Predictive Maintenance for the Optical Synchronization System of the European XFEL: A Systematic Literature Survey

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Abstract: The optical synchronization system of the European X-ray Free Electron Laser is a networked cyber-physical system producing a large amount of data. To maximize the availability of the optical synchronization system, we are developing a predictive maintenance module that can evaluate and predict the condition of the system. In this paper, we report on state-of-the-art predictive maintenance methods by systematically reviewing publications in this field. Guided by three research questions addressing the type of cyber-physical systems, feature extraction methods, and data analytical approaches to evaluate the current health status or to predict future system behavior, we identified 144 publications of high quality contributing to research in this area. Our result is that especially neural networks are used for many predictive maintenance tasks. This review serves as a starting point for a detailed and systematic evaluation of the different methods applied to the optical synchronization system.

Keywords: Predictive maintenance; Condition monitoring; Fault analysis; Cyber-physical systems; Systematic literature review

1 Introduction

The European X-ray Free Electron Laser (EuXFEL) is the largest currently operated linear particle accelerator in the world and opens cutting-edge research opportunities in molecular and material science and system biology on atomic scale [So20]. Those precise measurements require timing with an error margin in the femtosecond range for most subsystems within the facility. To provide this high-precision timing, an optical synchronization system is installed at the facility to synchronize critical accelerator components in time. Due to the high demands on operating the optical synchronization system accurately, even small decreases in performance can have a huge impact on the overall system [Sc19].
To monitor the health status of the optical synchronization system, different kinds of sensors are installed for measuring environmental conditions like temperature or relative humidity, but also for monitoring more complex properties like numerous control loop variables.

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Especially, the frequency domain of these control loop signals provides information about electrical, mechanical, and optical disturbances. Since the optical synchronization system contains several interconnected devices like laser oscillators, controllers, and motors, we consider the system as a networked cyber-physical system (CPS). Due to the huge complexity of the optical synchronization system and the partially high data rate (up to 300 kHz), detecting and tracking all kinds of failures is not feasible for a human. Therefore, we plan to develop an automated mechanism for the optical synchronization system that identifies and, if possible, prevents potential failures to decrease machine downtime.
The process of automatically identifying faulty behavior of a system and if possible initiating countermeasures using data-driven methods is known as Condition Monitoring (CM) [Ha11]. CM methods use signal processing techniques and fault analysis tools for evaluating the overall health of a system. Predictive Maintenance (PM) techniques try to predict future critical system conditions in advance to initiate countermeasures before potential bad system states occur [PVB21].
To get a full overview of what kind of PM and CM methods exist and which of them can be applied to the optical synchronization system, we conducted a systematic literature review that aims to determine state-of-the-art CM and PM techniques applied to CPS.
The rest of this review paper is organized as follows: Section 2 discusses related publications. Section 3 describes our approach to conducting a systematic literature review, including three research questions that we want to answer. Section 4 reports the main findings of the systematic literature review. Finally, we end with a conclusion in Section 5.

2 Prior research

Most publications reviewing CM, PM, or fault analysis methods give an overview of methods with respect to their respective research area but do not differentiate between CM and PM, i.e., robotics [Hu21, ITK19, Ki18a, Le18, MTT21], rotating machinery [Dr21, NUS21a, NUS21b], energy management [AC20, RTJ21a], transportation systems [AH20, Zh21b], or wind turbines [De21, RTJ21b].
Literature surveys focussing on predictive maintenance tend to evaluate the methods with respect to their industrial and economical context, i.e., [HB21, Ji20a, AA21, Ar21, BCC21]. The authors of [Bo19, SYD11, Li21] each report on predictive maintenance algorithms and future trends in their respective application areas. Literature surveys addressing condition based monitoring also focus on the concrete methods used in their respective application area, i.e, offshore-wind turbines [BRK21, Ma20], rail transport systems [KM21], and hydroelectric plants [dSGC22]. Since anomaly detection is a very prominent way to detect bad systems states, we are also interested in literature reviews covering anomaly detection for CPS. In [AC17, AKI21, Na21a, Se22] the authors review state-of-the-art anomaly detection methods being applied to time series sensor data of different CPS domains.
In conclusion, existing literature reviews focus on publications adhering to a domain different from ours. Furthermore, most existing publications do not differentiate between condition monitoring and predictive maintenance. Therefore, we conducted a systematic literature

review for identifying state-of-the-art methods and techniques that can be used for CM or PM for CPS.

3 Methodology

A systematic literature review is a formal and well-structured approach to synthesize evidence and thus allow researchers to come to an understanding of the current status and current challenges of a specific research area. The methodology of our systematic literature review follows the guidelines as proposed by [KC07]. A systematic literature review consists of four consecutive steps, namely Identification, Screening, Eligibility, and Quality (see Figure 1). First, a set of primary publications was built in the identification step that is successively reduced in the following steps. The filtering in each step is based on respective criteria that are based on a set of research questions.

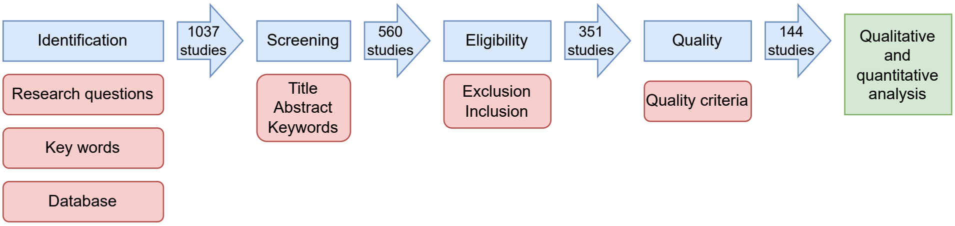

Fig. 1: Systematic literature process

3.1 Research questions and contribution

Our systematic literature review is complementary to existing research in the field of CM and PM for CPS by addressing the research questions depicted in Table 1.

3.2 Selection of primary studies

In the identification step, primary studies were identified by searching for specific keywords in well-known databases. The keywords are derived from the previously defined research questions (Table 1). The systematic literature review was carried out in July 2022 without any restrictions. The primarily identified studies originate from the databases **ACM Digital Library**, **IEEE Xplore**, **Elsevier Scopus**, **Springer Link**, and **Multidisciplinary Digital Publishing Institute**.
The keywords string is based on three different aspects, namely **CM and PM**, **data analysis**, and **Cyber-physical systems**. Each aspect is expanded with a list of various synonyms and phrases that have a similar meaning resulting in an aspect group. The keyword search string

Tab. 1: Research questions

Research questions	Discussion
RQ1: What kind of data is used for monitoring and predicting the health of a CPS?	For analysing the health status of CPS it is required to access sensor data provided by that system.
RQ2: What methods exist to extract meaningful features from data provided by CPS?	Sensor data can very often not directly be used for further machine learning tasks. Therefore the data recordings need some kind of data processing to make the data more meaningful. Thus, an overview of what feature extraction methods are commonly used in the literature as well as their respective CPS areas are determined.
RQ3: What methods exist for CM and PM for CPS?	The most prominent data driven methods for PM and CM for CPS are identified.

is created by connecting the phrases and synonyms of each single aspect group with a logical `OR` and the three aspect groups are connected with a logical `AND`. We split the two aspect groups `CM and PM` and `data analysis`. Merging these two aspect groups, we came up with a lot of publications that do not follow our research goal which is to detect a degradation in the system. We also generalized the optical synchronization system part, where we found out that the term `CPS` is the most general form of a complex system like the optical synchronization system and is the best fit for our research goal. The final search string looks as follows:

```
(''predictive maintenance'' OR ''health monitoring'' OR ''condition
monitoring'') AND (''data analysis'' OR ''fault diagnosis'' OR ''fault
analysis'' OR ''fault detection'' OR ''anomaly detection'' OR ''outlier
detection'' OR ''time series forecasting'' OR ''time series prediction''
OR ''data forecasting'')
AND (''Cyber Physical System'' OR ''CPS'' OR ''Cyber-Physical System'')
```

Combining the results of the different databases results in a total of 1037 studies.

3.3 Screening

In the initial screening phase, we filtered the studies following a set of very broad guidelines to ensure that no important studies are filtered out in the first stage. A publication passed the first screening phase if it follows one of the following criteria:

- The study describes what kind of data is extracted from a CPS (RQ1)
- The study presents how data coming from a CPS is processed (RQ2)
- The concept of CM or PM in the context of CPS is explained in general (RQ3)

- The study describes how a specific CM or PM method is considered in the context of CPS (RQ3)
- Different predictive maintenance methods are compared and evaluated (RQ3)

The number of studies was decreased by 477 to 560 remaining studies.

3.4 Eligibility and Evaluation

The eligibility of the remaining publications was determined by examining the full texts of the papers against a predefined set of inclusion and exclusion criteria (see Table 2).

Tab. 2: Inclusion and exclusion criteria for the studies

Inclusion Criteria	Exclusion Criteria
• Original research study • Peer-reviewed publication • Study presents new methods for CM or PM for CPS • Study evaluates CM or PM methods for CPS	• Secondary research and review papers • Studies that are only available as presentations • Publications not in English or German • Studies covering network security of connected CPS

To proceed to the next evaluation phase, a study has to meet three of the four inclusion criteria and none of the exclusion criteria. In this phase, we reduced the number of studies by 209 to 351 remaining studies.

3.5 Quality Assessment and Synthesis

Each of the remaining studies is evaluated using a set of quality assessment criteria depicted in Table 3. Each study gets assigned a score between 0 and 6. All studies with a score of less or equal to 3 are excluded. After the quality assessment phase, we have a total of 144 publications of high quality according to our guidelines.

4 Data analysis

To provide insights into the current state and future trends in CM and PM for CPS, we performed a descriptive analysis of the remaining publications attained through the systematic attrition process (see Fig 1). Afterward, we performed a detailed qualitative analysis of the selected literature, addressing each research question individually.

Tab. 3: Quality assessment parameters

Parameter	Quality indicator	Score
CPS environment	No description of the CPS and the data used	0
	Basic description of the CPS and the data used	1
	Reasoning why data is valuable for PM or CM	2
Algorithms and modeling	No description of the methods used	0
	Basic description of the methods used	1
	Reasoning why methods are used for that specific problem	2
Empirical evaluation	No evaluation of the developed methods	0
	Basic empirical evaluation of the methods used	1
	Reasoning about the performance of the methods	2

4.1 Descriptive analysis

Following the process of filtering the publications as depicted in Figure 1, we were left with 144 publications that fulfill our criteria (Sections 3.3, 3.4, 3.5). This section includes an analysis of how much research was done in the field of CM or PM for CPS.

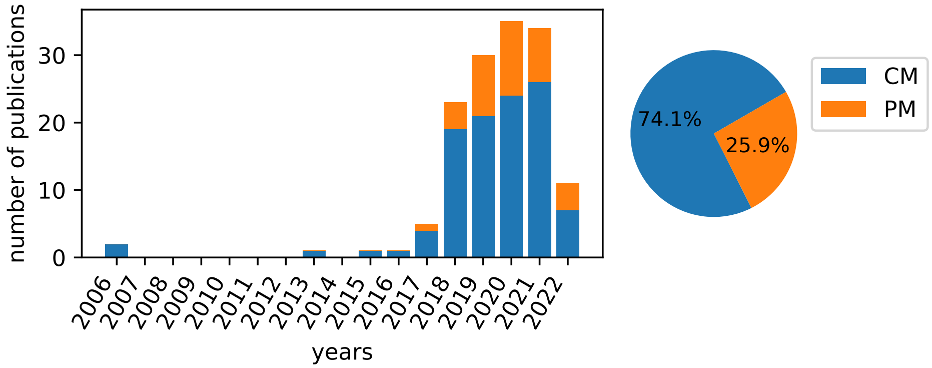

Fig. 2: Number of publications of high quality per year addressing CM or PM

The number of publications addressing CM or PM per year is shown in Figure 2. In general, papers addressing CM problems are published more often than papers addressing PM. The first CM publication was made in the year 2006, no publications matching our criteria were made from 2007 to 2012. Just three publications about CM were made in the years 2013, 2015, and 2016. In 2014, we found no publication of high quality about CM or PM for CPS. The first publications about PM were made in the year 2017. Starting in 2017, the number of publications about CM and PM increased heavily, such that the number of publications reached its maximum in the year 2020 to a total number of 35 publications. Since our study was done in the first half of 2022, the number of publications in the year 2022 is very low and not representative of a new potential trend.

4.2 Qualitative analysis

The final set of publications with a quality score of higher than 3 was also used for an in-depth analysis to answer the research questions (see Table 1). For that, we analyzed the full texts of each of the publications and extracted the **CPS area** (RQ1), **monitored data** (RQ1), **feature engineering technique** (RQ2), **machine learning type** (RQ3), and **CM or PM** (RQ3).

4.2.1 RQ1: What kind of data is used for monitoring and predicting the health of a CPS?

For evaluating the health of a specific system or to predict future system behavior it is required to gather data coming from that system by using different kinds of sensors. Most of the sensors interact with the environment and produce an electrical signal, but very often the electrical signal stands for a different physical unit. Depending on the sensor type, the electrical signal coming from the sensor is converted into the respective physical unit (i.e., temperature, acceleration, acoustics) that is monitored and used for CM or PM.

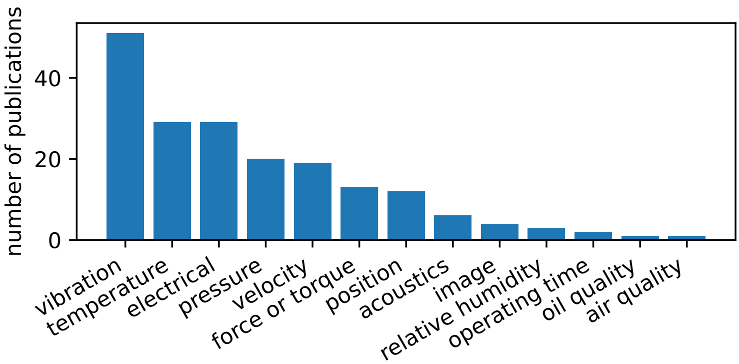

Fig. 3: Number of monitored data usages

A total of 51 publications from different domains use vibration data, e.g. [AH21, ANA20, Ki18b, Zh18]. 29 studies report on the successful use of temperature data, e.g. [CL20, Le20], also, 29 publications use electrical data, e.g. [EW18, GL18], 20 publications use pressure data, e.g. [Li18a, Ma21a], 19 publications analyze velocity data, e.g. [Bo21, LW19], 13 publications use either a force or torque as input, e.g. [Li20b, Sh21] and twelve publications use a specific position of the CPS [Ma21a, SG20]. Few papers report on the use of acoustics [Wu21], images [Vi19], relative humidity [Sy18], oil quality [Li19a], or air quality [Sy18]. Very often, a publication does not just monitor a single signal but combines different properties to a multivariate dataset, for instance, the authors of [Ma21b] combined temperatures, velocities, torques, and pressures from an industrial press to a joint monitoring dataset.

4.2.2 RQ2: What methods exist to extract meaningful features from data provided by CPS?

Data coming from CPS may contain noise that could lead to poor learning performance if not properly handled. Additionally, the high dimensionality of CPS data may lead to potential dropping performances. Due to these problems, it is very often required to not directly work on the data, but to extract meaningful features from the data and apply algorithms to the extracted features. We, therefore, identified feature extraction techniques that are successfully applied to CPS data. Figure 4 shows which feature extraction techniques are applied to what type of monitored data.

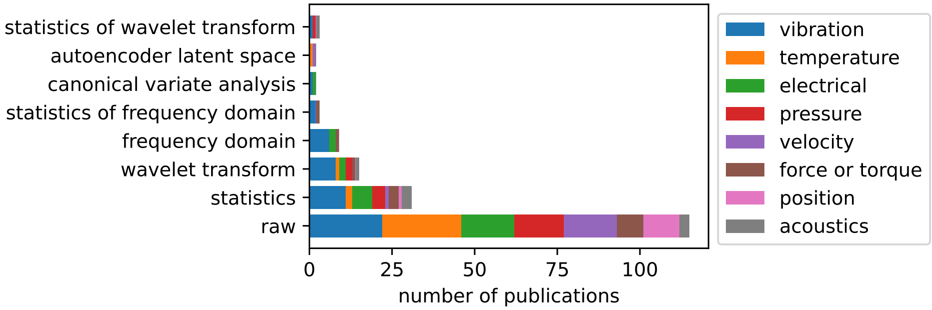

Fig. 4: Feature extracting methods with respect to the monitored data that are used more than once

Most of the publications do not use a feature extraction method, but they are applying machine learning algorithms directly to the recorded data. The most frequently used feature extraction method is to split the data into smaller segments and determine certain statistics of these segments. For example, in [DK18] the authors use the root mean square (RMS), kurtosis, crest factor, skewness, and entropy. The authors of [SZ21] calculate basic statistics (i.e., maximum, mean, root mean square, variance, standard deviation, skewness, kurtosis) from the time domain, but also from the frequency domain. These features are then combined into a common dataset as input for machine learning algorithms. The second most feature extraction method is to calculate the wavelet transform of the monitored signal [AJW20, Ca20]. Two publications [AJW21, LTT19] also compute certain statistics of wavelet transform and use these as features. Twelve publications utilize the frequency domain of the monitored signal, either by calculating the Fourier components or the power spectral density. Eight publications use the frequency components directly as data, e.g. [Xu17], and four publications compute certain statistics from the frequency domain [Zh22]. Two publications extract features by training an Autoencoder (AE) such that the latent space representation of the monitored signal is used as a feature [Fo20, Li18b]. The authors of

[ALK21, Wa21] use canonical variate analysis for extracting features.
The feature extraction stage results in a dataset consisting of multiple features for every point in time. Before applying the actual evaluation or forecasting of the system status, machine learning pipelines might contain dimensionality reduction techniques to decrease the number of features. Feature reduction techniques can also be applied directly to the monitored data because different CPS sensors tend to generate correlating signals (e.g. temperature, spinning speed). In the analyzed publications, twelve publications make use of principal component analysis, e.g. [CYM15, Ch20a, Fa20, LRN20]. Linear discriminant analysis [Na21b, KH22] is used by two publications and t-distributed stochastic neighbor embedding [Se21] by one publication.

4.2.3 RQ3: What methods exist for CM and PM for CPS?

For identifying the most prominent methods, publications processing either simulated data sets or real industrial case studies are analyzed. As a result of this, existing machine learning methods or algorithms were identified and evaluated according to their purpose, either PM or CM. To get a precise overview of methods and algorithms among the publications, we analyzed CM methods and PM methods separately.

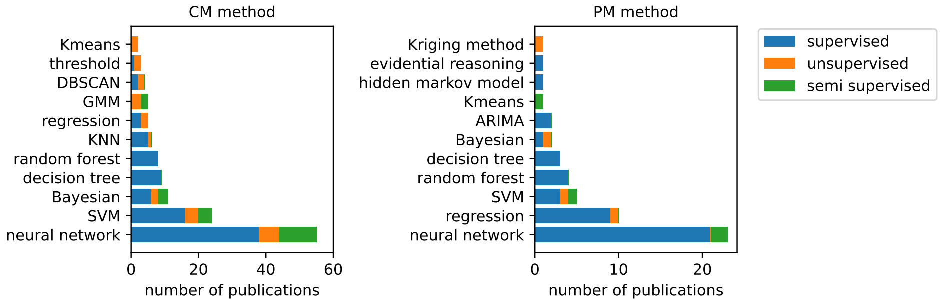

Fig. 5: Prominence of CM and PM methods

Figure 5 shows the distribution of the different methods that are used more than once for CM or PM and their general machine learning type. A general observation is that most of the described CM and PM problems are addressed by supervised learning approaches, followed by unsupervised learning and semi-supervised learning.
The machine learning technology that is used most often for both CM and PM is artificial neural networks since approximately half of the publications apply this technology in some way (e.g., deep neural networks, Convolutional Neural Networks (CNN), recurrent neural networks). Most of the publications taking advantage of neural networks use this technology for supervised learning, but neural networks are also applied in the context of unsupervised and semi-supervised learning. A more detailed overview of what kind of neural networks are utilized by the publications is given later in this section.
In the following, we concentrate on methods used in CM applications. The Support Vector

Machines (SVM) are used for supervised learning [AJW20, CCH19, GL18], unsupervised learning [BB21], and semi-supervised learning [YZ21]. Decision trees [Se18, Zh20] and random forest classifiers [Pa20, Xu19] are both mainly applied for supervised learning tasks. Different publications use algorithms that are based on Bayes' theorem (Bayesian estimation [Ly21, SG20], Bayesian filtering [FT21], Bayesian classification [EW18]). Six publications use different regression-based technologies, for instance, linear regression [Du20], polynomial regression [Vi18], or support vector regression [Sh21]. Different clustering algorithms, namely Gaussian mixture models [Ma21a], Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [Sy19] and K-means clustering [Na21b] are applied mainly for unsupervised and semi-supervised learning tasks. Few publications use the result of the feature extraction as an anomaly score to measure the faultiness of the respective system. By defining a specific threshold [CYM15] on that measure, the respective data is evaluated. The remaining methods that are used just once are hidden Markov model [Ki18b], hierarchical clustering [Ka19], a method based on belief rules [Yi17], AdaBoost [LN21], affinity propagation [Ha16], recursive graph model [Ch20b], and linear discriminant analysis [KH22].

In the following, we report on PM methods. Different regression-based algorithms are used second most, namely, linear regression [FHS21, Wu18], support vector regression [Kh21, Ni21a], and RANSAC regression [JZW17]. The authors of [Le19] use weighted least squares regression and feasible generalized least squares regression. In [GK20], the authors evaluate the different regression-based methods (linear, gradient boost, random forest, extra tree, AdaBoost). SVM [Fe19, GYS21, PK20, Ye19] are utilized third most. Random forest classifiers [Be19, Yu21] are used four times, and simple decision trees [Ca20] three times, both just for supervised learning purposes. ARIMA [Ji20b] and methods that are based on Bayes' theorem [Li19b] each are used two times. K-means [Li18c], hidden Markov model [Wu18], and Kriging method [Li19b] each are utilized once.

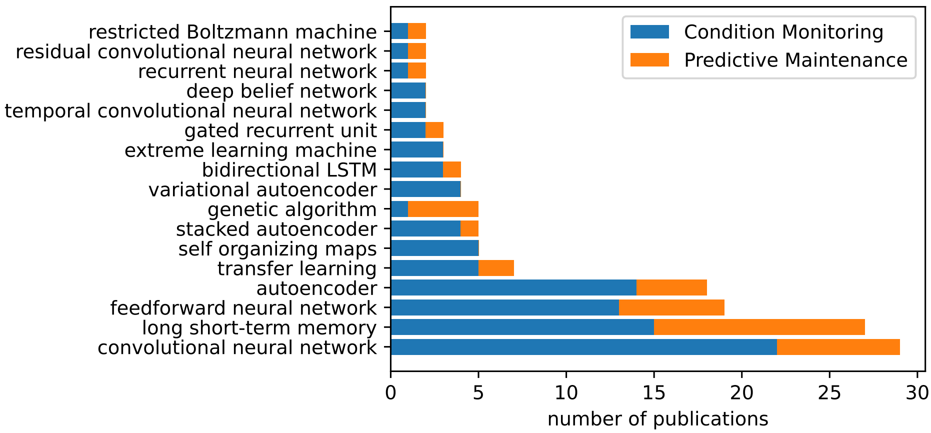

Fig. 6: Popularity of neural network types for CM and PM publications. Different architectural choices are counted individually

An overview of the neural network types used for CM and PM applications is given in Figure 6. Most of the neural networks contain either convolutional layers (*CM* [LRN20, Ni21b], *PM* [MK20, Ye19]) or LSTM cells (*CM* [TC19, VEN20], *PM* [AJW21, KC21, NZU20]). More PM publications use LSTM neural networks than convolutional-based neural networks. Pure feedforward neural networks are addressed by thirteen CM publications [Ad20, MPD18] and by six PM publications [Fa20]. Four publications use autoencoder for PM [MK20, Ye19] and 14 publications use autoencoder for CM [BB21, DK18, FG21, YZ21]. The remaining neural network technologies are more special and used less. The remaining technologies are transfer learning (*CM* [Ci21, Zh21a], *PM* [Kh21]), self-organizing maps (*CM* [Bi18, K.18, Li18a]), stacked autoencoder (*CM* [Al20, DK18], *PM* [Fo20]), genetic algorithms (*CM* [Ad20], *PM* [Fa20, KC21]), variational autoencoder (*CM* [Li18b, YZ21]), bidirectional LSTM (*CM* [So21], *PM* [Kh21]), extreme learning machine (*CM* [Xu17]), gated recurrent unit (*CM* [Zh21a], *PM* [Wi20]), temporal convolutional neural network (*CM* [S.19]), deep belief network (*CM* [Zh19]), basic recurrent neural network (*CM* [Li20a], *PM* [Ji20b]) residual convolutional neural network (*CM* [Ni21b], *PM* [MK20]), and restricted Boltzmann machines (*CM* [De22], *PM* [Fo20]).

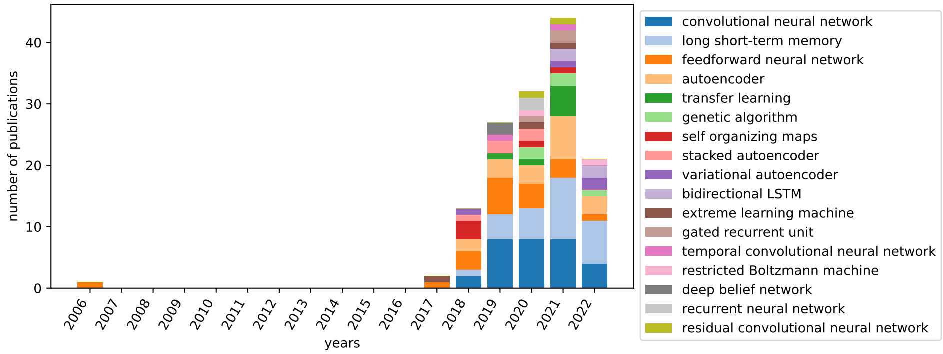

Fig. 7: Yearly distribution of techniques associated with neural networks

Figure 7 displays how the popularity of techniques that can be associated with neural networks for the purpose of PM or CM for CPS develops over the last decades. The developments give a good indication of which new trends are on the horizon and help to understand what techniques were successfully applied over a longer period of time.

CNN, LSTM, and pure feedforward neural networks are applied over the longest period of time. The number of pure feedforward neural network appearances decreased after 2019. Self-organizing maps were mainly used in the year 2018 and deep belief networks were only used in 2019. The number of AE usages grows from 2018 until now. The last appearance of a stacked AE was in the year 2020 while the number of VAEs increased in recent years. The number of bidirectional long short-term memory usage grows starting in 2021.

Transfer learning, extreme learning machines, and genetic algorithms are techniques that address the training process of neural networks. The number of usages increases over time.

5 Conclusion

The goal of this study was to report on state-of-the-art methods that are used for CM and PM tasks to fill the data engineering pipeline consisting of feature extraction and modeling. Our research questions are phrased such that we get an overview of methods that can be applied to a big variety of CPS. That was necessary since the optical synchronization system is a collection of several types of CPS. We came up with a list of publications, their addressed monitored data, feature extraction methods, and CM and PM methods.

The first research question is answered with a list of what kind of CPS data is addressed by CM and PM. Especially, CPS from different application areas producing vibration data are considered a lot. For the optical synchronization system, potential vibration sources exist such as stepper motors or water pumps. Therefore, it is planned to use accelerometers to directly identify vibration sources and apply the methods found.

The second research question addresses the topic of feature engineering. Most of the publications apply algorithms directly using the recorded signals. The identified feature extraction methods focus either on statistical analysis or on features coming from the frequency domain. The optical synchronization system can make use of that because the operators are heavily using the frequency domain of key signals for evaluating the health status of the system.

The third research question asks for CM and PM techniques. The main difference between PM and CM publications is, that CM uses more fault detection methods like clustering or anomaly detection while PM uses more regression-based algorithms. Also, the percentage of recurrent neural networks, including long short-term memory is higher among the PM publications compared to CM publications. This is because PM techniques are more likely to address the time-dependent behavior compared to CM techniques, which is a typical characteristic of recurrent neural networks.

The development of neural network-related techniques shows that recent publications tend to use more specialized learning algorithms like bidirectional LSTM or transfer learning. This shows that better planning in the neural network design reduces the costs of training huge neural networks with a simple structure.

Predictive maintenance often requires prior knowledge to build a model capable to predict future system states. Therefore, applying predictive maintenance techniques includes a manual inspection and monitoring of the system state over a longer time.

In conclusion, the review of existing PM and CM work builds an extremely helpful foundation for systematically evaluating the health status of the optical synchronization system and predicting future system outages.

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