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***Abstract*—Failure of power electronics can significantly impact the long-term power system reliability, especially for the systems with a high penetration level of the renewable energy-based units. Therefore, the analysis of power electronics reliability impact on the optimum system design needs to be included in the long-term planning. However, current long-term forecasting methods cannot provide generation and demand profiles suitable for the power electronics reliability evaluation typically due to a low time resolution. In this paper, a long-term forecasting method for power electronics-based system design is proposed. The method employs statistical and artificial intelligence-based models to provide forecasting profiles and their probability of occurrence with a high time resolution over the whole long-term planning horizon. The case study results show that the accuracy of the forecast profiles obtained with the developed model is suitable for power electronics reliability analysis.**

***Index Terms*—Long-term forecasting, power electronics, reliability, power system design**

I. Introduction

Nowadays the electrical systems are designed with the aim of contributing to the reduction of the fossil fuel usage and meeting the global sustainability goals [1]. A high installation rate of the renewable energy is today characteristic for modern power system design. During the long-term planning, the optimum capacity planning of renewable energy generation and storage units is carried out. This generation capacity needs to be sufficient to cover the load demand over a long-term planning horizon (e.g., 15-30 years) [2]. During this stage, the power system reliability analysis is employed to assure system adequacy [3]. However, failure-prone power electronics interface is an emerging challenge to the system reliability [4]. In fact, its failure can lead to the interruptions in power supply from the renewable energy generation units [5], [6]. Thus, to avoid this problem, power electronics reliability needs to be included in the future design of a modern power system.

Regarding the power electronics reliability analysis, the failure rate of the units is estimated based on the stress they experience during operation. As a first step, the mission profile (operating conditions) is translated into the stress profile, as shown in Fig. 1. Furthermore, to evaluate the damage of the different stress levels, the stress profile is decomposed into an equivalent set of reversals. Afterwards, the time at which the dominant failure mechanisms are triggered is estimated based on the accumulated stress. Finally, probabilistic evaluation is performed to account for uncertainties [7], [8]. The failure rate information can be used to avoid the unexpected system downtime due to power electronics failure. Moreover, it can help to reduce times with the insufficient generation capacity and improve the power system reliability [4]. Finally, it leads to a more realistic system cost with a reduced unplanned power electronics replacement cost.

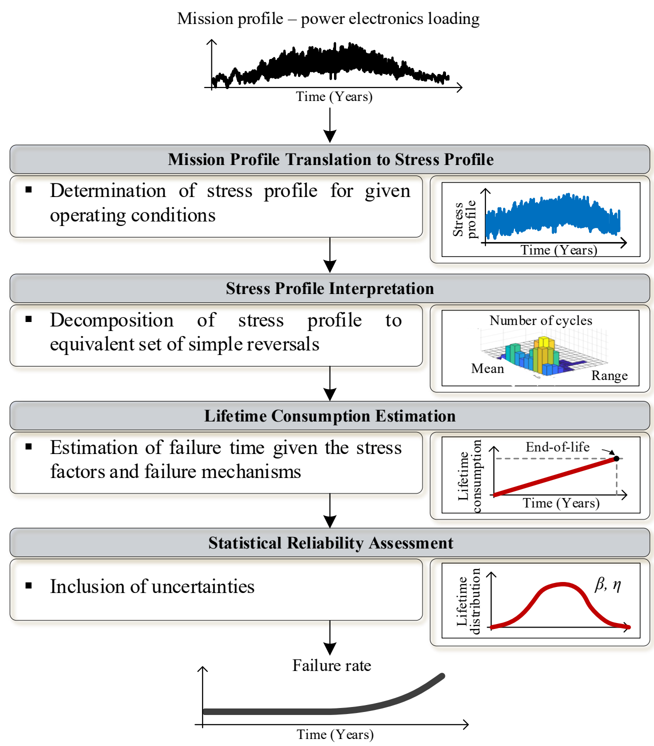

Fig. 1. Procedure for the power electronics reliability estimation [2]. The input to the procedure is a mission profile representing the operating conditions of the power electronic unit. The output is the corresponding failure rate.

The power electronics loading is directly influenced by the operating conditions [9], which depend upon the generation and load balance in the system. During planning, the generation and demand profiles are determined by means of long-term forecasting methods. The forecast profiles are characterized by low time resolution intervals (1 sample per month or a year) [10]–[12]. Those are suitable for power system capacity planning and reliability studies [13], [14], as shown in Fig. 2, which do not require high dynamics. However, during operation, the power electronics system experience substantial changes in loading due to the volatility and intermittency

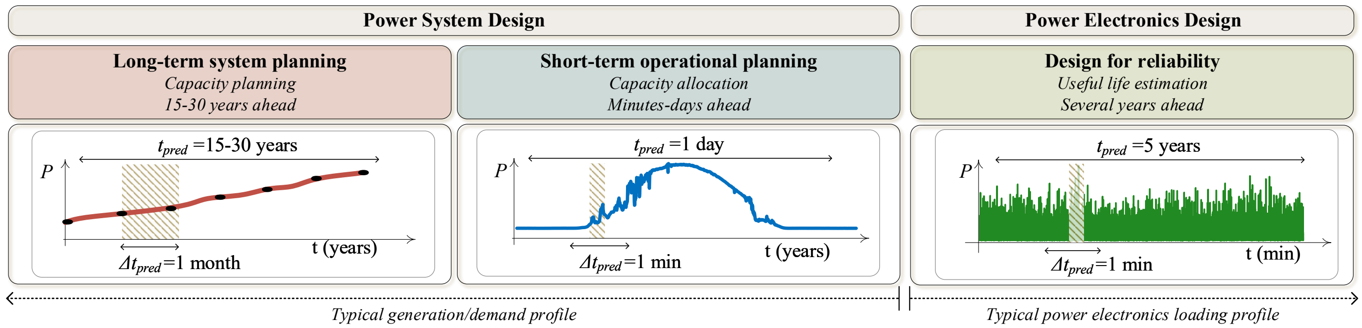

Fig. 2. Overview of the time resolution and horizon requirements for profiles within power system and power electronics design domains. P is a forecast profile with t_{pred} forecast horizon and Δt_{pred} time resolution interval.

of the renewable energy sources. Their loading profiles can significantly change in a short time span, e.g., within several minutes [15]. The large variations in loading result in accumulation of the additional stress. To evaluate its impact on the reliability, a high time resolution profile (1 sample per minute) is required [16] (see Fig. 2). Hence, the long-term forecasting methods with the low time resolution intervals [13], [14], [17] cannot be used to capture these dynamics. In [18], a need to incorporate volatility into long-term forecasting has been discussed. Furthermore, a connection between high time resolution forecasting (1 sample per hour) and long-term forecasting horizon is pointed out in [19]. However, both [18], [19] are limited to the deterministic time-series forecasting models. They do not account for uncertainty, which usually result in an increase in inaccuracy with the extension of the forecasting horizon. In such case, the advantages of the probabilistic forecast prevail over deterministic one [20]. However, the probabilistic models for long-term planning, which forecast profiles with a sufficient time resolution for power electronics reliability are still lacking.

Therefore, a long-term forecasting method suitable for both generation capacity planning studies and the estimation of the power electronics reliability is proposed in this paper. It employs artificial intelligence-based model to provide the prediction of the generation and demand profiles with a low time resolution (1 sample per month). Furthermore, a probabilistic forecasting is used to predict the main characteristics (intensity and intra-day variations) of profiles and their probability of the occurrence with a high time resolution (1 sample per minute). With respect to that, the rest of the paper is organized as follows. In Section II, a detailed description of the proposed long-term forecasting model suitable for power electronics-based systems is provided. In Section III, a numerical analysis is conducted. It includes accuracy evaluation of the proposed forecasting method for reliability studies. In Section IV, concluding remarks are provided.

II. Proposed Forecasting Model for Power Electronics-Based Systems

The outline of the proposed forecasting model is shown in Fig. 3. It consists of two parts: 1) Trend Determination and 2) Pattern Characterization. The former is used for forecasting with low time resolution e.g., 1 sample per month. In fact, it provides sufficient information for capacity planning studies. The latter is employed for forecasting with high time resolution e.g., 1 sample per minute suitable for power electronics reliability investigation.

A. Trend Determination

Trend determination is developed for forecasting of generation and demand trend several years ahead. Different methods commonly used in long-term capacity planning studies can be employed for this purpose [18], [19]. In this work, an artificial intelligence-based method is implemented. It provides more accurate results than the physics and statistical models [21].

The Long Short Term Memory Network suitable for dealing with issues related to time series due to the existence of cycle structure is developed [22]. It is a uni-variate single step network that can be used for forecasting a single step ahead in the time series profile. The network architecture includes the input layer with 12 neurons. They correspond to parameter values with monthly resolution P^{LR}_{hist}. Moreover, there is one hidden layer with 20 neurons. Finally, there is one neuron in the output layer. It represents the predicted parameter value for the next month, which corresponds to the P^{LR}_{pred} in Fig. 3.

B. Pattern Characterization

Pattern Characterization uses the historical data with a high time resolution P^{HR}_{hist} together with the results from Trend Determination P^{LR}_{pred} to determine the forecast profile with a high time resolution P^{HR}_{pred}. First, the historical data is classified into characteristic classes of daily profiles. Subsequently, the classified profiles and the forecast monthly trend are used to determine the probability of certain profiles occurring in the future. As a result, a high time resolution profile for long-term planning horizon is constructed from the daily profiles with the highest probability of occurrence.

1) Classification: The K-means clustering method is used for classification. It organizes the M input profiles into K mutually exclusive clusters based on the similarities of their features [20], [23]. The degree of association between the profiles belonging to one cluster needs to be the highest and

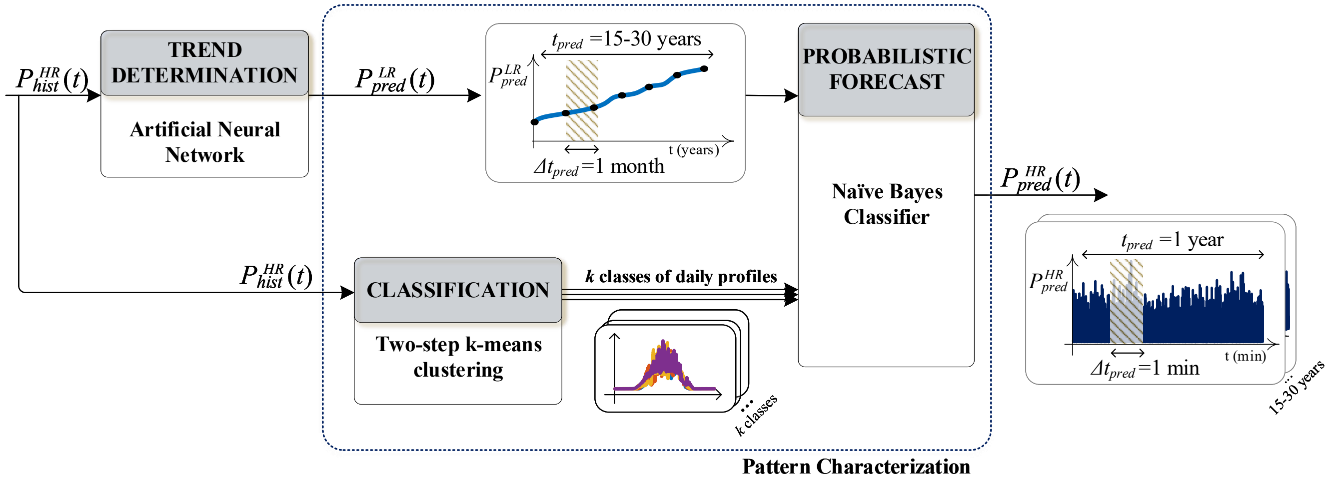

Fig. 3. Proposed model for the long-term forecasting that enables a power electronics reliability estimation within design of power electronics-based power systems. P_{hist}^{HR} are historical data with high time resolution interval (1 sample per minute), P_{pred}^{LR} are predicted data with low time resolution interval (1 sample per month), and P_{pred}^{HR} are predicted data with high time resolution interval (1 sample per minute).

vice versa. The objective function J to be minimized during the clustering process is:

$$J = \sum_{m=1}^{M} \sum_{k=1}^{K} u_{km} \|v_m - c_k\| \tag{1}$$

where u_{km} represents the membership of m-th daily profile feature v_m to a cluster k. c_k is a mean of all daily profiles that belong to the k-th cluster. It is a characteristic daily profile, i.e. centroid of a cluster k.

Daily generation and demand profiles are characterized by the intensity and intra-day variations. The parameters related to the two features are used to classify the daily profiles in a two-step clustering process. In the first step, the input daily profiles are clustered based on the intensity feature. The relevant intensity parameters are a daily peak and average daily value of each profile. Afterwards, each intensity class is clustered based on the intra-day variations characteristic. In this step, the difference between two successive points in a daily profile is used as a relevant feature. The optimal number of intensity clusters N_i is determined using Calinski-Harabasz criterion [23]. Afterwards, this criterion is used to determine the optimal number of variation classes $N_j(i)$ for each intensity class. Therefore, the classification output are K number of classes defined as:

$$K = N_i + \sum_{i=1}^{N_i} N_j(i) \tag{2}$$

The k-th class and corresponding centroids are denoted as C_{IiVj} and c_{IiVj}, where Ii and Vj represent the i-th intensity class and j-th variation class, respectively.

2) Probabilistic Forecast: Naïve Bayes Classifier is employed to determine the occurrence probability of a daily class C_{IiVj} over the span of the forecast horizon. Its working principle is based on Bayes rule, which describes the probability of event with respect to prior knowledge of relevant conditions. The benefit of including the conditional probability is the reduced impact of uncertainty on forecasting accuracy. In fact, it provides more information based on the knowledge of conditions. Furthermore, it gives a possibility to connect the long-term and short-term aspects of the model.

Therefore, Naïve Bayes Classifier determines prior probability distribution of each class based on input historical data P_{hist}^{HR}. Furthermore, it determines the conditional probability (likelihood), i.e., probability of conditions given the outcome class. The relevant conditions are defined by the five attributes in the attribute vector $X = \{x_1, x_2, ..., x_5\}$. The attributes x_1-x_3 provide information about the intensity and variations. The attributes x_1 and x_2 are the previous day mean and peak, respectively. The attribute x_3 is defined as a maximum variation of the previous day. Furthermore, attribute x_4 provides information about a month, where each daily profile is a part of it. The last attribute x_5 provides limited information about the future. It is defined as a monthly mean value, which corresponds to P_{pred}^{LR} obtained from Trend Determination model (see Fig. 3). It is assumed that the likelihood of each continuous attribute in X follow Gaussian distribution. For each new observation (daily profile) with the attribute vector X_o, the forecast of the next day profile class is done by finding the maximum posterior probability [20] :

$$\begin{aligned} &max(P(Y = C_{IiVj}|X_o)) = \\ &max\left\{ \prod_{m=1}^{5} P(X_m|Y = C_{IiVj}) \cdot P(Y = C_{IiVj}) \right\} \end{aligned} \tag{3}$$

Finally, the P_{pred}^{HR} for several years ahead is constructed based on the forecast of daily profiles with high time resolution obtained with (3).

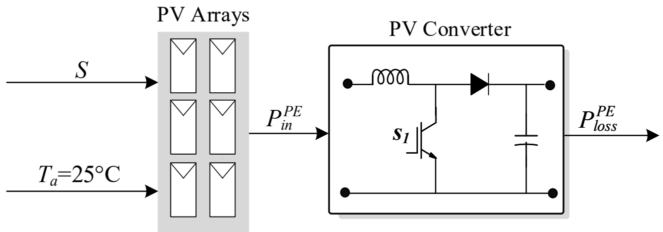

Fig. 4. Architecture of the system used in the numerical analysis: Photovoltaic (PV) arrays connected to the DC/DC converter. Input to the system are solar irradiance S and ambient temperature T_a. P_{in}^{PE} is converter loading and P_{loss}^{PE} is converter loss profile for given loading.

III. Numerical Analysis

An analysis is performed for a system that consists of a photovoltaic (PV) generation unit and a DC/DC converter, as shown in Fig. 4 to illustrate the method. The relevant system parameters are provided in Table I. To forecast the generation profile of this system, a prediction of the input parameters, i.e., solar irradiance S and ambient temperature T_a is necessary. For simplicity, only solar irradiance S is predicted, while the ambient temperature T_a is set to a constant value in this paper. The analysis can be extended to a larger system with several generation and loading units. In such case, it is necessary to determine the power electronics loading from the generation and load profiles as well as from the energy management strategy. The same procedure as in the case of solar irradiance S can be applied to obtain the rest of the relevant forecast profiles (e.g., load demand, ambient temperature, wind speed). The training and testing result for the developed model are presented first. Afterwards, the model validation for the power electronics reliability analysis is carried out.

A. Model Training & Testing

Long short term memory network (Trend Determination) and Naïve Bayes Classifier (Pattern Characterization) are trained and tested. To train the network, Adam optimizer is chosen [22], while the gradient threshold and the learning rate are set to 1 and 0.001, respectively. Furthermore, the loss function adopts mean-squared-error, and the dropout method is adopted to avoid overfitting.

The historical data between 2008 and 2020 from [25] is used. 70% of the data (2008-2016) is allocated for training, while remaining part (2017-2020) is used for testing. The accuracy of the developed models is evaluated by means of the relevant performance metrics. Those are Mean Average Error (MAE) for Trend Determination model and Accuracy Score (AS) for Naïve Bayes Classifier [26]:

$$MAE = \frac{1}{N}\sum_{n=1}^{N} |P_{pred}^{LR}(n) - P_{hist}^{LR}(n)| \quad (4)$$

$$AS = \frac{1}{N}\sum_{n=1}^{N} u_{CR}[C_{IiVj}^{pred}(n) = C_{IiVj}^{act}(n)] \quad (5)$$

TABLE I
Parameters of the System Used in Numerical Analysis

PV array rated power	7.2 kW
DC/DC converter rated power	6 kW (3kW x 2 units)
Reliability-critical component	IGBT (s_1)
Failure mechanism	Bond wire lift-off
Stress parameter	Junction temperature of s_1
Lifetime model	Number of cycles to failure [24]

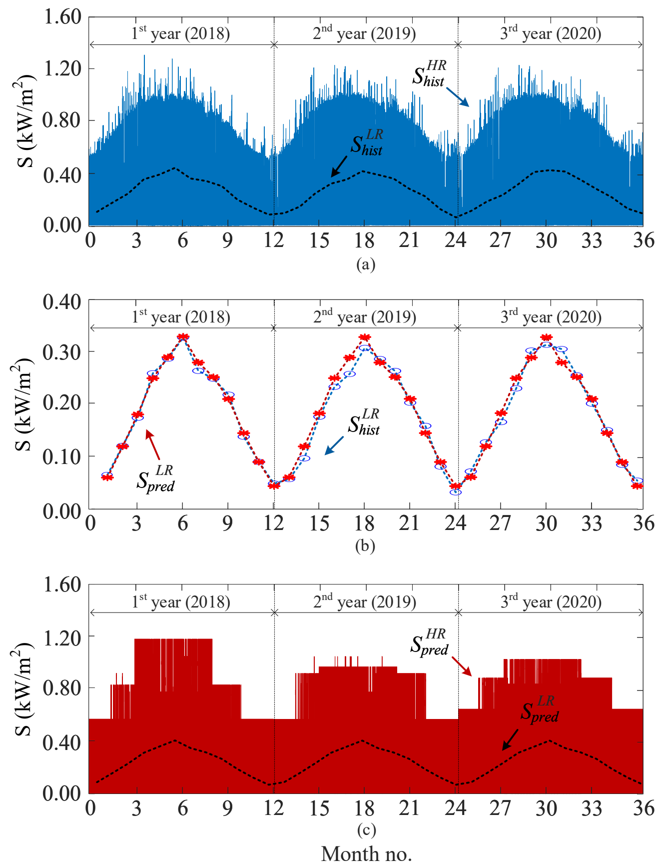

Fig. 5. Numerical analysis testing results: (a) Historical high resolution (1 sample per minute) profile for 2018-2020 S_{hist}^{HR}, (b) predicted low resolution (1 sample per month) profile S_{pred}^{LR} obtained with the Trend Determination model, (c) predicted high resolution (1 sample per minute) profile S_{pred}^{HR} obtained with the Pattern Characterization model.

where u_{CR} is a binary parameter defining the relationship of C_{IiVj}^{pred} and C_{IiVj}^{act} being predicted and actual class for n-th day.

Training results indicate a MAE value of 11.71 W/m^2 for Trend Determination model. Furthermore, in the Pattern Characterization model, the training data is clustered into 10 different classes, for which the Naïve Bayes Classifier yields AS value of 0.78. This refers to that a high score of the true positive rates is obtained for the majority of the classes. In both cases, the obtained values validate the competency of the proposed model. As a part of the testing process, the solar irradiance profile for 2017 is predicted based on the historical data of the previous years. The predicted profile is further

TABLE II
RELIABILITY VALIDATION STUDY: TWO-STEP CLUSTERING RESULTS FOR INPUT SOLAR IRRADIANCE PROFILE.

Class	No. profiles	Maximum Intensity (kW/m^2)	Maximum average variation (kW/m^2)
C_{I1V1}	7	0.24	0.15
C_{I2V1}	107	0.55	0.14
C_{I3V1}	82	0.79	0.18
C_{I3V2}	12	0.70	0.31
C_{I4V1}	26	0.99	0.24
C_{I4V2}	2	1.02	0.63
C_{I4V3}	87	1.0	0.21
C_{I5V1}	27	0.95	0.40
C_{I5V2}	13	0.93	0.33

on used as basis for prediction of the remaining three years in the testing set (2018-2020), like shown in Fig. 5(a). The prediction results for Trend Determination model are shown in Fig. 5(b). There are no large discrepancies in the predicted and actual values. This is also reflected in the MAE value of 10.66 W/m^2. Therefore, it can be concluded that the predicted low resolution profile (1 sample per month) is accurate enough and it can be used for optimum long-term capacity planning. Further on, the predicted monthly results are used in the Pattern Characterization model to obtain high time resolution (1 sample per minute) profile for the three years. The resulting predicted profile is shown in Fig. 5(c), and AS value of 0.79 is obtained. The high resolution prediction profile differs from the actual historical data shown in Fig. 5(a). In fact, the profile is a combination of several different daily profiles obtained within clustering process. It is used to evaluate the power electronics reliability. Therefore, an accurate prediction, as in case of Trend Determination model, where each predicted and actual value differ insignificantly, is not needed. Hence, it is only required that the predicted high resolution profile yields the same reliability results as the actual historical profile. This aspect is investigated further in the following.

B. Model Validation for Power Electronics Reliability Studies

To determine if the prediction accuracy of the proposed model is suitable for power electronics-based system design, a reliability study is performed. The classification represents a critical part of the proposed model. In fact, it is necessary to evaluate if the class centroid c_{IiVj} results in the same stress profile of the power electronic unit as all the daily profiles belonging to the class C_{IiVj}. For that purpose, lifetime consumption LC is evaluated for each daily profile belonging to a class. This is done by following the first three steps of the reliability procedure shown in Fig. 1. A detailed description of the reliability model and the parameters are provided in [27]. Afterwards, the distribution of the class LC is obtained and evaluated by means of the following expression:

$$\sigma_{LC}(C_{IiVj}) \quad \leq \quad 0.1 \cdot \mu_{LC}(C_{IiVj}) \tag{6}$$

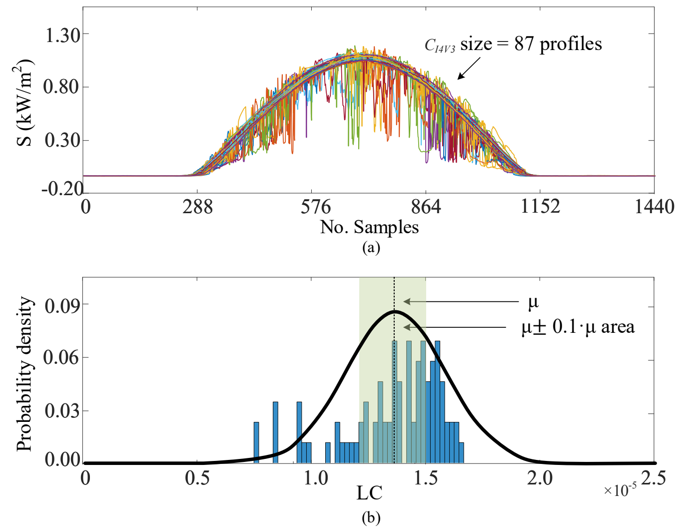

Fig. 6. Reliability validation results: (a) Daily solar irradiance profiles belonging to C_{I4V3} class, (b) Probability density of the C_{I4V3} class.

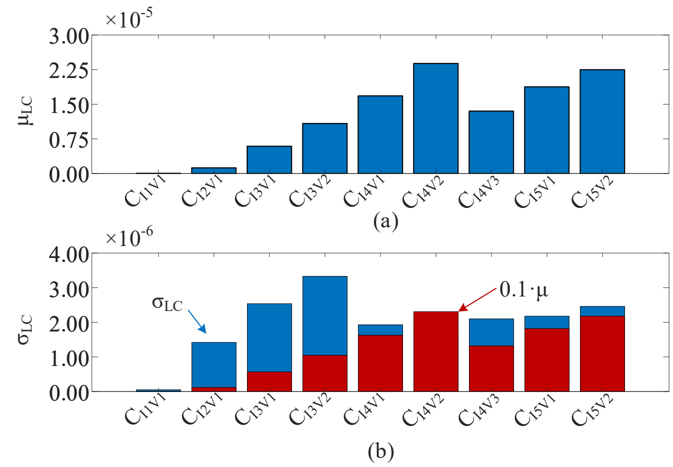

Fig. 7. Reliability validation results: (a) Average lifetime consumption μ_{LC}, (b) Standard deviation σ_{LC} and evaluation criterion $0.1 \cdot \mu_{LC}$ of each class (see Table II).

where μ_{LC} and σ_{LC} are the average LC value and standard deviation of a class C_{IiVj}.

If the majority of the daily profiles of a class C_{IiVj} fulfills the evaluation criterion, it is then sufficient to present them with class centroid c_{IiVj}. The first year of the solar irradiance profile with 1-minute resolution shown in Fig. 5(a) is input to the classification. In the first step of classification, $N_i = 5$ intensity classes are defined. Afterwards, each intensity class is divided into classes based on the variations by following the procedure in Section II. Overall, $K = 9$ classes are obtained, with the main characteristics provided in Table II.

The graphical results are shown with the example of class C_{I4V3} in Fig. 6, while the summary of the results for all 9 classes is presented in Fig. 7. There are overall 87 daily profiles in class C_{I4V3}. The profiles have similar average daily value and variation. However, the solar irradiance variations occur during different periods and intensity levels in a day for the daily profiles belonging to C_{I4V3}. Therefore, the daily power electronics loading profiles differ within a class. However, the results in Fig. 6(b) suggest that the majority of the daily profiles results in a similar LC of the DC/DC converter. Therefore, it can be concluded that the differences in the daily profiles within the class do not significantly influence the reliability results. Hence, the profiles belonging to the class C_{I4V3} can be represented with a single daily profile c_{I4V3}.

To further improve the results, the evaluation criterion in (6) can be adjusted according to the application requirements. Moreover, this reliability criterion can be directly added to the Calinski-Harabasz criterion within the classification process. In that way, a number of classes optimum for accurate reliability evaluation can be achieved.

IV. Conclusion

In this paper, a long-term forecasting model suitable for power electronics-based system design is presented. The model can be used for generation capacity planning and power electronics reliability prediction during long-term planning. First, an artificial intelligence-based model is developed for determination of the future trend in generation and demand. Afterwards, a pattern characterization model based on the two-step clustering method and Naïve Bayes Classifier is developed. Pattern characterization includes trend determination results to forecast high time resolution generation and demand profiles. The case study results on the example of solar irradiance forecast indicate that the model is suitable for power electronics reliability studies. Therefore, the proposed long-term forecasting model can be used for long-term planning of power electronics-based power systems.

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