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Techniques of infrared thermography for condition monitoring of electrical power equipment

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Abstract

The application of computer vision continues to widen with advancement in technology. Imaging systems which provide necessary inputs to the computer-vision-based models can come in various ways. Such as X-ray images, Computed Tomography (CT) scan images, and Infrared (IR) images. This paper is a review of different application areas of infrared thermography (IRT) for monitoring the status of electrical power equipment. It summarizes in tabular form recent research and relevant works within the field of condition monitoring of power assets. A general review of the application of IRT in power devices was undertaken before a specific review of selected works based on IRT for important electrical power equipment with a tabular review of possible causes of hotspots using photovoltaic installation as a reference. Results of previous works were presented with highlights on performance metrics used and accuracies achieved. Emphasis where made on the future potential of IRT and some associated techniques. The work saw that heat production within systems during operation is an important characteristic that enables IRT to become applicable for monitoring diverse physical systems, most importantly power systems. The high cost of high-definition, and long-range IR cameras limits the wide adoption of the technology for its potential applications for monitoring power installations. The work recommends future research in the development of affordable IR imaging systems with advanced features for condition monitoring of physical systems such as power installations.

Keywords: Infrared thermography, Condition monitoring, Electrical power equipment, Non-contact electrical inspection, Thermal imaging, Generative adversarial network

Introduction

According to Dhimish, et al. [1] as well as in another work by Solo´rzano and Egido [2], hotspots are abnormal high temperatures at connections between power equipment or in power system components themselves caused by faults and improper operation of equipment within the network. Normally, the temperature of objects has been used as a reliable index for gauging the health of biological and inanimate systems. In biomedical fields, Najimi et al. [3] opined that temperature measurements give easy insight into the existence of diseases within the body. The story is not different in physical industrial systems made of interconnected systems that usually convey energy from one point to another. Different types of thermal sensing devices have been developed for various temperature measuring applications; ranging from conventional thermocouples, thermostats, thermistors, thermopiles, thermometers, and state-of-the-art infrared (IR) thermal pointing devices, IR imaging cameras, etc. Hence, Bach et al. [4] saw that detection of hotspots in equipment or installations could become quite a challenge using the conventional methods of temperature measurements because they could become time-consuming, costly, and unsafe for personnel and equipment. However, Infrared imaging or thermography would be suited for applications where safety, cost, and time must be optimized. Moreover, Madding et al. [5] and Usamentiaga et al. [6] inferred that the need for good resolution, optimal temperature range, stability, and accuracy of the temperature measuring device encourages the adoption of the IRT application as the method of choice for condition monitoring of industrial systems.

In order to perform noncontact temperature recording, the camera will be appropriately set for optimal thermal imaging temperature. Some of these settings are not limited to emissivity, resolution, etc. Others include the transmission ability of the transmitting medium (usually air) and the temperature of that transmitting medium. All these settings will affect the ultimate output for the temperature of the object being viewed. These parameters and others ensure that the thermal imaging camera has become an excellent tool for condition monitoring of electrical and mechanical systems in the power industry.

For instance, Alvarado-Hernandez et al [7] pointed out that monitoring of power equipment would inadvertently aid the efficiency of the equipment and improve users' experience and give leverage for enhancing the operation of the device using advanced intelligent optimization techniques.

This work was organized to give insight into the importance of using IR imaging techniques for monitoring the status of equipment in electrical installation with tabular briefs of diverse works done by different authors using the concept of infrared thermography (IRT). Then, under specific application areas, critical reviews of research done using IRT were presented by showing observed drawbacks of the highlighted methodologies and concluded with recommendations for possible future research.

Review of IRT methodology in various works

Between 2002 till date, many research works have been published in reputable journals. More compelling is that the researches have grown over the years and some of the work are presented in Table 1 which shows the various methods and focus of the works.

One important advantage of IRT for power equipment monitoring lies in the fact that the effectiveness and efficiency of the technique to produce good results does not depend on the operating voltage of the equipment, hence it has found wide use in many areas of equipment monitoring.

Selected papers where infra-red thermography were applied in different areas or critical devices in the power installations was reviewed in the succeeding sections.

Table 1 Recent works in infrared thermography for monitoring electrical equipment

Reference	Methodology/focus of the research
Feng et al. [8]	The work presented a deployment of an electric transformer thermal assessment scheme using a matching heat model of the thermal circuit. The model sampled mean temperature values of the oil, coils, core, and ambient as well as thermal capacitors and the status of the ONAN/OFAF cooling schemes, whereas the corresponding output parameters are the oil changes in temperature at the inlet and outlet channels, the temperature of the hotspot, the position of the tap changer, loadability indices, and some evaluation criteria The model was simulated using an object-based technique in three parts: real-time capturing of temperature inputs, development of the thermal model and monitoring terminal, and internet application
Ali-Younus and Yang [9]	Studied IR thermal image using discrete wavelet at second decomposition level under four machine states: normal, bearing, mass-imbalance, and misalignment faults. The authors presented a mechanism for obtaining machine state indices from field IRT images using DWT. The method involves a setup of a 0.5hp variable dc motor fault simulator with a flexibly coupled 30 mm diameter shaft rotating at 3450 rpm and monitored by a FLIR Thermocam. Features of interest for the final analysis of each of the four machine conditions are the average, standard deviation, kurtosis, entropy, mean absolute deviation (MAD), and skew
Manana et al. [10]	Analyzed various electric motor manufacture-induced defect conditions like turn-turn faults, earth to live winding faults and disconnected winding, among other fault conditions, which can come from manufacturing of field poles and insertion inside the stator
Eftekhari et al. [11]	Presented a measure of inter-turn short circuit fault in induction motor in the stator electric circuit using IRT. Histogram of thermal images provided features of interest gotten and compared between good and abnormal 4pole, 2hp, 380 V IM driving servo motor load. The stator coils were supplied with 220 V to evade catastrophic harm to the machine, especially in the short circuit condition. In computing the distance of the r color vector to the average vector μ, the Mahalanobis distance was preferred over the Euclidean distance for measuring divergence in pixels of the IR image. The authors used $Hull_{index}$, Hot_{area}, and $Histogram_{mean\ values}$ to forecast hot spots in the stator
Cui et al. [12]	The work discussed the method of feature extraction, de-noising, and segmentation as used in image processing for improving accuracy of diagnostic models by the use of Backpropagation and Radial Basis Function in neural networks for intelligent solutions of faults
Jadin et al.[13]	The paper focused on a semi-automatic, qualitative IR image analysis for quick thermal fault detection and classification. Normalized Cross-Correlation (NCC) algorithm was adopted to detect related parts of interest in the pictures. Thereafter, important numerical features of the images were collected from each identified region and grouped with multilayer perceptron (MLP) for obtaining the temperature of the electrical unit
Huda and Taib [14]	The authors identified a system for checking the status of power equipment using intelligent networks taking features like component-based intensity features, first-order histogram-based statistics, and gray-level co-occurrence matrix gotten by analyzing the images, that are applied as input for the neural network model. Using four separate training algorithms like Resilient back propagation, Levenberg–Marquardt, Bayesian Regularization, and Scale conjugate gradient, the work trained the multilayered perceptron networks. With the component-based intensity features outperforming the other two features. Later, the Levenberg–Marquardt produced good classification results when training the MLP network algorithm for the classification of the status of electrical equipment
Huda and Taib [15]	The use of intelligent IRT for preventive and predictive maintenance for fault detection in electrical devices was the goal of the research, thermal defects in electrical equipment. The authors applied statistical structures to feed the classification network. And, used both MLP as well as discriminant analysis classification models. With a classification accuracy of 82.4%, the discriminant-based model outperformed that of the neural network classifier

Table 1 (continued)

Reference	Methodology/focus of the research
Garcia et al. [16]	IR image segmentation and statistical feature extraction for regions of interest by the application of a motor current signature analysis (MCSA) balancing technique for isolating bearing issues, lop-sided mass, and misaligned rotor
Karvelis et al. [17]	The paper focused on the automatic pattern recognition process in infrared images based on object matching by analyzing four abnormal electro-mechanical conditions of the IM like imbalances in the stator, failure of the cooling fan, defective bearings, and broken rotor structure. The authors divided the IM into the frame, fan cover, and motor coupling as well as using a combination of photometric and geometric invariant descriptors. The feature descriptors were obtained in 6 steps from the various points of interest located in the machine. SIFT key points were gotten from both the training and target image samples. Then, the geometric transformations between the two images were calculated after matching their respective SIFTs. Later, models of the test and train images were matched using earlier geometric transformations. The average intensity of any section of the IM together with its surroundings were obtained. Before classifying the temperature to isolate the nature of the problem. The research captured IR images of a 1.1-kW IM driving an auxiliary DC machine using a FLIR S65 IR camera. Applied the Naïve Bayes and C4.5 Tree-based classification models validated by a tenfold cross-validation model to gauge the classifier's performance
Janssens et al. [18]	Used two image-processing pipelines for identifying rotor imbalance irrespective of bearing defects by firstly discounting successive image frames that are thereafter abridged to their spread within the image coordinates and secondly identifying bearing defects notwithstanding machine imbalanced by the introduction of the standard deviation of the temperature, the Gini coefficient, and the Moment of Light
Zou et al. [19]	An original IR-based two-stage artificial intelligence classification technique for diagnosis of faulty states of electrical devices. The initial stage was based on the K-means algorithm for the extraction of region and thermal data. The next stage deals with the selection of IR image-relevant features. A set of seven features of both stages were taken as input and fed to the support vector machine (SVM) classification algorithm. The final SVM model was optimized using a coarse-to-fine parameter optimization method and compared with backpropagation
Munoz-Ornelas et al. [20]	Studied how camera position or location impacts monitoring of induction motors from 6 orientations not limited to distance from the object, the angle from the target and height above the target, etc.
Ramirez-Nunez et al. [21]	A new method of auto fine-tuning of the thermal camera with additional external temperature sensors to standardize IR images for improved accuracy of the actual temperature of the object
Singh et al. [22]	Electric motor transient analysis at different stages of operation using IRT and applicable pseudo-coloring method
Singh et al. [23]	Failure of cooling system recognition using IRT for no-load and loaded operating condition
Dragomir et al. [24]	The authors looked at the effects of dust from electrical assets on IR images and gauged the associated thermal stress. They presented a method of delineation of a copper bar into different six surface areas of various reflexivity with different thicknesses of dust particles on each surface area. Experimented with a 300A applied on the copper bar for 50 min until constant temperature was reached. The setup was accomplished with a FLIR T650°C alongside a temperature logger and a FLIR Max IR analytical software. And concluded that dust particles limit reflexivity from such metallic surfaces while enhancing its IR emissivity
Khan et al. [25]	Presented the application of a specific IR camera called IRISYS (IRI4010) for condition assessment of electric motors and power transformers used along with the IRISYS ISI 4604–4000 Series Imager Software

Table 1 (continued)

Reference	Methodology/focus of the research
Dutta et al. [26]	IR images of power equipment were captured and transformed to the appropriate HSI color model, taking cognizance of the hue region for further processing. Edge detection filters such as Sobel, Prewitt, and Roberts were applied to detect high-temperature areas within the IR image. The Otsu image segmentation algorithm was used for clustering the hue regions and with 27 IR images, analyzed with MSE and Peak SNR; the method provided improved segmentation results in comparison with its monochromatic images
Resendiz-Ochoa [27]	Achieved a segmented thermal image using manual thresholding of the IR images, for detection of hotspots in power equipment under investigation
Liu et al. [28]	Presented a rotor platform defect identification based on infrared image and convolution neural network (CNN) classification algorithm for auto-selection of IR image feature and fault type identification
Lopez-Perez and Antonino-Daviu [29]	Presents an illustrative model based on IR images that hinge on the study of Isotherms by showing the temperature gradient and locating the point of the defect using three case studies: a 4Pole 3ph 58 kW, 380 V motor driving a blower; a 2pole 3ph 10 kW, 380 V motor driving pump in polyol tank; and a 4pole 3ph 75 kW 380 V motor driving a fan cooling tower
Dragomir et al. [30]	The work focused on the application of IRT for heat stress detection in HV busbar under electrical load considering the extraneous conditions and correction indices necessary for getting valid results
Mariprasath and Kirubakaran [31]	The research identified various parameters and methods that can be used to assess the health of power transformers such as internal fault detectors, Recovery Voltage technique, Furan Current Analysis, Expert system based software, Frequency Response Analysis, online PD detection, Dissolved Gas Analysis, and Power quality systems. The authors highlighted the merits and demerits of each method and applied six case studies of IRT to depict different locations of hotspots in power transformers of different ratings and recommended IRT for effective, safe, and efficient CM
Sangeetha et al. [32]	The research obtained single- and dual-dimensional relationships between the distance of image capture, emissivity, and hotspot temperature having derived a relationship between the aforementioned three parameters
Fambrini et al. [33]	The research presented an auto-IRT-based system for fault real-time monitoring of power distribution networks using deep learning image processing-based neural networks. The legacy JSEG IR image segmentation was used and the result proved the method would supersede the manual monitoring method
Sahu et al. [34]	The work presented an IRT methodology for monitoring aging acceleration in transformer insulation, by calculating its per unit life. Thereafter, identified effects of transformer insulation's Aging Accelerating Factor (AAF_{TI}) caused by unusually high abnormal temperature on the equipment windings. Data were sourced from IR images of transformers as well as associated readings of oil temperatures at the top of the tank taken at different intervals. The proposal discussed the effect tank coefficient of reflexivity and oil emissivity on predicting the hotspot in the windings using digital image processing with mathematical expressions found in the IEEE Guide to Loading. The authors developed a model equation for calculating the revised temperature value of the existing hotspot and record any mismatch error found. The model indicated that the actual hotspot in the winding depends on the winding hotspot temperature, the top oil temperature read by the IR camera, and the top oil temperature pointed by the oil temperature indicator
Najafi et al. [35]	The authors proposed an interpretable Machine Learning containing an automated channel for assessing the status of power assets by means IRT dataset. The application of a pre-processing stage divides the images based on the unit's temperature, that is cold or hot conditions. Finally, a sliding window technique based on AdaBoost and Random Forest (RF)-based classifiers were utilized for segmentation

Table 1 (continued)

Reference	Methodology/focus of the research
Vidhya et al. [36]	Used Symlet wave transform to achieve flatter transformer breather image decomposition of typical parameters of IR images. The images were represented in discrete form by the mechanism of discrete transformation. The statistical information derived from the transformation under different states of decomposition reveals the changes in the temperature distribution within the breather piping system at defined functional states of the transformer. The Symlet technique shows very low asymmetric features in most types of Daubechies wavelets. Comparison of the decomposition was done for normal and abnormal operating conditions. Local regions were defined through feature descriptors like histograms. The result shows that wavelets can bring out inherent characteristics of the IR image
Mahami et al. [37]	The work used the Bag-of-Visual Word (BoVW) to capture anomalies in IR features with Speeded-Up Robust Features (SURF) detector and descriptor. Also applied the Ensemble learning-based Extremely Randomized Tree (ERT) to automatically identify anomalies in IM

Review of infra-red thermographs in critical power equipment

Power transformers

Utami et al. [38] presented a transformer monitoring scheme with IRT results of the tank, tap regulating device, cooling system, and external insulators. The work involves analyzing the top, bottom, sides, and center of two transformers (normal and abnormal) of the same rating and loading, whereas Asiegbu et al. [39] presented an RLC thermal network model that could reflect the basic equivalent circuit of the transformer which would be applied to develop a comparable analogous thermal model in terms of electrical parameters. Changes in the thermal capacitance of power equipment indicate the condition of the insulation in inductive loads like transformers and cause the working temperature to increase. The analogous model was then used to perform the thermal gradient evaluation of the system. On their part, Fang et al. [40] proposed a method of fault diagnosis of electric transformers using semi-supervised learning to train infrared image processed data. The work adopted a support vector machine for fault classification, whereas the infrared images were clustered utilizing the *K*-means technique. The authors used feature extraction and generative adversarial networks to get artificial data of the labeled images before applying a semi-supervised graph model to train both the labeled and unlabeled images. However, the SVM does not perform well for large datasets, requires a long period of training, and adversely affected by noisy datasets. Moreover, the SVM technique finds it difficult to compute local optimal condition and could be quite complex to implement. The major issue with *K*-means is linked to its vulnerability to outliers.

Mlakic et al. [41] applied modern machine learning tools for power asset monitoring inspired to present a fault identification technique in transformers using deep learning tools for the analysis of IR images of 10/0.4 kV distribution transformers. The authors applied the AlexNet CNN-based learning algorithm in Matlab for processing the raw image datasets. The work restated that as a diagnostic tool, the IR imaging tool can yield important insight into the heat intensity and its distribution within power equipment as well as the rate of energy flow from the hotspots in the device. These data can be applied to isolate the level of disorder within the unit. The authors emphasized that unequal distribution of heat radiated from the cooling fins could be a result of the presence of air pouches or low oil levels therein. The research described the CNN architecture with the human visual system and how its layers effect the process of image recognition. The case study involves image acquisition during normal and abnormal conditions of the equipment. The datasets are labeled based on the brightness of identified hotspots. However, large convolution filters used in the AlexNet is not quite optimal because of issue of overfitting, longer training time, etc. because it would increase the number of parameters, thereby raising the amount of unrelated features that can be extracted which limits the learning ability of the algorithm with respect to features common to different situations and therefore generalize poorly. And the depth of the AlexNet is not sufficient in comparison with other deep models like ResNet, VGGNet, etc. Again, the adoption of the normal distribution instead of the Xavier Glorot (XG) method for weight initialization, hinders the ability of the algorithm to overcome issues of vanishing gradient. The XG function can initialize weights of neural networks in a manner to limit the variance of the activations in each layer, thereby solving the problem of vanishing or exploding gradients, hence the XG function has been applied to later versions of AlexNet.

Similarly, Shiravan et al. [42] IRT and computational fluid dynamics (CFD) of 3 transformers of different ratings; 630 kVA, 400 kVA, and 50 kVA. And predicted faults in the transformers' cooling mechanism by a combination of both IRT and CFD techniques. The authors developed a thermal model of the transformers using nonlinear thermal resistive components which were developed further into differential equations considering design-dependent parameters (DDP) and empirical factors (EFs). The CFD technique used was finite volume based and simulated in ANSYS FLUENT version 19. Validation of the proposed model was done by comparing the maximum error and the root mean square error (RMSE) of the CFD model with that of the thermal model. Decision criteria were based on the difference in temperature between both methods was more than 4 °C for the radiator or top oil, then the unit is not okay; if it is 6 °C or more, then the unit is not only faulty but its cooling system is not good. The challenge of using the RMSE of evaluation metric lies in the fact that it is affected by the scale of data used such that as the error rises its value also increases. The RMSE is also dependent on the distribution of outliers within the dataset and would normally increase with the extent of the dataset.

But Jiang et al. [43] proposed a mask R-CNN and modified Pulse Coupled neural network joint method for determining faults in bushings of electrical equipment using IRT images. Noting that problems in bushings make up 5–50% of faults in transformers, the authors used relative position and coverage area of fault as parameters of concern for feature extraction. The work noted that when PCNN method was used for segmenting the target pixels around the feature-mapped areas and extraction of the faulty regions, the result was an image with lots of difficulties to remove noises. This encouraged them to apply a simple linear iterative clustering (SLIC) to produce definite frames, thereby limiting undesirable effects of borders on the PCNN by finding the mean of nearby colors. By this method, the metrics of the PCNN were enhanced. Different bushing fault conditions were evaluated as dielectric loss, connection fault, oil leakage, and partial discharge with regard to coverage areas. With over 2000 images from 51 stations in China, a batch size of 2, number of epochs and iterations per epoch set to 30 and 100, respectively; the work used validation steps of 50 and simulated with an XEON-W3 processor running Nvidia GTX 1080 graphics on Ubuntu 16.04 LTS operating system installed on 64 GB memory. Nevertheless, the use of the PCNN could become cumbersome with respect to the complexity and number of parameters required to be set for optimum performance according to Huang, et al. [44]. In the same way, the author's use of SLIC though commendable based on its preeminence over other methods could come with more challenges at the grouping stage of the *K*-means process, any improperly classified pixels may be transferred to yield undesirable superpixels and little regions are joined adjoining neighbor irrespective of the semblance in terms of the color Kim et al. [45].

Rotating machines

Electric machines constitute the main engine driving the power sector. Whether AC or DC-operated, they can be deployed as power generators or motors. Hence, they can function as sources of power or loads. The work by Phuc et al. [46] developed a thermal model independent of exact motor identification. The authors presented a Lumped-Parameter Thermal Network (LPTN) and Dual Kalman Filtering (DKF)-based technique to monitor the temperature profile of Rotors in Induction Machines. And stated that the accuracy of the system depends on the thermal parameters, low computational effort, and rotor temperature observed with IRT and applied to a dual Kalman filter for reviewing the evolution of thermal model parameters.

However, Zarghani et al. [47] revealed that the LPTN requires lots of human expertise to model the circuit especially when a large number of parameters are present, thereby making it more challenging to debug errors. Also, there could be a lack of clarity on the uncertainty concerning the requisite model of the power loss. Therefore, it would be very difficult to model the temperature using deep learning-based algorithms in line with the little number of model parameters that can fit easily with the LPTN to give the same estimation accuracy Kirchgässuer et al. [48].

Resendiz-Ochoa et al. [49] proposed automatic Infrared thermography for analyzing faults in induction motors. The proposed technique detects the concerned area with an automatic image segmentation based on Otsu thresholding process. The goal is to accomplish features extraction of temperatures for thermal analysis of the defective induction motor. The technique has the potential for automatic fault classification in pattern recognition to be applied in image segmentation applications. Anurag Choudhary et al. [50] diagnosed defects in the bearings of rotating machines by observing their operational thermal images and developed a Convolutional Neural Network better than the associated ANN. Six conditions of bearings including a good state were reviewed and compared, employing ANN and LeNet-5-based CNN structure. The suggested method consists of bearing thermal image data collection, extraction of features, and training of the ANN and CNN model, each used as the classifier to classify the different bearing conditions. The authors tested the CNN method on large datasets with up to 99.80% classification accuracy which significantly outperforms the ANN. The technique was not designed for a particular fault, hence Padmanabhan et al. [51] presented a method for identifying inter-turn faults in the status of operational electric machines. The authors applied Thermal and Magnetic Sensor Arrays to the Stator Ends of the winding, thereby obtaining the distribution of the heat and magnetic flux throughout the region encompassed by the end-winding. During abnormal conditions, it would be easy to observe the asymmetry in the thermal and magnetic signature caused by inter-turn short circuits. The presented HESA technique offered better versatility and early fault identification than the comparable IRSA method when viewed within a 1.5-kW induction motor test set. The potential of the techniques lies in their reliability, fast fault detection, and scalability to different types of machines. Moreover, there is an opportunity for future research into an estimation of the extent or expected severity of defects for different operating conditions.

Power electronics

As the power system becomes more sophisticated, demand for improved performance grows, and the need for automatic and fast-switching electrical devices becomes critical. Moreover, the need to ensure optimal performance of the power system makes power electronics systems vital for optimum system operation. Weifei Li et al. [52] presented a method of predicting in real-time the temperature at the PN junctions of an IGBT-based inverter with a concise specified model of the power loss. The model combines dual-impedance temperature model of the inverter with considerations for the results of computation fluid dynamics (CFD) analysis. CFD-based techniques are usually complex models that take more computing resources that impact on cost and simulation time. Also, they are generally built on approximations of practical models thereby limiting the accuracy of the models. They can be prone to errors due to factors like boundary conditions, mesh size, etc.

Leppänen et al. [53] proposed how to mitigate failure in power diodes used in converters by investigating humidity-induced failure in power diodes. Bearing in mind the adverse conditions such as high humidity, extreme temperature, and elevated reverse voltage profiles most power converters are regularly exposed during operation. Boost stage power semiconductor modules from two vendors were investigated. The leakage current measurement of the modules used for the study was monitored on-site during the test for two types of passivated modules, viz., glass passivation and polyimide passivation. And water treeing was found to dissolve lead in particular areas, and glass passivation could lead to multi-modal failures when exposed to the H3TRB-HVDC test conditions and appear as hotspots in the panels. The hotspots could stem from voltage-blocking degradation that finally causes short circuits. According to the authors, a "lock-in" thermography above the glass passivation enclosing the high voltage edge termination elements is susceptible to challenging humidity conditions, this is where the hotspots were observed. Further analysis using a scanning electron microscope (SEM) confirmed that the edge termination contained several tree-like structures growing from both ends of the edge termination on top of the passivation film. The use of SEM could be costly in many ways based on the price paid for the power electronic unit.

Surge arresters

Arup Kumar Das et al. [54], were interested in using IRT for the assessment of surge arresters (SA) using a transfer learning approach to gauge the extent and presence of surface contaminants such as dust, salt, etc. on metal oxide surge arrester (MOSA) to monitor the condition of the device in power installation and counteract the tendency of the SAs to fail before its lifespan. The authors applied IRT and studied the third harmonic leakage current drain by the device. Thereafter analyzed the relationship between the third harmonic leakage current and the temperature of the arrester using a neural network. The neural network was trained with three input parameters of arrester temperature, ambient temperature, and relative humidity of the environment, whereas its output is the third harmonic resistive current. IR thermal images of metal oxide surge arrester at different levels of pollution were observed, preprocessed, and its features of interest were extracted when applied to the ResNet50-based CNN. And, produced up to 98% testing accuracy on simulation with an 11 kV arrester. The authors applied the extracted features to classifiers like k-nearest neighbor, support vector machine, naïve Bayes, and random forest observing that the random forest showed the best performance. In terms of monitoring different pollution levels, the proposed technique shows the capacity to identify the severity of contamination of the surface of the surge arrester with good accuracy. The techniques give automatic, fast, reliable, and remote observation. As the SA ages, its leakage current increases with the deterioration of performance. The aging factor can also be monitored when the leakage current is observed with the temperature at the surface of the device. According to He et al. [55] the concept of ResNet for feature extraction was a game-changer in many computer vision applications as it has enabled the training of datasets with deeper neural networks without compromising the training error and addresses the issues of vanishing gradient, improved model accuracy and relatively fast training time through identity mapping or skip connections.

Andrade et al. [56] investigated the issue of heat transfer in ceramic surge arresters using thermography and computer simulations based on finite element analysis (FEA). Normally, the air gap within arresters could lead to more thermal resistance between the varistor's column and the ambient. So, techniques for proper analysis of the phenomenon are necessary and should include consideration for heat loss via conduction, convection, and radiation. The authors proposed the use of computational simulations in combination with thermography as a tool for a temperature-based estimate of the varistor's state.

For the analysis, thermography measurements were performed in a 69-kV ceramic-housed arrester subject to a thermal cycle and the results were compared with finite element simulations to picture the relationship between varistor's temperature and the temperature of the outer part of the arrester to aid field assessment of the polymeric and porcelain-housed surge arrester. The work highlighted better results for varistors enclosed with polymeric than ceramic materials. And showing the potential of the technique to be applied for optimization of parameters of heat transfer mechanisms that most define the thermal behavior of the arrester. The authors saw the prospect of developing an equivalent mathematical expression that can relate external temperature and that of the internal components for predicting the temperature of the varistor column. However, this method would not be generic because issues of heat loss are related to the physical shape and geometry of the device, hence different arrester shapes would need specific simulations to be effective.

Solar photovoltaic modules

Condition monitoring of Solar Photovoltaic systems is one area that has attracted the interest of researchers in power system analysts in recent years. The growing interest could be a result of a worldwide policy shift toward renewable sources of energy by the year 2030. There is a compelling need to optimize available sources of renewable energy by preventing or reducing energy loss. And, as solar PV systems become the easy focus of researchers, with hotspots known to contribute up to 49% of faults in PV modules. The concept of IRT has become a veritable choice technique for monitoring their performance. Pramana and Dalimi [57] were interested to identify hotspot faults in PV Modules with the hope of classifying them appropriately. Table 2 depicts the main cause of hotspot faults in PV panels. The hotspot faults can manifest due to internal or external factors in the PV modules. The external hotspots are caused by the prevalence of adverse environmental conditions within which the modules are operated, whereas the internal issues are usually linked to power diode failure.

Simons and Meyer [67], presented a method for Detecting and analyzing the occurrence of hotspots in PV solar cells by scanning the face of the modules to observe the thermal profile of the cells in reverse bias. Heterogeneous thermal distribution across the modules indicates hotspots. Thereafter, the authors used a scanning electron microscope (SEM), to further observe microscopic images of areas where the hotspots manifested and identified irreparable damage to the cells due to the heating effect. The work highlighted the relationship between contaminated portions of cells, especially by transition elements along with oxygen, carbon, iron, and platinum, and the hotspot phenomenon.

Pallavi et al. [68], highlighted the effect of hotspots on the energy output from solar PV modules. Localized heating within a solar cell gives rise to hotspot formation,

Table 2 Root cause analysis of hotspots in pv panels

Type of Fault	Parts/location	Process	Activity	Cause of hotspot fault
Cracking	Protective Glass & Active solar cells	Production, packaging, transport, Installation	Mismatch of bolts, poor tightening, External force, falling objects[58]	Water penetration, create shading[59]
Poor Interconnection (series & parallel cells or panels)[60]	Conducting portions	Production, packaging, transport, and Installation [61]	Mechanical stress, Imperfect solders	High resistance of junction conductor
Corrosion [62]-increased humidity in modules causes corrosion	Delamination, cracks, and encapsulation [63]	Moisture penetrates modules via the edge of the module frame	Reduce conductivity, cause leakage currents	Reduce power produced, high resistance, hotspots
Bypass Diode Fault	String (series of cells) shadowed by object	String output voltage less than adjacent strings	The reverse bias of shaded string due to current flow from good to bad string	A bad bypass diode not blocking the reverse bias current flow [64]. Heating in PV module hotspots
Shading, Soiling (External Factors)	Dark (100% cover) [65]/transparent shading (< 100% cover [66]. (home, tree/smoke, fog, dried liquid film, and bird droppings)	trigger moss on the surface of PV panels	Bad bypass diode not blocking the reverse bias current flow	Heating in PV module hotspots

which further leads to module damage and system degradation. A detailed model encompassing non-uniform temperature distribution across a series of connected PV cells is presented and is seen to give high accuracy with respect to the experimental measurements as compared to the average temperature and the standard conditions-based output prediction.

In this work, the output performance of such PV modules is estimated based on non-uniform temperature distribution and is shown to match well with the experimental results with 98% accuracy. The proposed method performs better than the average temperature-based approach with more than 5% improvement in maximum power point prediction accuracy. The proposed method would be inefficient for monitoring large-scale PV installation. And, there is a need for the acquisition and auto-processing of numerous IR images. And, the need to apply modern deep learning methods would entail the acquisition of numerous IR images which would be quite challenging. So, artificial intelligent solar panel monitoring systems would be appropriate as proposed by Wang et al. [69] whose work deployed a combination of U-Net neural network and a supervised machine learning model-like decision tree to achieve 99.8% fault diagnosis ability of PV panel faults. However, U-Net's use of a large number of parameters as a result of more layers and skip connections could cause overfitting when used on limited images.

Power lines

Transmission and distribution lines, generally referred to as power lines are to the power system what arteries and veins are to the human body. They are the physical channels through which electrical power is conveyed from one node to the other. They are the most vulnerable part of the power system and can reach thousands of kilometers in length, passing through very challenging weather and terrain; and must be in good condition always. Hence, the need to monitor their operating state is paramount to linesmen and system operators. Jalil et al. [70] proposed a technique for monitoring power lines using a FLIR A65sc IR camera mounted on an unmanned aerial vehicle (UAV) to acquire infrared and visible images of power lines, which they subjected to a fusion-based images processing algorithm. And passed through a canny edge detection model, before detecting the linear features in the images using the Hough transformation technique. The power lines were segregated from other portions of the pictures and a thresholding method based on histogram technique was used to profile and identify the hotspots in the lines. But Vozikis and Jansab [71] opined that one major issue with the Hough stems from the fact that it is highly susceptible to giving incorrect results when encountering complex geometric images as well as dark shadows in images.

Table 3 Results of techniques used for infrared thermography

Reference	Title of Paper	Results / Analysis
Karvelis et al. [17]	An Automated Thermographic Image Segmentation Method for Induction Motor Fault Diagnosis	The image segmentation method used with Naïve Bayes classification yielded 100% accuracy, while C4.5 gave 91.48%
Eftekhari et al. [11]	A novel indicator of stator winding inter-turn fault in induction motor using infrared thermal imaging	The Mahalanobis distance was used to measure changes in the IR image pixels. Also, forecast hot spots in the stator using $Hull_{index}$, Hot_{area} and $Histogram_{mean\ values}$ with RMSE error of 0.0097 translating to 99.13% accuracy
Ali-Younus and Yang [9]	Wavelet Co-efficient of Thermal Image Analysis for Machine Fault Diagnosis	Got the best result at the second level of decomposition
Fambrini et al. [33]	GPU Cuda JSEG Segmentation Algorithm associated with Deep Learning Classifier for Electrical Network Images Identification	The method resulted to 99.91% detection accuracy in transformers, 86.94% in knife wrenches, 84.88% in splice connectors, and 71.49% in bushings
Najafi et al. [35]	Fault diagnosis of electrical equipment through thermal imaging and interpretable machine learning applied on a newly-introduced dataset	The technique obtained 93.8% accuracy in 11 classes of equipment condition and 95.6% for 9 classes
Jadin et al. [13]	Thermal condition monitoring of electrical installations based on infrared image analysis	The normalization cross-correlation method got 95.804% classification accuracy
Dutta et al. [26]	Condition monitoring of electrical equipment using thermal image processing	The highest Peak Signal-to-Noise Ratio of 63.13 dB and least MSE of 0.03 was observed when Otsu method was applied
Huda and Taib [14]	Suitable features selection for monitoring thermal condition of electrical equipment using infrared thermography	The Multi-Layered Perceptron with Scale Conjugate Gradient and Levenberg–Marquardt training got the highest identification training degree of 82.89% and testing rate of 74.25% than other comparable methods
Huda and Taib [15]	Application of infrared thermography for predictive/preventive maintenance of thermal defect in electrical equipment	The optimum result achieved with the second-fold training dataset were 97.75% accuracy, 95.89% specificity, and 98.88% sensitivity. Whereas on the testing dataset, the performance fell to 80.40% accuracy, 75.29% specificity, and 83.98% sensitivity. And, the Discriminant Analysis classifier yielded the best accuracy of 82.40%
Zou et al. [19]	Novel intelligent fault diagnosis method for electrical equipment using infrared thermography	Optimization of the classification accuracy up to 97.8495% was achieved with SVM by the application of a coarse-to-fine parametric model
Liu et al. [28]	Infrared image combined with CNN-based fault diagnosis for rotating machinery	The 6 layered directly trained convolutional neural network achieved the best testing accuracy of 95.8% using 60 × 60 pixel images, without feature extraction
Janssens et al. [18]	Thermal image-based fault diagnosis for rotating machinery	Two image processing channels were processed by detecting rotor imbalance irrespective of the type of bearing defect and then identifying bearing issues notwithstanding any rotor imbalance. The model was up to 88.25% accurate for 8 machine anomalies
Singh et al. [22]	Fault diagnosis of induction motor cooling system using infrared thermography	The method obtained a correlation factor of 99.02% between the Hot_{index} with respect to the percentage of inter-turn short circuits. Hence, the Hot_{index} is proportional to the stator coil inter-turn faults

Table 3 (continued)

Reference	Title of Paper	Results / Analysis
Mahami et al. [37]	Induction motor condition monitoring using infrared thermography imaging and ensemble learning techniques	The proposed ensemble learning technique outperformed the SVM, Decision tree, K-nearest neighbor, Least Square SVM, and Deep Rule-Based methods by returning 100% classification accuracy
Vidhya et al. [36]	Transformer breather thermal image decomposition for fault diagnosis	Without image decomposition, the MAD of the Symlet wavelet transformations produced 99.68% for normal operation, 99.95% for mild faults, and 98.87% for severe winding faults. And, associated Standard deviations of 106.2, 106.6, and 106.5 of the respective three operational states But, with image decomposition, the symlet wavelet transformation produced significant variation in MAD (8.154, 1.25 and 3.677) as well as the standard deviation (12.66, 2.007 and 6.52) for each respective normal, mild and severe states
Zou Huang [72]	An Intelligent Fault Diagnosis Method for Electrical Equipment Using Infrared Images	Classification accuracy of 95.6989% was achieved using SVM with bestc2 and bestg2 parameters set to 223.5126 and 0.9639, respectively
Cui et al. [12]	The Methods in Infrared Thermal Imaging Diagnosis Technology of Power Equipment	The work used Radial Basis Probabilistic Neural Network to identify the level of contamination in string insulators with up to 91.12% accuracy
Fanchiang et al. [73]	Power Electric Transformer Fault Diagnosis Based on Infrared Thermal Images Using Wasserstein Generative Adversarial Networks and Deep Learning Classifier	The proposed model is a Wasserstein Auto-encoder Reconstruction-based Differential Image Classification (WAR-DIC). It is also a feather-weight network with only 0.223×10^3 parameters, 1.837 MB of weight storage, and 1.781×10^3 floating point calculations. Overheating of conducting wires, inter-turn faults, and overheating in connecting points were investigated for eight fault conditions on a balanced dataset. The classification accuracies that were gotten for four different datasets were 99.95%, 99.89%, 99.71%, and 99.46%
Fang et al. [74]	Fault diagnosis of electric transformers based on infrared image processing and semi-supervised learning	The application of GAN to synthesize sampled IR images enhanced the classification of equipment defects with an accuracy of 82.2%, recall of 84.7%, and precision of 83.1%. And, recognized overheating with an accuracy of 86.2%, recall of 84.8%, and precision of 83.5%
Fanchiang, Kuo [75]	Application of thermography and adversarial reconstruction anomaly detection in power cast-resin transformer	Overheating in 1MVA, 24/0.38 kV cast-resin transformers were investigated with Variational Autoencoder-based-GAN using the difference in the pixel-wise cosine between the real and synthetic images. The results achieved include: *F*1 score of 94.4%, AP of 94.1%, and AUROC of 94.5%

Results/analysis

The variety of methods applied and accompanying results in different works concerning infrared thermography are presented in Table 3 shows the predisposition of researchers to adopt intelligent techniques over classical methods when developing their models.

Conclusion

Infrared Thermography for the past two decades has continued to attract attention as a useful tool for monitoring electrical power equipment and installed system especially when in operation. There is no limit to areas they can be applied, whether biological or physical systems. Once heat is radiated from such objects above absolute temperature, then IR cameras can provide instantaneous images of the temperature distribution within that equipment. The focus of most research in IRT-based condition monitoring lies in the development of intelligent systems and improving the accuracy of neural network-based models. There is a need for more work in comparative assessment of the response times for most of the models. And, the importance of more research in developing models that would not require lots of IR images to train, yet give very good results, because data acquisition in this research area takes a lot of time, energy, human expertise, and money. There is a need to develop more affordable IR cameras with good video recording and storage features which would greatly aid data acquisition of infrared images of equipment and installations.

Abbreviations

AP	Average precision
AUROC	Area under the receiver operating characteristics
BoVW	Bag of visual word
CFD	Computational fluid dynamics
CM	Condition monitoring
CNN	Convolutional neural network
CT	Computed tomography
DDP	Design-dependent parameters
DGA	Dissolved gas analysis
DKF	Dual Kalman filtering
DWT	Discrete wavelet transforms
EF	Empirical factors
ERT	Extremely randomized tree
FCA	Furan current analysis
FEA	Finite element analysis
FRA	Frequency response analysis
GAN	Generative adversarial network
H3TRB	High humidity, high temperature and high voltage reverse bias test
HESA	Hall effect sensor array
HI	Health index
HIS	Hue, saturation, intensity
HSL	Hue, saturation, lightness
HSV	Hue, saturation, value
JPEG	Joint Photographic Experts Group
RVM	Recovery voltage method
HV	High voltage
IGBT	Insulated gate bipolar transistor
IM	Induction motor/machine
IRSA	Infrared thermopile sensor array
IR	Infrared
IRT	Infrared thermography
JSEG	Joint systems engineering group algorithm
LPTN	Lumped parameter thermal network
MAD	Mean absolute deviation
MCSA	Motor current signature analysis
MLP	Multi-layer perceptron
MOSA	Metal oxide surge arrester
MSE	Mean square error
NCC	Normalized cross-correlation
ONAN	Oil natural, air natural
OFAF	Oil forced, air forced
PCNN	Pulse coupled neural network
PNG	Portable network graphics
PSNR	Peak signal-to-noise ratio

PV	Photovoltaic
RESNET	Residual network
RF	Random forest
RLC	Resistive–inductive and capacitive
RMSE	Root mean square error
SA	Surge arrester
SEM	Scanning electron microscope
SIFT	Scale invariant feature transform
SLIC	Simple linear iterative cluster
SNR	Signal-to-noise ratio
SURF	Speeded up robust feature
SVM	Support vector machine
UAV	Unmanned aerial vehicle
VA	Variational autoencoder
WAR-DIC	Wasserstein autoencoder reconstruction-based differential image classification
WT	Wavelet transform

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