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INTELLIGENT ELECTRICAL POWER PREDICTION AND OPERATIONAL RESPONSE O. PTIMIZATION FOR RELIABLE MICRO GAS TURBINE ENERGY GENERATION

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Abstract

The accurate prediction of electrical power coupled with identification of the operating conditions that maintain high and stable output is essential for reliable operation of a micro gas turbine. This study characterized voltage-dependent electrical power behaviour, evaluated predictive models, and identified a balanced operating condition for reliable energy generation. Eight experimental runs with micro gas turbines were analysed, and six were used for the development of the model, while two were left for independent testing. Spearman correlation and linear/quadratic regression were used to study the voltage-power relationship, and the models Linear Regression, Random Forest and Gradient Boosting were compared based on the parameters MAE, RMSE and R^2. Predictor contributions and operating stability were also assessed. Electrical power showed a strong positive association with input voltage ($\rho = 0.9163$, $p < 0.001$), while the quadratic voltage-response model achieved $R^2 = 0.8831$. Linear Regression provided the strongest independent-test performance, achieving MAE = 8.0342, RMSE = 10.6132, and $R^2 = 0.9998$. Recent power-history variables contributed most strongly to predictive accuracy. Operational optimization identified 9.6316 V as the preferred condition, producing mean electrical power of 3101.5303 with a CV of 1.5943%. Through these findings, the advantages of using short-horizon power prediction in conjunction with operating-point optimization in order to ensure reliable energy generation for micro gas turbines are shown.

Keywords: *micro gas turbine, electrical power prediction, operational optimization, voltage response, reliability*

1. Introduction

The ability to supply reliable electricity will increasingly rely on energy systems that have the ability to deliver a steady supply while adjusting their output in response to the changing operating conditions. This transition has been driven by renewable technologies, which are increasingly becoming a key part of the solution, but also pose a challenge with their intermittent supply, which necessitates flexible generation, power conversion and system control requirements. Wind power is an example of this: The wind energy system is complex enough to need to interlink the electrical and control components to ensure that it delivers efficient power output, even when wind speeds fluctuate (Blaabjerg & Ma, 2017). The growth of onshore and offshore wind energy also has raised interest in complementary technologies that can enable a flexible and distributed energy system (Letcher, 2017). Ongoing developments in turbine design, control, and power electronics have enhanced the capacity of renewable generation (Bošnjaković et al., 2022), and aerodynamic optimisation has added to the increase in energy-conversion efficiency (Firoozi et al., 2024).

Micro gas turbine technology is an interesting complement, due to its small size, flexibility, and applicability to decentralised generation. They are particularly significant in distributed and hybrid energy systems where controllable generation resources are required in conjunction with variable energy resources. Micro gas turbines have been recognized as a future potential application for the energy transition in energy systems where flexible generation is necessary, or various fuel integration is desired (Banihabib & Assadi, 2022). They can also help integrate them with renewable energy resources and with local energy management (De Robbio, 2023). However, in order to operate the generator effectively, information is needed regarding the change in electrical output with operating conditions and the ability to accurately predict this change.

The importance of modelling the performance of a micro gas turbine when operating with varying conditions has been shown. Analytical models are useful for making predictions of turbine behaviour under variable energy inputs as applied to solar hybrid operation (Ssebabi et al., 2019). Fuel and combustion conditions can also have an impact on micro gas turbine performance, as evidenced by the assessment of various fuel blends of H2/CH4/CO2 and their impact on performance and emissions (Du Toit et al., 2020). These variations show the importance of measuring specific operating characteristics that are tightly coupled to electrical output.

The interaction between generation technologies and electrical power systems also has a part to play in voltage behaviour. The variability of generation can impact voltage situations and make operating the system more difficult. Assessment of voltage stability in power systems considering correlated variability of renewable energy generation has shown that generation conditions should be considered when determining electrical reliability (Xu et al., 2017). The correlation between input voltage and electrical power produced by the micro gas turbine can therefore be useful to analyse the operational response at the micro gas turbine level. Data comparison of linear and nonlinear response patterns can also help identify if the change in power output is proportional throughout the operating range.

Convenient methods of converting operational measurements into electrical power estimates are data-driven approaches. The usage of statistical and machine learning techniques for electrical energy forecasting has been growing, as they can reveal the relationship between operating conditions, historical observations, and the behaviour of subsequent electrical energy (Machado & Zhu, 2025). Power systems analysis also has a growing significance of data-driven predictive tools in forecasting and operational decision support (Strielkowski et al., 2023). However, this does not necessarily mean that the algorithm is more complex and thus more accurate at predicting. A comparison of the statistical approach and machine-learning approach for renewable energy forecasting studies shows that the accuracy of the methods is influenced by data characteristics, temporal structure and forecasting objectives (Dou et al., 2023).

There is a lack of research to link accurate prediction of electrical power with selection of operating conditions for micro gas turbine generation. Studies on turbine performance, forecasting, or turbine operational characteristics have been carried out one after another, with limited efforts to combine the power response, which depends on the voltage, the forecasting in time and the optimization considering reliability. However, achieving maximum electrical power may not be enough if greater variability is generated along with the greater electrical power. An approach that takes into account the output stability as well as the power magnitude may offer a more balanced basis for operational response. Independent experimental testing is also required to assess consistency of predictive and optimized responses beyond the experimental sequences used for developing the models.

The goal of the present study is to characterize the behaviour of electrical power and the relationship between electrical power and input voltage over various operating conditions of MTs, to develop and evaluate independently models for predicting electrical power given the operating conditions and recent information available about the power history, and to identify and validate an operating condition that maximizes the electrical power output while minimizing the output variability. These goals incorporate a combination of prediction and operational response assessment in a common framework for reliable micro gas turbine energy generation.

2. Methodology

2.1 Research Design

The experimental design was quantitative and analytical and studied the electrical power generation under various operating conditions of a micro gas turbine. Electrical characteristics, voltage–power relationships, power prediction, predictor contribution and optimizing the operating conditions were analyzed. The separation used in the experiment was predefined, and six experiments were used for model development and two experiments were used for independent testing.

2.2 Data Source

The data were extracted from the UCI Machine Learning Repository and were experimental measurements of micro gas turbine electrical energy generation measured by Bielski et al. (2024). The variables that were available were time, input voltage and electrical power. The measurements were spread over 8 experimental runs (6 training and 2 test experiments).

2.3 Data Preparation and Descriptive Analysis

Experimental files were merged together, keeping their experiment IDs as well as their training-test assignment. The missing values, duplicate observations, non-finite values, ranges of variables and ordering of observations chronologically were checked prior to analysis. Descriptive statistics comprised the mean, standard deviation, median, minimum, maximum, quartiles and coefficient of variation (CV). Operating segments consisted of consecutive observations that were made under the same voltage condition. To describe the output under various operating conditions, the mean electrical power, power variability and CV were calculated for each segment.

2.4 Voltage–Power Response Analysis

Spearman's rank correlation was used to determine the relationship between input voltage and electrical power. The voltage–power response has been modeled by a linear or quadratic regression model. The quadratic model contained a centered voltage and the squared term of the voltage. The R^2, adjusted R^2, mean absolute error (MAE), root mean squared error (RMSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC) were used to compare the model performance. The following prediction-error measures were computed:

$$MAE = (1 / n) \times \Sigma |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{[(1 / n) \times \Sigma (y_i - \hat{y}_i)^2]}$$

$$R^2 = 1 - [\Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2]$$

where y_i represents observed electrical power, $\hat{y}_i$ represents predicted electrical power, $\bar{y}$ is the mean observed electrical power, and n is the number of observations.

2.5 Feature Engineering and Predictive Modelling

Predictive features were created independently in each experiment but in chronological order. Eight predictors were utilized: input voltage, elapsed time, previous voltage, voltage change, previous power, previous power change, historical power mean and historical power standard deviation. Lagged and rolling variables were used solely as a function of previous observations in order to prevent leakage to the target. Six training experiments were used to train the Linear Regression, Random Forest and Gradient Boosting models. The two test experiments were left out when fitting the model and were used for independent testing. The performance of predictions was evaluated by MAE, RMSE and R^2.

2.6 Model Diagnostics and Interpretation

Assessment of the selected prediction model was made using residuals, median absolute error, mean absolute percentage error (MAPE) and absolute errors based on percentiles. The independent test experiments as well as the different electrical-power ranges were also analyzed separately. Standardized coefficients and permutation importance based on RMSE after permutating the predictors were used for the evaluation of predictor contributions. Also tested were operational-only, autoregressive-only, and complete predictor sets. Single-predictor models and the Spearman correlations were examined to look at individual predictor relationships with electrical power.

2.7 Operational Response Optimization

The operating conditions were evaluated by the mean electrical power and the power CV, as an output and a stability measure, respectively. The power and stability scores were both normalized to achieve a range of 0 to 1 with lower variability being associated with a higher stability score. an overall operational score was determined as:

Operational Score = (Normalized Power Score + Normalized Stability Score) / 2

The voltage condition that has the highest operating score was chosen as to be the preferred operating voltage. The chosen condition was then compared with the nearest available voltage condition in the independent test experiments based on mean electrical power and CV.

2.8 Statistical Analysis

Two-sided tests at $p < 0.05$ were considered to be statistically significant. Association analysis was performed using Spearman's rho and performance of regression was assessed with MAE, RMSE, and R^2. The voltage-response models were also compared with the use of the AIC and BIC.

3. Results

3.1 Overall Electrical and Operating Characteristics

The data set comprised 71,225 observations over a wide range of operating conditions for the turbines. The descriptive statistics of the variables of the study are presented in Table 1. Input voltage ranged from 3.000 to 10.000 V, with a mean of 5.590 ± 2.631 V. Electrical power ranged from 932.837 to 3393.229, with a mean of 1872.317 ± 747.656 and a median of 1609.915. Input voltage and electrical power had coefficients of variation (CV) of 47.067% and 39.932%, respectively, indicating substantial variability across the complete experimental series.

Table 1. Descriptive characteristics of the study variables

Variable	N	Mean	SD	Median	Minimum	Maximum	CV (%)
Time	71,225	5611.277	2923.609	5477.865	758.426	12636.840	52.102
Input voltage	71,225	5.590	2.631	5.000	3.000	10.000	47.067
Electrical power	71,225	1872.317	747.656	1609.915	932.837	3393.229	39.932

3.2 Voltage–Power Response Characteristics

The power gain was strong as the input voltage was increased in the operating segments. A very high correlation coefficient of 0.9163 ($p<0.001$) was obtained in Spearman analysis when the voltage was correlated with the power for the segment level. The comparison between the linear and quadratic models of the voltage response is given in Table 2. R^2 values were higher in the quadratic model (0.8831) than in the linear model (0.8516) and the quadratic model was used to obtain the best fit. The quadratic specification also showed lower prediction errors with the mean absolute error (MAE) of 150.9538 and the root mean square error (RMSE) of 234.0304. An additional advantage of its lower AIC and BIC values was a better representation of the observed response pattern.

Table 2. Linear and nonlinear voltage-response models

Model	R^2	Adjusted R^2	MAE	RMSE	AIC	BIC
Linear voltage-response model	0.8516	0.8480	167.3391	263.6540	4745.6576	4780.0650
Quadratic voltage-response model	0.8831	0.8799	150.9538	234.0304	4667.0872	4705.3177

In addition, the voltage-dependency was reflected in both the training and the independent test experiments. For both datasets, mean electrical power generally increased with input voltage, as seen in figure 1A, and was very similar in its response over much of the voltage range. As shown in Figure 1B, high electrical output coincided with low power variability around the identified optimal voltage, whereas greater variability occurred at some other operating conditions.

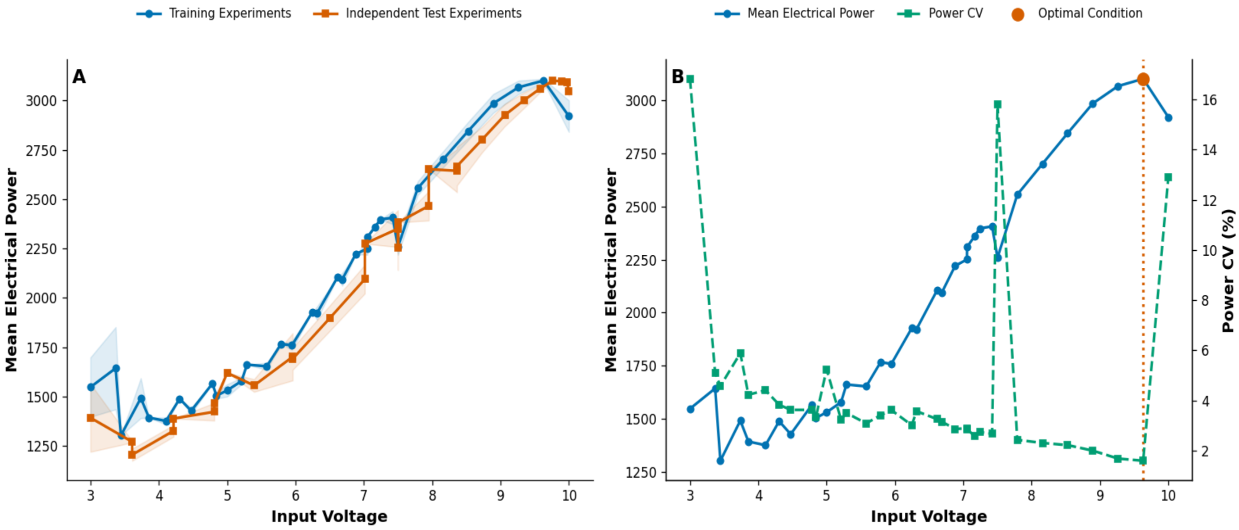

Figure 1. Voltage–power response and operating stability. (A) Training and independent test responses. (B) Mean power, power CV, and optimal condition.

3.3 Electrical Power Prediction Performance

The prediction models were tested with 18,281 observations from two independent test experiments that were not used in training the models. The independent test-set performance of the three prediction models is given in Table 3. Linear Regression had the best overall results with an MAE of 8.0342, an RMSE of 10.6132, and an R^2 of 0.9998. Gradient Boosting had an R2 of 0.9973, but with higher MAE and RMSE values of 26.6280 and 42.3318. Random Forest returned an R^2 of 0.9958, an MAE of 26.2332, and the highest RMSE of 52.5731.

Table 3. Independent test-set prediction performance

Model	MAE	RMSE	R^2
Linear Regression	8.0342	10.6132	0.9998
Gradient Boosting	26.6280	42.3318	0.9973
Random Forest	26.2332	52.5731	0.9958

The performance of the Linear Regression model was also confirmed by Prediction Diagnostics. The results of the electrical power predictions are shown in Figure 2A, and these predictions were quite close to the observations with most of the observations being close to the perfect agreement line. As illustrated in Figure 2B, the residuals were mostly clustered around the zero line throughout the range of electrical power predicted, with a few large positive and negative errors.

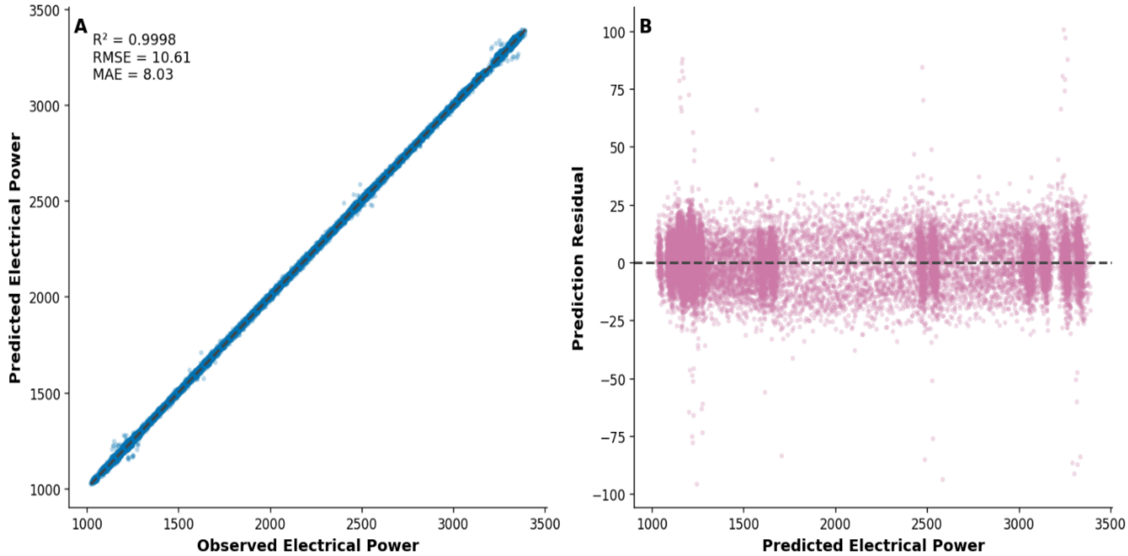

Figure 2. Prediction performance and residual diagnostics. (A) Observed versus predicted power. (B) Prediction residuals.

The mean residual was 0.2258, with a 95% confidence interval of 0.0720–0.3797. The median absolute error was 6.5799, while the 90th, 95th, and 99th percentile absolute errors were 16.4370, 19.8984, and 27.2018, respectively. The MAPE attained was just 0.4655%. The failures exceeded 20 in 4.8520% of the predictions, and those that failed were more than 30 in 0.5798% of the predictions. The results of the two independent experiments were similar with MAE of 7.9918 for ex 22 and 8.0711 for ex 4, respectively.

3.4 Contribution of Predictive Variables

The model interpretation showed that most of the predictive information was in the recent power measurements. Finally, it can be seen from Figure 3 that the greatest improvement in RMSE after permutation is achieved by Previous Power, Previous Power Change and Historical Power Mean. The conditional contributions of previous voltage, input voltage, and elapsed time, voltage change and historical power SD were significantly smaller with the autoregressive variables added on, while the conditional contribution of input voltage was negligible.

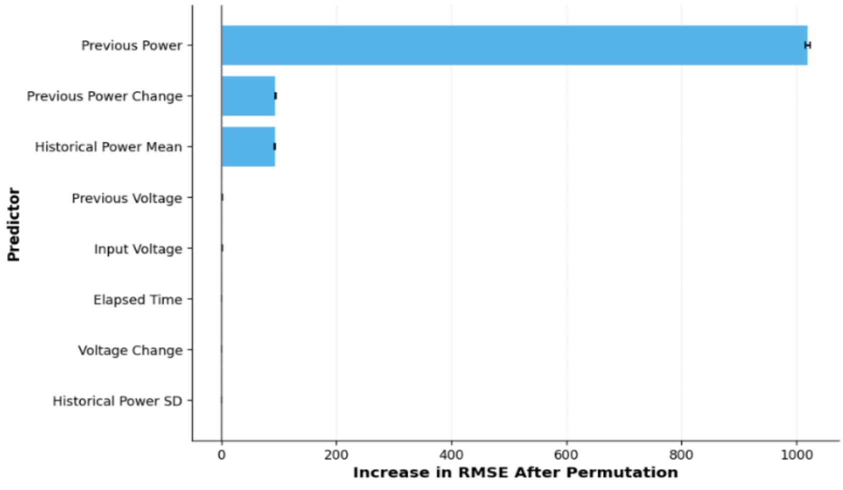

Figure 3. Permutation importance of electrical power predictors.

This pattern was confirmed by the results of the ablation analysis. The autoregressive-only predictor set achieved an MAE of 7.5133, RMSE of 10.1324, and R^2 of 0.9998, whereas the operational-only predictor set achieved an MAE of 217.1764, RMSE of 378.3024, and R^2 of 0.7812. The best individual predictor was Historical Power Mean (R^2 = 0.9969) followed by Previous Power (R^2 = 0.9908). The value of R^2 for the Input Voltage was 0.7760. Predictor correlations were similar, with Spearman's correlation coefficient equal to 0.9874 for Historical Power Mean, 0.9698 for Previous Power and 0.8717 for Input Voltage.

3.5 Operational Response Optimization and Validation

A high-output condition was found that also provided a low electrical power variability, which was associated with reliability. The optimal operating condition is given in Table 4 and it has been verified with independent test (independent-test). The optimum was found at 9.6316 V with a mean electrical power of 3101.5303 and a CV of 1.5943% and an operational score of 1.0000. The closest independent test condition was at 9.5778 V with the mean electrical power at 3060.1493 and CV of 1.6690%.

Table 4. Optimal operating condition and independent-test validation

Assessment	Input Voltage	Mean Electrical Power	Power CV (%)	Operational Score
Training-derived optimum	9.6316	3101.5303	1.5943	1.0000
Nearest independent test condition	9.5778	3060.1493	1.6690	—

The optimization criteria led to 9.6316 V for the highest electrical power, highest stability and most well-balanced operating response. This is the opposite of what was seen with the maximum input of 10.0000 V, where the mean electrical power during training dropped to 2920.8121, with a significant rise in CV to 12.9096%. The independent test result around the optimized voltage so, then, duplicated the high output and low variation properties obtained in the training experiments.

4. Discussion

It was found that the short-horizon prediction was mainly controlled by recent power behaviour whereas the electrical output of the micro gas turbine was strongly voltage dependent. The correlation between input voltage and electrical power at the segment level was high (ρ = 0.9163) and the quadratic response model was superior to the linear response model both in terms of explained variance and prediction error. This feature indicates that the electrical output was not proportional over the entire range of voltage. The mean power decreases and variance increases at 10 V, further suggesting that there is a practical operating region and not just an assumption that higher voltage leads to better performance. The performance for predictions was especially good on the two independent test experiments. Linear Regression performed better than two other models: Gradient Boosting and Random Forest by getting an R^2 of 0.9998, an MAE of 8.0342 and an RMSE of 10.6132. The observed and predicted values showed close agreement, with a low mean absolute percentage error of 0.4655%, indicating limited overall deviation in short-horizon electrical power prediction. Therefore, the short-term electrical trajectory was somewhat captured by the model with little overall deviation. The predictor analysis explained this accuracy. Previous power, previous power change and historical power were the strongest contributors, while the voltage-related predictors made very little contribution when the recent power history was available. The autoregressive-only model was the one that achieved an R^2 value of 0.9998 whereas the operational-only model had an R^2 value of 0.7812. This was the distinction that voltage was important to explain the larger operating response, but immediate power history was more informative for short-horizon prediction.

The voltage–power relationship, which is found in the model, aligns with research focusing on coordinated power management in varying network and load scenarios. When the system response alters as a function of loading conditions, a combination of electrical operating characteristics must be evaluated, not just one (Yong et al., 2020), as is done in active and reactive power optimization. The non-linear response seen here is also consistent with the recent micro gas turbine performance research, where the dynamic or non-linear modelling is needed to capture variations in output with operating state when running off-design (Li et al., 2025). Adaptive control research has also demonstrated that continuous adjustment of operation of micro gas turbines is necessary when the system behaviour is not nominal (Yang et al., 2024). The identified optimum operating condition is also in line with the main trend of the optimization of the turbine with the help of artificial intelligence. Data-driven operating-point selection, as previously demonstrated, is valuable and can be supported by using AI-based methods to optimise the operation of micro gas turbines to change fuel and microgrid conditions (Banihabib et al., 2024). The concept of optimizing the gas turbine performance has also been focused on balancing the operational variables instead of optimizing a single performance criterion (Ekechi, 2020). The present power–stability criterion has the same concept, but it takes into account the mean electrical output as well as relative variability.

Intelligent gas turbine power-management studies support the merits of combining prediction with operational control. The coordinated neural-network control under variable loads has shown that incorporating predictive information with operating decisions can enhance the system's response (Wen et al., 2024). The same ideas can be found in smart microgrid optimization, in which distributed generation and demand response are synchronized to optimize the operation of the microgrid under varying system conditions (Wang et al., 2018a). Energy-management studies have also demonstrated that distributed resource control will be more effective if generation and response characteristics are taken into account (Wang et al., 2018b). The historical power variables have been important in the current analysis, which aligns with micro gas turbine research with data, indicating that sequential operating information can be of value for predicting longer-term performance behaviour (Olsson et al., 2021).

The practical applications are focussed on monitoring and point of operation. Recent power measurements can be used to aid accurate estimation of electrical output at the short horizon, and voltage-response analysis can be used to establish a separate basis for identification of stable operating regions. The training-derived optimum of 9.6316 V had a low standard deviation and a high mean power, and the independent test condition closest to this (9.5778 V) was nearly as responsive. The selected voltage region seems to be more applicable for operation guidance in the experimental voltage range within this agreement. The results also indicate why it would not be suitable to maximize voltage alone: The mean power for the 10 V condition was lower, and the variability was considerably greater.

Some limitations should be noted. The data available consisted only of time, input voltage and electrical power and thus factors such as fuel flow, temperature, pressure, speed, emission and efficiency were not considered for optimization. Eight experimental runs were used in the analysis, two of which were to be used separately as independent tests. The framework should be further tested with other operating variables of micro gas turbines, wide experimental scenarios, and external data sets in future works. The identified predictive and stability patterns could also be evaluated in real-time for their reliability under varying load and fuel conditions.

5. Conclusion

Although the micro gas turbine is of great value, it is necessary to accurately estimate the power generation amount and identify the operating conditions that can keep the power stable. The operating pattern of electrical power was better captured by the quadratic response model than the linear model, and there was a strong positive relationship with input voltage. The performance of the short-horizon prediction was remarkably accurate with Linear Regression showing R^2 of 0.9998, MAE of 8.0342 and RMSE of 10.6132 on independent test experiments. The most important power-history variables were recent power and historical power mean. For optimization of operations, the condition 9.6316 V was identified as the optimal condition, which gave the mean electrical power of 3101.5303 with a CV of 1.5943%. The closest independent test point (9.5778 V) continued to achieve high output levels with a similar level of fluctuation, continuing to affirm the stability of the identified operating region. In general, the framework offers a concise solution for the coupling of electrical power forecasting and the selection of an operating point for a micro gas turbine energy generation system that optimizes reliability.

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