Chapter 2

Literature Survey

2.1 Introduction

The solar PV systems are being implemented in many places to provide electricity to buildings, organisations, society, and industries too. This significant growing rate of PV systems has attracted the attention of researchers towards its development. The electricity generation from solar PV systems depends on the availability of sun light with good irradiation. The availability of PV generated electricity affects the grid power supply and distribution either in direct or indirect way. Therefore, the connection between grid supply and PV system generation should be given attention so that power can be utilized properly. This will help in achieving a good generation-supply management system from the utility grid with cooperation of solar PV systems. Along with the reliability and availability of grid-connected PV system, the condition monitoring of its components is also crucial. Hence, RACM is focused in this chapter for grid-connected PV system. This helps to produce an accurate prediction of grid-connected PV-based energy generation system and to plan for a scheduled maintenance [1,30]. It aids in the identification of components that can have a significant influence on overall availability and also the cause of failure of the complete system. It may also be used to plan and operate PV systems according to the health status of the system and its components. In case of any fault, the proposed system will warn much earlier so that one can schedule the maintenance date and time rather than sudden shutdown. The research works done in solar PV modules [31–34], Balance of System (BOS) [35,36], and inverters [37] are constrained since reliable data on the failure and repair rates of PV systems is not accessible. Therefore, most of the works available in the literature have considered either one subsystem or subsystems with larger number of components of PV system.

The repair time of components of PV system affects its availability which needs to be considered. In literature, some of the researchers have discussed the dependability and availability of PV system and its component with simple assumptions considered. The authors in [15, 38] have discussed it in detail. The authors have also mentioned the discrepancies coming by the assumptions made while doing simulation and actual experiment with PV system.

For adequate functioning of grid-connected PV system, the availability and dependability are important parameters as discussed in [39–41]. In literature, the most commonly used techniques for reliability analysis including availability and dependability of large system involve RBD and Fault Tree Analysis (FTA) [42]. As discussed by the authors in [39], in FTA, a logical diagram is formed which represents the system and each block of the logical diagram represents its failure rate. Most of the research papers have discussed the system dependability involving with failures of each sub-system which concludes that any single failure is going to be critical for that system. In some research works, dynamic FTA technique is used which involve calculation of failure rates using time-dependent probability density function as discussed in [43]. This method is also having one demerit of not using optimal probability density functions for each sub-system.

An exponential distribution based RBD approach is used in this chapter to analyse the dependability of grid-connected solar PV system. Despite the fact that most of the components of PV system are considered non-repairable equipment, the restoration of life time will have an impact on the device function and should not be overlooked. Thus, the input data for various subsystem failure and repair rates that are necessary for this research are gathered from worldwide databases. The condition monitoring system is very crucial in knowing the current health status of PV system components. This is also helpful in showing the affect of maintenance on life cycle of the component. There are various methods available in the literature for condition monitoring of any equipment like supervised, unsupervised type machine learning techniques and deep learning techniques such as ANN and Convolution Neural Network (CNN). In this chapter, a unsupervised type machine learning technique is used for the monitoring of inverter of PV system. Although it is used when one does not have the historical data or failure data but it is quite simple technique to be applied even if one has the data. The name of the technique is PCA which is well know data dimension reduction technique and unsupervised machine learning technique as well. This technique is used to reduce the dimension of higher dimensional data set and to do statistical analysis of the data for feature extraction. In literature, it has been used for feature extraction also with other machine learning techniques such as SVM and KNN. Therefore, looking at the simplicity and flexibility of PCA technique, it is implemented in this chapter for condition monitoring. The second aim of this thesis is to list the components of PV system according to its criticality so that the weakest component is recognised which fails most frequently.

The main contributions of this chapter are as follows:

- Reliability, availability, maintainability, and condition monitoring of PV system.
- Reliability and availability analysis using RBD method with exponential probability distribution function.
- Listing of components of PV system based on the need of maintenance.
- Condition monitoring of inverters of PV system for failure prediction using PCA technique.

The comparison of the proposed method with the existing methods is shown in Table 2.1. The Reliability, Availability, and Maintainability (RAM), FTA, and RBD techniques are taken from literature for comparison.

Table 2.1: Comparison of the proposed method with existing methods

Parameter	[42]	[8]	[6]	Proposed method
Method used	FTA	FTA	RBD	RBD-PCA
Focused on	Reliability	Reliability	RAM	RACM
Data used	Failure	Failure	Failure and repair	Failure, repair, and monitoring data
Health Prediction	No	No	No	Yes

2.2 Layouts of Solar-PV Systems

Basically, PV systems are classified into two different systems namely, grid-connected and stand-alone systems. The grid ensures reliability of the system by serving as an ideal component for storage in grid-connected PV system, while a battery is required for stand-alone PV system for storage. Fig. 2.1 depicts the arrangement of components in PV system connected with grid. The primary source of generation of electricity for a grid connected solar system is PV array. The operation of grid connected system is intended in parallel and synchronously with the utility network. If more power is obtained than needed during the day, the PV arrays from commercial and residential can sell the excess amount of power to the grid. The power can be bought from the grid during night times or when more power is needed by the sites. Thus, for PV arrays the grid serves as a means of storage during the day. Sometimes batteries can also be present for these PV arrays and they can choose whether to sell the excess power to the grid or store it in the batteries. Stand-alone PV systems are generally sized and designed to supply certain AC and/or DC loads and operation is not dependent on electric grid. For energy storage, a battery is needed by a stand-alone PV system. The battery gets charged when energy is produced in excess or at times of low or no loads. The battery will discharge to meet the load when there is low radiation from sun. In order to ensure a longer lifetime for battery, this charging and discharging process is supervised by a charge controller [44–47].

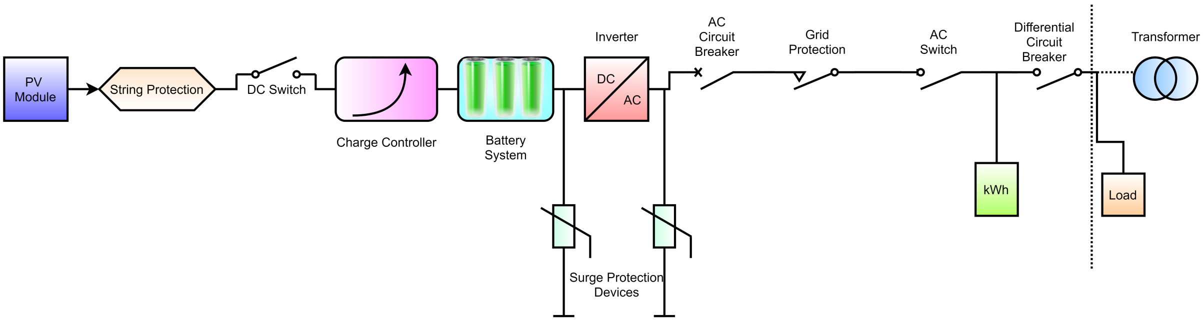

Figure 2.1: Arrangement of components in PV system connected with grid.

The choice of the precise type of system has a large effect on reliability [16, 48]. The PV systems are labelled according to its reliability level having lower or higher reliability. There are two types of PV systems: grid-connected and standalone. The grid connected solar system is preferably positioned near the grid, which without delay fed through its output power. In this type of system, the battery storage is not needed. In case more power is needed, it is fulfilled by the grid. This helps the grid-connected PV system to have high reliability as it can fulfil the demand of the local loads. The loads are also categorized based on the interruption level that can be tolerated by the loads. Based on this, there are three types of loads: non-essential (high interruption is allowed), essential (very small interruption is acceptable), and critical (no interruption is acceptable). Energy storage requirement comes only when the grid is unreliable, in this case for supplying critical loads, storage system is useful then the total system becomes uninterruptible power system. The loads which are placed faraway from the grid-connected PV system, the standalone PV system and grid can be a good solution to fulfill those loads. The battery storage system plays an important role in this case to balance the energy demand. The loads are further divided into two types based on the requirement of the battery storage. The non-deferrable is first kind of load which needs continuous power supply and second one is deferrable loads where the interruption of supply is acceptable and based on the availability of PV power and grid supply, the demand is supplied. Therefore, battery storage is must in non-deferrable loads whereas, it can be neglected for deferrable loads. In this type of loads, battery storage is not recommended. Water irrigation pumping system comes under the deferrable loads [30].

The PV system which is connected with a less reliable grid, an Automatic Static Transfer Switch (ASTS) is used for instantaneous response to the islanding condition of PV system. At this condition, power outage problem or power quality problem arise as the grid gets disconnected. The PV system under islanding condition provides power to the essential and critical loads which needs continuous power supply. The non-essential loads can compromise with the power supply so these loads are disconnected under islanding condition. The main focus of this chapter is on the PV system connected with low reliability gird.

2.3 Reliability and Availability Analysis

The reliability is defined as the probability of system or device performing its function adequately for the period of time intended under the operating conditions intended. The intention is to get a better knowledge of device failure so that product designs may be changed to extend product life and reduce the negative effects of failure. Electric power systems are a prime example of a system that requires a high level of reliability. The key quality of reliability, according to the basic definition, is the probability of the system completing its function adequately. As a result, probability calculations are required for system dependability evaluations. Probability gives an idea how likely an event will occur. The reliability function ($R_{PV}(t)$) can be written in term of probability ($P_{PV}(t)$) as eq 2.1 [6, 15].

$$R_{PV}(t) = P_{PV}(T > t) \tag{2.1}$$

The failure probability $F_{PV}(t)$ is a cumulative distribution function (CDF) is given as eq 2.2 [6, 15].

$$F_{PV}(t) = 1 - R_{PV}(t) = P_{PV}(T \leq t) \tag{2.2}$$

The reliability and unreliability expressed in eqs 2.1 and 2.2 can further written in terms of probability density function ($f_{pdf}(t)$) as given in eqn 2.3 and 2.4 respectively.

$$R_{PV}(t) = \int_{t}^{\infty} f_{pdf}(t)dt \tag{2.3}$$

$$F_{PV}(t) = \int_{-\infty}^{t} f_{pdf}(t)dt \tag{2.4}$$

By using the reliability function or probability density function, the mean time to failure of component 'c' ($MTTF_c$) of PV system can be calculated by the expression given in eq 2.5.

$$MTTF_c = \int_{0}^{\infty} (t \times f_{pdf}(t))dt = \int_{0}^{\infty} R_{PV}(t)dt \tag{2.5}$$

As the PV system components are considered to be of non-repairable type so they can be connected in series in the reliability block diagram and the overall reliability of such system will be given by eq 2.6 where, R_{si} is the reliability of sub-assembly 'si'. For 'm' number of sub-assemblies 'si', the total reliability of the sub-assembly 'si' is given by eq 2.7 where, λ_{si} is the failure rate of sub-assembly 'si'. For 's' number of series connected components with 'P' parallel sub-assemblies, the overall reliability of the system is given by eq 2.8.

$$R_{overall} = \sum_{si=1}^{n} R_{si} \tag{2.6}$$

$$R_{msi} = exp(-\sum_{si=1}^{n}(m_{si}\lambda_{si}t)) \tag{2.7}$$

$$R_{overall} = 1 - (1 - R^{s})^{P} \tag{2.8}$$

2.3.1 System Decomposition

In reliability analysis, the first step is the system decomposition. Based on the working function of each sub-system, the complete PV system is decomposed into its sub-systems during this phase. Each sub-system is further decomposed into its assemblies which is very complicated task for reliability analysis. Therefore, most of the works done in literature are focused on major systems or components but not the sub-assemblies. The another reason for this is the unavailability of the failure, repair and maintenance related information of the sub-assemblies of the larger PV systems. The PV system can be divided into five major components as discussed in [42]. The five major components are: BOS, PV module, DC converter system, DC-AC inverter, and battery system. These five major components are further divided into sub-components as shown in Fig. 2.2. The major drawback observed from the literature is the non-involvement of BOS sub-component of PV system while doing reliability and availability analysis of PV systems. There are only limited works that have considered the reliability and availability of BOS along with the PV modules while doing reliability analysis of the PV system as discussed in [42]. The authors have also discussed the fault tree technique for the reliability analysis of PV modules.

2.3.2 Reliability Evaluation of Inverter System

The layout of the solar power system depends on the architectural design. Based on the number of inverters present in the PV system and the structure of inverter connection with other components, reliability block diagram of inverter is decided. There may be the case when all components are connected to the inverter which is present singly as a central inverter or there may be single inverter present in each line connecting to other components [7]. This affects the overall reliability and availability of the PV system. In case, if only one central inverter is present, the reliability level depneds on the availability and reliability of that single inverter. If multiple inverters are present in the system then, groups of strings are counted as per the number of inverters available for each components.

To do a better analysis of RACM of PV system, a layout has been proposed in this chapter containing a typical three-phase PV system. The sub-systems are IGBT power module, cooling fan, software, DC link capacitors along with Printed Circuit Board (PCB), and AC and DC contactors. In PV module, the 36 cells are connected in series. The inverter part is the most crucial in RACM analysis of PV system.

2.3.3 Reliability Modeling

The data needed for RACM of each component is collected from various resources as mentioned in this chapter wherever needed. The PV module can be further divided into a large number of sub-components but due to the lack of data and to avoid the complication of the system, the whole PV module is considered as a single system for RACM analysis.

RACM evaluation of large PV systems connected with grid is carried out by the usage of a number of reliability methods. Among them, FTA and RBD are considered in most of the reliability works done in the literature. In FTA, the system configuration is represented by a logical sketch and components are represented by each block and they are defined by failure rates. On the opposite hand, RBD is preferred when the failure and repair rates are taken into consideration. Components of an RBD system are understood as series or parallel blocks that are interconnected depending on their impact on the system as a whole. Component failure and repair rates are described by the blocks. Through reliability point of view, the entire system appears to be of sub-assemblies which are in series, in parallel, in a grid, or a series-parallel combined structure of sub-assemblies. This chapter only considers series and parallel processing.

The overall failure rate and repair rate of series connected system are given by the eqs 2.9 and 2.10 respectively and also, the overall failure rate and repair rate of two parallel connected systems are given by eqs 2.11 and 2.12 respectively [6].

$$\lambda_{sys} = \sum_{si=1}^{n} \lambda_{si} \tag{2.9}$$

where, 'si' is representing the sub-system and 'sys' is representing the overall system.

$$\mu_{sys} = \frac{\sum_{si=1}^{n} \lambda_{si}}{\sum_{si=1}^{n} \frac{\lambda_{si}}{\mu_{si}}} \tag{2.10}$$

$$\lambda_p = \frac{\lambda_1 \lambda_2 (\mu_1 + \mu_2)}{\mu_1 \mu_2} \tag{2.11}$$

$$\mu_p = \mu_1 + \mu_2 \tag{2.12}$$

In the series connected system as shown in Fig. 2.2, for the successful operation of the system all the sub-assemblies have to work. If any of one of the sub-assemblies fail then that can result in the failure of the whole system. On the other side, the parallel connected system

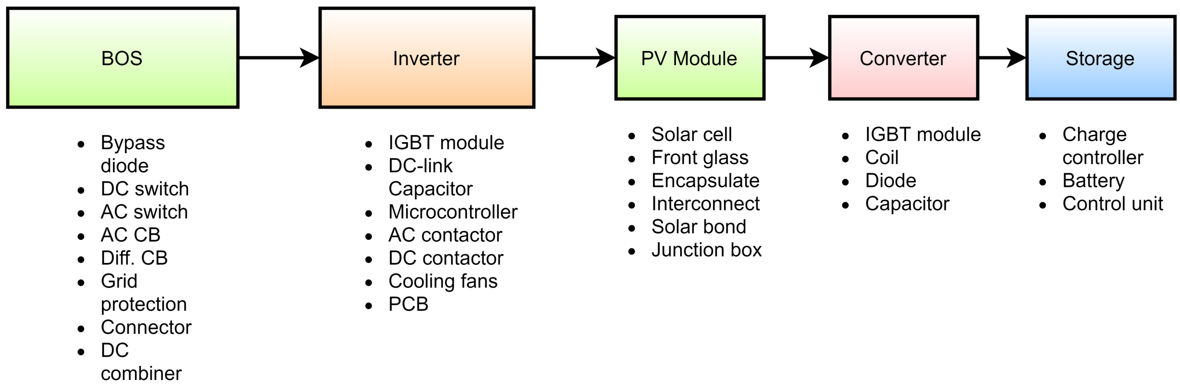

Figure 2.2: Division of PV system into its components and sub-components and reliability block diagram.

failure takes place if all sub-assemblies linked in parallel path are failed and if at least any one of the sub-assembly working is enough to result in the successful operation of the entire system. Therefore, the series connected system is considered as a non-redundant system and the parallel connected system is considered as a totally redundant system. In a system of two components, when failure rate and repair rate of each component are known, the overall failure rate and repair rate are given by eqs 2.11 and 2.12 respectively.

2.3.4 Data Collection

Collecting data of system reliability is one of the main challenging and the most important step in RA analysis. A huge amount of data including failure rate and repair rate of different components of PV systems is gathered from the literature in which different technologies and layouts of PV system are used. The obtained data is first sorted and then median value is calculated for each of the sub assembly. This is because when compared to the calculation of average values, the median values give least uncertainties in the analysis of the data. The Tables A.1 and A.2 in Appendix A show the collected data of each sub-assembly failure and repair rates of solar PV system.

As mentioned in the Tables A.1 and A.2, some of the literature which are used to collect the reliability data, some data which are not available are indicated as Not Available (NA). The main objective of this chapter is to collect the huge amount of data including repair and failure rates of large PV systems. This is done to find the sub-assemblies accurate failure and repair rates values. It can be observed from the Tables A.1 and A.2 in Appendix A that the data gathered is varying a lot and very inconsistent. This is mainly because the data is collected from systems with various configuration and located at various locations, in addition having different climatic conditions. If we consider one reference as the input then so many doubts will be raised like what if the reference that we considered is having an unexpected value which may be occurred when an assumption is made to avoid the absence of data of few sub-assemblies. Therefore, this type of errors and unexpected values in the collected data are avoided by calculating the median of the data after sorting. When compared to the average values calculation the median value will decrease the uncertainties occurred from the unexpected values.

For the evaluation of RA of each sub assembly, the nominal power of the considered PV systems ranges from 100kW to 2500kW. Each sub-assembly of the PV systems contains identical battery (12 CS 11P, 475 Ah, 12 V) is analysed twice for the operation over one year and over 20 years with 8.5 hours of operation per day. There can be different structure of battery connection based on the requirement of the storage capacity [49]. In this chapter, the each battery used has the reserve capacity of two days. The power output of the PV system can not be considered completely for reservation. Only a part of it can be kept as reserved capacity. In this chapter, it is assumed that 5% of the power generated from PV is reserved. The battery storage used for this is having two batteries connected in series where, each battery is of 12 V. After connecting 30 such battery structures, 200 kW rating storage system is prepared. If two batteries of 12 V are used then, 24 V capacity battery will be prepared and the parallel combinations required is 15. For high output power PV systems, the sub-assemblies are increased as shown in Table 2.2 and discussed in detail in [8].

The Tables 2.3 and 2.4 shows the failure rate and repair rate respectively of 7 PV systems of different ratings. These rates are calculated based on the data shown in Tables A.1, A.2 and 2.2 using RBD method as mentioned in eqs 2.9, 2.10 for series connection and eqs 2.11, 2.12 for parallel connection.

2.4 Availability Estimation

The authors in [50] have considered the availability importance measures for enhancing the system reliability. These are important as they help to know the weakest component of the system and one can work on that component to improve the overall reliability and availability of the system.

Table 2.2: Details of sub-assemblies of each component of PV system.

Power (in kW)	100	200	500	1000	1500	2000	2500
PV modules	437	874	2166	4351	6517	8702	10868
Converter	3	6	15	27	42	57	72
Bypass diode	23	46	114	229	343	458	572
AC circuit breaker	1	2	5	9	14	19	24
AC Switch	1	1	1	1	1	1	1
DC switch	3	6	15	27	42	57	72
Differential CB	1	1	1	1	1	1	1
Grid Protection	1	1	1	1	1	1	1
connector (coupler)	874	1748	4332	8702	13034	17404	21736
Inverter	1	2	5	9	14	19	24
Charge controller	1	1	1	1	1	1	1
Battery system	16	30	76	150	224	298	372

Table 2.3: Subsystem failure rate (YR^{-1}) estimated from Tables A.1 and A.2.

Power (in kW)	100	200	500	1000	1500	2000	2500
PV modules	0.020337	0.040674	0.100800	0.20248	0.30328	0.40497	0.50577
converter	0.065153	0.130305	0.325763	0.58637	0.91214	1.23790	1.56366
Inverter	0.124100	0.248200	0.620500	1.11690	1.73740	2.35790	2.97840
BOS	0.077680	0.119890	0.245500	0.43700	0.64710	0.85810	1.06820
Storage System	0.019856	0.019856	0.019856	0.01986	0.01986	0.01986	0.01986

Table 2.4: Subsystem repair rate (YR^{-1}) estimated from Table 2.2

Power (in kW)	100	200	500	1000	1500	2000	2500
PV modules	11.790	11.790	11.790	11.790	11.790	11.790	11.790
converter	310.250	310.250	310.250	310.250	310.250	310.250	310.250
Inverter	6.515	6.515	6.515	6.515	6.515	6.515	6.515
BOS	59.207	57.806	56.554	55.676	55.593	55.541	55.520
Storage System	49.950	49.950	49.950	49.950	49.950	49.950	49.950

Availability importance measure depends on the failure and repair rates and also on the system structure. For every subsystem, it is given by a value between 0 and 1. Among them 1 indicates the best level of importance and on the other hand 0 value indicates the low level of importance. For a system containing n subsystems, the availability importance of subsystem 'si' is given by $I_A^i = A_{sys}/A_{si}$ where, A_{sys} is representing the availability of system and A_{si} is representing the availability of each sub-system. The impact of the availability of the subsystem 'si' on the overall system's availability can be obtained with the aid of using availability importance measure. With the help of availability importance measures, the availability of each sub-system can be calculated and impact of availability of each sub-system on the overall availability can also be analysed. The availability analysis of each sub-system helps to know the weakest sub-component of the system and helps in improving the overall availability of the system.

In availability importance measures, the first motive is to find the sub-system which is affecting the availability of the system most. There are two types of importance measures. One is based on the failure rate and another one is based on the repair rate. As per the name of these importance measures from the failure rate based availability measure, the effect of failure of each sub-system on the overall availability of system can be observed. On the other hand, the repair rate based availability measure helps in knowing the affect of repair of any sub-system or component of system on the overall availability of the system as given in eq 2.13 [6].

$$A_{si} = \frac{\mu_{si}}{\lambda_{si} + \mu_{si}} \tag{2.13}$$

where, λ_{si} is the failure rate of subsystem 'si' and μ_{si} is the repair rate of the subsystem 'si'. When n sub-systems which are independent to each other are connected in series then, the availability of the overall system is as given in eq 2.14. For a subsystem 'si' of a series connected system, the availability importance measure is defined as in eq 2.15 [15, 51].

$$A_{sys} = \prod_{si=1}^{n} A_{si} = \prod_{si=1}^{n} \frac{\mu_{si}}{\lambda_{si} + \mu_{si}} \tag{2.14}$$

$$I_A^{si} = \frac{\partial A_{sys}}{\partial A_{si}} = \prod_{k=1, \neq si}^{n} A_k = \frac{A_{sys}}{A_{si}} \tag{2.15}$$

From eq 2.14, it can be concluded that the availability of subsystem 'si' is not affected importance measure of that particular sub-system. For the subsystem which is having less availability estimate that subsystem must be given the highest priority for the increased availability. The two types of availability importance measures are given by the eqs 2.16 and 2.17 [15,51].

$$I^{si}_{A,\lambda_{si}} = A_{si} \times \frac{1}{\lambda_{si} + \mu_{si}} \tag{2.16}$$

$$I^{si}_{A,\mu_{si}} = A_{sys} \times \frac{\lambda_{si}}{\mu_{si}(\lambda_{si} + \mu_{si})} \tag{2.17}$$

When system is having constant failure rate and constant repair rate, then the easiest way to determine the availability of a system with operating time t is exponential availability model which is given by the eq 2.18.

$$A_{sys}(t) = \frac{\mu}{\lambda + \mu} + \frac{\lambda}{\lambda + \mu} e^{-(\lambda+\mu)t} \tag{2.18}$$

2.5 RACM of Inverters of PV Systems

The condition monitoring refers to the process in which the system or its components are checked regularly to know whether it is functioning properly or not. It can be online or offline process. Due to advancement in the digital technology, the industries are moving towards industry 4.0 revolution and automation of the processes. Each equipment and its components are monitored from a single monitoring screen which is the visualization of the results obtained from reliability, availability, maintainability and maintenance process. Once any system or equipment is given maintenance either as per the scheduled maintenance or predictive maintenance, the reliability and availability of the that system must be updated. This system is possible only when there is an integral condition monitoring system which keeps record of each failure and maintenance.

Being the weakest component of PV system, the inverter is mainly focused in this chapter for condition monitoring. In the similar way, other components can also be monitored. The data set including the reliability and availability can be handled separately. In this chapter, reliability data of inverter is used for the condition monitoring of the inverter. The complete methodology proposed in this chapter is shown in Fig. 2.3. The reliability, availability, and maintainability of the system is already discussed in the earlier sections in this chapter. Now, this section is focused on the condition monitoring of the inverter of PV systems. The first step in monitoring is data pre-processing in which data is normalized or any other statistical method is applied to make the data useful. The most important factor to be taken care in condition monitoring is that the selected data or parameter must be a good predictor of the health of that system or component. In this case, reliability data is found to be a good predictor for inverter. After pre-processing of the data set, the smoothed data is sent to the PCA-based monitoring algorithm. The PCA technique gives the current health status of the inverter and helps in knowing the degradation in health by a visualization output. The PCA-based monitoring algorithm is shown in Fig. 2.4. The collected data set is smoothed or normalized to get the accuracy in the results. The loading matrix is formed using the co-variance matrix of the data set $A_{p\times q}$ where, p and q indicating the number of rows and columns of the data set matrix A respectively. The Principal Components (PCs) are assessed using the loading matrix that has been created. The number of PCs used in the reliability data set is the same as the number of attributes used in the data set. Effective PCs are chosen from among the PCs. The first two PCs are determined to be useful in this scenario, covering 100 percent of the data variation. Using the PCs which are covering most of the data set and the normalized data set, the mean, standard deviation and average path followed by the data, starting and ending points of data, and range of PCs in the scale of score are determined for the further analysis. A boundary is set, based on the nature and coverage of score values by the data set, to monitor the movement direction of data which indicates the degradation in case the data moves away from the centroid. Once maintenance is done for the component, it regains its life cycle and hence, the data again starts from centroid.

In this chapter, RACM of PV systems of seven different ratings and with an average of 8.5 hours operation per day is presented. Reliability for non-repairable system which contains n independent sub-assemblies which are connected in series can be calculated by eq 2.19 [51].

$$R_{system} = \prod_{si=1}^{n} R_{si} \tag{2.19}$$

where, R_{si} is representing the sub-assembly 'si' reliability. The overall reliability of sub-assembly in case of exponential distribution is given by eq 2.20 where, m_{si} is representing the total number of 'si' sub-assembly, and λ_{si} is representing the failure rate of 'si' sub-assembly.

$$R_{sub-assembly,Tot} = exp(\sum_{si=1}^{n} m_{si}\lambda_{si}t) \tag{2.20}$$

The proposed algorithm helps in getting the health monitoring of the inverter as shown in Fig. 2.5. It depicts the alarm system created using the PCA approach. If the data points are inside the inner rectangle which is shown in green color, the inverter is operating normally; if the

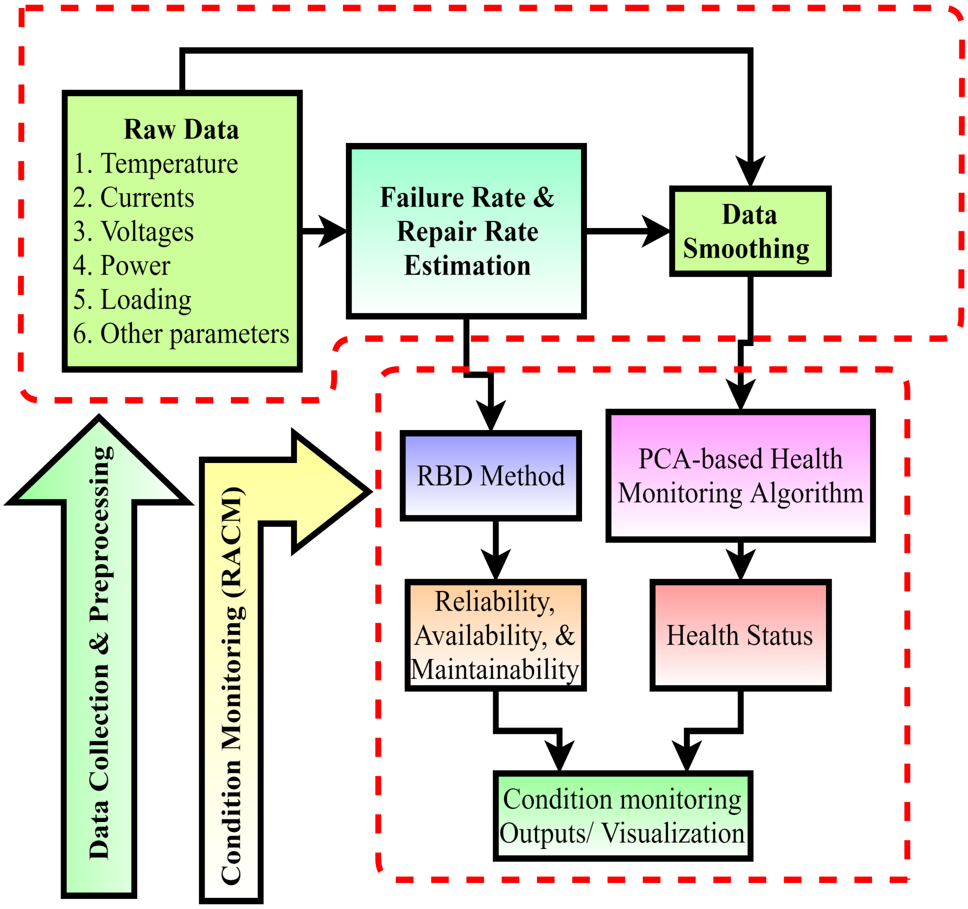

Figure 2.3: The proposed methodology for RACM in PV systems.

data points are lying in the rectangle of orange color, there is a problem with the inverter and it is degrading, and the system will automatically raise an alarm; and if the data points are moving to the region of red rectangle, the system will raise an alert that the inverter is not operating normally and that a problem has occurred. The coverage and boundary of distinct operating conditions are computed using the PCA technique and the score coefficients of the PCs, rather than being chosen at random. The score coefficients of PCs are key factors for inverter health monitoring. When the maintenance crew and the operator get an automated health status update via an alarm system, email, and text message, the condition monitoring system will be reliable. When a fault scenario is detected, the system sends an email to the maintenance team members as well as an appropriate alarm.

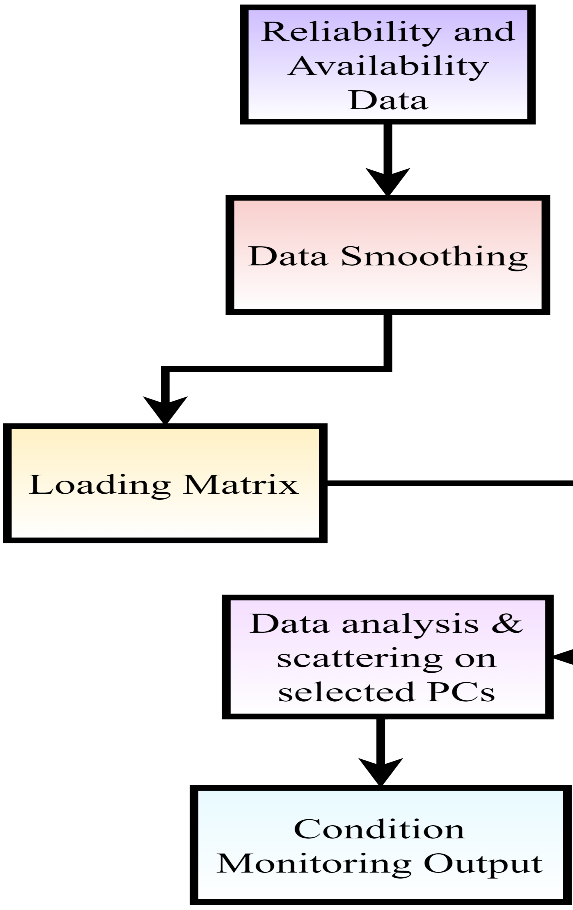

Figure 2.4: Flow chart of PCA-based condition monitoring algorithm.

2.6 OC Fault Diagnosis of Inverters

It is clear from the literature that inverter making an important part of electrical drives system, EVs, PV and power system. It is also known that inverter is the weakest component of PV system and needs maintenance and monitoring system. Hence, the next chapters of this thesis are going to deal with the condition monitoring of inverters using different techniques.This thesis work discusses the detection algorithms for OC faults occurring in power inverters due to high stress in industrial drive systems and also in EVs. Two types of faults mainly occur in inverter's switches: SC fault and OC fault. In SC fault, the current increases by 4 to 5 times of the normal value but in OC fault, there is no such difference is observed for a long time. Hence, detection of OC faults is difficult and crucial too. For the condition monitoring system to be reliable, the faults must be detected at minimum possible time. Otherwise, the OC fault which causes distorted output waveform of inverter, may damage the drive system and the whole process may gets disturbed. For this, fault detection time must be as short as possible. As

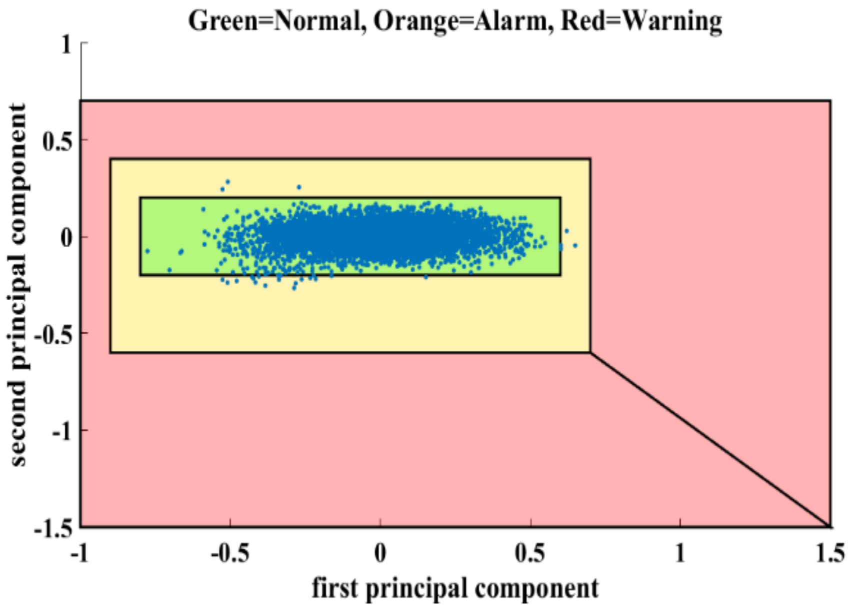

Figure 2.5: Condition monitoring output showing the data points lying in normal, warning, and alarm range.

a result, the focus of this thesis is on the detection and localization of OC faults in three-phase inverter switches.

The converters and inverters form vital part of electrical power system. The proper functioning of the whole power system depends on its components [1]. Therefore, each component should be reliable and diagnosable. Once the fault is known in a reasonable amount of time, the tolerant capability of the IGBT-based Multilevel Inverter (MLI) and MMI improves under OC faults. In the event that the IGBTs fail, it will use the redundant switches. As a result, the switches, converters, and inverters' fault diagnosis system must be predictable, precise, and quick to respond.

The OC fault detection of inverter switches has been focused in the literature by many researchers. In [52], the various OC fault detection and localization methods have been discussed and compared. The authors in [53] have proposed an OC fault detection method for MMI in which the faulty Sub-Module (SM) is detected. For this, the measured state variables and the estimated state variables are compared using a Kalman Filter. Similar work has been done in [54] for detecting the faulty SM of MMI using various machine learning techniques including mixed Kernel type Support Tensor Machine (STM) and single Kernel function based STM such as linear, radial, sigmoid and polynomial types. These methods are able to detect the faulty SM but not able to detect and localize the exact faulty switch. The paper [55] discussed the OC fault detection for switches of cascaded H-bridge MLI using PCA- based feature extraction technique and Multiclass Relevance Vector Machine (MRVM) for classification of fault. The PCA being used for feature extraction and dimension reduction of the collected data set, consumes more time and having large computational burden. Also, before feature extraction, the signals of inverter is passed through a Fast Fourier Transform (FFT) algorithm which again adds complication and time to the detection system. The paper [56] also used the PCA and deep PCA (DPCA) techniques for OC fault detection in inverter but localization of faulty switch is not possible by the proposed method. The Sliding Mode Observer (SMO) based OC fault detection algorithm is proposed in [57] for MMI which is found to be very simple and effective. It can distinguish the fault from noise and other uncertainties but still the detection time is 50 ms which can be further reduced by using different fault detection algorithms involving less computational burden. Similar work has been done in [58] using Extended State Observer by estimating and observing the voltage signal for detection of OC fault within 15 ms.

The fastness of the detection algorithm can be represented either in terms of time unit or percentage of the time period of the operating signal. The work done in [59] is focused on the detection of OC faults of IGBTs in three-phase inverter using Park's transformation of three phase currents for feature extraction. The detection time is found to be 54% of the cycle of operating signal. Another method discussed in [60] is based on Radial Basis Function Neural Network (RBFNN) which is capable of detecting the OC fault in lesser than half cycle of the signal. The OC fault detection based on residual difference of estimated and actual DC-link voltages has been proposed in [61] which claims the detection of the fault in lesser time and it is smaller than quarter time period. The authors [62, 63] found algorithms based on Variable Parameter Moving Average Method (VPMAM) to diagnose the OC faults in switches of three-phase inverter which can detect the fault in 14.9% and 15.5% of the time period of current signal. These are the least time observed in the literature for OC faults detection but the time of detection can be reduced further by alternating methods. For the accurate and better fault localization algorithm, the features used must be good predictors so that miss-classification can be avoided. The authors in [64] have proposed the method of finding energy at each node of different frequency components of signal decomposed using signal symmetry reconstitution prepossessing method. For localization of fault, ANN based technique is used which uses the energy as feature for classification. The work done in [64] claims fault localization time to be 50 ms and detection time is to be 10 ms which is for single IGBT fault detection. The

Table 2.5: Comparison of fault detection time of proposed methods with existing techniques

Technique	Detection Time (ms)	Reference
ESO	150	[66]
Kalman Filter	100	[53]
SMO	50	[57]
Wavelet-RBFNN	less than half cycle of current waveform	[60]
PCA-MRVM	more than one cycle	[55]
Residual-based observer	15-20	[67]
2 sample-EWP-SVM Technique	less than 0.33 ms	Proposed Technique

method is not validated for faults in multiple IGBTs. For ANN to be trained properly, data of all different possible OC faults need to be collected and learnt by the model. In literature, there are various machine learning techniques available which are suitable for OC fault detection and localization. Again, [65] proposed an OC fault detection algorithm which indicates the fault condition in 0.5 ms but not able to localize the faulty switch. It is also not validated for faults in multiple switches. Among supervised and unsupervised machine learning techniques, the supervised type machine learning techniques give better and accurate results as discussed in [52] in which the authors found MLP and SVM techniques to be better than k-Nearest Neighbor (KNN) and PCA. The fault detection time and localization time definitely affect the reliability of the detection algorithm and the overall system.

The signal processing based algorithms including wavelet packets and wavelet energy and wavelet entropy are also found to be effective in OC fault detection of IGBTs in inverters [68]. The accuracy of the fault localization method depends of the features used for its learning. The accuracy of the SVM method used in [68] for OC fault localization is 94.12% which can be increased by using strong features which can be good predictor of the working condition of the IGBTs. The comparison of the proposed methods with existing methods in the literature is provided in Table 2.5.

In the next coming chapters of this thesis, wavelet entropy based, two sample based, and Walsh-Function based features have been used to detect and localize the faulty IGBTs. The proposed methods are able to detect the OC fault in just two consecutive samples and less than 10% of the cycle of the operating signal. The accuracy of the localization of faulty switches is 99-100% using KNN and MLP algorithms. The methods are discussed in details in the next chapters.

2.7 Summary

In this chapter, the detailed literature related to reliability analysis, availability analysis of PV system is discussed. In PV system, wind system, EVs, and other electrical drive systems, the inverter is found to form the weakest part as discussed in chapter one and chapter two. Therefore, inverter is focused in the next chapters of this thesis for reliability, availability and condition monitoring. The overall method is called as RACM which utilizes the various condition monitoring techniques which are proposed in this thesis and discussed in detail in chapters three, four, and five. In this chapter, PCA based condition monitoring algorithm is discussed along with RBD based reliability and availability analysis method for the RACM of inverter. The proposed method in this chapter is observed to be good for reliability enhancement of the system but for improving the results and reliability of the condition monitoring methods, supervised machine learning techniques are proposed in the next chapters. The supervised machine leanring based approaches use strong features extracted from the three-phase currents and voltages of the inverter to provide better, faster, and reliable condition monitoring system. In the next chapter, two-samples based OC fault diagnosis algorithm and SVM based fault localization algorithm utilizing EWP as feature is used for RACM of inverter which is found to give accurate and faster results as compared to unsupervised techniques and other techniques available in the literature.