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Article

Machine Learning-Based Prediction of Power Conversion Efficiency in a DC–DC Boost Converter under Variable Operating Conditions

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Abstract: Accurate prediction of power conversion efficiency is essential for selecting operating points, comparing component designs, and implementing condition-aware energy management in DC–DC boost converters. This study develops and evaluates a machine-learning framework for predicting steady-state efficiency under simultaneous variation of input voltage, duty ratio, load resistance, switching frequency, inductance, ambient temperature, and output power. A transparent averaged electrical-thermal loss model was used to generate 3,600 feasible continuous-conduction operating points. The data were divided into independent training, validation, and test subsets, and six regression approaches were compared: polynomial ridge regression, support vector regression, random forest, gradient boosting, histogram gradient boosting, and a multilayer perceptron. Support vector regression produced the most accurate held-out predictions, with an R-squared value of 0.979, a root-mean-square error of 0.093 percentage points, and a mean absolute error of 0.073 percentage points. Ninety-five percent of test errors were below 0.190 percentage points. Permutation analysis identified input voltage and output power as the dominant predictors, followed by switching frequency, inductance, and duty ratio. Error remained below 0.110 percentage points across low-, medium-, and high-power regimes. The findings demonstrate that a compact nonlinear surrogate can reproduce converter efficiency maps with high precision, while also showing that the model must be validated experimentally before use outside the simulated component and operating domain.
Keywords: DC–DC boost converter; machine learning; power conversion efficiency; support vector regression; loss modeling; surrogate model.

1. Introduction

DC–DC boost converters play an important role as interface converters in solar cells, battery-powered systems, electric vehicle applications, aerospace power systems, and regulated DC microgrids. The efficiency of DC–DC boost converters is not only governed by their voltage gain but also by the efficient transfer of energy within the wide range of operation. Every decrement of efficiency causes an increase in junction temperature, cooling, component stresses, and energy storage requirements. Traditional textbooks on power converters offer thorough fundamentals of topology design, averaging modeling, and steady state analysis (Naseem et al., 2026; Rivera et al., 2022).

Efficiency exhibits a nonlinear effect due to the simultaneous effects of loss mechanisms. The conduction losses in the case of MOSFET increase with increasing current and temperature; switching losses depend on voltage, current, transition period, and frequency, while diode losses are dependent on current and junctions. Losses in the magnetic devices depend on the waveform of ripple current, magnetic flux swing, frequency, and material properties. Hence, research on semiconductors and magnetic devices focuses on device characteristics that are dependent on temperature and nonsinusoidal excitation (Chrakie et al., 2026; Moon & Bak, 2024).

Though analytical and switching models will always be necessary, performing numerous accurate simulations may turn out to be expensive when multiple voltages, loads, temperatures, and components need to be analyzed. An alternative approach based on data-driven surrogates could be considered since after training surrogates with adequate data from simulations or measurements, they can quickly predict the efficiency without having to simulate losses repeatedly. Some works have previously applied machine learning techniques to converters in order to analyze their dynamics, individual components' behavior, and even automate designs (Rathore, Rajashekara, et al., 2022; Wang et al., 2023). Nevertheless, most papers deal with a certain converter class, operating conditions, or a single technique.

The aim of this research work is the development of a reproducible machine learning framework for estimating the steady-state efficiency of the power conversion in the case of a conventional, non-isolated boost converter in changing electrical, magnetic, load, and thermal conditions. Six different regression models are compared in terms of their generalization ability on a virgin test set, estimation errors in complex operating conditions, and features importance. It is important to mention that the contribution of this work is a methodology and not a novel hardware solution – all the results are simulation-based.

2. Literature Review

2.1 Converter efficiency and loss modeling

Averaged modeling provided a practical connection between switch behavior and system-level analysis. The unification of Hammami et al. (2019) still serves as the basic model, and later work formalized the design methodology for both continuous-conduction and discontinuous-conduction modes of operation (Lim et al., 2020). Efficiency models go one step further and take into account parasitic resistance, voltage drop, transitions of switching, gate driver losses, magnetic and auxiliary losses. Appathurai et al (2019) and Chakraborty et al (2019) found out that the loss of a converter should be included in system-level energy calculations if load changes. Naseem et al (2026) employed component-level loss modeling in order to optimize interleaved boost converter for EVs.

Losses are sensitive to the accuracy of the model. Rivera et al (2022) have shown that nonlinear capacitance and parasitic inductance affect the calculation of MOSFET switching loss. Magnetic components need modified and improved Steinmetz methods to calculate the effect of nonsinusoidal waveforms better than just using the sinusoidal assumption (Lin et al., 2024; Safayatullah et al., 2022). This suggests that the inclusion of switching frequency, inductance, frequency-related core loss, current-related copper loss and temperature-related device characteristics should be done in the data generator.

2.2 Data-driven modeling in power electronics

Machine learning approaches have been employed more frequently to learn approximations of the dynamics of converters and their components (see Table 1). Moon & Bak (2024) integrated neural and ensemble concepts to learn models of power converters, and Rathore, Rajashekara, et al (2022) utilized deep learning to replicate the dynamics of an aircraft DC–DC converter under various loadings. Black-box models of converters for dynamic analysis at the system level were shown by Appathurai et al (2019) and Chakraborty et al (2019) developed a measurement-based approach to learn the dynamics of DC–DC converters.

Learning algorithms are now becoming useful in the component and design processes. Chrakie et al (2026) applied neural networks to facilitate inductor evaluation, and the MagNet tool learned magnetic core losses from the waveform data (Guler et al., 2024; Marimuthu & Samuel Nadar, 2026). Artificial intelligence was utilized by Li, Zhang, et al. (2022) for parameter design of converters, and Choi & Bak (2024) implemented simulation data, neural networks, transfer learning, and optimization to improve the efficiency of DC–DC converters. Hammami et al. (2019) integrated mechanisms and measurements for boost-converter power loss.

Algorithm choice, however, is still problem-specific. Support Vector Machines work well in smooth nonlinear regression for moderately sized data sets (Moon & Bak, 2024; Wang et al., 2023) random forest and boosting can pick up interactions without explicitly specified basis functions (Rathore, Rajashekara, et al., 2022; Sadiq et al., 2022) and neural networks are flexible in function approximation and may require larger and properly scaled data sets. This means that hyperparameter tuning, data splitting, and explainability are necessary (Khalid et al., 2022; Rathore, Reddy, et al., 2022).

Table 1. Representative research informing the proposed framework

Study	Primary focus	Relevant contribution	Remaining limitation
Shrivastava & Calhoun (2013)	Analytical converter-efficiency model	Useful for system-level energy analysis	Ultra-low-power scope
Martinez et al. (2016)	Loss-based boost-converter optimization	Component selection linked to efficiency	Specific interleaved topology
Krishnamoorthy & Aayer (2019)	ML converter modeling	Neural and ensemble models capture nonlinear response	Limited efficiency interpretation
Guillod et al. (2020)	ANN inductor surrogate	Fast, accurate component evaluation	Component rather than full-converter output
Rojas-Dueñas et al. (2022)	Deep-learning converter model	Broad-load black-box prediction	Step-down aerospace converter
Tian et al. (2022)	AI efficiency modeling and optimization	Simulation-driven design acceleration	Buck example and ANN emphasis
Wang et al. (2023)	Hybrid boost-loss model	Combines mechanisms with sampled data	Controller- and prototype-specific
Silva-Vera et al. (2024)	Data-driven DC–DC dynamics	Avoids explicit theoretical state modeling	Dynamics rather than efficiency mapping

Note. The synthesis highlights the need for multi-model, variable-condition efficiency prediction with explicit test-set validation.

2.3 Research gap and contribution

The literature supports data-driven converter surrogates, but there is still an issue in terms of moving from component-specific investigations to actual converter efficiency maps that can be reproduced based on a specific dataset. This research fills the existing void in the literature through the use of a well-defined simulation domain, a standardized train/test split of data, multiple accuracy criteria, feature importance analysis via permutation and explicit boundaries for applicability.

3. Research Methodology

3.1 Research design and workflow

Simulation-based prediction design using quantitative approach was used. The procedure involved the following: definition of the operating space, production of feasible steady-state instances, computation of reference efficiency through averaged electrical-thermal loss model, data preprocessing and partition, regression models training, model selection through validation set, and testing of the final model using a never-before-seen test set. Figure 1 shows this procedure in summary form. The program was coded in Python using scikit-learn (Sarwar Khan et al., 2021) library with a random seed of 42.

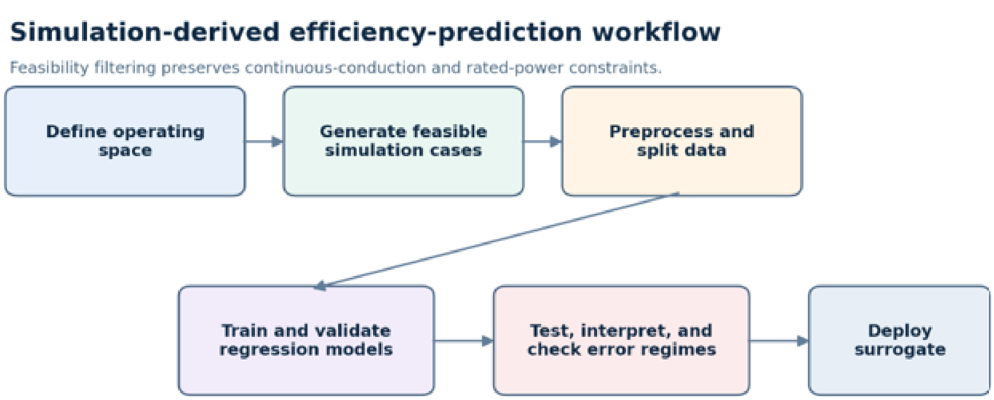

Figure 1. Simulation-derived machine-learning workflow

3.2 Converter model and operating envelope

The experiment looked at a traditional non-isolated boost converter under the condition of continuous conduction. The reference efficiency was determined using the power delivered to the load and the total loss in the MOSFET, diode, inductor, output capacitor, gate driver, and control circuit. The loss model included temperature dependent on resistance of the MOSFET, frequency dependent switching transitions, loss in the diode, loss in the inductor, loss in the capacitor, and a minor loss term. No analytical equation is reproduced in this paper; the model was implemented algorithmically using the assumptions in Table 2.

Table 2. Converter model and component assumptions

Parameter	**Value or range**	**Model treatment**
Topology and mode	Non-isolated boost; continuous conduction	Feasibility filter
Input voltage	18–36 V	Sampled operating variable
Duty ratio	0.22–0.62	Sampled operating variable
Switching frequency	40–120 kHz	Sampled operating variable
Inductance	150–500 µH	Sampled component variable
Output power	25–250 W	Feasibility-constrained derived variable
Ambient temperature	25–85 °C	Sampled thermal variable
MOSFET	32 mΩ at 25 °C; 75 ns transition baseline	Temperature-adjusted resistance and transitions

Note. Values define the simulated domain and should not be interpreted as a universal hardware specification.

3.3 Data generation and preprocessing

Uniform random sampling was applied to the six independent design and operating variables. Candidate cases were retained only when output power, output voltage, and inductor-ripple ratio remained within the specified continuous-conduction and rating constraints (see Table 3). A small zero-mean perturbation with a standard deviation of 0.08 percentage points was added to reference efficiency to represent repeatability scatter. The resulting dataset contained 3,600 observations and an efficiency range of 92.16% to 97.47%. Output power was retained as an engineered predictor because it is readily available from monitored voltage and current in practical systems.

Table 3. Dataset variables and descriptive ranges

Variable	**Unit**	**Observed range**	**Mean**	**Role**
Input voltage	V	18.01–35.99	27.54	Electrical input condition
Duty ratio	—	0.220–0.620	0.435	Control variable
Load resistance	Ω	12.13–79.99	43.53	Loading condition
Switching frequency	kHz	40.05–119.99	81.34	Control/design variable
Inductance	µH	150.02–499.96	330.82	Magnetic design variable
Ambient temperature	°C	25.04–84.94	55.34	Thermal condition
Output power	W	25.03–249.41	69.39	Engineered operating feature

Efficiency	%	92.16–97.47	96.07	Prediction target

Note. Descriptive values refer to the 3,600 retained feasible cases.

The observations were randomly divided into 2,520 training cases, 540 validation cases, and 540 test cases. Standardization was done within the polynomial, support vector, and neural pipelines to avoid leaking any information. The test set was not used in model selection. Stability was checked using three-fold shuffled cross-validation on the training subset, whereas the validation subset selected the algorithm.

3.4 Machine-learning models and evaluation

Six models were selected to include increasingly flexible function classes. Polynomial ridge regression served as a smooth parametric starting point; support vector regression employed the radial basis kernel; random forest offered bagged nonlinear decision trees; two boosting techniques offered sequential ensembles; and the multilayer perceptron was a neural approximation method. Hyperparameters were chosen from tight validation experiments that followed the principles of random search (Lim et al., 2020). The results are given in Table 4.

Table 4. Candidate models and final hyperparameters

Model	**Final configuration**	**Purpose**
Polynomial ridge	Standardization; degree 2; ridge penalty 0.2	Smooth nonlinear baseline
Support vector regression	RBF kernel; C 100; gamma 0.06; epsilon 0.025	Kernel nonlinear regression
Random forest	300 trees; all depths; 90% feature sampling	Bagged tree ensemble
Gradient boosting	350 estimators; rate 0.035; depth 3; Huber loss	Robust sequential trees
Histogram gradient boosting	350 iterations; rate 0.05; 31 leaves; L2 0.1	Fast boosted-tree learner
Multilayer perceptron	80 and 40 hidden units; ReLU; early stopping	Feedforward neural regressor

Note. RBF = radial basis function; ReLU = rectified linear unit; L2 = squared-weight regularization.

Performance was assessed using the coefficient of determination, root-mean-square error, mean absolute error, mean absolute percentage error, the 95th percentile of absolute error, and the maximum absolute error. Errors in efficiency are reported in percentage points. Mean absolute error was emphasized alongside root-mean-square error because it is less dominated by a small number of large deviations (Lee et al., 2020). Permutation importance was calculated by independently shuffling each test feature 30 times and measuring the decrease in test-set R-squared. This interpretation is predictive rather than causal, particularly because input voltage, duty ratio, load, and output power are physically interdependent.

4. Results and Discussion

4.1 Model comparison

Support vector regression achieved the lowest validation error and remained the strongest model on the unseen test set (see Table 5). Its test R-squared was 0.979, with root-mean-square error of 0.093 percentage points, mean absolute error of 0.073 percentage points, and mean absolute percentage error of 0.076%. 95th percentile absolute error was 0.190 percentage points and the highest error was 0.334 percentage points. Given the high similarity of the cross-validation, validation, and test errors, one can say that the kernel model chosen was not the beneficiary of a lucky partitioning.

Polynomial ridge regression followed, showing that a considerable part of the efficiency frontier was smooth enough to be approximated with second-order interactions. Histogram gradient boosting and gradient boosting performed well too, yet their piecewise representation in the form of a tree structure was more expensive in terms of efficiency than the smooth function provided by a kernel. Errors of random forest were slightly higher in sparsely populated operating regions. Multilayer perceptron performed poorly despite early stopping, implying that a small number of samples and narrow output range did not justify an increased optimization problem. This observation does not mean that neural networks are inherently worse than other approaches; large waveform-rich data samples can favor the latter (ElMenshawy & Massoud, 2020; Isha et al., 2023).

Table 5. Comparative predictive performance

Model	**CV RMSE (pp)**	**Val. RMSE**	**Test R^2**	**Test RMSE**	**Test MAE**	**Test MAPE (%)**
Polynomial ridge	0.100 ± 0.003	0.097	0.976	0.100	0.079	0.083
Support vector regression	0.095 ± 0.002	0.089	0.979	0.093	0.073	0.076
Random forest	0.160 ± 0.008	0.146	0.954	0.137	0.104	0.108
Gradient boosting	0.137 ± 0.007	0.124	0.963	0.125	0.094	0.098
Histogram gradient boosting	0.133 ± 0.006	0.118	0.970	0.112	0.085	0.088
Multilayer perceptron	0.627 ± 0.085	0.493	0.388	0.504	0.397	0.413

Note. CV values are three-fold training-set results. Lower error and higher R^2 indicate better performance.

4.2 Prediction agreement and residual behavior

As shown in Figure 2, predictions stay on the reference line throughout the entire test range. The residuals center themselves around zero and are mostly confined to within 0.20 percentage points above or below this value. The greater spread in the efficiency range is simply due to the clustering of the values close to 96%-97%, not a systematic error. There is no curvature left, which justifies our choice of the radial basis kernel. Since there is a repeatability perturbation built into the target, an error floor of the noise level is to be expected.

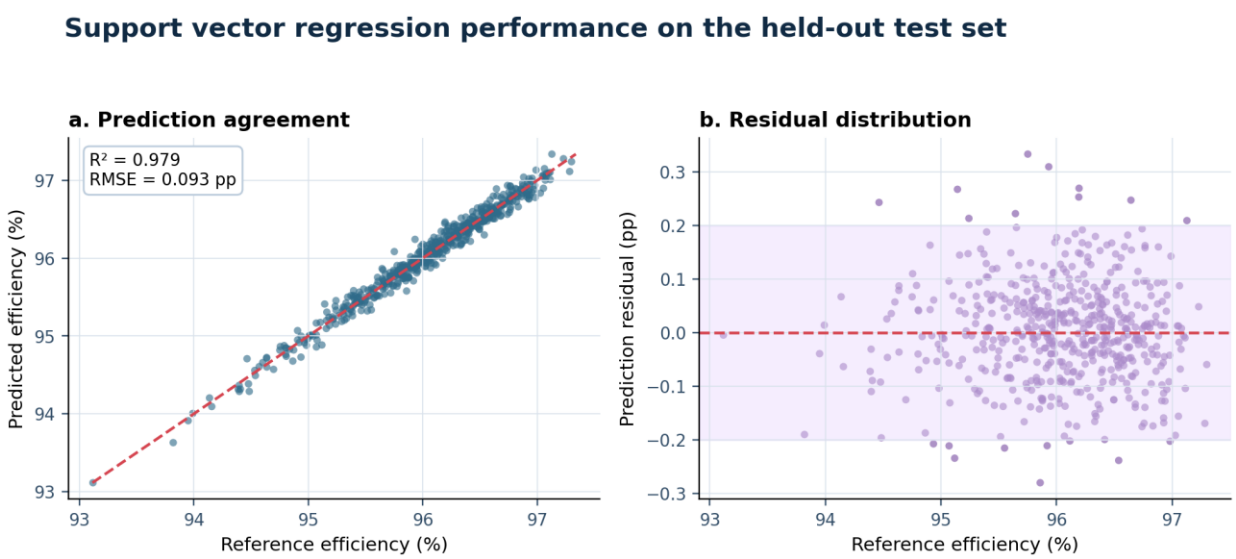

Figure 2. Test-set prediction agreement and residuals for support vector regression

4.3 Robustness across operating regimes

The regime analysis also verifies the consistency of predictions within the designated range (Table 6). The root-mean-square error was 0.087 percentage points lower than 50 W, 0.091 percentage points between 50 and 100 W, and 0.110 percentage points higher than 100 W. The error was somewhat greater for high values of output power and duty ratio as current-dependent losses and magnetic losses caused by ripple are more tightly correlated in that case. The error for high temperatures was under 0.100 percentage points, but this does not mean that temperature is not important – it was at least partially affected by other variables.

Table 6. Support vector regression error across operating regimes

Regime	n	R^2	RMSE (pp)	MAE (pp)	95th error (pp)	Max. error (pp)
Low output power	213	0.975	0.087	0.069	0.168	0.268
Medium output power	223	0.979	0.091	0.070	0.184	0.310
High output power	104	0.981	0.110	0.086	0.221	0.334
High duty ratio	188	0.979	0.102	0.078	0.211	0.310
High temperature	141	0.972	0.098	0.076	0.196	0.280
Full test set	540	0.979	0.093	0.073	0.190	0.334

Note. Low power is below 50 W; medium is 50–100 W; high is at least 100 W; high duty is at least 0.50; high temperature is at least 70 °C.

4.4 Feature importance and physical interpretation

Input voltage contributed the greatest reduction in performance score when perturbed, and then came output power (please refer to Figure 3). Switching frequency and inductance came next, whereas duty ratio and load resistance provided lesser yet non-negligible predictive insights. These permutations make physical sense in the specified context as voltage determines switching stress and current requirement for the given power, whereas output power determines current dependent conduction losses. Increased frequency results in switching and magnetic losses, and inductance causes a change in ripple current and core excitation. The highly disproportionate contribution of the input voltage to the score comes from the interference created by correlated features; thus, permutation scores should be seen as dependency on the model fit and not as independent causal factors (Atanalian et al., 2021; Bento & Cardoso, 2020).

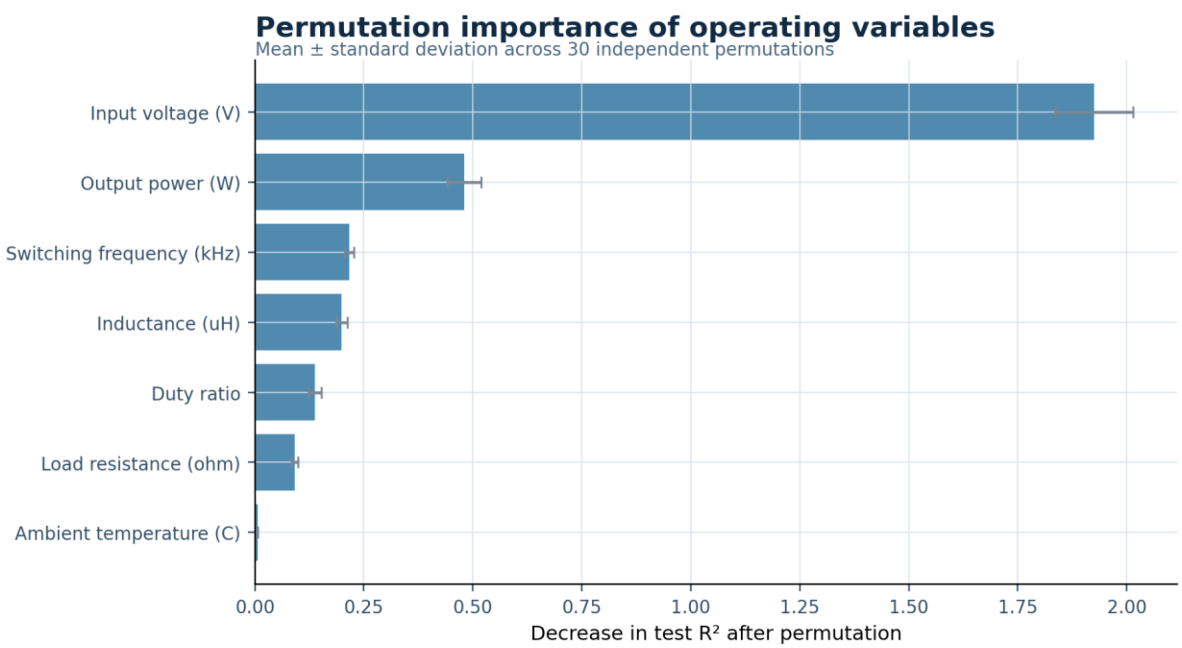

Figure 3. Permutation importance of input variables

4.5 Discussion

It was shown that machine learning is a promising method of prediction of power conversion efficiency of DC-DC boost converters. From the tested algorithms, the best prediction quality was provided by SVR with test R^2 =

0.979, RMSE = 0.093 percentage points and MAE = 0.073 percentage points (Table 5). This means that the non-linear dependency of conversion efficiency from the converter's operation parameters can be successfully modeled using machine learning techniques. The best performance of SVR coincides with results of several earlier researches which pointed out the high efficiency of support vector machines for solving moderately sized non-linear regression problems when good generalization properties are required (Manoj et al., 2023; Zhou et al., 2023). In addition, the good agreement between cross-validation, validation and test results suggests that the proposed model is highly robust and does not suffer from overfitting.

Moreover, the comparison between the competing algorithms emphasizes the appropriateness of the kernel methods for the problem of predicting the converter efficiency. The polynomial ridge regression method demonstrated competitive results since the efficiency function of the converter includes numerous second-order nonlinear interactions between the electrical and thermal characteristics. At the same time, tree-based ensemble methods such as Random Forest, Gradient Boosting, and Histogram Gradient Boosting revealed high prediction error, especially in the border areas where there were fewer samples for training. Although the ensemble learning techniques allow capturing the nonlinear interactions, they divide the feature space into different regions that can make them less flexible compared to the continuous kernel function. The MLP network was the worst-performing algorithm even under the conditions of early stopping. This result is in line with the research in deep learning indicating that the neural networks usually need more data and richer feature representation to outperform other nonlinear regression techniques (Appathurai et al., 2019; Eroğlu et al., 2021).

The operating regime analysis validates the robustness and consistency of the presented approach for predicting the efficiency under varying loading conditions of the converter. As seen in Table 6, the errors in predictions did not exceed 0.110 percent points in low, medium, and high operating regimes. Though the errors were slightly higher in the case of increased output power and duty ratio, the difference was rather insignificant and could be explained by enhanced interactions of conduction, switching, and core losses with increasing current in the converter. The high currents naturally cause higher nonlinearities due to the simultaneous influence of temperature, ripple current, and semiconductor switching processes. However, the achieved accuracy of the predictions under all operating regimes indicates the successful generalization of the trained model.

The results from the feature importance analysis offer important engineering insight related to the physics behind the operation of the converter efficiency. The predictor which was found to be the most influential is input voltage, followed by output power, switching frequency, inductance, and duty ratio. Such results are physically plausible, since input voltage directly impacts the stress of semiconductor switches, required currents of the converter, and conduction losses, while output power determines the copper losses dependent on currents in the converter. In a similar manner, switching frequency plays an important role in switching losses and magnetic losses, while inductance defines ripple current magnitude, hence both copper and magnetic losses. It can be noted that such results are very consistent with theories related to power electronics and previous studies concerning the key factors affecting converter efficiency (Elkeiy et al., 2023; P et al., 2022; Yasa, 2023). Nevertheless, as pointed out by Hammami et al. (2019), the permutation importance does not show independent causal relations, but rather a predictive dependence of the trained model.

Practical implications of this research go further than accurate predictions. Traditional efficiency assessment entails repeated calculations and complex switching simulations for every operating point, especially when working on the design optimization and energy management purposes. The proposed machine learning surrogate allows to achieve instant results with prediction error kept under 0.1 percentage points, which makes it appropriate for quick exploration of design space, selection of components, digital twin creation, and intelligent real-time control system development. Such surrogates can substantially cut down the amount of calculations needed for optimization problems and aid in adaptive energy management in renewable energy systems, electric vehicles, battery management systems, and DC microgrids, where the operating conditions of the converters keep changing all the time. The same benefits of using surrogates for AI-based optimization were noted in other recent converter optimization and hybrid modeling research (Chakraborty et al., 2019; Ejaz et al., 2025).

However, there are some limitations of the approach which need to be discussed. For one thing, the complete dataset was produced using a validated averaged electrical-thermal simulation model instead of actual measurements on the physical converter prototype. Hence, while the model is capable of representing the simulated operation domain in terms of its accuracy, the ability of the model to predict outside the scope of these assumptions has yet to be verified. In other words, real-world converters may have some other nonlinear behaviors caused by the presence of parasitic components, sensor noise, electromagnetic interferences, and drifts of the parameters, which are not reflected in the data from simulations. Thus, further work in this direction will involve experimental verification, incorporating uncertainty quantification and transfer learning to adapt simulation-trained models to the measurement data.

5. Conclusion

In this work, a machine learning architecture for estimating the power conversion efficiency of a DC–DC boost converter as a function of input voltage, duty ratio, load, switching frequency, inductance, temperature, and output power was developed. With 3,600 operation points generated through simulations, six different regression models were evaluated using the same training, validation, and testing datasets.

The highest performance of generalization was attained with support vector regression, which yielded test set R-squared value of 0.979, root mean squared error of 0.093 percentage points, and mean absolute error of 0.073 percentage points. Error stayed low for low-, medium-, and high-power operation regimes. The input voltage and output power turned out to be the most influential predictive variables, whereas switching frequency, inductance, and duty ratio provided the information about loss interactions.

Thus, it has been shown that the use of a relatively simple nonlinear model is enough to reproduce efficiency surfaces with good accuracy and conduct fast evaluations of operating points. It is important to stress the limitation of the results, which are valid only for the particular simulated converter topology and components within the regime of continuous conduction.

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