X-AMINOR: A Mobile Multi-Sensor Platform for Lifecycle-Monitoring of Transformers

Ferdinand Fuhrmann[1], Konrad Diwold[2], Jakub Waikat[3], Jakob Gaugl[4], Fredi Belavic[5] and Franz Graf[1]
[1]*JOANNEUM RESEARCH, Graz, Austria*
[2]*Pro2Future, Graz, Austria*
[3]*Siemens Energy Austria, Wien, Austria*
[4]*Siemens Energy Austria, Weiz, Austria*
[5]*Austrian Power Grid, Wien, Austria*

Keywords: Transformer, Lifecycle-Monitoring, Transmission System.

Abstract: The current developments in the energy system especially the increased integration of renewable and the introduction of dynamic loads lead to a decoupling of consumption and production. Digitalization is one of the major tools for grid operators to tackle these challenges, as it allows them to implement flexible and advanced operation and planning strategies, which reduce costs while increasing service security. In the context of operation, transformers represent one of the most important assets in the transmission grid. Their optimal utilization is of utmost importance to ensure the optimal operation for dependable feed-in. The article presents the project X-AMINOR, which aims for the development of novel minimal invasive transformer monitoring solutions designed to complement existing monitoring strategies to enable continuous monitoring over a transformer's entire life cycle to improve its operation.

1 INTRODUCTION

The increased integration of renewables and the introduction of dynamic loads into the energy systems creates new challenges for grid operators, as they lead to a decoupling of consumption and production (Sinsel et al., 2020). Digitalization can be seen as one of the major tools for grid operators to tackle these challenges, as it allows to implement flexible and advanced operation and planning strategies, reducing costs while increasing service security. In the context of medium and low voltage distribution grid operation this led to a number of smart grid technologies (Tuballa and Abundo, 2016), allowing the operator to proactively control grids and provide ancillary services. These transformations also impact the transmission level, where the integration of renewables can lead to instabilities (e.g., voltage fluctuations), overloading of transformers and injection of harmonics (Shafiullah, 2016).

Transformers constitute core infrastructure components in energy grids on all voltage levels. Their availability and longevity can thus be seen as integral variables in the context of security of supply. Continuous monitoring and predictive maintenance are therefore an important factor to increase the longevity of these infrastructure elements and reduce unplanned outages. Transmission systems utilize monitoring solutions (Pudlo et al., 2002)(Al-Ali et al., 2004), tailored towards specific power transformers, and monitor transformers' KPIs based on its operation parameters (Pudlo et al., 2002). These monitoring solutions are integrated into a monitoring scheme via Supervisory Control and Data Acquisition (SCADA) systems. The amount of information available from a transformer during operation depends on the transformer itself. While new transformers provide a multitude of information (winding hotspot sensors, dissolved gas analyzers, etc.), operation parameters available from legacy transformers are often limited.

Usually, the condition of a transformer is regularly inspected by a human expert to guarantee fault-free operation. Here, abnormal noise could indicate the malfunctioning of an oil pump, or changes in its thermal properties could indicate looming faults. Currently such inspection information is only available to

Fuhrmann, F., Diwold, K., Waikat, J., Gaugl, J., Belavic, F. and Graf, F.
X-AMINOR: A Mobile Multi-Sensor Platform for Lifecycle-Monitoring of Transformers.
DOI: 10.5220/0011968800003491
In *Proceedings of the 12th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2023)*, pages 121-128
ISBN: 978-989-758-651-4; ISSN: 2184-4968

experts themselves. Additionally, the inspection process is based on experience, which enables the human expert to correctly identify, classify and interpret deviations.

The project X-AMINOR aims at developing an automatic transformer lifecycle-monitoring solution to detect and evaluate information, which previously could only be captured by experts during inspection. The project develops a mobile multi-sensor platform (audio, video, thermal) providing additional information to complement existing monitoring. X-AMINOR will utilize sensor data to build data models, forming the basis for predictive maintenance and continuous product improvements. The developed monitoring solution is applicable in the entire lifecycle of a transformer, thus providing additional information from its cradle to grave. The developments are therefore driven by two application scenarios in the life cycle of a transformer: final (end of line) testing after production as well as operation.

The technical result of the project constitutes a functional monitoring prototype, which will be deployed and tested in the context of transmission grid operation as well as end-of-line tests. Long term evaluation scenarios will be used for an in-depth quantitative and qualitative evaluation of the system and will allow the quality assessment of the developed methods as well as its benefits in the context of end of line testing and automated condition monitoring.

The remainder of the article is structured as follows: Section 2 depicts the general challenges X-AMINOR addresses and outlines potential monitoring use-cases. Section 3 discusses the overall system design and introduces the utilized sensing technologies. Finally, Section 4 concludes the article and gives an outlook on the next steps towards the envisioned monitoring solution.

2 CHALLENGES

Climate protection, the energy system transformation and the required market efficiency create major demands for today's energy suppliers. The increasingly volatile utilization of the grid operation components is particularly challenging. This is grounded in the growing availability of renewable forms of energy, the European exit from coal and nuclear power, as well as new "energy-hungry" industrial sectors with dynamic consumption patterns (Shi et al., 2016). However, the digitalization of the energy system offers new opportunities to increase efficiency. In the following, the challenges addressed by X-AMINOR are listed together with the associated, demand-oriented solution approaches.

Network Utilization and Redispatch. The transmission and distribution grid are particularly challenged by the volatile performance of sources (Janda et al., 2017) – e.g., photovoltaics or windfarms. In order to guarantee reliable supply, a redispatch is carried out whenever grid bottlenecks are detected (Hedman et al., 2011). With this redispatch power plant operators are instructed to reschedule their performance to avoid possible network bottlenecks, causing significant costs for grid operation and energy trading. To avoid future bottlenecks and corresponding redispatches, specialized monitoring and control solutions can be used to continuously supervise and control the grids and their assets. In contrast to distribution grids, digitalization is already well advanced in the transmission grid. By using SCADA (Supervisory Control and Data Acquisition) systems (Pliatsios et al., 2020), the grid can be monitored, analyzed, and optimally controlled over a large area. In addition to information on the current utilization of a resource, its status as well as information on its past activities, SCADA systems offer the possibility of calculating load scenarios more precisely. This applies to transformers, which - in addition to the network itself - represent the most important asset of a transmission network.

Transformer Utilization and Fault-Related Outages. Optimal operation of transformers is required to ensure continuous reliability of supply. The operator currently calculates the possible utilization of a transformer on the basis of selected overload parameters (nominal power, oil and winding temperature, etc.), which are continuously recorded. While these parameters enable an estimation of the overload, expanding existing models with additional information would enable a better assessment of the current load and the associated possible time-limited overload of transformers or substations. Expanding existing models requires additional information, such as an accurate assessment of the transformer's current thermal state. A possible consequence of an inaccurate assessment of the overload capacities of transformers is a shortened service life or premature failure. Here, the failure distribution of a transformer during its lifetime follows a so-called bathtub curve (Klutke et al., 2003), showing an increased probability of fault at the beginning and end of its service life (Figure 1).

Faults at the beginning of the transformer's life are caused by incorrect design, manufacturing errors or defects in production. At the end of its life, the failure probability increases due to age and fatigue. Hence we identified a number of use-cases to be addressed

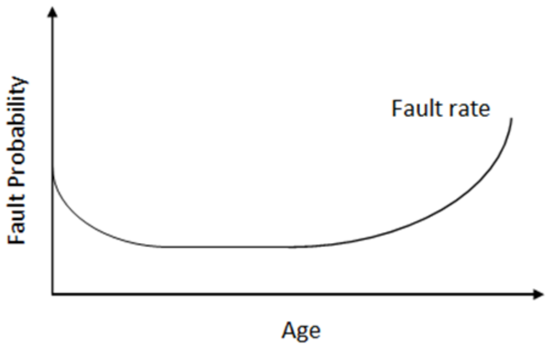

Figure 1: Fault rate distribution of transformers over its lifetime.

by the X-AMINOR monitoring system, ranging from transformer development to operation. These use-cases thus encompass encompass the whole life-cycle of transformers. In the following we outline exemplary monitoring use-cases at different stages of a transformer's life-cycle, which X-AMINOR aims to automate and optimize.

Manufacturing. Currently, various quality aspects of the individual manufacturing steps are checked manually, requiring a training phase and many years of experience. With X-AMINOR, parts of the quality check could be carried out automatically via the monitoring system. For instance, a 3D variance analysis for manually isolated transformer parts could yield vital information to identify potential error sources during operation.

Factory Acceptance Test. During the end of line test, manual noise measurements are currently performed. Since the transformer is under load during the test, this method poses a safety risk for employees. With the help of a mobile monitoring solution this test can be automated. In addition, the system allows the generation of a 3D sound model of the transformer, which can be used as a fingerprint for reference in later analyses.

Operation. During operation, transformer information is continuously collected via SCADA systems and used in the context of condition monitoring systems (CMS). Such systems can utilize transformer parameters which are actively collected via the SCADA system (e.g., voltages, temperature, etc.). X-AMINOR will enable a continuous external inspection of a transformer (acoustically and visually) and thus the detection of errors which start to manifest themselves (e.g., small leaks or the beginning of insulation defects), which currently can only be discovered in later stages. Moreover, peripheral systems of the transformer (e.g., fans) can also be monitored in this way.

Post Mortem Analysis. Currently, the planning of new transformers does not involve data gained from a post mortem analysis nor any other historical data. Making such data available via X-AMINOR can further reduce errors caused by uncertainties in the dimensioning of new transformers, as well as using this information for optimizing the state of the grid.

3 X-AMINOR SYSTEM DESIGN AND ASSOCIATED TECHNOLOGIES

X-AMINOR is designed to collect and analyze visual and acoustic information in addition to already available operating parameters in order to enable a more precise assessment of the transformer's condition. For an autonomous operation it requires suitable transportation means (mobile platform) and IT technologies (middleware and edge computing). The next section outlines the envisioned system design and the underlying technologies that will be applied in the context of the cross-sensor lifecycle-monitoring platform.

3.1 System Design

The overall X-AMINOR system design is sketched in Figure 2. The system contains a scalable (on-premise cloud) backend, which performs acoustic and visual data analytics, as well as X-AMINOR middleware nodes, which are installed at specific transformer locations to monitor their behavior during operation.

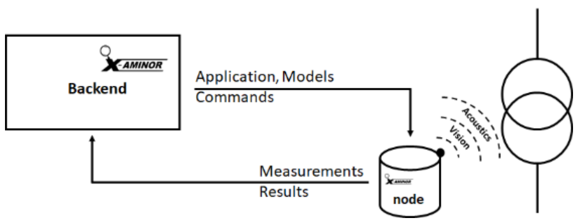

Figure 2: X-AMINOR system design.

In this context, X-AMINOR utilizes recent developments in the area of the Internet of Things (IoT), where a range of protocols and architectures for instantiating intelligent monitoring systems have been proposed (Wang et al., 2013). To guarantee scalability, edge computing will be utilized via GPU-enabled computing nodes. This will allow nodes to preprocess data streams and perform first analyses, while the backend performs computation-heavy analytics as well as model training and development. In regard to its system design X-AMINOR takes inspiration from a number of middleware systems and solutions for distributed monitoring, which have been developed in the context of smart grid operation (Cejka et al., 2018)(Diwold et al., 2018). To increase the integrity of the node applications, they will be isolated in runtime containers, which have almost negligible influence on the performance of programs compared to their native execution (Morabito, 2017).

The core methodology of X-AMINOR concerns the visual and acoustic assessment of transformers. State of the art of acoustic and visual technologies as well as the contribution in these areas from X-AMINOR, together with a first glimpse into applying such technologies in the context of transformer monitoring are outlined in the following subsections.

3.2 Visual Diagnostics

Visual diagnostics in X-AMINOR rely on three pillars: a reasonable accurate mapping of the transformer and localization of detected conditions and findings, the visual detection of specific defect types known in advance, as well as the detection of generic changes on the transformer surface.

3.2.1 Mapping and Localization

Acquiring an as-built 3D model is a prerequisite for the mapping and localization of conditions.

Related Work: Numerous methods based on RGB (Taketomi et al., 2017) and RGB-D (Kähler et al., 2016) sensors are known for 3D mapping. Although these offer low hardware costs, the accuracy is usually limited to a range of several millimeters. Higher accuracies can be achieved with other sensors, in particular with terrestrial LIDAR scanning. Commercial solutions (e.g., Leica[1]) are routinely used for such tasks. RGB or RGB-D cameras are also suitable for localizing aspects relative to 3D models (Sattler et al., 2019). Here, efficient transfer learning for new scenes is currently the main challenge (Balntas et al., 2018).

Contributions: Within X-AMINOR we will apply state of the art methods for 3D model data generation like LIDAR scanning, RGB-D sensors and Structure from Motion (SfM). We will apply associated localization techniques, both for the initial scanning of the transformer and the periodic scanning with a mobile device later on. Figure 3 and 4 depict first results of localization experiments performed within the project.

Figure 3: As-built 3D transformer model acquired with a Leica BLK360 scanner.

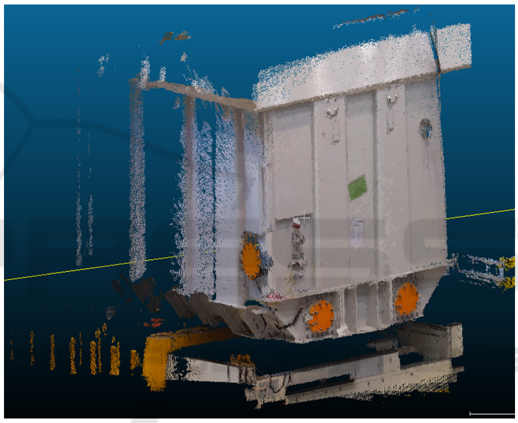

Figure 4: View on a transformer with an RGB-D sensor (Microsoft Azure Kinect).

3.2.2 Visual Inspection of Known Defect Types

This task deals with the visual detection of specific defect types known in advance.

Related Work: The literature on visual detection of surface defects is yet extensive, an up-to-date overview can be found here (Czimmermann et al., 2020). In most approaches, classifiers are trained with existing training data using machine learning. More recent works (see (Tabernik et al., 2019)) try to minimize the number of examples required for suitable training. Also, thermal infrared information is used to create 3D temperature models of the measured surfaces using LIDAR data (Borrmann et al., 2013), through 3D reconstruction with a depth camera (Vidas et al., 2013) or using CAD models (Sels et al., 2019). Moreover, in existing transformers analog measuring devices are often used, from which

[1] https://leica-geosystems.com

digital values cannot be read out easily. (Lee et al., 2018) proposes an approach for realtime automatic instrument status monitoring using deep neural networks.

Contributions: In the literature, a majority of approaches focuses on the detection of defects in individual 2D images. In the X-AMINOR project individual 2D detection results are integrated and consolidated in a 3D model of the transformer. This way, the reliability of detections can be improved by correcting individual false positives via the results from other images. Based on the given 3D transformer model and the localization information of the sensor system relative to the device, a holistic detection model can be established, linking the different modalities. Additionally, the system reads analog displays from images acquired via the sensor system. The first challenge here is the reliable detection and identification of the display elements and furthermore a reading at unfavorable viewing angles which can falsify the result. In X-AMINOR, the reading of thermometers as well as the control of pump flow indicators are considered.

3.2.3 Change Detection with Mobile Sensors

In contrast to specific visual inspection tasks change detection focuses on observing a scene over a longer period and register all types of expected or unexpected changes.

Related Work: For mobile inspection one could detect purely geometric changes compared to a reference model (Palazzolo and Stachniss, 2017). However, if changes such as contamination or corrosion need to be found the paradigm of visual change detection must be adapted to mobile cameras. A first work in this direction was published with the aim of finding changes in street scenes which can lead to map updates (Alcantarilla et al., 2018). For inspection tasks, comparable methods for the surface assessment of concrete pipes were examined (Stent et al., 2015). Here, the (semi-) automatic generation of sufficient training data plays a central role (Sakurada et al., 2020). More recent works even aim to find a textual interpretation of the changes (Park et al., 2019).

Contributions: On the one hand, a system for change detection must be sufficiently robust in terms of recording conditions and localization accuracy, but on the other hand, the high level of generalization must be achieved with a low training effort. X-AMINOR aims to build on the robustness of current methods from the literature, which fundamentally seems promising but has to be evaluated in detail for the present scenario. The effects of small amounts of training data as well as transfer learning methods are examined. A further approach to improve the performance is the aforementioned consolidation the detected changes from several individual images in the 3D model of the transformer. Last but not least, the creation of an evaluation data set, in which the targeted irrelevant changes (lighting, seasons, weather) as well as relevant changes (contamination, leakage, corrosion etc.) are adequately covered is another contribution.

3.3 Acoustic Condition Assessment and Evaluation

In X-AMINOR, we analyze the emitted airborne sound via acoustic monitoring. Our aim is to reconstruct a complete 3D representation of the transformer's sound radiation (acoustic heat map). We will utilize microphone arrays to record the transformer's location dependent sound radiation. By analyzing different recording positions all around the transformer, we construct a complete representation of the emitted sound pressure levels, which we then use for further analyses. Figure 5 shows an example sound radiation pattern recorded during the first measurement sessions of the project.

Related Work: Acoustic monitoring refers to the automatic detection of abnormal events through the analysis of acoustic signals. In acoustic condition monitoring, a statistical model is formed from the acoustic signals of a predefined "normal" condition of the process. The task of this model is the automatic detection of deviations from this normal condition given new input data. Acoustic event monitoring is restricted to the detection of predefined acoustic events, which are often associated with certain error states. Using pre-recorded error-state examples and machine learning methods, classifiers for the automatic detection of these events are developed (Heittola et al., 2018). Literature reports systems for acoustic monitoring of traffic flows (Graf and Gruber, 2018), production machines (Siebald et al., 2017), industrial plants (Koester et al., 2018) as well as urban spaces (Bello et al., 2019).

Contributions: To create an acoustic heat map, we transform the sensory data into a spatial 3D representation and adapt them to the 3D model of the transformer. We use the heat map for consistency validation in condition monitoring during the transformer's life-cycle. We first construct an initial sound radiation model during factory acceptance testing. Once the 3D representation is constructed, we use it as a reference for later comparisons. During the transformer's operation, we record new data which resulting 3D representation is compared to the reference. If we detect certain deviations, we trigger an alarm, and a manual check is initiated. Moreover, we derive a failure detection analysis from the sound radiation model. Certain failure states such as broken cooling fans or cooling units produce characteristic sounds, which we use to construct specific failure event classifiers. During data acquisition, we record data from these, mostly simulated, failure states and construct specialized detectors. In order to obtain meaningful results from the acoustic modeling, sound source localization, signal characteristics and the position of the sensor array must be analyzed together. The merging of these dimensions into a single, closed model leads to new possibilities for the statistical modeling of acoustic signals.

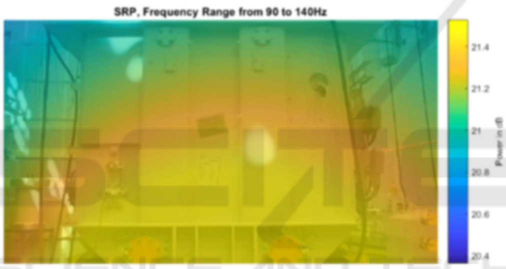

Figure 5: Sound radiation pattern for frequency band 90-140Hz of a transformer.

3.4 Transformer Modelling

Within X-AMINOR the sensor data will be used for modelling a transformer's aging process during operation. A multitude of transformer models have been proposed, focusing on different aspects such as capacity estimation and prediction (Alvarez et al., 2019) or thermo-hydraulic aging (Seitlinger, 2000). It has been shown that a multitude of factors must be considered to achieve accurate modelling (Raith et al., 2020), including the transformer's thermal behavior, insulation moisture as well as the dynamic variation of loading and temperatures. Modelling typically utilizes assumed initial conditions and operation assumptions for the evolution of the simulation. The data established with the X-AMINOR monitoring system will allow to validate and tune existing aging models based on operational data. Moreover, such data can be used as additional model input to individually model a specific target transformer. Additionally, this information allows the development of new models which relate acoustic, visual, and thermal information established during end-of-line testing with operational data, allowing for a continuous evaluation of the transformer.

4 OUTLOOK AND CONCLUSIONS

In this article we have outlined the vision of the X-AMINOR project, which aims to study and demonstrate a novel cross sensor platform monitoring solution for transformers. X-AMINOR is designed to complement existing monitoring solutions and enable continuous monitoring of a transformer to improve its operation. The project will address use-cases in the context of manufacturing (end-of-line tests) and operation to ensure the applicability of the solution across the whole lifecycle of a transformer. Besides demonstrating such holistic monitoring concepts, the project will advance methods of visual, thermal and acoustic condition monitoring and demonstrate their application in the context of grid installations. Currently the project is at a very early stage, as of now initial data acquisition campaigns have started to enable the development of data-driven methods as well as refining existing transformer models. In parallel the target hardware and overall system is currently under design.

ACKNOWLEDGMENTS

This research is funded by the Austrian Research Promotion Agency (FFG) within the project X-AMINOR (881186) and the FFG-COMET-K1 Center "Pro2Future" (Products and Production Systems of the Future), Contract No. 881844.

REFERENCES

Al-Ali, A.-R., Khaliq, A., and Arshad, M. (2004). Gsm-based distribution transformer monitoring system. In *Proceedings of the 12th IEEE mediterranean electrotechnical conference (IEEE Cat. No. 04CH37521)*, volume 3, pages 999–1002. IEEE.

Alcantarilla, P. F., Stent, S., Ros, G., Arroyo, R., and Gherardi, R. (2018). Street-view change detection with deconvolutional networks. *Autonomous Robots*, 42(7):1301–1322.

Alvarez, D. L., Rivera, S. R., and Mombello, E. E. (2019). Transformer thermal capacity estimation and prediction using dynamic rating monitoring. *IEEE Transactions on Power Delivery*, 34(4):1695–1705.

Balntas, V., Li, S., and Prisacariu, V. (2018). Relocnet: Continuous metric learning relocalisation using neural nets. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 751–767.

Bello, J. P., Silva, C., Nov, O., Dubois, R. L., Arora, A., Salamon, J., Mydlarz, C., and Doraiswamy, H. (2019). Sonyc: A system for monitoring, analyzing, and mitigating urban noise pollution. *Communications of the ACM*, 62(2):68–77.

Borrmann, D., Elseberg, J., and Nüchter, A. (2013). Thermal 3d mapping of building façades. In *Intelligent autonomous systems 12*, pages 173–182. Springer.

Cejka, S., Frischenschlager, A., Faschang, M., Stefan, M., and Diwold, K. (2018). Operation of modular smart grid applications interacting through a distributed middleware. *Open Journal of Big Data (OJBD)*, 4(1):14–29.

Czimmermann, T., Ciuti, G., Milazzo, M., Chiurazzi, M., Roccella, S., Oddo, C. M., and Dario, P. (2020). Visual-based defect detection and classification approaches for industrial applications—a survey. *Sensors*, 20(5):1459.

Diwold, K., Mayer, S., Einfalt, A., Parreira, J. X., Hodges, J., Anicic, D., and Mosshammer, R. (2018). Grid watch dog: A stream reasoning approach for lightweight scada functionality in low-voltage grids. In *Proceedings of the 8th International Conference on the Internet of Things*, pages 1–8.

Graf, F. and Gruber, M. (2018). Rapid incident detection in tunnels through acoustic monitoring–operating experiences in austrian road tunnels.

Hedman, K. W., Oren, S. S., and O'Neill, R. P. (2011). A review of transmission switching and network topology optimization. In *2011 IEEE power and energy society general meeting*, pages 1–7. IEEE.

Heittola, T., Çakır, E., and Virtanen, T. (2018). The machine learning approach for analysis of sound scenes and events. In *Computational Analysis of Sound Scenes and Events*, pages 13–40. Springer.

Janda, K., Málek, J., and Rečka, L. (2017). Influence of renewable energy sources on transmission networks in central europe. *Energy Policy*, 108:524–537.

Kähler, O., Prisacariu, V. A., and Murray, D. W. (2016). Real-time large-scale dense 3d reconstruction with loop closure. In *European Conference on Computer Vision*, pages 500–516. Springer.

Klutke, G.-A., Kiessler, P. C., and Wortman, M. A. (2003). A critical look at the bathtub curve. *IEEE Transactions on reliability*, 52(1):125–129.

Koester, L. W., Taheri, H., Bigelow, T. A., Bond, L. J., and Faierson, E. J. (2018). In-situ acoustic signature monitoring in additive manufacturing processes. In *AIP Conference Proceedings*, volume 1949, page 020006. AIP Publishing LLC.

Lee, E., Hong, J., and Kim, D. (2018). Automatic instrument status monitoring using deep neural networks. *ECCV Demo Sessions*.

Morabito, R. (2017). Virtualization on internet of things edge devices with container technologies: A performance evaluation. *IEEE Access*, 5:8835–8850.

Palazzolo, E. and Stachniss, C. (2017). Change detection in 3d models based on camera images. In *9th Workshop on Planning, Perception and Navigation for Intelligent Vehicles at the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS)*.

Park, D. H., Darrell, T., and Rohrbach, A. (2019). Robust change captioning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4624–4633.

Pliatsios, D., Sarigiannidis, P., Lagkas, T., and Sarigiannidis, A. G. (2020). A survey on scada systems: secure protocols, incidents, threats and tactics. *IEEE Communications Surveys & Tutorials*, 22(3):1942–1976.

Pudlo, G., Tenbohlen, S., Linders, M., and Krost, G. (2002). Integration of power transformer monitoring and overload calculation into the power system control surface. In *IEEE/PES Transmission and Distribution Conference and Exhibition*, volume 1, pages 470–474. IEEE.

Raith, J., Bonini, C., and Scala, M. (2020). Simulation of long-term transformer operation with a dynamic thermal, moisture and aging model. In *5th International Colloquium on Transformer Research and Asset Management*, pages 211–226. Springer.

Sakurada, K., Shibuya, M., and Wang, W. (2020). Weakly supervised silhouette-based semantic scene change detection. In *2020 IEEE International conference on robotics and automation (ICRA)*, pages 6861–6867. IEEE.

Sattler, T., Zhou, Q., Pollefeys, M., and Leal-Taixe, L. (2019). Understanding the limitations of cnn-based absolute camera pose regression. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 3302–3312.

Seitlinger, W. (2000). A thermo-hydraulic transformer model. *Proceedings of the Conference of Electrical Power Supply Industry*.

Sels, S., Verspeek, S., Ribbens, B., Bogaerts, B., Vanlanduit, S., Penne, R., and Steenackers, G. (2019). A cad matching method for 3d thermography of complex objects. *Infrared Physics & Technology*, 99:152–157.

Shafiullah, G. (2016). Impacts of renewable energy integration into the high voltage (hv) networks. In *2016 4th International Conference on the Development in the in Renewable Energy Technology (ICDRET)*, pages 1–7. IEEE.

Shi, K., Chen, Y., Yu, B., Xu, T., Yang, C., Li, L., Huang, C., Chen, Z., Liu, R., and Wu, J. (2016). Detecting spatiotemporal dynamics of global electric power consumption using dmsp-ols nighttime stable light data. *Applied energy*, 184:450–463.

Siebald, H., Hensel, O., Beneke, F., Merbach, L., Walther, C., Kirchner, S. M., and Huster, J. (2017). Real-time acoustic monitoring of cutting blade sharpness in agricultural machinery. *IEEE/ASME Transactions on Mechatronics*, 22(6):2411–2419.

Sinsel, S. R., Riemke, R. L., and Hoffmann, V. H. (2020). Challenges and solution technologies for the integration of variable renewable energy sources—a review. *renewable energy*, 145:2271–2285.

Stent, S., Gherardi, R., Stenger, B., and Cipolla, R. (2015). Detecting change for multi-view, long-term surface inspection.

Tabernik, D., Šela, S., Skvarč, J., and Skočaj, D. (2019). Deep-learning-based computer vision system for surface-defect detection. In *International Conference on Computer Vision Systems*, pages 490–500. Springer.

Taketomi, T., Uchiyama, H., and Ikeda, S. (2017). Visual slam algorithms: A survey from 2010 to 2016. *IPSJ Transactions on Computer Vision and Applications*, 9(1):1–11.

Tuballa, M. L. and Abundo, M. L. (2016). A review of the development of smart grid technologies. *Renewable and Sustainable Energy Reviews*, 59:710–725.

Vidas, S., Moghadam, P., and Bosse, M. (2013). 3d thermal mapping of building interiors using an rgb-d and thermal camera. In *2013 IEEE international conference on robotics and automation*, pages 2311–2318. IEEE.

Wang, C., Daneshmand, M., Dohler, M., Mao, X., Hu, R. Q., and Wang, H. (2013). Guest editorial-special issue on internet of things (iot): Architecture, protocols and services. *IEEE Sensors Journal*, 13(10):3505–3510.