Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)
Edited by Maria Chiara Leva, Edoardo Patelli, Luca Podofillini, and Simon Wilson
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-18-5183-4_R22-18-603-cd

Monitoring Degradation of Insulated Gate Bipolar Transistors in Induction Cooktops by Artificial Neural Networks

Chenyang Lai

Energy Department, Politecnico di Milano, Italy. E-mail: chenyang.lai@polimi.it

Piero Baraldi

Energy Department, Politecnico di Milano, Italy. E-mail: piero.baraldi@polimi.it

Ibrahim Ahmed

Energy Department, Politecnico di Milano, Italy. E-mail: ibrahim.ahmed@polimi.it

Enrico Zio

MINES Paris-PSL, CRC, Sophia Antipolis,
Energy Department, Politecnico di Milano, Milan, Italy. E-mail: enrico.zio@polimi.it

Alejandro Del Cueto

BSH Electrodomésticos España, Spain. E-mail: Alejandro.delcueto@bshg.com

Javier Gil

BSH Electrodomésticos España, Spain. E-mail: Javier.Gil@bshg.com

Sergio Llorente

BSH Electrodomésticos España, Spain. E-mail: Sergio.llorente@bshg.com

Insulated Gate Bipolar Transistors (IGBTs) are among the most critical components of inverters of induction cooktops. Their degradation is mainly caused by the thermal stress which they are subject to. Since the thermal stress is proportional to the IGBT case temperature, this work develops a method for predicting the case temperature of IGBT modules using signals monitored during in-field operation of induction cooktops. The main challenge to be addressed is that induction cooktops are typically used under variable, user-dependent settings, which generate very different evolutions of the temperature profiles. The proposed method is based on the selection of the measured signals to be used as input of the prediction model through a wrapper feature selection approach which employs a multi-objective genetic algorithm (MOGA). Then, an Artificial Neural Network (ANN) is used to predict the case temperature. The proposed method has been verified using real data collected by BSH Electrodomésticos España (BSHE) in laboratory tests. The obtained results show that the developed ANN model is able to provide accurate estimations of the case temperature, which is at the basis of the condition monitoring of induction cooktop IGBTs.

Keywords: Induction cooktop, IGBTs, Feature selection, Wrapper, MOGA, ANN.

1. Introduction

With the development of new generation induction cooktops, data about their domestic usage, measured by embedded sensors, can be acquired and transmitted to the producers. This work considers the possible use of these data for enhancing the reliability of the electronic components of induction cooktops. Specifically, we consider Insulated Gate Bipolar Transistors (IGBTs) which are used for their fast-switching speed, low on-resistance, simple driving circuits, large current capacity and low on-stage power dissipation, but are among the most critical components from the point of view of the system reliability. This is due to the fact that IGBTs experience large levels of thermal and electric stresses during operation, which cause thermo-mechanical fatigue and deterioration of their electric properties (Oh et al. (2014)). As a consequence, the heat transfer inside the inverter is modified, accelerating the degradation of the bond wires, the solder layer and the interior of the chip and possibly leading to the IGBT failure if proper countermeasures are not taken. Therefore, the evaluation of the IGBT health state requires to estimate the temperature in the most critical locations of the IGBTs, such as the junction and the case (Wang et al. (2020), Chen et al. (2012)). Since the installation of temperature sensors is not feasible in commercial induction cooktops, the objective of the present work is the development of a data-driven model for the estimation of the IGBTs case temperature using signals that can be measured during operation in commercial induction cooktops.

With respect to the prediction of temperatures in IGBTs, the following works have been published. To estimate the IGBT junction temperature from the case temperature measurements, an electrical-thermal model is proposed in (Wei et al. (2019)). A neural network is developed to predict the case temperature using monitored electrical parameters and the residuals between the predicted and measured case temperature are used for detecting anomaly of IGBTs in (Chen et al. (2012)). A multi-layer Foster Resistor–Capacitor (RC) network is developed to estimate the IGBT junction temperature using the thermal resistance and electrical parameters of IGBTs in (Reigosa et al. (2015)). The junction temperature is estimated by developing the model of the power loss and the IGBT equivalent thermal model in (Ghimire et al. (2013)). Although these works have been reported to achieve satisfactory prediction performance, they require the availability of measurements of physical quantities, such as temperatures, which are difficult to obtain from commercial induction cooktops. For this reason, the objective of the present work is to predict the case temperature resorting only to the measurements of sensors that can be installed in commercial induction cooktops.

In this context, the main challenges to be addressed for the model development are:

1) induction cooktops are typically used under variable, user-dependent settings, which generate very different evolutions of the temperature profiles.

2) hundreds of signals can be, in principle, measured during in-field operation.

The proposed method is based on the selection of the set of measured signals to be used as input of the prediction model through a wrapper feature selection approach, which employs Multi-Objective Genetic Algorithms (MOGAs). The optimization aims at the identification of a set of signals, which allows obtaining a satisfactory trade-off between prediction accuracy, computational burden, memory demand and cost of the measurement system. Once the feature selection has been performed, an Artificial Neural Network (ANN) is developed to predict the case temperature.

The proposed method has been verified using real data collected in laboratory tests performed at BSH Electrodomésticos España (BSHE). The obtained results show that the developed ANN model is able to provide accurate estimations of the case temperature using a reduced set of features.

The work is organized as follows: Section 2 formulates the problem; in Section 3, the approach for optimal feature selection based on the use of a Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) wrapper algorithm is described; the application to real data is described in Section 4, whereas in Section 5 conclusions are drawn.

2. Problem Formulation

The objective of this work is to estimate the case temperature, y, of inverter IGBTs on the basis of $n \gg 1$ signal measurements, $z_i, i = 1, \ldots, n$, provided by sensors that can be installed in commercial induction cooktops. We have an available dataset $D = \{(\boldsymbol{z}^k, y^k), k = 1, \ldots, N\}$ containing N patterns made by the signal values $\boldsymbol{z}^k$ and the corresponding case temperature y^k, which has been obtained by performing laboratory tests using a cooktop on which the n sensors and a thermocouple for the measurements of y have been installed for the objective of the present work.

Since the number n of signals that can be measured in induction cooktops is large, the solution of the problem requires a preliminary step of selecting the signals to be used for the estimation of the case temperature y. The objectives of the selection task, which is typically referred to as feature selection, are:

(1) to maximize the performance of the model estimating the IGBT case temperature;

(2) to minimize the cost of development of the condition monitoring system.

With respect to (1), the performance of the case temperature estimation is assessed considering the prediction error:

$$E = \frac{1}{N}\sqrt{\sum_{k=1}^{N} \|y^k - \hat{y}^k\|^2} \quad (1)$$

where $\hat{y}^k$ is the case temperature estimation provided by the model and N is the number of test patterns.

With respect to (2), the cost of deployment of the condition monitoring system depends from the number of sensors to be installed in the commercial cooktops and the computational time and memory demand needed by the model to process the measurements. We assume that these quantities are directly proportional to the number of selected sensors:

$$n_{sel} = \sum_{i=1}^{n} x_i \quad (2)$$

where $x_i \in \{0,1\}$ is a Boolean variable associated to signal i, with $x(i) = 1$ indicating that signal i is selected and $x(i) = 0$ indicating that signal i is not selected.

3. Method

The method developed in this work to address the problem formulated in Section 2 is based on the two sequential steps of feature selection and temperature estimation. With respect to the feature selection problem, the possible methods are typically classified as filter, wrapper and embedded (Baraldi et al. (2016)). Wrapper methods select an optimal subset of features using the regression model itself, i.e., the regression model is wrapped within the search algorithm, which aims at identifying the feature subset providing the 'best' regressor. Embedded methods perform feature selection as part of the training of the regression model. Filter methods rank the features according to their statistical association (e.g., mutual information) with the response.

This work develops a wrapper method, since it has been shown to provide more accurate predictions than filter and embedded methods in many applications (Baraldi et al. (2016)), despite the large computational effort that it typically requires.

3.1. Wrapper-based Feature Selection

Figure. 1 shows the scheme at the basis of a wrapper-based feature selection. The search engine builds a candidate group of features $\boldsymbol{x}$, whose performance is evaluated using properly defined fitness functions. In this work, we consider the E and n_{sel} defined by Eq. (1) and Eq. (2) as fitness functions, $\boldsymbol{F}_1(\boldsymbol{x})$ and $\boldsymbol{F}_2(\boldsymbol{x})$:

$$\boldsymbol{F}(\boldsymbol{x}) = [\boldsymbol{F}_1(\boldsymbol{x}), \boldsymbol{F}_2(\boldsymbol{x})] = [E(\boldsymbol{x}), n_{sel}(\boldsymbol{x})] \\ , \boldsymbol{x} \in \{0,1\}^n \quad (3)$$

Since we deal with a Multi-Objective Optimization (MOO) problem, the final objective is the identification of the Pareto Optimal Set, $\mathcal{P}^* = \{\boldsymbol{x} \in \boldsymbol{F}(\boldsymbol{x})\ is\ Pareto - optimal\}$, i.e., the set of optimal solutions among which we will select the preferred solution $\boldsymbol{x}_{opt}$. According to the desired trade-off among the objectives, a vector of decision variable $\boldsymbol{x}_{opt} \in \mathcal{F}$ is Pareto optimal if it is non-dominated with respect to $\mathcal{F}$, i.e., it does not exist another solution $\boldsymbol{x}' \in \mathcal{F}$ such that $\boldsymbol{F}(\boldsymbol{x}')$ dominates $F(\boldsymbol{x}^*)$:

$$\forall \alpha \in \{1,2\},\ F_\alpha(\boldsymbol{x}') \leq F_\alpha(\boldsymbol{x}^*), and$$

$$\exists \tilde{\alpha} \in \{1,2\}, such\ that\ F_{\tilde{\alpha}}(\boldsymbol{x}') \leq F_{\tilde{\alpha}}(\boldsymbol{x}^*) \quad (4)$$

The wrapper approach developed in this work uses a Multi-objective Genetic Algorithm as search engine.

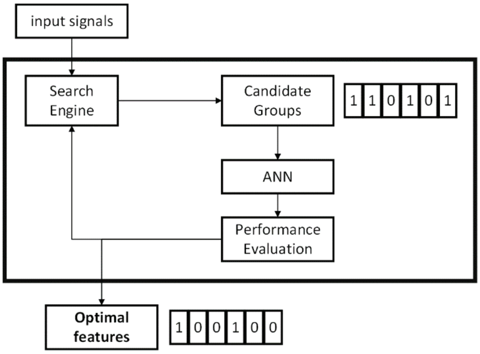


Fig. 1. The wrapper approach for feature selection.

3.1.1. Multi-objective Genetic Algorithm

Performing an exhaustive search of the best solution among all the possible 2^n solutions is typically impracticable unless n is very small. For this reason, different combination of optimization heuristics such as Ant Colony, Genetic Algorithm, Particle Swarm Optimization (PSO), Binary Genetic Algorithms, and Binary Differential Evolution BDE have been used within wrapper approaches for feature selection (Baraldi et al. (2016); Ghosh et al. (2020); Butler-Yeoman et al. (2015); Huang et al. (2007)). In this work, we resort to a NSGA-II algorithm to address the MO feature selection problem. Main steps in NSGA-II are initiation, crossover, mutation, and selection (Deb et al. (2002); Singh et al. (2017)).

(1) Initialization

In NSGA-II, each candidate solution $\boldsymbol{x}_{p,G}$, called target vector, of the G^{th} population is encoded by a binary sequence (chromosome) of n bits (genes) for n decision variables, where each bit indicates whether a feature is present (1) or discarded (0) in the candidate solution $\boldsymbol{x}_{p,G}$. The initialization of $\boldsymbol{x}_{p,G}$ is realized by the mapping operator init(·), $x_{p,k,G} = \text{init}(rand)$:

$$\text{init}(rand) = \begin{cases} 0 & if\ rand \in [0,0.5) \\ 1 & if\ rand \in [0.5,1] \end{cases} \quad (5)$$

where $rand$ is a random number in [0,1] and $x_{p,k,G}$ is the gene of each chromosome of the G_{th} population in which the $k = 1{:}\,n$, n is the number of features, the $p = 1{:}\,NP, NP$ is the number of chromosomes.

(2) Crossover

In order to increase diversity of the perturbed parameter vectors, crossover can be introduced. This procedure is typically referred to as recombination. To this aim, the new chromosome $\boldsymbol{u}_{p,G} = (u_{p,1,G}, u_{p,2,G}, \dots, u_{p,n,G})$ is generated from the parents' chromosomes, $\boldsymbol{x}_{f,G}$ and $\boldsymbol{x}_{m,G}$.

$$\boldsymbol{m, n = irand(NP)}, \qquad \boldsymbol{m \neq n} \qquad \textbf{(6)}$$

where $irand(NP)$ is a discrete random number in the set {1,2, … , NP}.

$$\boldsymbol{u_{p,G}} = \left(\boldsymbol{x_{f,1,G}}, \dots, \boldsymbol{x_{f,ind,G}}, \boldsymbol{x_{m,ind+1,G}}, \dots, \boldsymbol{x_{m,n,G}}\right), \quad \boldsymbol{ind = irand(n)} \qquad \textbf{(7)}$$

where $irand$ is a discrete random number in the set {1,2, … , n}. $\boldsymbol{u}_{p,G}$ is the crossover chromosome recombined from $\boldsymbol{x}_{f,G}$ and $\boldsymbol{x}_{m,G}$.

(3) Mutation

The mutation procedure is performed after every crossover operation. the chromosome $\boldsymbol{v}_{p,G} = (v_{p,1,G}, v_{p,2,G}, \dots, v_{p,n,G})$ is generated from $\boldsymbol{u}_{p,G}$.

$$\boldsymbol{v_{p,k,G}} = \begin{cases} \boldsymbol{u_{p,k,G}} & \boldsymbol{if\ rand > MR} \\ \boldsymbol{1 - u_{p,k,G}} & \boldsymbol{if\ rand \leq MR} \end{cases} \qquad \textbf{(8)}$$

where MR is the defined mutation rate in [0,1], $rand$ is a random number in [0,1]. $\boldsymbol{v}_{p,G}$ is the new chromosome after mutation operation.

(4) Selection

In this work, the fast non-dominated sorting and ranking selection scheme of NSGA-II is applied in each generation for population selection. In practice, at the G^{th} generation the combined population of size $2NP$ comprising $\boldsymbol{v}_{p,G}$ is ranked using a fast non-dominated sorting algorithm that identifies the ranked nondominated solutions of the Pareto optimal set. Then, the first NP candidate solutions are selected according to the *crowding distance*.

3.2. Artificial Neural Network

In this work, an ANN is used as the regression model for the IGBT case temperature prediction. The choice is justified by the robustness of ANNs, their good regression performance (Chen et al. (2012)) and the need of having a model fast to train since the wrapper approach requires the training of several ANNs during the MOGA search. Also, more complex deep-learning models have not been considered in this phase of the work, since they typically require longer computation time.

4. Case study

The dataset is obtained from 11 laboratory tests performed on induction cooktops. Each test executes a different cooking process characterized by different operating conditions. The measurements of 466 signals, which contain 385 quantities measurable in both laboratory and client applications and 81 temperatures measurable only in laboratory are collected during the tests.

The available data have been split into a training set formed by 8 cooking processes, which is used for the feature selection task, and a test set formed by 3 cooking processes, which is used for the evaluation of the accuracy of the case temperature estimation. The training set have been further split into 3 folds to perform a 3-fold cross-validation within the wrapper feature selection.

The setting of parameters of the NSGA-II search is reported in Table 1.

Table 1. Setting of the NSGA-II parameters

Parameters	Value
Population size of NSGA-II	50
Maximum number of generations	100
Crossover rate	1
Mutation rate	0.01

A shallow ANN with 1 hidden layer and 10 neurons is used to estimate the case temperature of two IGBTs of the inverter. Table 2 reports the architecture of the ANN and employed activation function.

Table 2. ANN architecture

Parameters	Value
Number of inputs	Number of selected features
Number of outputs	2
Number of hidden layers	1
Number of neurons in the hidden layer	10
Activation function	Relu

With respect the training of the ANN, the Adam optimization algorithm, which is an extension to the stochastic gradient descent algorithm, is applied, and the Mean Squared Error (MSE) is used as loss function. Table 3 reports the setting of the training parameters.

Table 3. ANN training parameters

Parameters	Value
Epoch	50
Batch size	256
Optimizer	Adam
Loss function	MSE
Learning rate	0.005

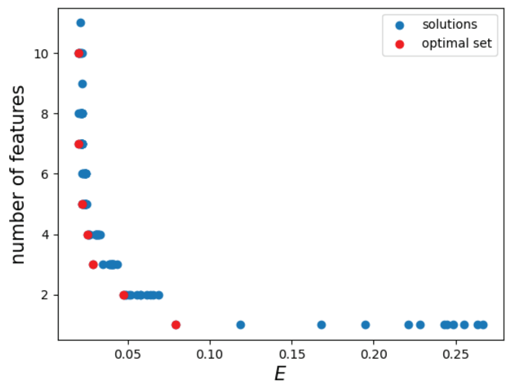
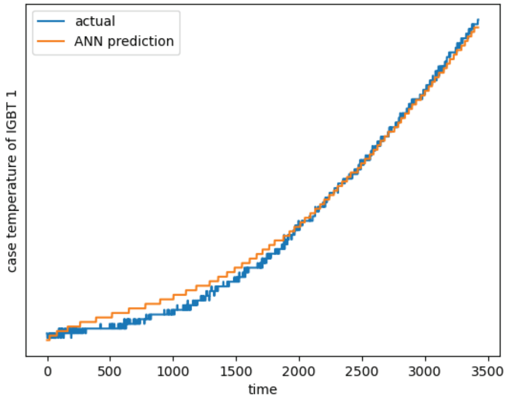


Fig. 2. Solution at the last generation and Pareto optimal set.

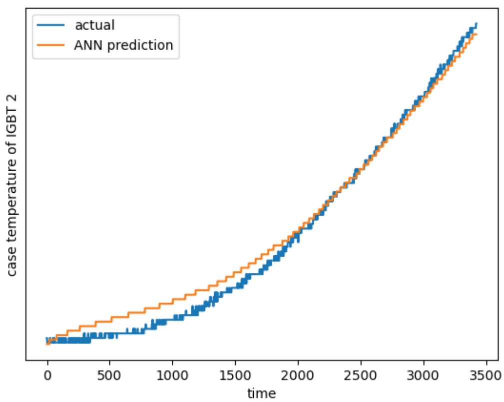
Fig. 2 shows the performance in terms of the two fitnesses E and n_{sel} of the chromosomes of the last generation of the MOGA search. Non-dominated solutions of the optimal Pareto set are represented using red dots.

Table 4 reports the performance of the feature sets of the optimal Pareto set when the corresponding NN model is applied to the data of the test set. As expected, smaller the number of selected features, larger the prediction error.

With respect to selected features, which are not reported here for confidentiality issues, it is interesting to notice that there is one signal selected by all solutions of the Pareto optimal set whose correlation with the IGBT case temperature has been confirmed by field experts.

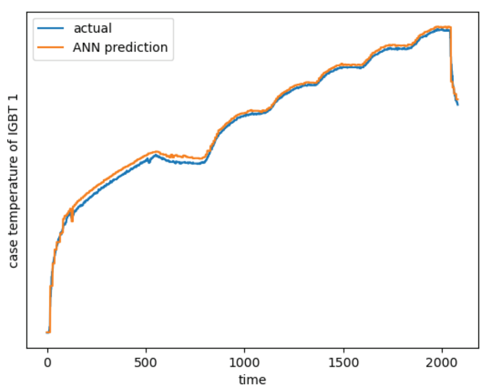


(a) IGBT 1

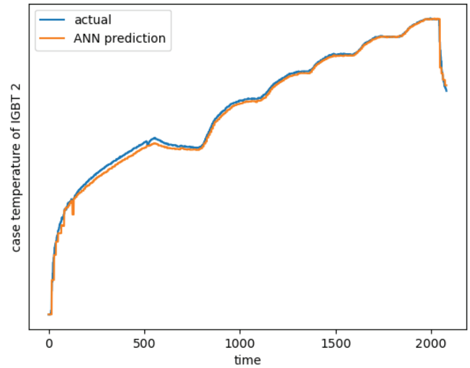


(b) IGBT 2

Fig. 3. ANN prediction on 1st cooking process.

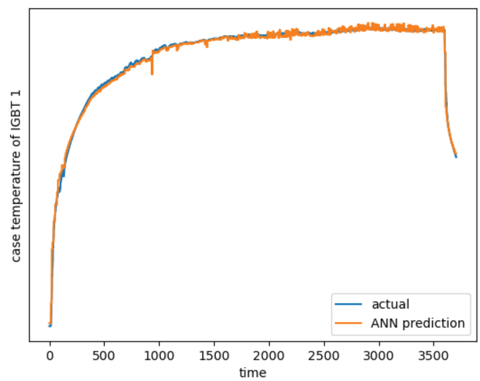


(a) IGBT 1

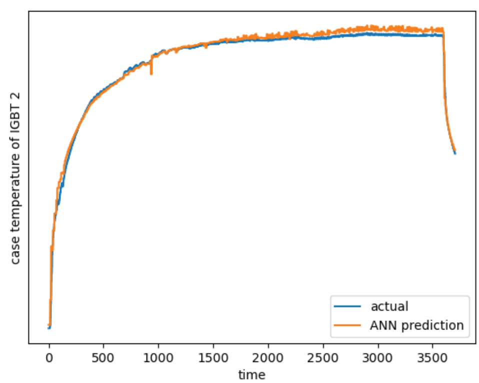


(b) IGBT 2

Fig. 4. ANN prediction on 2nd cooking process.



a) IGBT 1



((b) IGBT 2

Fig. 5. ANN prediction on 3rd cooking process.

Table 4. Feature selection results

Number of selected features	RMSE on the test set
1	5.09℃
2	1.66℃
3	1.76℃
4	0.84℃
5	0.83℃

From the accuracy point of view, the solution of the Pareto optimal set with 5 features is the best performing, although also the solution with 4 features is very accurate. Hence, the ANN model is trained using the 5 selected features.
The temperature estimations of the ANN fed by the set of 5 features of the corresponding Pareto optimal set on 3 test cooking processes are shown in Fig. 3, Fig. 4 and Fig. 5. The obtained estimations are satisfactory in all phases of the cooking processes. Therefore, the developed ANN model of the IGBT case temperature can be used for monitoring the degradation of the IGBTs in the induction cooktops.

5. Conclusions

In this work, we have developed a framework for estimating the IGBT case temperature in induction cooktop inverters. The signals to be used for the estimation are selected by developing a wrapper feature selection approach. The search engine is a Multi-Objective Genetic Algorithm whose objectives are the minimization of the estimation error and the number of signals selected which reduces the cost of the condition monitoring system. An ANN is, then, used to estimate the case temperatures. The developed approach has been applied to laboratory test data of induction cooktops performing different cooking processes under variable working conditions. The obtained results show that it is possible to obtain a satisfactory accuracy on the case temperature estimations.

Further research work will be devoted to the use of the estimated case temperatures to compute the overall stress acting on the components.

Acknowledgement
Chenyang Lai gratefully acknowledges the financial support from the China Scholarship Council (No. 202006290009).

iRel40 is a European co-funded innovation project that has been granted by the ECSEL Joint Undertaking (JU) under grant agreement No 876659. The funding of the project comes from the Horizon 2020 research programme and participating countries. National funding is provided by Germany, including the Free States of Saxony and Thuringia, Austria, Belgium, Finland, France, Italy, the Netherlands, Slovakia, Spain, Sweden, and Turkey.

Disclaimer
The document reflects only the authors' view and the JU is not responsible for any use that may be made of the information it contains.

References

Oh, H., Han, B., McCluskey, P., Han, C., and Youn, B. D. (2014). Physics-of-failure, condition monitoring, and prognostics of insulated gate bipolar transistor modules: A review. *IEEE Transactions on power electronics, 30*(5), 2413-2426.

Wang, C., He, Y., Wang, C., Wu, X., & Li, L. (2020). A fusion algorithm for online reliability evaluation of microgrid inverter IGBT. *Electronics*, *9*(8), 1294.

Chen, M., Xu, S., Ran, L., Xiang, D., & Wallie, P. (2012). Prediction of case temperature for monitoring IGBT power module using artificial neural network. *Int. Rev. Elect. Eng., 7*(1), 3240-3247.

Wei, K., Wang, W., Hu, Z., & Du, M. (2019). Condition monitoring of IGBT modules based on changes of thermal characteristics. *IEEE Access, 7*, 47525-47534.

Reigosa, P. D., Wang, H., Yang, Y., & Blaabjerg, F. (2015). Prediction of bond wire fatigue of IGBTs in a PV inverter under a long-term operation. *IEEE Transactions on Power Electronics, 31*(10), 7171-7182.

Ghimire, P., Bęczkowski, S., Munk-Nielsen, S., Rannestad, B., & Thøgersen, P. B. (2013, September). A review on real time physical measurement techniques and their attempt to predict wear-out status of IGBT. *In 2013 15th European Conference on Power Electronics and Applications (EPE)* (pp. 1-10). IEEE.

Baraldi, P., Cannarile, F., Di Maio, F., & Zio, E. (2016). Hierarchical k-nearest neighbours classification and binary differential evolution for fault diagnostics of automotive bearings operating under variable conditions. *Engineering Applications of Artificial Intelligence, 56*, 1-13.

Ghosh, M., Guha, R., Sarkar, R., & Abraham, A. (2020). A wrapper-filter feature selection technique based on ant colony optimization. *Neural Computing and Applications, 32*(12), 7839-7857.

Butler-Yeoman, T., Xue, B., & Zhang, M. (2015, May). Particle swarm optimisation for feature selection: A hybrid filter-wrapper approach. *In 2015 IEEE congress on evolutionary computation (CEC)* (pp. 2428-2435). IEEE.

Huang, J., Cai, Y., & Xu, X. (2007). A hybrid genetic algorithm for feature selection wrapper based on mutual information. Pattern recognition letters, 28(13), 1825-1844.

Deb, K. (2002). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-2. *IEEE Trans. Evol. Comput., 6*(2), 182-197.

Singh, U., & Singh, S. N. (2017). Optimal feature selection via NSGA-II for power quality disturbances classification. *IEEE Transactions on Industrial Informatics, 14*(7), 2994-3002.