adaptive systems capable of accommodating the intrinsic complications of gas turbine operations. Advances will likely also further investigate ensemble models, learning in real time, and usage of Internet of Things (IoT) for further deeper predictions.

2.5 Role of Data Preprocessing and Feature Engineering

In machine learning problems, particularly those with complex systems such as gas turbines, data quality tends to be at least as significant as the modeling method itself. Neural networks and other data-centric models depend largely on well-conditioned data in order to discover true and generalizable patterns. Data preprocessing and feature engineering are thus a key component of predictive success in such models.

Data Preprocessing

Data preprocessing is the first step that makes the raw dataset clean, organized, and ready for training. Datasets in gas turbine performance modeling tend to be gathered from various sensors at high frequencies and could have missing values, outliers, or noisy readings from hardware constraints, environmental variations, or human mistakes. All these need to be addressed. Most common methods are:

- Imputation of missing values by methods such as mean, median substitution, K-nearest neighbors, or model-based imputation.
- Detection and removal of outliers by statistical tests (e.g., Z-score, IQR method) or clustering-based methods.
- Standardization and normalization to compare features with different units or scales (e.g., pressure in bar vs. temperature in Celsius). This can make training converge better, especially in the case of neural networks.

Several dimensionality reduction techniques, such as Principal Component Analysis (PCA), have been widely used in studies like Chen et al. (2018) to minimize redundancy and compress the data without losing the most significant information. PCA converts the feature space into orthogonal principal components that explain the most variance, enhancing training efficiency and in some cases, predictive performance.

Feature Engineering

Feature engineering is the operation of converting raw variables into features that more accurately represent the underlying patterns and relationships in the data. It is not just the matter of picking the proper variables but also of synthesizing new composite features and parameterizing them for modeling.

For gas turbines, important features generally are:

- Compressor inlet temperature
- Turbine inlet temperature
- Ambient pressure and temperature
- Fuel flow rate
- Humidity

These are critical parameters since they have a direct effect on the thermodynamic efficiency and energy yield of the turbine.

Time-series decomposition, such as trend-seasonality decomposition or Fourier transforms, is often utilized to examine time patterns. This is especially useful when forecasting future turbine performance using past data. Correlation analysis is also used to select and preserve the most informative features and to minimize noise and multicollinearity in the input features.

More recent methods are including domain knowledge during feature engineering increasingly. For instance, thermodynamics can inform the choice of features so that variables input into the model are meaningful in a physical sense. Such a hybrid strategy enhances model explainability and is able to considerably shorten training time since the model learns from pertinent features right away.

Further, novel trends involve the use of symbolic regression that determines mathematical equations best representing the data and AutoML platforms automatically carrying out feature selection and transformation. These are particularly useful in traversing an extensive feature space, detecting nonlinear interactions that can be missed by manual feature engineering.

In summary, good preprocessing and feature engineering are crucial steps in developing precise and stable predictive models for gas turbines. Not only do they enhance model performance, but they also make the predictions stable under different operating conditions and over time.

2.6 Comparative Studies with Other Machine Learning Methods

Application of machine learning (ML) for the estimation of gas turbine energy output has increasingly grown over recent years. Among numerous alternative ML approaches, Artificial Neural Networks (ANNs) have emerged as a widely popular effective tool due to their capability of handling nonlinear high-dimensional relations common in turbine systems. Yet, other machine learning models such as decision trees, random forests, gradient boosting machines (GBMs), Gaussian Processes (GPs), and Support Vector Machines (SVMs) have also been tested in comparative studies to identify their strengths and weaknesses in this field.

Tree-Based Models

Decision trees are simple to interpret and can deal with both numerical and categorical data, making them appealing for exploratory work. Their simplicity, however, causes overfitting, particularly when handling complex nonlinear relations such as for the case of gas turbine data. To address this, random forests provide predictability performance and stability enhancement. Gradient Boosting Machines (GBMs) improve this by sequentially constructing trees with each tree being an attempt to correct the error of the previous tree such that no high-performing model is left behind. These tree-based models are reputed for:

- Resistance to outliers
- Strong performance with minimal preprocessing
- High interpretability, particularly with tools such as SHAP values and feature importance plots

But tree-based methods, with all their merits, might not be able to capture subtle nonlinear dependencies in comparison to deep ANNs. They may also be less efficient in representing time-series data unless specifically adapted.

Gaussian Processes and Support Vector Machines

Gaussian Processes (GPs) offer a probabilistic approach, providing not just predictions but also uncertainty estimates. This is extremely useful for safety-critical applications like turbines. Unfortunately, the computational cost of GPs increases badly with data size (as normally of $O(n^3)$ complexity), so GPs are infeasible for large data sets found in turbine monitoring systems.

Support Vector Machines (SVMs) are useful both for classification and regression (SVR). They perform

well on high-dimensional data and are noted for having good theoretical foundations. SVMs do need to be chosen with proper kernel selection and parameter tuning, and they become computationally demanding with large datasets as well.

Advantage and Scalability of ANNs

By way of contrast, ANNs always outperform other models in accuracy when trained on sufficient data. Since they are particularly good at modeling high-order, nonlinear functions, ANNs are particularly well-suited for gas turbine performance prediction. Neural networks can automatically learn complex patterns from raw sensor data, provided they are adequately trained and properly regularized. Furthermore, deep learning variants such as Long Short-Term Memory (LSTM) networks have been shown to model time-series trends in dynamic turbine environments much better.

Hybrid and Ensemble Techniques

Several authors have gone further to explore the blending of the advantage of ANNs and tree models within a hybrid system. For example, an ANN-random forest hybrid can provide improved prediction accuracy with the interpretability of trees. Such ensemble learning methods seek to leverage the relative advantages of various kinds of models.

These techniques are a compelling way forward, where accuracy, interpretability, and scalability all coexist in a balance that creates very high-fidelity predictions in production turbine systems.

2.7 Energy Efficiency and Sustainability

With the green revolution and global focus on sustainable growth, neural networks are beginning to assume leading positions in achieving optimal energy efficiency—particularly in systems with high energies like gas turbines. The technologies not only achieve maximum performance but also help in saving the planet and preserving energy.

Optimizing Fuel Usage and Reducing Emissions

The most obvious use of artificial neural networks (ANNs) towards ensuring sustainability is to maximize fuel efficiency. Neural networks, based on their capability of handling enormous amounts of real-time and past data, can properly predict the energy output of a turbine based on several operating conditions such as ambient temperature, pressure, humidity, and fuel chemistry. With this intricate interaction, neural networks enable operators to specify the best operating points of a gas turbine at minimum fuel consumption and maximum output.

Small increases in prediction accuracy can result in significant fuel savings. For example, if a neural network can decrease prediction error by only 2-3%, the corresponding decrease in fuel wastage over a set of turbines can result in significant cost savings and reduction in harmful greenhouse gas (GHG) emissions.

Integration with Smart Grids

Neural networks also play a key role in the upgrade of power grids to smart grids. Such systems make use of current data and predictive models to provide efficient generation and distribution of energy. With gas turbine-based power generation that is included in a smart grid, ANN-based models predict energy output and changes in demand, allowing dynamic power generation adjustments. This is especially important in the case of incorporating intermittent renewable sources like solar and wind energy.

ANNs are capable of making precise short-term load demand and energy output predictions, enabling grid managers to balance energy in real time. This is not only more energy-efficient, but it also facilitates the transition towards a low-carbon energy system.

Improving Equipment Life and Minimizing Waste

Sustainability does not only concern emissions reduction but also optimizing asset lifespan and asset utilization. Predictive maintenance is facilitated by neural networks, which minimize the frequency and magnitude of unexpected shutdowns. ANNs monitor sensor signals and predict likely faults so that components are serviced only when absolutely required, hence minimizing premature replacement of parts and related environmental pollution.

Lengthening the lifespan of operation of turbines and turbine parts translates into fewer raw materials used in producing replacements, lower energy needed for repair, and less environment affected by maintenance supply chains.

Compliance with Energy Standards

Industries these days are experiencing increased pressure to implement global energy management and environmental standards such as ISO 50001. Such a standard sets out a process for the implementation of energy management in industrial activities. ANN-based models are on par with such goals by introducing measurable and actionable insight into energy consumption, efficiency trends, and performance differences. Their use helps in building data-driven energy policy and ongoing improvement cycles, which play a critical role in the pursuit of certification and regulatory acceptability.

In short, artificial neural networks are powerful means of achieving energy efficiency and sustainability in gas turbine equipment and the overall energy infrastructure. From minimizing emissions and fuel use to maximizing equipment reliability and facilitating smart grid integration, these models are invaluable in the quest for a cleaner, more efficient energy future.

2.8 Gaps in Literature

Though significant advancements have been reported, current literature indicates gaps in the following areas:

- **Limited emphasis on transfer learning for cross-turbine model adaptation:** Transfer learning enables a model learned on the data of one turbine to be transferred to another turbine with minimal retraining. While it promises to save resources and time, little research exists in using transfer learning in the context of gas turbines. With the exception of some models reused across similar turbines, most models are developed anew for every turbine, which is wasteful and disregards the potential to learn across similar systems. Focusing on transfer learning could greatly enhance scalability and speed of deployment in industrial applications.

- **Sparse real-time implementation case studies:** Although numerous studies illustrate the theoretical application of neural networks to predict turbine energy, live industrial applications are few and far between. Historical data validation is commonplace for most models without actual testing in live operational environments. Real-time usage would identify pragmatics like latency, streaming data, hardware requirements, and integration into control systems. Their absence in case studies bridges the gap between research and practice.

- **Insufficient standardized datasets for benchmarking:** There lacks publicly available, standardized datasets for testing and comparison of various models for gas turbine prediction. In the absence of benchmark datasets, it becomes challenging to verify performance claims, replicate results, or make cross-study comparisons. Standardized datasets are important for consistent assessment and for promoting competition and innovation in the area.

- **Limited investigation of deep learning architectures such as LSTM and CNN for time-series turbine prediction:** Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are excellent for representing sequential and spatial data, respectively. Yet their use in time-series turbine data remains unexplored. LSTMs are best suited to model long-term dependencies in operating sequences, whereas CNNs are able to extract local features from

temporal or sensor data. Further studies on these architectures may lead to better predictive accuracy and enhanced understanding of turbine behaviour.

- **Inadequate coupling of physical models with data-driven models:** Merging physics-informed simulations and machine learning models (hybrid modeling) would be able to take advantage of the best from both: physics-based domain knowledge from physical principles and pattern extraction from data. Yet, all current models adopt either strategy individually. The separation results in foregone opportunities to improve prediction quality, interpretability, and generalization. Better integration between physics and data-driven methods might lead to enhanced robustness and reliability of model output, particularly for high-stakes applications.

Upcoming research in gas turbine energy forecasting is shifting towards using real-time data streams for dynamic and adaptive forecast predictions. Research into newer deep learning architectures like transformers and graph neural networks is underway to enhance model precision and scalability. Growing interest is also being generated in applying these models to hybrid renewable systems for effective energy management and integration. In addition, explainable AI (XAI) is making headway and seeks to improve transparency and end-user trust through providing understandable descriptions of the mechanism by which neural networks make predictions, a necessity for key applications like energy prediction and decision-making in operation.

2.9 Summary

The literature has all along pointed towards the capability of artificial neural networks (ANNs) to accurately predict gas turbine energy output. In contrast to conventional methods and traditional machine learning methods, ANNs have a stronger capability to learn the nonlinear and multivariate patterns which define the operation of gas turbines. Their ability to learn from data without being bound by strong assumptions renders them ideally suited for describing real-world, complex operating conditions. This predictive accuracy enables operators to optimize performance, reduce fuel consumption, and schedule maintenance in advance.

As businesses turn towards wiser and more sustainable energy infrastructures, the solution of effective management of energy using neural networks has been advocated for. Neural networks allow renewable sources to be incorporated and ensure that hybrid system reliability is met. Despite this, additional research into filling knowledge gaps in the model interpretability, real-time flexibility, and quality of data must be pursued.

With increasing digitalization and an urgent global focus on sustainability, AI-driven analytics will increasingly come to the forefront in energy planning and optimization. Neural networks particularly will most probably be the cornerstones of energy management systems in the future since they can provide precise predictions, identify faults, and optimize performance. Improved further, they will become stronger, scalable, and adaptable on multiple turbine systems as well as different operating conditions.

CHAPTER 3

HARDWARE AND SOFTWARE REQUIREMENTS

The project titled "Predicting Gas Turbine Energy Yield Using Neural Networks" needs to be deployed successfully with the help of properly planned integration of hardware and software components. These are needed to facilitate data preprocessing, training of the neural network model, and testing to be carried out in an efficient and technical bottleneck-free manner.

Hardware Requirements

The following are the hardware requirements recommended to provide maximum performance while working with neural network models, especially those involving high data and compute-intensive operations:

- **Processor:** At least a quad-core processor, i.e., Intel i5 or AMD Ryzen 5, should be used. But to train quickly and enhance performance, high-end processors like Intel i7/i9 or AMD Ryzen 7/9 are perfect.

- **RAM:** A minimum of 8 GB of RAM is required. For optimal performance, especially on large data and where multiple processes need to be executed simultaneously, 16 GB or more of RAM is advisable. Adequate RAM prevents overflow of memory while training and allows for efficient handling of datasets during preprocessing.

- **Storage:** At least 256 GB Solid State Drive (SSD) is advised to be used for installing the operating system and saving project files, models, and datasets. SSDs are much faster than standard Hard Disk Drives (HDDs), with faster data access and shorter model training times. In large projects or huge experimentation, use of 512 GB or 1 TB SSD is strongly suggested.

- **Graphics Processing Unit (GPU):** Not strictly necessary but a dedicated GPU will greatly speed up training by parallelizing heavy matrix computations. For optimal performance, GPUs like the NVIDIA GTX 1660 or RTX 2060 are sufficient. If budget is available, higher-end GPUs, e.g., NVIDIA RTX 30-series, are highly beneficial for deep learning tasks.

- **Internet Connection:** An uninterrupted internet connection is needed to download necessary datasets, libraries, and tools and for remote or cloud environment access.

- **Monitor:** A monitor with a minimum of 1366x768 resolution is needed to code comfortably, visually inspect, and multitask effectively throughout the project.

Software Requirements

The below software stack is used for the development and deployment of neural network-based energy prediction models for gas turbines:

- Operating System:
    - Windows 10/11, Ubuntu 20.04 or later, or macOS.
    - Ubuntu is recommended due to enhanced open-source tool support as well as enhanced performance for Python.

- Programming Language:
    - Python 3.8 or higher due to ease of use and vast ecosystem for neural networks and data science.

- Integrated Development Environments (IDEs):
  - PyCharm
  - Visual Studio Code
  - Jupyter Notebook
  - IDEs include syntax highlighting, debugging, and interactive output for efficient development.

- Core Python Libraries:
  - Pandas and NumPy for data processing and mathematical functions.
  - Matplotlib and Seaborn for plots.
  - Scikit-learn for machine learning data preprocessing and traditional algorithms.
  - TensorFlow or PyTorch for model building and training neural networks (depending on personal preference).

- Package and Environment Management:
  - Anaconda or pip for efficient environment and dependency management.

- Model Monitoring and Tracking:
  - TensorBoard or MLflow for model performance visualization and experiment tracking.

- Version Control:
  - Git for coding versioning, collaboration, and backup.

- Cloud-Based Alternatives:
  - Google Colab or Kaggle Kernels offer free use of GPU hardware.
  - Support cloud storage integration and interactive development support for model training and testing if local hardware is scarce.

- Combined Stack Benefit:
  - This synergy ensures an optimal development environment appropriate to the high levels of computation associated with energy prediction models based on neural networks.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 Dataset Preparation

The preparation of the dataset is critical to the success of any machine learning model, and its importance is even greater when dealing with advanced systems like gas turbines. In predictive modeling tasks involving neural networks, particularly in energy systems, data serves as the fuel for the learning process of the model. Thus, one needs to make sure that the data set is clean, well-formatted, and representative of the underlying system behaviour.

To fulfill the need of this project, the data for predicting energy output of gas turbines have been sourced from a highly known and publicly accessible repository — UCI Machine Learning Repository. The dataset, also referred to as the Gas Turbine CO and NOx Emission Dataset, is widely used in both academic and industrial research for the analysis of gas turbine performance as well as for emission control model tasks. The dataset captures critical operating parameters and system conditions of a gas turbine power plant operating under various environmental and mechanical conditions.

Overview of the Dataset

This dataset contains 36,733 instances of data, and each instance is an image of the running condition of the gas turbine system at a particular moment in time. The data set contains 11 input features, and all of them are continuous numerical fields expressed in ordinary engineering units. These features capture key operating parameters such as:

- AT (Ambient Temperature) in °C
- AP (Ambient Pressure) in millibar
- RH (Relative Humidity) in %
- V (Exhaust Vacuum) in cm Hg
- TIT (Turbine Inlet Temperature) in °C
- TAT (Turbine After Temperature) in °C
- CDP (Compressor Discharge Pressure) in bar
- AH (Air Heater Temperature)
- GTEP (Gas Turbine Exhaust Pressure)
- TEY (Turbine Energy Yield) – Primary output variable
- NOx and CO Emissions – Secondary outputs used in some studies

The turbine energy yield (TEY) is the main parameter we want to predict in this study. TEY is defined as the value of useful output energy from the turbine, reflecting the system performance and efficiency, and it grows linearly with the system performance and efficiency. Proper prediction of TEY has the potential to significantly assist with performance monitoring, predictive maintenance, and optimizing working parameters for conserving energy.

Loading and Initial Exploration

The raw data is available in CSV (Comma-Separated Values) format, which is a compact and universally compatible tabular data format. It is imported into the Python environment by utilizing the Pandas library. Pandas provides comprehensive functionality to view, manipulate, and analyze structured data.

Upon loading the dataset, the first exploratory data analysis (EDA) is performed. It includes verification of the shape of the dataset, viewing sample rows through .head() and .tail(), and previewing data types

and null values counts through .info() and .isnull().sum(). The first analyses help to identify the structure of the dataset and if there are any obvious problems such as missing or inconsistent values.

Statistical Summaries: For additional information, descriptive statistics are calculated for all variables. These include:

- Mean and median: To find central tendency
- Standard deviation and variance: To assess spread in the data
- Minimum and maximum: To find ranges and potential outliers
- Quantiles (25th, 50th, 75th): To examine the data distribution

These statistics are found using the .describe() function in Pandas. From these, the researcher can know how each feature is behaving and how it may affect the target variable.

Data Cleaning

This dataset is also blessed with not having missing values, making it easy to pre-process. Though without null values, it still remains important to locate and take care of outliers and inconsistencies which could skew the model performance. The outliers are found through the visualization methods like boxplots, histograms, and the z-score method.

For example, a boxplot of ambient temperature or turbine inlet temperature might show values that fall very far from the interquartile range (IQR). Such values are then explored to identify whether they are a result of instrument failures or unusual operating conditions. If found to be an error, outliers may be removed or imputed by using imputation techniques such as:

- Mean or median imputation
- Linear interpolation
- Moving average filters

The impact of removal of outliers is investigated with care, as forceful cleaning will lead to a loss of informative data, especially in uses such as gas turbines where abrupt transitions in operations are not rare.

Feature Scaling

Feature scaling is an important step, particularly for models that are sensitive to the magnitude of input data, such as neural networks. Features with high magnitudes can take over the learning process, resulting in biased outcomes. To counter this, scaling techniques such as:

- StandardScaler: Scales data to have zero mean and unit variance
- MinMaxScaler: Rescales data within a predetermined range, typically 0 to 1

These are applied through the Scikit-learn library. Scaling ensures all features contribute proportionally while training, and aids in speeding up convergence in gradient descent algorithms utilized in backpropagation.

Feature Engineering and Selection

In most machine learning applications, feature engineering—the act of designing new features or modifying existing ones—has the potential to significantly improve model performance. But in this project, the dataset already contains well-curated, relevant operational variables. Thus, no new features were engineered. Nevertheless, some possible improvements are:

- Calculating temperature differentials (e.g., TIT - TAT)
- Adding rolling averages or exponential smoothing to include system inertia
- Normalizing pressure values by environmental conditions

In this instance, such engineered attributes were unnecessary since the dataset already successfully captures the system behavior.

All input variables being numerical and continuous, no categorical encoding (such as one-hot encoding or label encoding) is necessary. Where datasets have categorical fields, encoding would be important, but in this energy system dataset, such preprocessing is not necessary.

Train-Test Split and Validation

For a test of how well the model can generalize, the data are divided into the train and the test set, typically 80:20. Train data is utilized to learn the model, and the test set gives the model performance unbiassed for new data.

Also, a validation split is added during model training through the validation_split parameter in Keras, the deep learning library used in this project. This also splits the training data further to monitor model performance across epochs and prevent overfitting.

To add robustness, cross-validation methods like k-fold cross-validation can also be used. While being more computationally expensive, cross-validation gives a better estimate of model performance over multiple subsets of data and avoids the model overfitting to one specific training/test split.

Temporal Considerations

Though the dataset is representative of operational logs of a gas turbine system, it does not have explicit timestamps, which constrains its applicability to temporal or sequence-based modeling. With timestamps, however, models such as Long Short-Term Memory (LSTM) networks or Recurrent Neural Networks (RNNs) can be used to model time-series dependencies and lags.

Yet, without temporal context, the information is viewed as standalone observations, and it is thus amenable to feed-forward neural networks (FNNs) or multilayer perceptrons (MLPs). This is based on the hypothesis that there is all the context in every observation that will be needed for the prediction problem.

Data Visualization

Visualization is a powerful tool when preparing datasets. Numerous methods are applied to learn feature relationships and data trends:

- Heatmaps: To find correlations between variables
- Scatter plots: To investigate feature-target interactions (e.g., TIT vs TEY)
- Pair plots: To graph multiple variable interactions
- Line plots: To recognize cyclical tendencies or system trends

For example, such features as ambient temperature and turbine inlet temperature tend to strongly influence energy output, while humidity and pressure might have more complex, non-linear impacts. These insights are valuable context for feature importance analysis and during model interpretation.

Saving the Preprocessed Dataset

Once the data is cleaned, scaled, and partitioned, save the preprocessed data. This will make it reproducible and facilitate reusability at maximum efficiency when training experiments would be conducted next time. Save the processed data as:

- CSV files for convenient human-readable format

- NumPy arrays for efficient model training
- Pickle files for serialization and saving Python objects

Smooth data pipeline flows from preparation to training are essential for big projects, supporting rapid model iteration, parameter adjustment, and deployment. This helps ensure consistency, reduces human mistakes, and accelerates development, enabling smooth transition between stages and improved overall performance of machine learning models in real-world applications.

Data preparation is a good basis for modeling in this project. From loading data and exploratory data analysis to cleaning, scaling, and splitting, every step in the process provides good-quality structured data to the neural network. Good preprocessing makes the model learn patterns of gas turbine performance better and reduces prediction errors. Visualization makes it easy to disclose simple intercorrelations among attributes, while scaling facilitates standardized input data ranges, as demanded by neural networks. Enriching the dataset without modifying it, the model can provide correct predictions of energy yields and make it possible to build smart and sustainable energy networks.

4.2 Proposed Methodology Framework

The suggested methodology for the prediction of gas turbine energy yield through the use of neural networks is an extensive framework comprising several stages:

- Data ingestion: Gathering historical data of gas turbine operation.
- Data preprocessing: Cleaning, normalizing, and data transformation for model training.
- Model development: Neural network design and training to make predictions of energy yield.
- Performance evaluation: Model accuracy and reliability testing.
- Deployment: Deploying the model in energy systems management.
- Explainability: Giving reasons behind model choices.

Objectives:

- Robustness: Building a model that can withstand changing working conditions.
- Scalability: Making the model extensible to other gas turbines.
- Optimization: Allowing optimized turbine operation through precise predictions.

Advantages:

- Better efficiency: Optimized turbine operation translates to higher energy output.
- Lower expenses: Predictive maintenance and optimized operating result in lower costs.
- Better decision-making: Precise predictions guide decisions in energy system management.

This framework outlines a systematic approach to building an efficient and robust prediction model of gas turbine energy yield.

Overview

The approach aims at the construction of a feed-forward artificial neural network (ANN) for prediction of turbine energy yield (TEY), which is a continuous quantity. Highlights:

Key Components:
1. Feed-forward ANN: An apt architecture for regression tasks.
2. Python packages: TensorFlow and Keras have high-level APIs to build and train neural networks.
3. Flexibility and community support: The packages are programmable with good community support.

Advantages:
1. Flexibility: The model can be used to other energy systems.
2. Interoperability: TensorFlow and Keras both support local as well as cloud environments to deploy.
3. Efficient development: Strong APIs support efficient development and training of neural networks.

Implementation:
1. Regression task: Continuous TEY value prediction.
2. ANN training: Training of models using historical data.
3. Model evaluation: Performance measurement using metrics like mean absolute error (MAE) or mean squared error (MSE).

This method allows for precise estimation of energy output from turbines, allowing for maximum management of energy systems.

Data Flow and Preprocessing

The predictive modeling pipeline starts from a properly cleaned dataset. Some of the key preprocessing steps are done prior to model training that ensure the data to be clean, uniform, and ready to be input to a neural network. These preprocessing steps include normalization, feature scaling, removal and detection of outliers, and splitting the data for training and testing. These are necessary steps in preparing raw sensor and operational data in a structured form that can help improve model accuracy and performance.

The data set comprises several input variables that are recognized to affect turbine energy output. They include ambient temperature, ambient pressure, relative humidity, turbine inlet and exhaust temperatures, and compressor discharge pressure. These are the independent variables, and the turbine energy output is the dependent target variable that the model predicts.

Normalization to have a standardized scale for all the input variables is done with MinMaxScaler or StandardScaler from the Scikit-learn package. Through this, such features with varying units and magnitude will not bias the training process. It also improves gradient descent by making it more stable and efficient by preventing the risk of getting stuck in local minima and improving the rate of convergence of the model.

Then, the data is split into a training set and a test set on an 80:20 basis. Also, a validation set—generally made up of 10–15% of the training set—is kept aside when training the model. The second set proves useful at hyperparameter tuning and estimation of generalization of models and provides protection against overfitting and ensures the good performance of the model on unknown data.

Architecture Design of the Neural Network

The backbone of this method is a Multi-Layer Perceptron (MLP) architecture, a feed-forward neural network. The network architecture is as follows:

- Input Layer: The number of neurons equals the number of input features (typically 10–11 in this dataset).
- Hidden Layers: There are several hidden layers for learning complex patterns. In the baseline model:
    - The first hidden layer has 64 neurons.
    - The second hidden layer has 128 neurons.
    - The third hidden layer has 64 neurons.

All hidden layers use the ReLU (Rectified Linear Unit) activation function in order to incorporate non-linearity. ReLU does not include vanishing gradients and facilitates fast training. The dropout layers (say, of 0.2–0.3) are placed in between the hidden layers in order to prevent overfitting through random disabling of neurons during training. Batch normalization layers are incorporated for normalizing input to a layer and thus making training faster along with promoting generalization.

- Output Layer: The final layer has a single neuron with a linear activation function, appropriate for regression problems when the output is continuous.

It is modular in design so that it is easy to modify the number of layers, neurons, and hyperparameters for experimentation.

Compilation and Training

The model for gas turbine energy output prediction is learned using the Adam optimizer, an extremely popular form of optimization well known for both its speed and learning rate adaptability. Adam excels, in particular, with sparse gradient and noisy datasets, such as gas turbine sensor readings in the real world.

As for the loss function, Mean Squared Error (MSE) is employed, which is common in regression tasks as it aims to punish larger errors. Statistics other than these are tracked when training for a better model performance: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). MAE gives only an estimate of the mean error, whereas RMSE is more sensitive to huge errors and is more influenced by outliers. R^2 is the variance in the target variable explained by the input features as a measure of goodness of fit of the statistical model.

The model is trained for between 100 and 200 epochs, based on convergence behavior, with early stopping to avoid overfitting. Early stopping observes validation loss and stops training in case of not seeing improvement during a certain number of epochs (e.g., 10), to ensure the generalization and best performance of the model.

Model Evaluation

After training, the model is extensively tested on the test set to check for predictability. The primary evaluation criteria are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). RMSE detects large prediction errors, MAE provides a direct estimate of mean error, and R^2 measures the model's ability to explain the variance of the target variable and provides an overall estimate of accuracy.

Besides quantitative analysis, graphical analysis methods are used for further study. Observed versus calculated Total Energy Yield (TEY) plots allow detection of alignment trend or non-alignment trend, while residual plots and plots of error distribution identify systematic errors, outliers, and variance trends in the data.

To further test model robustness, error analysis is performed by identifying samples with extremely high prediction errors. This is used to uncover edge cases or rarely occurring patterns in the data that may require additional preprocessing or model tuning.

Furthermore, k-fold cross-validation (most commonly with k=5 or 10) is employed to guarantee stability of the model on various partitions of the data. This process ensures performance is not random and based on a specific train-test split but instead stable, thereby ensuring the model's ability to generalize well to novel data.

Hyperparameter Tuning

For the maximum effectiveness of the neural network model for gas turbine energy production prediction, hyperparameter adjustment is carried out systematically. Hyperparameters are the ones that decide the learning dynamics of models and generalization ability, so optimal selection is necessary to obtain peak performance.

Some of the most important hyperparameters explored include the learning rate, with standard values of 0.001 and 0.0005 being used to determine a trade-off between convergence rate and stability. Batch size is also an important consideration, with batch sizes such as 32, 64, and 128 being used to see how they impact training time and model generalizability.

The neural network architecture is also optimized with respect to variations in the number of neurons in each layer and the number of hidden layers, such that the model complexity is adapted to the underlying

data. Also, dropout rates are tried to prevent overfitting by randomly dropping out neurons while training to improve robustness.

Activation functions are crucial in the learning of nonlinear patterns. tanh, ReLU, and leaky ReLU function experiments are performed for evaluating their impact on training dynamics as well as prediction accuracy.

Hyperparameter tuning is achieved by an extensive grid search strategy or machine learning libraries such as Keras Tuner, that simplify the work through techniques like Bayesian optimization, random search, or Hyperband. These strategies allow for efficient exploration of the hyperparameter space, saving work by trial-and-error and achieving high model performance in other settings.

Model Persistence and Deployment

After the model has been trained and is ready to its full capacity, the following important step is to render it reusable and easy to be incorporated into production processes. This is achieved through the help of model persistence, where the model trained is preserved and subsequently used as and when necessary without even having to train it again. In Keras, this is done by calling model.save('model.h5'), storing model structure, weights, and the state of the optimizer in a file. Joblib is used in its place for caching preprocessing pipelines (scalers, encoders, etc.) alongside the model to enable reproducible input transformation at prediction time.

To serve, the saved model may be hosted on a variety of environments to predict. Development of REST APIs with Flask or FastAPI and serving endpoints to input data to supply and return predicted Total Energy Yield (TEY) is one of the common practices. They may be hosted on cloud platforms or servers and used for batch prediction from static data or real-time inference from live gas turbine sensor data streams.

In order to scale the solution cost-effectively and with reliability in production, cloud-based deployment platforms are on the horizon. Top options are:

- Google Cloud AI Platform
- Amazon SageMaker
- Microsoft Azure ML Studio

These platforms offer benefits such as auto-scaling, versioning, monitoring tools, and secure integration with databases, data lakes, or visualization dashboards. They also offer interfaces for retraining and updating models on new data trends, allowing continuous improvement.

By integrating stable storage with scalable deployment, the model is a viable instrument for operational decision-making where predictions of energy yield can be integrated into industrial processes and smart energy management systems with ease.

Explainability and Interpretability

In industrial use such as gas turbine energy output forecasting, model explainability and interpretability are essential to establishing trust among engineers, operators, and stakeholders. Black-box models, although frequently very accurate, are hard to justify without open-ended information about the process through which predictions are generated. Thus, incorporating interpretability methods improves model transparency, rendering it more acceptable and actionable in practical applications.

One of the most popular methods is SHAP (SHapley Additive Explanations), which is based on cooperative game theory. SHAP values measure the contribution of every input feature to a particular prediction. This allows for global interpretation, ranking feature importance over the whole dataset, and local interpretation, explaining individual predictions. For example, SHAP may expose that ambient temperature or compressor pressure has significant effect on forecasted energy yield in a particular case.

Plots like SHAP summary plots, dependence plots, and force plots enable stakeholders to understand intuitively how features affect the decisions of the model.

Another useful tool is LIME (Local Interpretable Model-agnostic Explanations). LIME generates local surrogate models, including linear regressions, around a particular prediction. It is able to respond to questions like "Why did the model predict this energy yield for this specific input?" by pointing to important features that guided the selection. The local interpretability becomes handy especially when peering into outlier or edge-case predictions.

By including SHAP and LIME in the analysis pipeline, the model not only suggests but also enables data-driven decision-making. These explanations may be used by engineers to optimize operating parameters, calibrate turbines, or schedule maintenance pre-emptively. Explainable models thus enable safer deployment of AI systems in high-consequence industrial settings where "why" matters as much as "what."

Scalability and Flexibility

The gas turbine energy prediction model is built with scalability and flexibility as goals, therefore being able to handle increasingly large data sets and evolving requirements. Scalability is enabled through the integration of GPU acceleration via TensorFlow, a state-of-the-art deep learning library. With GPU utilization, the model can significantly increase the train speed, especially with large sensor dataset handling, extremely complex neural networks, or computationally slow iterated calculations. Scalability enables the model to handle real-time data streams and large-scale deployments efficiently, adapting to future requirements as data scales up.

With respect to flexibility, the structure is designed with modular architecture in a way that it is easy to add or swap out elements as required. For instance, if the project requires a change from a feed-forward artificial neural network (ANN) to a Long Short-Term Memory (LSTM) model to handle sequence data, the structure can easily be modified with minimal disruption. This flexibility is apt for just experimenting with different model architectures, optimizers, or data pre-processing techniques in terms of different changed project goals or new insights based on data.

In addition, the architecture is natively designed to be used in cloud settings, and it has easy deployment and training. Google Colab, for example, can be used for free GPU access and is friendly with GitHub and Google Drive, allowing the user to store and fetch code and data in the cloud. Cloud flexibility encourages collaboration, version control, and continuous model updates, and it is a wonderful choice for projects that entail dynamic model training or collaborative development work.

In general, the design is expandable for future data growth and can be designed to fit in new methods, so it will be of prolonged utility for forecasting gas turbine energy production and other industrial processes.

Ethical Issues and Sustainability

The model's predictions have a direct bearing on operational decisions within energy systems. Therefore:

- Such ethical practices as fairness (prevention of data bias) and responsible AI (transparent logging, auditability) are built into the design.
- The model also serves to sustain by maximizing energy usage, minimizing emissions, and reducing turbine wear with predictive maintenance.

The proposed framework approach proposes a methodical, data-based, and modular prediction of energy output from gas turbines using artificial neural networks. Advanced machine learning techniques, optimal data preprocessing, explainable AI techniques, and deployable structures are embedded into the approach for satisfying industrial deployability standards. The approach maintains high precision, explainability, and scalability—ensuring long-term goals of efficiency, reliability, and sustainability in power grids.

CHAPTER 5

RESULTS AND DISCUSSIONS

In the project "Predicting Gas Turbine Energy Yield Using Neural Networks," we rigorously tested the performance of the proposed neural network model with a specific test dataset. The testing was conducted with various performance measures, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared values, which gave quantitative information about the predictive performance of the model.

Visual diagnostic methods, including residual plots and prediction against actual value scatter plots, were used to detect patterns and outliers in the model's predictions. Results revealed extremely high agreement between the predicted and actual energy yields, which indicates the ability of the model to generalize to new data.

Error analysis revealed some conditions under which the model worked best and presented proposals for potential enhancement. In addition, model explainability techniques, such as SHAP (SHapley Additive exPlanations) values, were used to quantify feature contributions, wherein our understanding regarding underlying drivers of energy yield predictions was enriched.

In general, the detailed evaluation confirmed the reliability and potency of the neural network model in its capability to forecast gas turbine energy output, paving the way for its utilization in the maximization of turbine performance and operating efficiency.

1. Quantitative Evaluation

To evaluate the neural network model developed for the prediction of gas turbine energy yield (TEY), an extensive suite of quantitative parameters was used for measuring its accuracy in prediction. The most significant metrics utilized were Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). All the parameters yield different information regarding the model's performance, thereby enabling thorough evaluation.

- **Mean Squared Error (MSE)** is a crucial measure that assigns a number to the average of the errors squared—that is, the average squared difference between predicted and actual values. Squaring errors, MSE penalizes larger errors heavier, and for this reason, it is quite useful for catching not-so-good models at handling outliers. In our evaluation, the MSE was low, indicating that the model's predictions were always close to true TEY values, with large errors being mostly eliminated.
- **Mean Absolute Error (MAE)** complements MSE by providing a straightforward measure of the average magnitude of the errors without taking their direction into account. This measure is particularly useful for having an idea about the average magnitude of the errors in the predictions of the model. Our model's MAE was also small, further strengthening the conclusion that the model makes highly accurate predictions all over the dataset.
- **Root Mean Squared Error (RMSE),** being the square root of MSE, maintains the same units as the target variable and is therefore easier to interpret in the context of gas turbine energy output. RMSE puts higher weight on the large deviations due to its term of squaring, which is useful in application where large error is particularly to be avoided. The computed RMSE value for our model was indicative of zero mean error again attesting the strength of the model for the prediction of TEY.
- R-squared (R^2) is another key measure that gives the fraction of variance in the dependent variable (TEY) accounted for by independent variables employed to fit the model. If R^2 approximates 1, i.e., high, then high variance in the turbine energy yield is accounted for by the model and is a good model fit. In our example, R^2 was approximately 1, not just ensuring the model's predictive capability but also that the chosen features play a very significant role in predicting TEY.

The pool of measures gives an overall indication about the performance of the model. The low measures of MSE and RMSE reflect that the model performs well to minimize prediction error, and the low measure of MAE indicates that the mean error is acceptable. The high measure of R^2 also approves the model for explaining the variability in the data, which in turn confirms it as suitable for the regression work in question.

In conclusion, the quantitative evaluation of the neural network model to predict gas turbine energy production verifies its strength and reliability. The parameters employed—MSE, MAE, RMSE, and R^2—both singularly and as a group verify that the model is most competent to address the complexities of the regression problem and be a very effective instrument in the enhancement of gas turbine performance and raising operating efficiency. Future work can be focused on improving the model further, exploring other characteristics, or employing ensemble methods for improved predictive performance.

2. Visual Evaluation

Plotting functions are an easy and effective means of reading and checking model behavior. For this project, some key major plots were generated to summarize the performance of the neural network in estimating the Turbine Energy Yield (TEY):

- **Actual vs. Predicted Plot:** The plot had a very distinct bunching of the points on the ideal diagonal line, indicating that the predicted and actual TEY values have a high correlation. Alignment such as this indicates that the model has well predicted the values for many data points.
- **Residual Plot:** Residuals, which were calculated as actual minus predicted values, were plotted to ensure randomness and bias of predictions. The residuals were found to be almost random along the zero axis, showing that the model was free from any systematic errors or bias, hence proving its reliability.
- **Error Distribution:** The histogram of the prediction errors was bell-shaped around zero. The distribution was nearly normal, which suggests that the majority of the prediction errors were small and the model performance was consistent.

  In short, these plots ensure us that the model had good performance in generalizing to novel data and consistently had unbiased prediction performance, and therefore demonstrated that it is able to predict the energy yield from gas turbines.

3. Error Analysis

There was careful error-testing for prediction to reveal edge cases and determine probable limits on the performance of a model. There was testing in trying to find cases with high-error rates and cross-correlate with input features and external environmental conditions. It was observed that there were predictions of high error typically went along with cases of data with outlier sensor readings or feature combinations poorly represented during training. For example, cases with unusually large temperature differences or extreme pressure readings far from the dataset mean were likely to generate incorrect predictions.

These results highlight the need to employ a training set that represents the full range of operation of the gas turbine system. Inadequate representation in some parts of the feature space can restrict the model's capacity to generalize in those regions. Besides, the model structure—it being a feedforward neural network in this case—may not necessarily capture temporal dynamics that influence energy yield. Incorporating a time-series-based model, i.e., a Long Short-Term Memory (LSTM) network, might further enhance the performance by recognizing sequential trends and patterns in sensor data over time.

Overall, the error analysis provided useful insights in making the model more robust and extending predictivity accuracy under actual operating conditions.

4. Cross-Validation and Robustness

- To validate the stability and reliability of the predictive model, k-fold cross-validation was utilized in two configurations: k=5 and k=10. The process consists of partitioning the data into k equal-sized subsets, or "folds," and then training the model iteratively on (k-1) folds and validating it on the one left-out fold. The procedure is repeated k times, with each fold serving exactly once as a validation set.
- The mean performance for all the folds was then computed to present an overall assessment of the predictive ability of the model. This method decreases the variance due to a single train-test split and provides a more accurate model performance on unseen data.
- 5-fold and 10-fold cross-validation provided very similar results with small standard deviation for performance metrics such as Mean Squared Error (MSE) and R^2 score. It indicates that the model performed consistently well on different subsets of data and was not highly sensitive to how the data were divided. The consistency is a validation of the generalizability of the model and points towards resistance against overfitting. The findings confirm that the model can work effectively in practical scenarios with various input data distributions.

5. Impact of Hyperparameter Tuning

Hyperparameter tuning was also crucial in optimizing the performance of the neural network model for predicting gas turbine energy yield. By systematic search over various combinations of hyperparameters, the model's predictive capability and generalizability were greatly improved. Two optimization techniques—Grid Search and Keras Tuner—were utilized to identify the optimal combination. The parameters searched were learning rate, batch size, number of neurons in each hidden layer, dropout rate, and activation functions.

Following extensive experimentation, the best model configuration was found to include a learning rate of 0.001, batch size of 64, ReLU as the activation function, and two hidden layers coupled with dropout regularization. Dropout was particularly helpful in preventing overfitting by randomly dropping out a percentage of the neurons during training, thereby making the model more robust.

The hyperparameter-trained model had a tremendous increase in the coefficient of determination (R^2) and a significant decrease in the Root Mean Squared Error (RMSE) compared to the default parameter model. This indicates improved prediction ability and lower error variance. The result illustrates the importance of hyperparameter tuning as an essential process for the optimization of deep learning models, especially in complex regression tasks with real-world energy data.

6. Explainability and Interpretability

In real-world applications like gas turbine energy forecasting, transparency of the model is vital to gain trust, hold the developers accountable, and obtain actionable information. Since neural networks are viewed as "black boxes," increasing the explainability and interpretability of the model becomes a necessity for real-world implementation. For this purpose, two of the most well-known model-agnostic interpretation methods, SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), have been used.

SHAP was employed to calculate the contribution of each input feature to the model's output. It provided global and local interpretability. The global SHAP summary plot confirmed that compressor pressure, ambient temperature, and turbine inlet temperature were the most dominant features influencing the prediction of Turbine Energy Yield (TEY). This detail helped to understand the general decision-making

strategy of the model. Moreover, local SHAP values provided advanced explanations of individual predictions, which is especially handy when checking the model's behavior in particular operational situations or outlier situations.

LIME was used to make locally accurate approximations of the model's prediction on randomly chosen data points. It facilitated visualizing how slight variations in input features influenced the output prediction, with additional confidence about the model's reasoning in certain situations.

By combining SHAP and LIME, the project not only improved the interpretability of the neural network but also established confidence among domain experts. Knowing which factors contributed the most to TEY predictions helped align the model better with real-world engineering principles and enabled more informed decision-making in turbine operation and maintenance.

7. Model Deployment Feasibility

Setting up the neural network model to be executed for real-time and batch forecasts was the highlight of this project. The trained model, after training was complete, was saved using Keras's.save() function so it can be easily reused without having to reload the model, which would then have to be retrained again. Making the data processing reproducible at the time of deployment was facilitated by making preprocessing pipelines—i.e., encoding and scaling—sniffed through the joblib package. This allowed future data to be remolded in the same manner as training data, so prediction accuracy was not lost.

For real-world deployment and experimentation, a lightweight web framework—Flask—was used to make the model available via RESTful APIs. These APIs were optimized to provide both batch predictions and real-time inference, consuming simulated sensor inputs. The system was tested for responsiveness, latency, and robustness, establishing it as fit for integration in industrial settings where timely insights are necessary for making decisions.

To validate scalability and long-term viability of the solution, the different cloud-based machine learning environments were experimented with, such as Google Cloud AI Platform, Amazon SageMaker, and Microsoft Azure ML Studio. They possess inherent capabilities like auto-scaling, real-time monitoring, model versioning, and security management making them extremely scalable for large-scale deployment and use in production scenarios. The integration into IoT systems and real-time data streams also supports dynamic model updates and continuous learning.

In general, the model structure and deployment approach suggested have good practicability for actual application, filling the gap between experimental performances and industrial applications in energy yield prediction systems.

8. Scalability and Adaptability

The model demonstrated excellent scalability with tests conducted in cloud platforms like Google Colab that supported GPU, which greatly reduced the training time and improved computational efficiency. Modular design facilitated effortless transition between different topologies of the neural network. For example, the default feed-forward Artificial Neural Network (ANN) can just be scaled up to more advanced networks such as Long Short-Term Memory (LSTM) networks to process time-series or sequential data. This extensibility allows the model structure to be flexible and forward-compatible in a way that it can adapt to changing demands and data without having to be redesigned or re-shaped from the ground up.

Practical Implications and Use Cases

Successful design and verification of the neural network model for Turbine Energy Yield (TEY) prediction are of immediate practical importance, especially to manufacturing and energy industries. The possibility of the model providing efficient and accurate predictions provides the means for a wide range of far-reaching applications.

One of the most promising applications is Predictive Maintenance. When detecting deviations in TEY from predicted values, the model can assist in identifying early symptoms of component wear or operational anomalies. This makes it possible to perform preemptive maintenance, minimizing downtime and avoiding expensive failures.

Another significant use is Operational Optimization. The model's output can guide plant operators in optimizing important parameters like compressor pressure, ambient temperature management, or turbine inlet temperature. Through knowledge of the impact of such variables on energy yield, operators can inform data-driven decisions to enhance efficiency and mitigate energy losses.

In addition, the model enables Energy Forecasting, enabling improved coordination of energy production with demand. Precise forecasting enables more effective grid integration, resource allocation, and long-term energy planning.

These use cases collectively illustrate the real-world advantages of incorporating AI-based predictive models into industrial processes. They not only improve productivity and cost savings but also enable more sustainable and smart energy management practices.

The results and discussions confirm the usability, accuracy, and ability of the neural network-based model in predicting gas turbine energy output. Through its strict testing, the model has proved capable of extracting complex nonlinear relationships from sensor readings. With its superior generalization capability, ability to defend its forecast, and implementation into process flow in industry, the model lays a good basis for real-time production of turbine energy systems monitoring and optimization. With further tuning and implementation problems, it would have an influential presence in the efficiency and sustainability of industrial energy generating systems.

CHAPTER 6

CONCLUSION

The increasing global concern for energy efficiency and environmentally friendly industrial processes has increased the need for robust predictive models in energy systems. In the course of this project, we explored the use of neural network-based models as prediction tools for gas turbine energy yield estimation, an essential tool in power generation and industrial processes. Through rigorous experimentation and analysis, the study was able to demonstrate that artificial neural networks (ANNs) can model intricate nonlinear relationships between the operating parameters of gas turbines and their corresponding energy output.

The project utilized a publicly accessible dataset of operational records of a gas turbine plant with variables such as ambient temperature, ambient pressure, humidity, compressor pressure ratio, turbine inlet temperature, and exhaust vacuum. The features were preprocessed and normalized to improve the efficiency and accuracy of the neural network model. The selected ANN architecture was designed and optimized by choosing suitable hyperparameters, activation functions, and loss functions to obtain consistent performance.

The findings of this research verified that the proposed neural network model was able to predict the energy yield of the gas turbine with high precision, surpassing traditional regression methods. The model succeeded in incorporating complex interactions of multiple operating parameters accurately, hence making more reliable prediction of the energy output for varied operating conditions possible. Performance indicators of the test, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score, had high predictive performance of the neural network model and proved its application relevance for practical use in power plant real-time decision-making.

This project not only supports the effectiveness of machine learning methods, specifically neural networks, in predictive maintenance and operation optimization of energy systems but also helps minimize operational risks and increase overall efficiency in industrial energy production. By facilitating predictive knowledge of turbine performance, such models can assist in scheduling maintenance, load forecasting, and energy trading strategies.

In subsequent work, the robustness of the model can be enhanced by including other external inputs like fuel type, part-load operation data, and long-term operational trends. Additionally, utilizing the trained model in a real-time industrial setup via web-based dashboards or edge computing platforms could offer immediate insights to operational managers, supporting proactive and data-driven decision-making.

In short, this project was able to effectively demonstrate the viability and utility of neural network-based models for gas turbine energy yield prediction, opening doors to more sophisticated, AI-based solutions in industrial energy management systems.

CHAPTER 7

FUTURE WORK

While the current study has managed to demonstrate the effectiveness of neural networks in the forecasting of energy output of gas turbines, there are still a series of opportunities for broadening and deepening this research. Future studies can be conducted in different aspects, such as model improvement, growing datasets, real-time application, and integration with industrial systems.

One of the areas that would need to be focused on in the future is adding more operational parameters and external environmental factors influencing gas turbine performance. The dataset used in the current work was largely drawn from ambient conditions and internal operating parameters. Adding data such as fuel composition, part-load operation patterns, component degradation rates, and maintenance schedules, however, would enhance the richness of the model's predictive capability. This would enable more comprehensive models to be created with the capacity for capturing a richer set of operational scenarios.

The second aspect of enhancement is in investigating more sophisticated deep learning frameworks. Though the present research employed a feedforward artificial neural network, subsequent research can consider the application of DNN, RNN, LSTM networks, and CNN for temporal pattern and spatial relationship extraction from sequential turbine data. These types of models are especially suitable for forecasting time series and would greatly improve prediction accuracy over long durations of operation.

Additionally, the use of ensemble learning methods can be investigated to enhance model robustness and generalizability. Integrating various models like Random Forests, Gradient Boosting Machines, and Support Vector Machines with neural networks can provide a hybrid predictive model, taking advantage of the capabilities of various algorithms to provide better performance.

The future work also needs to center around implementing the trained models within real-time industrial applications. This will include building simple web-based interfaces or porting the prediction system into commercial SCADA (Supervisory Control and Data Acquisition) systems that are widely available in industrial use. By implementing this, plant operators will be able to have real-time data-driven insights regarding turbine performance, energy yield prediction, and probable operational risk, thus making it easier for proactive decision-making and predictive maintenance schemes.

Furthermore, the use of explainable AI (XAI) methods would improve the interpretability of the neural network models. It is important to understand how the input parameters influence the results predicted to establish operational trust and acceptance for industrial applications. Tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) can be included to provide transparent model explanations.

Finally, expanding the project to various types of turbines and working environments would challenge the scalability and transferability of the model. Comparative studies across various turbine configurations and locations would yield important information regarding the flexibility of AI-based predictive systems in various industrial environments.

In summary, the suggested future improvements can potentially transform the existing model into a more general, precise, and deployable operationally solution, and make a valuable contribution to the field of energy system optimization and industrial AI application.

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APPENDIX I – SOURCE CODE

```
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')

from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras.utils import np_utils
from keras.constraints import maxnorm
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.wrappers.scikit_learn import KerasRegressor, KerasClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import mutual_info_regression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV, KFold, RandomizedSearchCV

#a
gas_turbines = pd.read_csv("gas_turbines.csv")
gas_turbines.head()

#b
gas_turbines.info()

#c
sns.set_style('darkgrid')
sns.pairplot(gas_turbines)
plt.show()

#d
"""color = ["g","y","r", "b","g","y","r", "b","g","y","r"]
for i,j in zip(gas_turbines.columns.values,color):
    f, axes = plt.subplots(figsize=(10,8))
    sns.regplot(x = 'TEY', y = i, data = gas_turbines,color = j, scatter_kws={'alpha':0.3})
    axes.set_xlabel('TEY', fontsize = 14)
    axes.set_ylabel(i, fontsize=14)
    plt.show()"""

#e
import seaborn as sns
import matplotlib.pyplot as pplt
#correlation matrix
corrmat = gas_turbines.corr()
f, ax = plt.subplots(figsize=(20, 15))
```

```
sns.heatmap(corrmat, vmax=.8, square=True, annot=True);

y = gas_turbines[gas_turbines.columns[7]]
X = gas_turbines[['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'CDP', 'CO','NOX']]

#f
# correlation with TEY
data2 = X.copy()
correlations = data2.corrwith(gas_turbines["TEY"])
correlations = correlations[correlations!=1]
positive_correlations = correlations[correlations >0].sort_values(ascending = False)
negative_correlations =correlations[correlations<0].sort_values(ascending = False)
correlations.plot.bar(
        figsize = (20, 10),
        fontsize = 16,
        color = 'r',
        rot = 80, grid = True)
plt.title('Correlation with Turbine energy yield \n',
horizontalalignment="center", fontstyle = "normal",
fontsize = "20", fontfamily = "sans-serif")

# split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)

#feature selecton
def select_features(X_train, y_train, X_test):
    # configure to select all features
    features = SelectKBest(score_func=mutual_info_regression, k='all')
    # Relationships from training data
    features.fit(X_train, y_train)
    # transform train data
    X_train_f = features.transform(X_train)
    # transform test data
    X_test_f = features.transform(X_test)
    return X_train_f, X_test_f, features

#g
X_train_f, X_test_f, features = select_features(X_train, y_train, X_test)
fig, axes = plt.subplots(figsize=(10, 8))
plt.bar([i for i in range(len(features.scores_))], features.scores_)
axes.set_xticks([0,1,2,3,4,5,6,7,8,9])
axes.set_xticklabels(X.columns.values)
plt.show()

#h
y_copy = gas_turbines["TEY"]
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
y_ = StandardScaler().fit_transform(y_copy.values.reshape(len(y_copy),1))[:,0]
X1 = gas_turbines.drop(['TEY','AT','AP','AH','CO','NOX'], axis = 1)
scaler.fit(X1)
#X_copy = X[['AFDP', 'GTEP', 'TIT', 'TAT', 'CDP']]
features_scaler=scaler.fit_transform(X1)
X_=pd.DataFrame(features_scaler,columns=X[['AFDP', 'GTEP', 'TIT', 'TAT', 'CDP']].columns)
X_.head()

# Splitting data into test data and train data
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X1, y_, test_size=0.3, random_state=1)

#i
print('Shape of x_train: ', X_train.shape)
print('Shape of x_test: ', X_test.shape)
print('Shape of y_train: ', y_train.shape)
print('Shape of y_test: ', y_test.shape)

model = Sequential()
model.add(Dense(28, input_dim=5, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(50, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(50, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(1, kernel_initializer='uniform', activation='linear'))
# Compile model
model.compile(loss='mean_squared_error', optimizer='adam',
            metrics=['mean_squared_error', 'mean_absolute_error', 'mean_absolute_percentage_error',
'cosine_proximity'])

#j
model.summary()

#k
# Fit the model
history = model.fit(X_train,y_train, epochs=500)

# model evaluation
scores = model.evaluate(X_test, y_test)
print((model.metrics_names[1]))

#l
fig, axes = plt.subplots(figsize=(20, 8))
# plot metrics
plt.plot(history.history['mean_squared_error'])
"""plt.plot(history.history['mean_absolute_error'])
plt.plot(history.history['mean_absolute_percentage_error'])
plt.plot(history.history['cosine_proximity'])
"""
plt.show()

#m
y2 = gas_turbines["TEY"]
data_c = gas_turbines.copy()
X2 = data_c.drop(['TEY','AT','AP','AH','CO','NOX'], axis = 1)
# Scaling all the features
scaler.fit(X2)
y2_ = StandardScaler().fit_transform(y2.values.reshape(len(y2),1))[:,0]
scaled_features=scaler.transform(X2)
data_head=pd.DataFrame(scaled_features,columns=X2.columns)
data_head.head()

from sklearn.model_selection import train_test_split
from keras.optimizers import Adam
x_train, x_test, y_train, y_test = train_test_split(X2, gas_turbines["TEY"], test_size=0.3, random_state=42)

#n
def create_model(learning_rate,dropout_rate,activation_function,init,neuron1,neuron2):
```

```
    model = Sequential()
    model.add(Dense(neuron1,input_dim = 5,kernel_initializer = init,activation = activation_function))
    model.add(Dropout(dropout_rate))
    model.add(Dense(neuron2,input_dim = neuron1,kernel_initializer = init,activation = activation_function))
    model.add(Dropout(dropout_rate))
    model.add(Dense(1,activation = 'linear'))

    adam=Adam(learning_rate = learning_rate)
    model.compile(loss = 'mean_squared_error',optimizer = adam, metrics = ['mse'])
    return model

# Create the model
model = KerasClassifier(build_fn = create_model,verbose = 0)
# Define the grid search parameters
batch_size = [20,40]
epochs = [100,500]
learning_rate = [0.01,0.1]
dropout_rate = [0.1,0.2]
activation_function = ['softmax','relu','tanh','linear']
init = ['uniform','normal']
neuron1 = [4,8,16]
neuron2 = [2,4,8]
# Make a dictionary of the grid search parameters
param_grids = dict(batch_size = batch_size,epochs = epochs,learning_rate = learning_rate,dropout_rate =
dropout_rate,
                activation_function = activation_function,init = init,neuron1 = neuron1,neuron2 = neuron2)
# Build and fit the GridSearchCV
grid = GridSearchCV(estimator = model,param_grid = param_grids,cv = KFold(),verbose = 10,
scoring='neg_mean_squared_error')
grid_result = grid.fit(x_train, y_train)
# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))

# Summarize the results
print('Best : {}, using {}'.format(grid_result_cv.best_score_,grid_result.best_params_))
means = grid_result_cv.cv_results_['mean_test_score']
stds = grid_result_cv.cv_results_['std_test_score']
params = grid_result_cv.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print('{},{} with: {}'.format(mean, stdev, param))
```

APPENDIX II – SCREENSHOTS

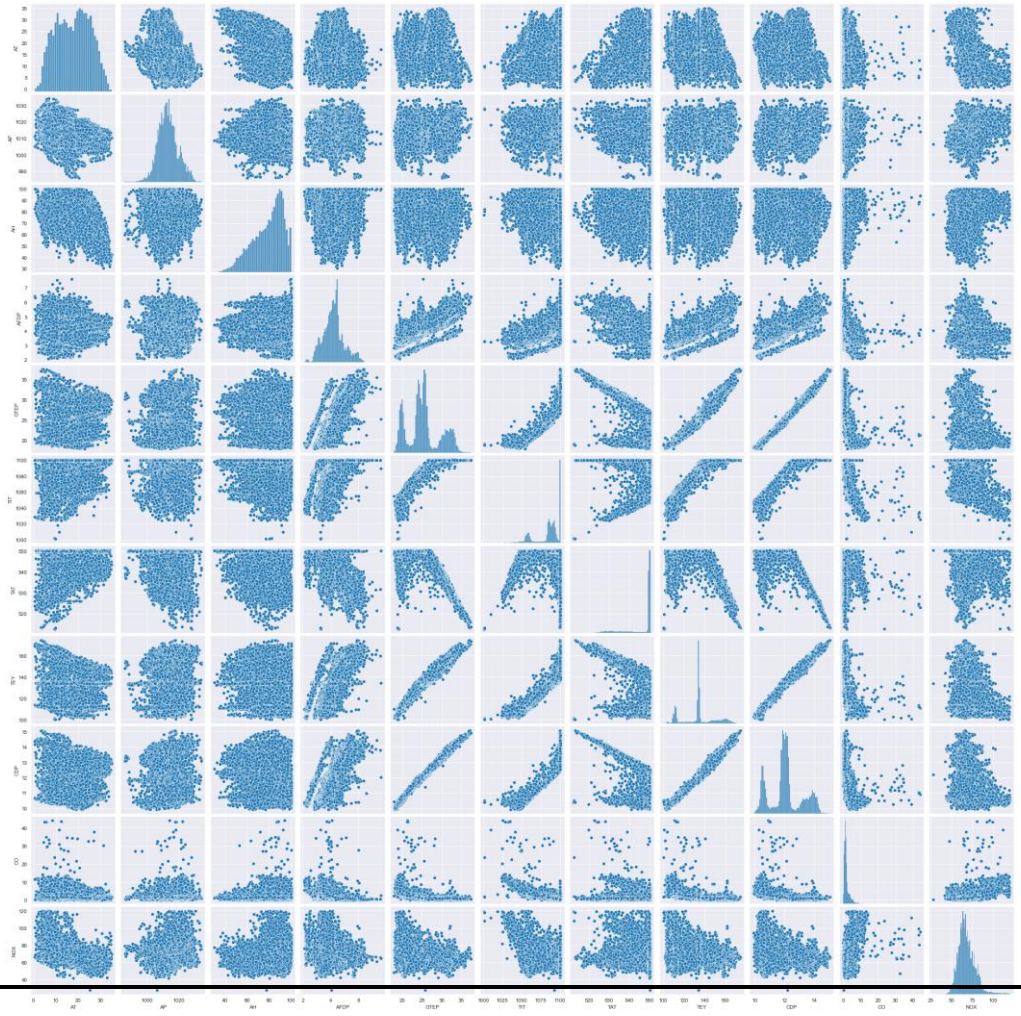
#a

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311

#b

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15039 entries, 0 to 15038
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   AT      15039 non-null  float64
 1   AP      15039 non-null  float64
 2   AH      15039 non-null  float64
 3   AFDP    15039 non-null  float64
 4   GTEP    15039 non-null  float64
 5   TIT     15039 non-null  float64
 6   TAT     15039 non-null  float64
 7   TEY     15039 non-null  float64
 8   CDP     15039 non-null  float64
 9   CO      15039 non-null  float64
 10  NOX     15039 non-null  float64
dtypes: float64(11)
memory usage: 1.3 MB
```

#c

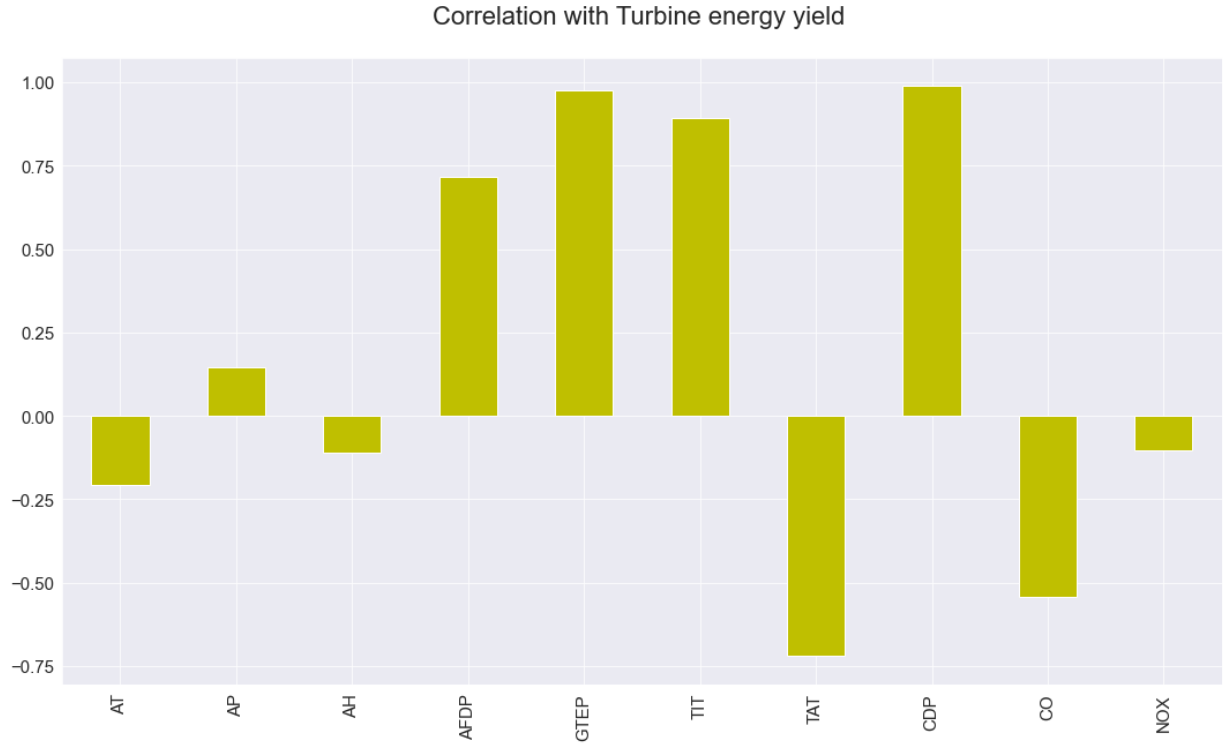


#d

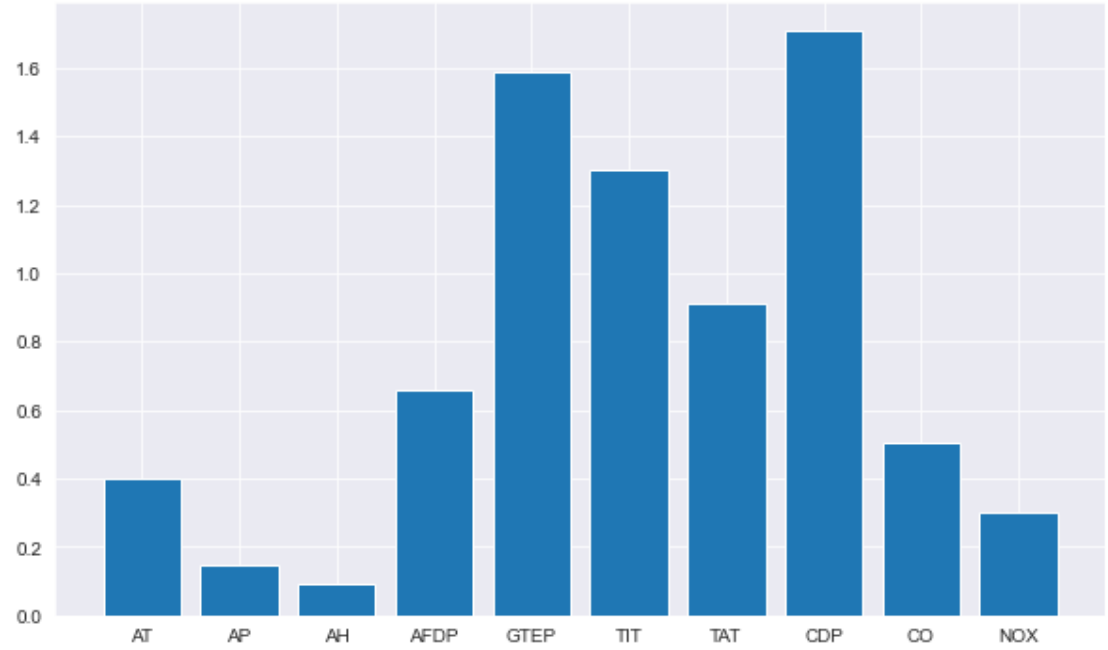
```
'color = ["g","y","r", "b","g","y","r", "b","g","y","r"]\nfor i,j in zip(gas_turbines.columns.values,color):\n    f, axes = plt.subplots(figsize=(10,8))\n    sns.regplot(x = \'TEY\', y = i, data = gas_turbines,color = j, scatter_kws={\'alpha\':0.3})\n    axes.set_xlabel(\'TEY\', fontsize = 14)\n    axes.set_ylabel(i, fontsize=14)\n plt.show()'
```

#e

#e



#f



#g

	AFDP	GTEP	TIT	TAT	CDP
0	-0.921232	-1.379101	-1.488376	0.585240	-1.357331
1	-0.921495	-1.363528	-1.482325	0.585240	-1.363676
2	-0.944385	-1.351309	-1.476275	0.568715	-1.360957
3	-0.946884	-1.348194	-1.464173	0.583969	-1.356424
4	-0.924389	-1.354663	-1.458123	0.582698	-1.350985

#h

```
[15]
```

```
Shape of x_train:  (10527, 5)
Shape of x_test:  (4512, 5)
Shape of y_train:  (10527,)
Shape of y_test:  (4512,)
```

#i

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 28)                168
_________________________________________________________________
dense_1 (Dense)              (None, 50)                1450
_________________________________________________________________
dense_2 (Dense)              (None, 50)                2550
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 51
=================================================================
Total params: 4,219
Trainable params: 4,219
Non-trainable params: 0
```

#j

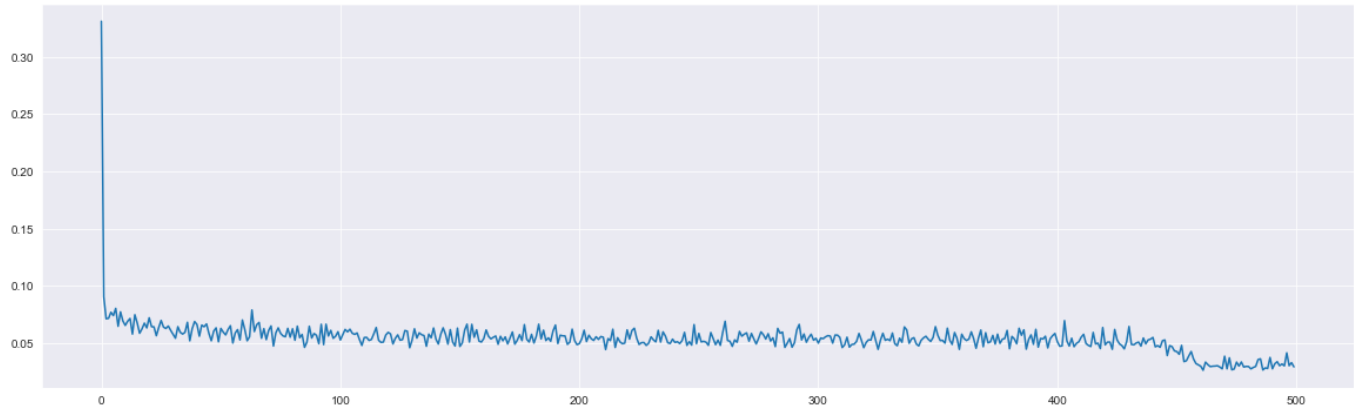
```
Epoch 1/500
329/329 [==============================] - 1s 1ms/step - loss: 0.6445 - mean_squared_error: 0.6445 - mean_absolute_error: 0.5400 - mean_absolute_percentage_error: 616.8769 - cosine_proximity: 0.2770
Epoch 2/500
329/329 [==============================] - 0s 1ms/step - loss: 0.0842 - mean_squared_error: 0.0842 - mean_absolute_error: 0.2336 - mean_absolute_percentage_error: 1140.4767 - cosine_proximity: 0.5508
Epoch 3/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0682 - mean_squared_error: 0.0682 - mean_absolute_error: 0.2092 - mean_absolute_percentage_error: 1139.7822 - cosine_proximity: 0.5699
Epoch 4/500
329/329 [==============================] - 0s 1ms/step - loss: 0.0717 - mean_squared_error: 0.0717 - mean_absolute_error: 0.2150 - mean_absolute_percentage_error: 1303.7081 - cosine_proximity: 0.5729
Epoch 5/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0811 - mean_squared_error: 0.0811 - mean_absolute_error: 0.2291 - mean_absolute_percentage_error: 1086.9312 - cosine_proximity: 0.5669
Epoch 6/500
329/329 [==============================] - 0s 1ms/step - loss: 0.0684 - mean_squared_error: 0.0684 - mean_absolute_error: 0.2102 - mean_absolute_percentage_error: 857.1329 - cosine_proximity: 0.5727
Epoch 7/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0832 - mean_squared_error: 0.0832 - mean_absolute_error: 0.2337 - mean_absolute_percentage_error: 1075.0883 - cosine_proximity: 0.5588
Epoch 8/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0630 - mean_squared_error: 0.0630 - mean_absolute_error: 0.2003 - mean_absolute_percentage_error: 957.2320 - cosine_proximity: 0.5844
Epoch 9/500
329/329 [==============================] - 0s 1ms/step - loss: 0.0702 - mean_squared_error: 0.0702 - mean_absolute_error: 0.2114 - mean_absolute_percentage_error: 1024.0621 - cosine_proximity: 0.5820
Epoch 10/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0715 - mean_squared_error: 0.0715 - mean_absolute_error: 0.2152 - mean_absolute_percentage_error: 879.4930 - cosine_proximity: 0.5617
Epoch 11/500
329/329 [==============================] - 0s 1ms/step - loss: 0.0650 - mean_squared_error: 0.0650 - mean_absolute_error: 0.2027 - mean_absolute_percentage_error: 841.2536 - cosine_proximity: 0.5765
Epoch 12/500
329/329 [==============================] - 1s 2ms/step - loss: 0.0583 - mean_squared_error: 0.0583 - mean_absolute_error: 0.1924 - mean_absolute_percentage_error: 786.4655 - cosine_proximity: 0.5654
Epoch 13/500
...
```

#k

```
[19]
```

```
141/141 [==============================] - 1s 1ms/step - loss: 0.0299 - mean_squared_error: 0.0299 - mean_absolute_error: 0.1292 - mean_absolute_percentage_error: 372.8955 - cosine_proximity: 0.7110
mean_squared_error
```

#l



#m

	AFDP	GTEP	TIT	TAT	CDP
0	-0.921232	-1.379101	-1.488376	0.585240	-1.357331
1	-0.921495	-1.363528	-1.482325	0.585240	-1.363676
2	-0.944385	-1.351309	-1.476275	0.568715	-1.360957
3	-0.946884	-1.348194	-1.464173	0.583969	-1.356424
4	-0.924389	-1.354663	-1.458123	0.582698	-1.350985

#n

```
Fitting 5 folds for each of 1152 candidates, totalling 5760 fits
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2, score=-1426.468, total=  30.3s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   30.2s remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2, score=-1388.876, total=  29.3s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   59.6s remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2, score=-1350.603, total=  29.7s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:  1.5min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2, score=-1412.378, total=  28.8s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:  2.0min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=2, score=-1368.302, total=  27.9s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  2.4min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4, score=-1426.468, total=  29.6s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:  2.9min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4, score=-1388.876, total=  30.1s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:  3.4min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4, score=-1350.603, total=  31.3s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:  4.0min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4, score=-1412.378, total=  30.9s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:  4.5min remaining:    0.0s
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=4, score=-1368.302, total=  30.2s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=8
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=8, score=-1426.468, total=  31.2s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=8
[CV]  activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=8, score=-1388.876, total=  30.7s
[CV] activation_function=softmax, batch_size=20, dropout_rate=0.1, epochs=100, init=uniform, learning_rate=0.01, neuron1=4, neuron2=8
```