

A Review: CNC Machine Fault Detection Sensor for Oil and Gas Application

Raja Siti Nur Adiimah Raja Aris^{1, 2 *}, Fahmi Samsuri¹,
Damhuji Rifai², Kharudin Ali², Zulfikri Saleh², Nor Hana
Mamat² and Siti Nurshafina Zaharah Saffinee@Shafie²

¹Faculty of Engineering Technology, University Malaysia Pahang, Pahang, Malaysia

²Faculty of Engineering Technology, University College TATI, Terengganu, Malaysia

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ABSTRACT

Due to the excessive growth of technology, the demand of CNC machine become more significant in the industries. This paper presents a review on variety of sensor used to implement for fault detection applied to the CNC Machine. The variety sensor used to measure fault detection is investigated and discussed, focus the studies that were published within the latest five years duration. The first part will explain the CNC machine application on manufacturing industry. The second part represented an overview of a various sensor usage in CNC machine. The implementation of a different sensor such as vibration sensor, sound **Keywords:** CNC Machine, Fault Detection, Vibration Sensor, Sound Sensor, Sensor Fusion

I. INTRODUCTION

Over the past decades, the manufacturing system has changed greatly. This revolution is boost by the introduction of a manufacturing machine that was completely control by a numeric control system (NC). The overview of mathematical control technology has allowed machine work direction to be monitor via computerized control (CNC). A processor is used in this system to carry out all mathematical controls of CNC machines [1]. Computer numerical control (CNC) network also known as machine tool's intelligence regarding to the capability to control the motion of machine tool automatically [2]. In manufacturing industry, the Computer Numerical Control (CNC) machine used to fabricate part of object such as bolts, screw, nuts and desired design based on requested [3]. The manufacturing sector is using CNC Machining proses that involves the use of computers to control machine tools. Grinders, mills, lathes and machines are examples of tools that can be controlled in this approach [4]. The mechanical work used based on CNC machines such as drilling, engraving, cutting and others. The workstation

sensor and a fusion sensor have been developed by previous researchers. Normally, the fault detection will occur a few time in a certain duration. In order to overcome this problem, a multiple recognition technique is desired. Previous research discusses only for single sensor. However, a single sensor signal has some limitations which lead to propose for multi sensors monitoring system due to its good performance and strength. Finally, this paper discuss the trend involved for different application for fault detection on a various sensor usage. The review also revealed that enhancement of different sensor will improve on the accuracy of fault detection system. technology's function to execute, conduct and analyze [5] certain devices based on client instruction. The usage of CNC machines has a significant impact on enhanced production in the manufacturing industry [6]. A CNC machine follows programmed guidelines to alter a blank piece of material (wood, plastic, metal, composite or ceramic) to match precise specifications without the use of a manual operator. A CNC machine modifies a blank sample of material (composite, wood, metal, ceramic or plastic) to comply precise descriptions by following programmed guidelines and without a guide operator. CNC machines consist of a motorized manoeuvrable platform and, in some cases, a motorized manoeuvrable tool, both remain controlling by a computer central [7].

The tool is important part in CNC machine tool processing, often regarded as the "tooth" of the machine tool. The extent of tool wear significantly impacts the quality and dimensional accuracy of the workpiece, while the condition of the tool is also critical for ensuring the stable operation of the CNC machine tool system [8]. In general, tool condition monitoring involves collecting monitoring signals such as cutting force signals, vibration signals, acoustic emission signals, and spindle current, and analysing the mapping of these signals to tool wear[9].

The tool will unavoidably wear out or even break during high-speed milling because of environmental or human causes. Thus, it is crucial to do research on more sophisticated, affordable, and trustworthy tool wear condition detecting technologies [10]. The researcher [11] was proposed sensor that provides precise monitoring of the tool condition, as wear directly affects the sensor, simplifying the system and enhancing its reliability. Additionally, the study investigated the impact of tool temperature on the sensor during machining operations to assess the displacement or deformation of the tracing and polymer substrate at various service temperatures.

Meanwhile, another research [12] introduces a novel method for monitoring the wear of cutting tools employed in the micromilling process which is SVM (Support Vector Machine) artificial intelligence model along with vibration and sound signals. These signals were collected from microchannels machined using carbide microtools coated with (Al, Ti) N with a cutting diameter of 400 μm . The proposed classification approach achieved a classification accuracy of up to 97.54%, demonstrating its potential for effectively monitoring cutting tool wear. Based on [13], the wear condition of the end mill is used as the research object, and the established tool acquisition cylindrical model is implemented to collect the wear condition of the side edge of the end mill. This approach provides an effective means of obtaining tool wear information, ensuring prompt replacement of worn tools, and averting tool failures.

CNC machines significantly contribute to the oil and gas industry by playing a crucial role in manufacturing and maintaining various components and equipment used in exploration, extraction, refining, and transportation. The CNC machine are employed for precision machining of valve components, pump parts, drill bits, downhole motors, and structural components like pipelines and flanges. Additionally, CNC machines are integral in welding and fabricating large structures such as offshore platforms, and they play a key role in the repair and maintenance of components, extending the lifespan of equipment. Furthermore, these machines are utilized for rapid prototyping, manufacturing specialized tools, and integrating into automated production lines to enhance overall efficiency in the industry. Their precision measurement capabilities also ensure the accurate fabrication of components, meeting the industry's stringent quality standards. This paper will study the various types of sensor used for fault detection and the trend in the application for various sensor function will discussed for the CNC machine process.

II. CNC MACHINE FAULT DETECTION SENSOR

CNC (Computer Numerical Control) is a instrument that is applied in the production business to generate a products or parts like screws, bolts, nuts and the appropriate arrangement depending on our requirements. When the CNC instrument is turned on, it causes a vibration, the amplitude of the vibration express the energy produced in a specific frequency range [3]. Fault detection and diagnosis (FDD) is critical for industrial equipment to operate in a stable, dependable, and safe manner. It encourage the research on fault detection that is capable of detecting and predicting faults and conducting predictive maintenance[14]. By identifying appropriate sensor location to achieve feedback signal periodically, a several sensor data fusion network is predicted as important for observing the cutting operations[15]

2.1 Vibration Sensor

Machine health management is an important aspect of every industry. In CNC machine, every construction has a mechanical component, such as a bearing. [16] Proposes a three-step process for diagnosing bearing faults that is not conventional (data classification, data acquisition and signal processing, and). The ceramic shear piezoelectric accelerometer with a sensitivity of 10.2 mV/(m/s²), is implemented for data acquisition. Signal processing is applied to exchange time domain vibration data into a time-frequency domain image through the continuous wavelet transform (CWT). Four types of bearing samples is used for experiment and approval of the suggested method.

In a different study, [17] present a machine learning technique to defect diagnostics of a face milling tool. During machining, spindle vibration signals in the feed direction are recorded in both healthy and faulty milling tool conditions. The vibration signals are converted into a set of discrete wavelet characteristics using the discrete wavelet transform (DWT) method. Figure 1 show an experimental arrangement contains of general milling machine with the accelerometer measurement Another studies by Mishra, 2021 [18] discuss a strategy for identifying the best fault indicators from vibration signatures and developing a reliable model for bearing fault diagnostics using the Support Vector Machine (SVM). The vibration signatures are obtained at three different speeds while the load remains constant. The proposed method compares the performance of SVM models that have been trained with the best features. Result shows that the performance of the multi-domain time-frequency structures improved compare to the individual domain signals.

Machines will produce a vibrations during operation causes unwanted vibration occurred that disturb the machine system, resulting in problems such as imbalance, wear, and misalignment. As a result, vibration analysis has become a useful tool for monitoring the machine's health and performance. Over the years, a variety of methodologies for evaluating machinery vibration data have been developed with different set of characteristics, advantages, and disadvantages. According to an investigation by [19] a systematic review of latest vibration analysis for machine monitoring and diagnosis is presented. It combines data collection (using instruments such as analyzers and sensors), feature extraction, and artificial intelligence-based defect detection approaches (AI). Previous research has shown that a method for identify initial faults in time-varying conditions by [20]. In this research, a depth learning pattern is built to systematically identify impulse responses through vibration signals over a 288-day period. The dynamic properties are recognised from the designated impulse responses in

order to identify the early mechanical fault under time-varying conditions.

A conducting controller is designed to discover an abnormality in the milling operation and provide the solution in Field Programmable Gate Array (FPGA) chip. The controller continuously monitors the vibration signal by implementing the acceleration sensor on the milling machine. Studies have found that this situation attempting to extract new vibration patterns that are distinct from those generated during the proper milling procedure from [21]. In a different study, [22] investigated on a chatter recognition technique named reinforced k-nearest neighbours to recognize both model self-learning and chatter recognition. Chatter represent a self-excited vibration that will seriously impact the production procedure. During upper-speed milling operation, where chatter exists frequent, we conducted an experiment on a computer mathematical control milling machine with several classes of sensors. Table 1 provides a summary of previous studies on vibration sensor application and finding from the researchers.

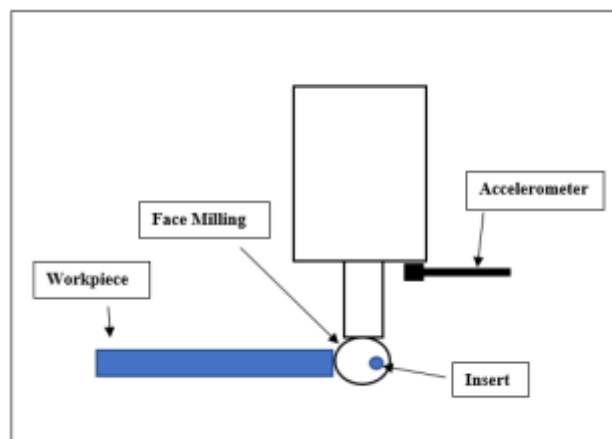


Fig. 1. The structure of accelerometer with Tool-Workpiece Material (TWM)

Meanwhile the researcher from [23], [24], [25] also use a vibration sensor to measure the tool wear condition for milling process.

Table 1. Summary of previous studies on vibration sensor application and finding from the researchers

Author	Method	Application	Observation and Finding
[16]	Continuous wavelet transform Visual geometry group	Bearing machine	The implementation of vgg-19 and a mesh of CWT for signal processing, feature extraction, and data classification, respectively, is innovative in these work.
[17]	Discrete wavelet transform Support vector machine	Face milling tool	Findings shows that the C-SVC model with polynomial kernel of SVM offered a satisfactory classification precision of about 94.5% for the given experimental situation and workpiece of superior steel alloy 42CrMo4.
[18]	Support Vector	Rotating machines	The finding showed that multi-domain

	Machine		characteristics have a high diagnostic capability for classifying various bearing conditions in rotating machines.
[19]	Artificial Intelligence	Machines	A systematic review of vibration analysis is conducted for machine monitoring and diagnosis in this research, which can be separated into three stages: data collecting, feature extraction, and problem recognition.
[20]	Deep learning model	CNC machine	Massive amounts of data were obtained and analysed, and the researchers concluded that the system can accurately predict the health of the machine tool.
[21]	Auto-Associative Neural Network	Milling machine	The paper described about the current phase of the project that create a real-time directing controller for the milling process.
[22]	Reinforced K-nearest neighbours method	Milling machine	The signals from several sensors were compared in the milling experiments, and the suggested chatter identification was tested. The outcomes show the effectiveness of the proposed technique approach.

2.2 Sound Sensor

Studies have found that the fault analysis of the face milling tool utilizing sound signal is presented in this paper. While milling, sound signals from the face milling tool are captured under normal and unhealthy situation. The characteristics of the obtained sound signals are retrieved using the discrete wavelet transform (DWT). The support vector machine (SVM) technique is employed to identify the face milling tool conditions using the retrieved DWT features. Based on [27], result show that the SVM technique is the best classifier matched to other classifiers where it produced 83% efficiency for the given experimental circumstances and component of steel alloy 42CrMo4.

In some applications, the empirical wavelet transform (EWT) has found to be beneficial. However, when nonstationary signals and noisy are investigated, part of local maxima may exist and be wrongly preserved in the peak arrangement, resulting in inadequate frequency domain segmentation. To overcome the EWT's boundary segmentation issue according to [28] the morphological EWT (MEWT) method is studied, which is based on the 1-D Otsu method and morphological filters (MFs). With its good enforcement in determining the appropriate chatter frequency band, this method can be used in chatter detection. The strength of the MEWT and the recent chatter detection approach with high sensitivity

to chatter has been proved using simulation and experimental signals. According to [29] summarized that the investigation of non-intrusive and an affordable approach of considering tool wear can be detected by the audible sound generated during a milling operation. A microphone is used to record the operation sound of S50C steel, which was square shoulder milling with HSS end mill using a computer numerical control (CNC) milling machine. Studies show that the centre frequency and amplitude of the CNC machine resonant sounds developed by the CNC milling process are analysed using a sound detection approach. The Fast Fourier Transform (FFT) is applied in spectral measurement and microphone used as a sound detector during milling process in the LabVIEW embedded system is demonstrated in this research [3]. The study of Qi [30] was the sound emission is applied to investigate the correlation among machining specifications and the sound emission signal covered by various processing specifications parameters when monitoring high-speed micro-milling. Figure 2 show the device used for micro-milling testing using AE sensor. Another researcher that implement the sound sensor application for tool wear condition measurement including [31] and [32] respectively. Table 2 provides a summary of previous studies on sound sensor application and finding from the researchers.

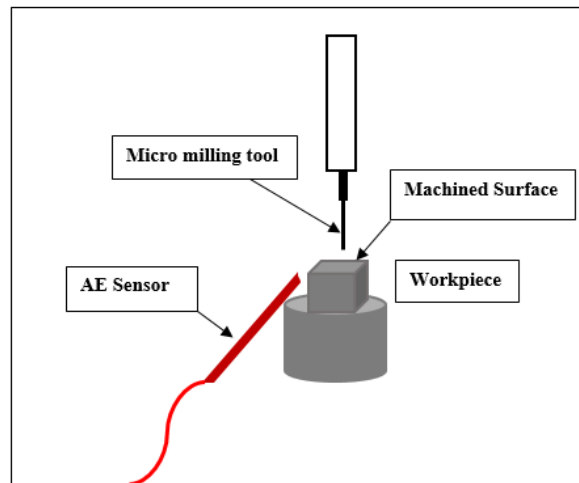


Fig. 2. The micro-milling experiment device using AE Sensor

Table 2. Summary of previous studies on sound sensor application and finding from the researchers

Author	Method	Applic a- tion	Observation and Finding
[27]	Discrete wavelet transform Support vector machine	Face milling tool	The SVM method is the great classifier where it provided an encouraging output in this research, with 83% classification accuracy for the particular experimental setting and workpiece of steel alloy 42CrMo4.
[28]	Morphological empirical wavelet transform	Milling machine	The approval of the MEWT and the innovative chatter detection approach with high sensitivity towards chatter has been verified using simulation and experimental signals.
[29]	Fast fourier transform	Milling machine	The results showed that the magnitude of mean sound pressure existed proportional to tool wear, but that the magnitude of mean cutting sound increased approximately as tool wear improved.
[3]	Fast Fourier Transform	CNC machine	The real-time embedded structure calculated amplitude values and resonance frequency using CNC milling

			process noise based on the test results. Its capacity to acknowledge high and low frequency noises as well as responsive to voice recognition for CNC machine sounds.
[30]	Singular value decomposition	Micro milling machine	The outcomes show that the typical values of the acoustic emission signal can produce changes in machining parameters like spindle speed, and that the acoustic emission signal is effective for micro-milling process monitoring.

2.3 Sensor Fusion

In micro-milling applications, tool condition monitoring systems are critical. The slenderness of a tool needs a great-precision monitoring devices for online measurements by [33] discuss about an analysis of vibration signals and cutting force using a frequency- and time-frequency-based to evaluate the tool condition of a high-speed micro-milling progress. Regarding to [34], a multi sensor are used for fault detection. The data were sampled by three different varieties of sensors which are current sensor, acoustic emission sensor and vibration sensor. A sensor fusion were reported at several places on the CNC machine. For structure modelling, the Principal component analysis (PCA) will handle the new data during the process of fault detection for interval-valued data methods. As a result, the PCA method with complete evidence is used as an instrument for modelling uncertain sensor data for analysis purpose due to its simplicity and competence compared to other well known PCA for interval-valued data methods.

Similar work has also been pursued by others [35] in which the three types of sensor (vibration sensor, current sensor and acoustic sensor) are used to collect a data from different locations of milling machine. The data is acquired using a high-speed data collecting board through a sampling frequency of up to 100 KHz. More recent work by [36] used an applied methodology to develop an innovative health indicator based on heterogeneous sensor measurements to observe system conditions efficiently. In order to analyse the different fault categories, this indicator is applied an adaptive neuro-fuzzy inference structure

pattern. The experiment tests were carried out in three-dimensional space under various operational conditions and were monitored by several parameters (force, vibration, current and torque signals).

This paper applies a multi device tool wear assessment technique based on blind source partition technology were investigated by [37] to address this problem. The technology of stationary subspace analysis (SSA) is used to convert multi device data to nonstationary as well as stationary sources without any prior knowledge of the signals.

On other situation, [38] is proposed a monitoring system with different sensor which are vibration, noise and acoustic emission to collect the data during the milling process. Based on the output result, the system is capable to produce a great recognition system for tool wear monitoring with the accuracy of 90%.

The researcher [39] obtained a technique that involves extracting multidomain features from cutting force and vibration signals and merging them into feature sensors. The method utilizes a proposed hypercomplex position encoding and high-dimensional self-attention mechanism to compute a new representation of the input feature tensor. This process emphasizes the sensitive information related to tool wear while mitigating the influence of extensive background noise. The experimental findings validate that the prediction accuracy achieved by the proposed method significantly surpasses that of other state-of-the-art methods. Table 3 provides a summary of previous studies on fusion sensor application and finding from the researchers.

Table 3. Summary of previous studies on fusion sensor application and finding from the researchers

Author	Method	Applica-tion	Observation and Finding
[33]	Fast Fourier Transform Continuous Wavelet Transform	Micro milling	The findings show that tool wear causes fluctuations in the dominating frequencies. The analysis results generated after the two process signals produce more consistent results and increase the sensing bandwidth.
[34]	Principal component analysis	Milling Machine	A simulation sample and a milling machine operation, and thus a Monte-Carlo investigate for validation, are used to demonstrate the proposed fault detection scheme's performance.
[35]	Support Vector Machines Convolution Neural Network	Milling machine	The AE is employed to investigate the use of deep learning in feature extraction. The good characteristics might be identified based on both quantitative and qualitative factors. The output display that AE is capable of obtaining features.
[36]	Adaptive neuro-fuzzy inference system	Robot cutting tool	The experiment tests were carried out in three-dimensional space under different working conditions and were monitored by several parameters (vibration, force, current and torque signals). The achieved results showed the proposed health indicator's robustness across a variety of system operating modes and signal types.
[37]	Stationary	Milling	The outcomes

subspace analysis Least squares support vector regression	machine	showed which the root mean square error and correlation coefficient of the suggested technique were approximately better than PCA + LS-SVR and LS-SVR toward two milling TCM experiments
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III. TRENDS IN THE APPLICATION OF VARIOUS SENSOR FUNCTION IN CNC FAULT DETECTION

The trend in the application of various sensor in CNC fault detection research can be viewed in Fig 3. Since 2019, 21 articles were published which include research paper, review paper and conference paper. The number of publications in 2019 is 3 and by year 2020 is 5 and 2021, the publication is increased to 6. Meanwhile the number of papers for year 2022 and 2023 publication is 4 and 3 respectively. The sensors are the most widely used in CNC machining that have the ability to detect and predict faults detection and handling predictive maintenance. However, many researchers are still attempting to enhance the accuracy of sensor detection on CNC machine. The existing research [18] proposed a method for determining the best fault indicators from vibration signatures. Then, the Support Vector Machine (SVM) method is applied to develop a robust model for bearing problem diagnostics. Another researcher [27] presented that the fault diagnosis for face milling tools can be analyzed

using sound signal. Sound signal from two conditions of face milling instrument which is under healthy and fault conditions (breakage, flank wear and chipping) are monitored. A good classification accuracy based on SVM classifier that provided 83% through the DWT structures and it can be applied in the monitoring/fault analysis state. Current trends show that a significant amount of research has combined various sensors in producing the fault detection investigation.

[34],[35] summarized that a fusion sensor is able to detect a different condition of fault detection indicators from the milling machine. The data from three types of sensors (vibration sensor, current sensor and acoustic sensor) at various locations of milling machine were compiled at a different position. Results show that the best suited interval evidence for fault recognition is evaluated based on good detection ratio and uncertainty ratio. It validates the perceived enhancements over the traditional PCA error detection strategy. Generally, these studies verified that the application of sensors is improved in the accuracy of fault detection analysis of CNC machines.

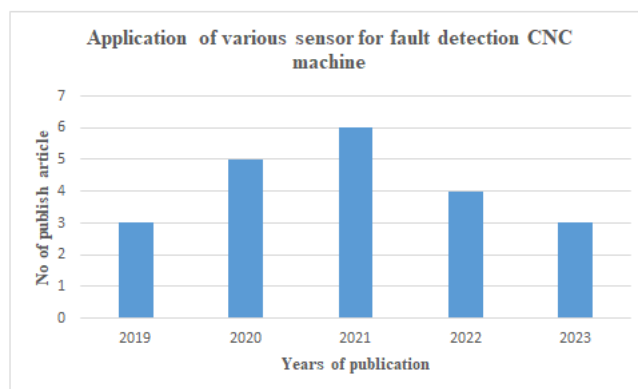


Fig. 3. Five years of previous research trend on the various sensor for fault detection CNC machine

IV. FAULT DETECTION FOR INTELLIGENT APPLICATION

In recent centuries, deep learning prototypes successfully applied in data-driven Fault detection and diagnosis (FDD) regarding to their autonomous characteristic learning ability. This paper proposes [14]

a deep transfer convolutional neural network (TCNN) structure as an online fault detection technique. A specialty TCNN structure consists of an online CNN occupied with LeNet-5 and some offline CNNs with a narrow arrangement. The online CNN is competent to identify faults by classifying these images when the

fault information collected is sufficient. There are three case studies have been investigated which are on rolling mill bearing, centrifugal pump fault data sets and the motor bearing. The accuracy of fault analysis is improved after various intelligent technology approaches have been established. Another new approaches is discuss on statistical characteristics, variational mode decomposition (VMD) and SVM such as permutation entropy (PE), energy entropy (EE) and variance contribution rate (VCR). A great tools based on the combination of WPT is applied to remove the noise influence on original vibration signal. The VMD is function as decomposition system to extract the feature meanwhile the SVM use as a fault classifier. The experiment have be done on rolling bearing test data from Electrical Engineering Laboratory, Case Western Reserve University as the analysis to prove the method [40].

The condition regarding to the machine tool failure can be recognize by a professional knowledge-based system. This system presented [41] method to detect the irregular roots of failures by apply the analysis data process provided by the PLC Data Logger. The data analysis of machine fault condition is using the Fuzzy Logic algorithm technique. A model system to detect electro spindle defect that occur on CNC machining was developed. Based on the result achieved, the proposed system is successfully capable to perceive failure triggered by impact events and reduces period time during analysis by 80%. The paper [42] discussed on a pattern recognition algorithm for self-healing mechanism called Logical Analysis of Data (LAD). By implementing multiple distance techniques, this algorithm produces patterns that characterise the out-of-requirement stage and offer a corrective setting inside the recovery patterns of the within specification stage. In this study [43], a new non-invasive approach for the stray flux collected over the spindle-motor based on the time–frequency evaluate is proposed. The method purposely applied on cutting tools to sense and measure the wearing level. A feed-forward neural network (FFNN) is used to provide the final analysis automatically to determine a fault level indicator based on the stray flux time–frequency where is refer to the classifying the wear on the cutting tool in the machining process. The output found that the cutting tool wear have a low sensitivity on the axial stray flux. The automatically of measurement and arrangement regarding to the wear on the cutting tool is successfully in this research.

V. CONCLUSION

The review of various sensor for implementation in the appropriate system is

investigated for fault detection in machining process. Machine will generate the vibration during the operation, thus its will produce the unwanted vibration that will disturb the machine system. The vibration sensor is represented to monitor the condition of machine during healthy and fault condition. In addition, the sound sensor shown a significant part in the fault detection analysis. An investigation of the frequency and amplitude based on sound signal received from machine is implemented using support vector machine and Fast Fourier Transform (FFT) method. The combination of sensor have capability to predict the best analysis on fault detection and high-precision monitoring system. A lot of application are using the sensors as a tools to predict a fault detection such as milling machine, face tool milling and bearing machine.

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