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K-Nearest Neighbors (KNN) Regression as a Tool for Failure Rate Prediction of Si MOSFET

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ABSTRACT

Forecasting the operational lifetime of a Metal-Oxide-Semiconductor Field-Effect Transistor (MOSFET) is crucial for ensuring the stability and robustness of electronic systems. These devices experience temperature cycling, voltage stressing, and high-frequency switching over time, which subsequently degrades their electrical characteristics, including threshold voltage, on-resistance, and gate charge. If these changes go unchecked, they may result in issues that compromise the control and safety of the entire system. Life prediction enhances the performance of electronic systems by focusing on the mitigation level of their failing subsystems, thereby improving overall efficiency. The lifetime of a MOSFET can be determined by tracking the drain-to-source ON resistance ($R_{DS(on)}$) curve over its lifespan. The experimental result of the proposed system at a power level of 1100W with a regulated output voltage of 211 VDC has an output voltage ripple of ~ 4.256 %, and the efficiency of the system is 93.51 %. The K-Nearest Neighbors (KNN) Regression method serves to estimate the $R_{DS(on)}$ variability and predict well in advance. It utilizes a deep learning model that is trained on a provided dataset encompassing the lifecycle of power MOSFETs. The results obtained are highly optimistic, indicating that the proposed method is efficient. The presented method achieves over 99 % training efficiency. When evaluating this predictive model, the root mean squared error (RMSE) was at 0.0006, alongside a 0.9987 R^2 score.

Keywords: Power MOSFET; K-Nearest Neighbor's; Regression Method; Root Mean Squared Error

1. INTRODUCTION

Generating high voltage and high power requires a complex power converter consisting of multiple subsystems, such as MOSFETs, capacitors, gate drivers, control circuits, and cooling. The most critical devices which is also susceptible to wear-out failure are the power modules/converters MOSFETs. The reliability of these components varies based on factors such as the mechanical strength of the devices, the electrical loads applied, climatic conditions, control and switching schemes, etc. These factors result in the deterioration of component materials due to prolonged working of the converter. Therefore, the converter reliability can influence the system reliability based on its applications. On the other hand, the converters are sensitive elements, and they are especially highly susceptible to failures due to aging and external stress factors[1].

Continuous monitoring and prediction of drain-to-source ON resistance $R_{DS(on)}$ can help in preventive maintenance and failure prediction of MOSFETs in industrial applications. The scalability of the predictive marker to the degradation status of the electronic device is a vital issue for estimating the residual life of a device, which also makes a major concern for industry. There are few Artificial Intelligence (AI)-based approaches developed with the aim of predicting the residual lifetime of an electronic system[2].

Following are the $R_{DS(on)}$ effect on MOSFET Lifetime:

- Increased Power Losses: A higher $R_{DS(on)}$ leads to greater conduction losses, thereby reducing efficiency.
- Thermal Stress: Increased heat dissipation accelerates electro-migration and degradation of internal MOSFET structures.
- Aging and Wear-Out: Over time, factors such as hot-carrier injection (HCI), negative bias temperature instability (NBTI), and oxide breakdown cause $R_{DS(on)}$ to increase, thereby affecting performance.

A data-driven approach using a Takagi–Sugeno multiple models-based framework is proposed in[3]. This framework is used to assist in diagnostic decisions and to estimate the residual lifetimes of a MOSFET.

A review is provided of online and offline system lifetime modeling, highlighting predictive indicators of the degradation of power devices[4]. Data-driven approaches are investigated through friendly statistics, namely linear regression models and Werner or Gamma Processes, as well as artificial intelligence methods, such as genetic algorithms, deep learning, and artificial neural networks. One such advantage of AI-based methods is their high generalization capability, as pointed out in the survey.

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A framework called DEEP Learning Reliability Awareness of Converters at the Edge (DEEP RACE) was proposed in[5] to predict the lifetimes of high-speed MOSFET power electronic converters. Long-Short-Term-Memory cells form the basis of the AI engine, and the results related to lifetime prediction of the MOSFET power device reveal an average miss prediction of 8.9 %.

One of the primary advantages of KNN is its flexibility in handling non-linear patterns. Unlike linear regression, which assumes a predefined relationship between input parameters and $R_{DS(on)}$, KNN makes no such assumptions. Its allows it to adapt well to highly complex datasets, provided the proper hyper parameter tuning is applied[6].

Another significant benefit is that KNN does not require extensive training. In contrast to artificial neural networks (ANN), which demand substantial computational resources and prolonged training periods, KNN operates solely based on stored data and distance computations. This simplicity makes it an attractive choice for scenarios where quick implementation is required[7].

Additionally, KNN is highly adaptable to changing data. When new MOSFET data becomes available, it can be incorporated directly without the need to retrain a model, unlike regression-based approaches or ANN, which require periodic retraining. It makes KNN particularly useful for real-time applications where data distribution may evolve over time[8].

Finally, KNN is well-suited for applications with small datasets. Unlike ANN, which typically requires a large volume of data to train effectively, KNN can often deliver reasonable performance even when data availability is limited. This makes it a viable option in scenarios where gathering extensive MOSFET degradation data is challenging[9]-[12]. However, despite its simplicity and effectiveness in various classification and regression tasks, it presents some limitations that constrain its broader applicability. KNN is highly sensitive to noisy data and outliers, which can distort distance calculations and negatively impact prediction accuracy. Additionally, the choice of the parameter '*k*' significantly influences the model's results, and selecting an inappropriate value can lead to overfitting or underfitting.

This paper utilizes variations in the drain to source ON resistance $R_{DS(on)}$ and MOSFETs temperature data to develop a model for predicting the useful life of MOSFETs and examines an intelligent health monitoring system for power MOSFET devices to assess the degradation level of the device using artificial intelligence[13]. The $R_{DS(on)}$ curve operates within a range corresponding to the correct life cycle. This curve rises above a certain point when the device begins to exhibit the first signs of degradation. K-Nearest Neighbours (KNN) is the model used, to predict the Remaining Useful Life (RUL) of electrical devices[14].

2. DESIGN AND SIMULATION

The data is gathered from a Power Factor Corrected Switched Mode Power Supply prototype designed to create a high-power-density, high-efficiency AC-DC converter with power factor correction capabilities. The proposed hardware prototype was tested at a power level of 2.2 kW and the rated input voltage, yielding an output voltage of the second stage at 292 ± 28 V, along with output voltages of 5 V and 15 V from the auxiliary power supplies. The efficiency at this power level is approximately 85 %, with the system temperature recorded at 40 °C under these conditions. The hardware system measures 10×6.65×2.95 inches and utilizes forced air cooling.

A two-stage converter is required in the proposed prototype. The first part, which is an AC to DC power converter, has two main parts. The first part's design is primarily focused on power factor correction, which aims to optimize the harmonic distortion on the AC side[15]. It is achieved by adjusting the AC input current to match both the phase and shape of the desired AC input voltage. A measuring device integrated into a control circuit compares the input voltage and current and then adjusts the duty cycle of the switching device. The input waveform of the AC source is Fourier transformed such that the current aligns with the voltage. The drive stage employs a type-boost AC-DC converter, which gives the system an output voltage of V_{o1}, while the overall output voltage needed is V_{of}, which is around 270 VDC to V_{of} to be what is termed as low range. Due to this, the output voltage has to be reduced. The second part of the system functions as a converter, converting DC to DC, allowing the system to operate properly and adjust the output voltage to 270 DC. The transformation down process is crucial, as it protects the system from exceeding the output voltage limitations and ensures the correct and reliable operation of the system.

Table 1. Specifications of the converter

Parameters	Value
Input voltage	230V ±10 % AC
Output voltage	210 ± 10 VDC
Output power	1.1 kW
Operating temperature	-20 ^{0}C to +55 ^{0}C
Cooling	Force Air cooling

PLECS software is utilized to model the specified topologies. Upon meticulous evaluation, the interleaved boost topology succeeded by a buck configuration presents the following comprehensive advantages[16]:

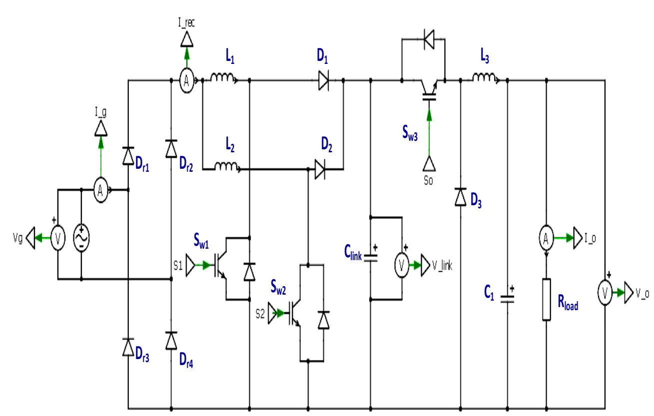


Figure 1. Simulation schematic of interleaved boost converter followed by buck converter. MOSFET switching circuit consist of three MOSFETs (S_{w1}, S_{w2}, S_{w3}), three gate drivers (S1, S2, S0), Inductors (L_1, L_2, L_3) and rectifiers (D_{r1}, D_{r2}, D_{r3}, D_{r4}, D_1, D_2, D_3).

- It provides a decrease in inductor dimensions relative to alternative topologies
- The output voltage ripple and total harmonic distortion in the input current are minimal and within acceptable limits
- Parallel power processing enhances the number of power components yet diminishes the current rating of each individual channel, hence permitting the utilization of power semiconductors with decreased current ratings.

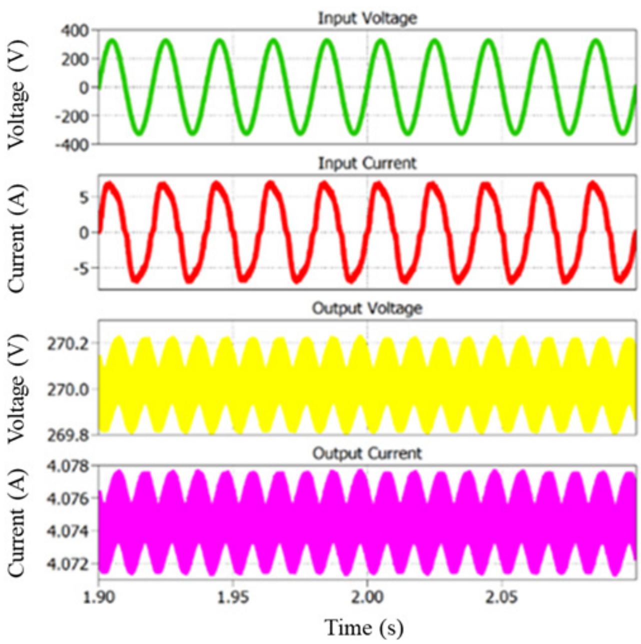


Figure 2. Simulation result of proposed system operating at 1100W where (a) the input ac voltage (V_g); (b) input AC current (I_g); (c) voltage of the buck converter(V_o); and (d) Output current of the buck converter(I_o).

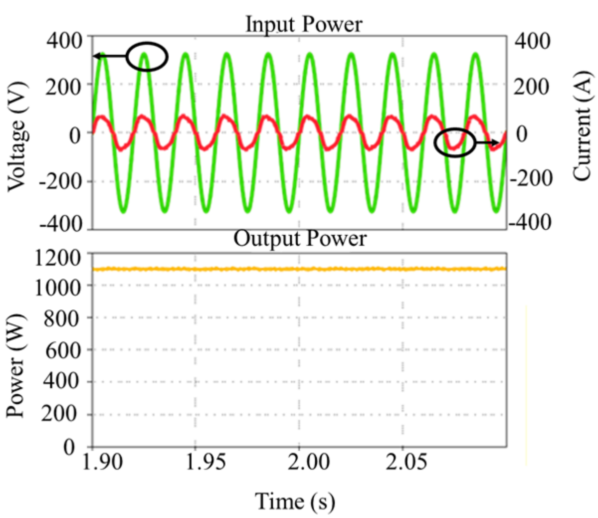


Figure 3. Simulation results showing input AC current in-phase with input AC voltage, output power, and loss analysis at 1100 W power level.

This topology is chosen for the power factor adjusted supply necessary for this project. The suggested system operates in an open-loop mode at a power level of approximately 1.1 kW.

Table 2. Specifications of the MOSFET

Symbol	Parameters	Value	Unit
VDSS	Drain to source voltage	650	V
VGSS	Gate to source voltage, DC	±30	V
ID Max	Drain current	44	A
PD	Power dissipation	312	W @ TC = 25°C
Tj, TSTG	Operating and storage temperature range	−55 to +150	°C
$R_{DS(on)}$, Max	Drain to source on resistance	72	mΩ @ 10 V

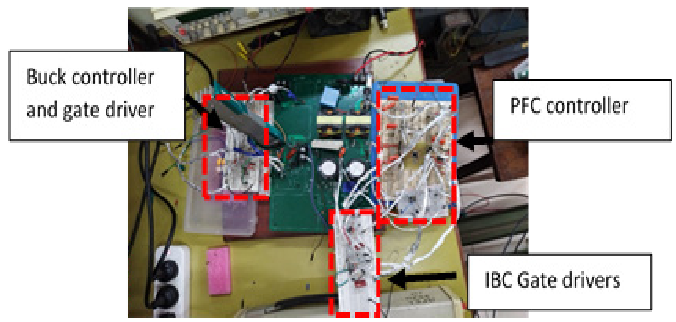


Figure 4. Hardware setup.

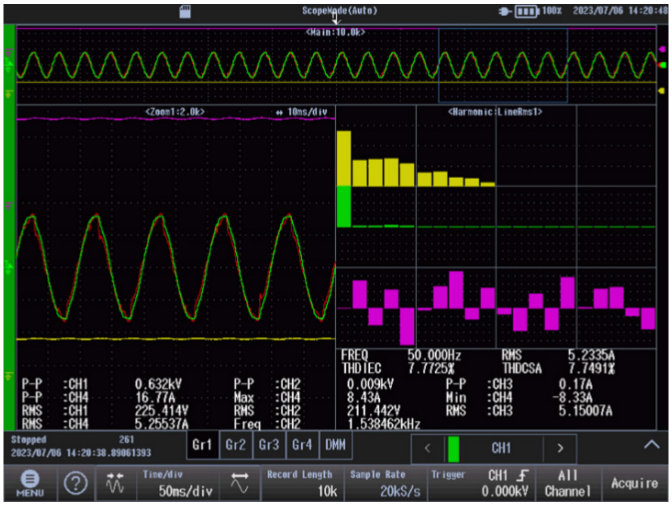
Simulation of the proposed converter based on the specifications summarized in Table I. Figure 1 illustrates the simulation schematic of the system implemented in PLECS. The interleaved boost and buck stages can be easily identified in Fig. 1. Figures 2 and 3 show the various waveforms corresponding to the simulation model in Fig. 1.

After performing a preliminary analysis, the inductor and capacitor values are plugged into the simulation model of the proposed converter shown in Fig. 1. The calculated efficiency (η) of the system as per the simulations is 96.63 %.

3. EXPERIMENTAL SETUP

The experiment is conducted at the power level of 1100 W and rated input voltage. The NVHL072N65S3 from onsemi MOSFET is used as a switching device. The specifications are given in Table 2[17].

The buck output voltage is 211V. In Fig. 4, testing of proposed system with an enclosure involves evaluating its performance and functionality within a controlled environment. The enclosure provides a realistic operating environment that simulates real-world conditions and potential challenges. Through this testing, one can assess the system's compatibility with the enclosure, verify its structural integrity, evaluate thermal management, and identify any potential interference or connectivity issues. Experimental results shown in Fig. 5 involve the operation of the proposed system at a power level of 1100W with a regulated output voltage of 211.011 ± 9 VDC at a rated input voltage as per specifications. The output voltage ripple is ~ 4.256 %. The input current total harmonic distortion (THD) of the system is ~7.772 %. The system's efficiency is 93.51 %. The hardware operated without any disruptions or fluctuations, demonstrating its improved stability and resilience under higher voltage conditions. The efficiency (η) is 93.51 %. During the measurement process, a controlled voltage is applied between the drain and source terminals and the resulting drain current is simultaneously measured by a source measure unit (SMU). The $R_{DS(on)}$ value is then calculated by dividing the voltage drop across the MOSFET by the measured drain current.



CH2: Output voltage of the buck converter	RMS :CH2 = 211.442V
CH1: Input AC voltage	RMS :CH1 = 225.41V
CH4: Input AC current	Current THD : 7.7725 %
CH3: Output current of the buck converter	RMS :CH3 = 5.15A

Figure 5. Experimental result at 1100 W.

Table 3. Simulation & practical results

Power level (W)	Simulation result		Hardware results	
	Efficiency (in %)	% voltage Ripple	Efficiency (in %)	% voltage Ripple
1100	96.63	0.24	93.51	4.256

4. PROPOSED ALGORITHM

The described work, which utilizes KNN for predicting the MOSFET's on-resistance ($R_{DS(on)}$) is significant in the context of power electronics, semiconductor device modeling, and reliability analysis. It provides an alternative approach to traditional regression models and Artificial Neural Networks (ANN) for predicting device characteristics based on experimental or simulated data[18].

K-Nearest Neighbors (KNN) is a straightforward yet effective tool for classification and regression in machine learning. Rather than learning, it keeps the whole set of data in order to make a forecast. KNN determines the likelihood of the point by estimating the distance between it and all the points in the training dataset in metrics such as Euclidean, Manhattan or Minkowski[19]. To classify a new data point, KNN employs a majority vote based on its K nearest neighbors. It acts as follows for regression problems - it takes these K closest neighbors and finds their mean to estimate the value of a new point. When K is too small, overfitting occurs, as the noise in the dataset is included, and when it is too large, the underlap is too smooth since the predictions are overly confident. Due to the way KNN works, it has high prediction times because it finds the distance of all training points when making a prediction, which makes it hard to scale due to high operational costs. To predict values accurately, KNN is sensitive to irrelevant features and distance measures, which can hinder successful predictions. KNN, however, is still one of the most widely used algorithms in recommendation systems for collaborative filtering, financial predictions, medical diagnosis, image and facial recognition, document classification, and detecting spam messages. When explainability is needed, and the problem is simple enough, it is easy and intuitive, which is why it is effective[20-23].

For regression tasks, KNN is evaluated using the Root Mean Square Error (RMSE) and coefficient of determination. As far as being a model accuracy measurement is concerned, RMSE in itself is the error measurement, and it does estimate and indicate what is the magnitude of evaluation error. RMSE can be described as the distance between predicted and actual values, but on a large scale, because it assumes the average of squared differences between the predicted and actual values and then extracts the square root from it[24].

RMSE is denoted by:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \qquad (1)$$

where, y_i represents the actual value, $\hat{y}_i$ the predicted value, and in the number of observations.

The R^2 score, also known as the coefficient of determination, indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. The R^2 score of 1 indicates perfect predictions, while a score of 0 indicates that the model does not explain any of the variance.

The R^2 is obtained as:

$$1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \qquad (2)$$

where $\bar{y}$ is the mean of the actual values. Together, RMSE and R^2 provide a comprehensive assessment of a KNN model's performance, with RMSE quantifying the prediction error and R^2 explaining the model's explanatory power. These metrics are crucial for fine-tuning the algorithm and ensuring it delivers reliable and accurate predictions in practical applications[25-26].

In the current implementation of KNN for MOSFET reliability prediction, no metaheuristic optimization technique (such as Genetic Algorithm, Differential Evolution (DE) or Particle Swarm Optimization (PSO)) was applied. The number of neighbors (k) is set manually based on trial and error or cross-validation. Typical values of k are 3, 5, 7,…. and are selected based on the one that gives the best accuracy. For this optimization, the model is trained for 30 values of k, and the optimal result of *RMSE* and R^2 are achieved for k=2. The Euclidean distance is used as distance matrix.

5. OPTIMIZATION TECHNIQUES

Essential configuration variables that are set before a model is trained are called hyper parameters. Hyper parameters

Table 4. Comparison with previously used approaches

Ref.	Device	Parameter	Performance Metric used	Approach(s) used
29	MOSFET (Metal Oxide Semiconductor Field Effect Transistor)	Threshold Voltage (V^{th})	Root Mean Squared Error (RMSE): 0.0135 R^2: 0.98	K-Nearest Neighbor (KNN) regression
30	Bitcoin	Historical Data	RMSE: 389770	K-Nearest Neighbor (KNN) regression
31	Shallot Price	Euclidean Distance	RMSE: 72	K-Nearest Neighbor (KNN) regression
32	Complementary metal oxide semiconductor (CMOS) circuits and metal gate/high-K (MGK) circuits at the 22 nm technology node.	Threshold Voltage (Vth), On-State Resistance (R_DS (on)).	Explicitly not mentioned (Accuracy: 99 %)	Adaptive Neuro-Fuzzy Inference System (ANFIS), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF)
33	Photovoltaic (PV) strings	Current, voltage, power, irradiance, temperature	Explicitly not mentioned (Accuracy: 0.994)	K-Nearest Neighbor (KNN)
34	Second-order sallen-key band pass filter, fourth-order chebychev type 1 low pass filter	Damping ratio,	Explicitly not mentioned (Accuracy: greater than 95 %)	Second-order Sallen-Key band pass filter, Fourth-order Chebychev Type 1 low pass filter
35	Proton Exchange Membrane Fuel Cell (PEMFC)	Electrochemical impedance, average single chip voltages, currents	Explicitly not mentioned	Proton Exchange Membrane Fuel Cell (PEMFC)
36	MOSFET (Metal Oxide Semiconductor Field Effect Transistor)	Remaining useful life (RUL)	Root Mean Squared Percentage Error (RMSPE): 1.25 %,	Random Forest classifier, Bayesian Ridge regressor.
Proposed	Si	RDS(on)	RMSE:0.00140 R^2 :0.9999	KNN Model with Evolutionary Optimization

have a direct impact on the learning process, in contrast to parameters, which are discovered through the data[27]. A critical stage in machine learning is hyper parameter tuning, which involves determining the best values for these variables. The objective is to identify the hyper parameter values that maximize the model's performance on a specific task. There are several types of hyper parameter tuning techniques, a few of which are discussed as follows[28-32].

Algorithm I: Evolutionary Optimizations Learning Model Algorithm for Reliability Aged Model

Step 1: Initialization
Start by collecting historical $R_{DS(on)}$ measurements from MOSFET degradation cycles and organizing them into a dataset. Each sample is structured as a time series window containing the last n values of $R_{DS(on)}$.

Step 2: Distance Computation
For a given input vector x containing the most recent n values of $R_{DS(on)}$, compute the Euclidean distance between x and each stored vector *y* in the training dataset:

$$d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}$$

Step 3: Neighbor Selection
Sort all distances and select the *K* closest vectors from the dataset. These represent the most similar past instances to the current input vector.

Step 4: Prediction Computation
Estimate the next $R_{DS(on)}$ value by averaging the corresponding next-step values from the *K*-selected neighbors:

$$\hat{R}_{DS(on)}(t+1)=\frac{1}{K}\sum_{i=1}^{K}R^{i}_{DS(on)}(t+1)$$

Step 5: Iteration
Update the input vector by appending the predicted $R_{DS(on)}$ value and sliding the window forward. Repeat the process for further predictions.

6. RESULT AND DISCUSSION

The results obtained after training the KNN model with its Evolutionary optimization techniques is discussed in the following sections.

In the KNN model optimized by using the evolution optimization technique, it is seen that the values of RMSE and R^2 obtained were 0.0018 and 0.999968 respectively. Figure 6 shows the graph ON resistance vs time for the entire dataset using evolution.

One of the significant drawbacks of KNN is its computational cost, as it requires storing the entire dataset and making predictions based on distance calculations, which becomes computationally expensive as the dataset size grows. Another significant limitation is as the number of features/ stresses increases, KNN's performance tends to degrade because distance-based methods struggle in high-dimensional

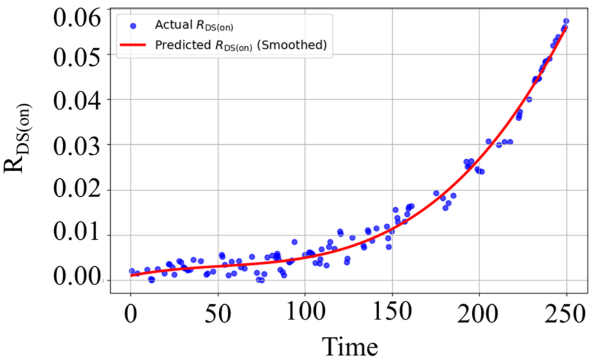


Figure 6. ON resistance vs time for the entire dataset using evolution.

spaces. This issue is less pronounced in regression models, and artificial neural networks (ANN) can effectively learn and adapt in such environments[37].

Additionally, KNN is highly sensitive to noisy data and outliers. Since it relies on the nearest neighbors, the presence of incorrect or extreme values can significantly impact predictions. On the other hand, regression models and properly trained ANN can generalize better and exhibit greater robustness against noise[38]. A comparative study with previously published work is given in Table III.

Real-time measurement of the on-state resistance $R_{DS(on)}$ of MOSFETs presents numerous implementation challenges, particularly in high-speed and high-power applications. One of the most critical issues is the temperature dependency of $R_{DS(on)}$. Since the resistance increases with junction temperature, real-time monitoring must include thermal tracking or compensation to avoid misinterpretation of the device's health or efficiency. Additionally, electromagnetic interference (EMI) and high-frequency switching noise in power electronic circuits complicate the accurate sensing of voltage and current during the conduction phase. These noise sources can distort real-time signals, leading to erroneous $R_{DS(on)}$ calculations unless advanced filtering or differential sensing techniques are employed[39-40].

7. CONCLUSION

The measurement of the on-resistance $R_{DS(on)}$ of MOSFETs holds significant industrial relevance, particularly in power electronics, automotive systems, and consumer electronics. Accurate $R_{DS(on)}$ characterization is crucial for evaluating conduction losses, thermal performance, and overall energy efficiency of power devices. The proposed K-Nearest Neighbour's (KNN) Regression techniques are trained and tested. It is observed that the RMSE and R^2 score parameter values are 0.0006 and 0.9987. From the obtained values, it can be concluded that the KNN model optimized using the Evolution hyper parameter optimizing technique outperforms the other optimization techniques in terms of precision and accuracy. Further, our proposed model predicts with almost minimal error and has a good degree of fitting.

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