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Review of Standards and Systems for Predictive Maintenance

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ABSTRACT

This paper aimed to the analysis of the systems for predictive maintenance. It discusses the methods for maintenance of the industrial equipment and facilities, as well as the requirements and standards set for the predictive maintenance software. It compares the capabilities of the most popular non-commercial and commercial software systems and platforms for predictive maintenance as OSA-CBR, PHM, MIMOSA, PLM, CMMS, etc.

Keywords: Predictive Diagnostics Standards, Predictive Maintenance Software.

INTRODUCTION

The economic success and competitiveness of companies in the chemical, petrochemical, nuclear, energy, metallurgy and mining industries strongly depend on the safety of technological equipment and low maintenance costs.

Predictive diagnostics and maintenance of technological equipment is a methodology that extends the life of technical equipment and systems and at the same time optimizes their repair costs. According to leading companies in the field, every dollar invested in predictive maintenance leads to between seven and thirty-five times the return.

This research focuses on the analysis of software systems for predictive maintenance. It comments on the methods for technical maintenance of the facilities and the requirements and standards formulated for the software for predictive maintenance. The capabilities of the most popular software systems and platforms for predictive maintenance and support, such as OSA-CBR, MIMOSA, PHM, PLM, CMMS, etc.

TECHNICAL MAINTENANCE METHODS

The following methods for technical [1 - 3] maintenance are known:

- **Breakdown maintenance**, which is the oldest approach to maintenance. The unit is repaired only in the event of damage or accident.
- **Preventive maintenance** known as well as time-based maintenance or risk-based maintenance. It is related to repairs at constant

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intervals. Here the maintenance is time consuming and ineffective in identifying problems that occur between planned inspections and is not cost effective. In order this method to work effectively, it is of particular importance to determine the optimal maintenance interval. Preventive maintenance does not eliminate emergency damage, and in many cases requires unnecessary maintenance [4].

- **Predictive Maintenance** or Condition-Based Maintenance (CBM) is based on inspection and repair according to the technical condition. It is advanced maintenance based on diagnosis. This prolongs the life of the devices and units, reduces downtime and maintains an optimal level of production. It allows effective management of equipment maintenance by using the least staff and costs, as well as planning ongoing and

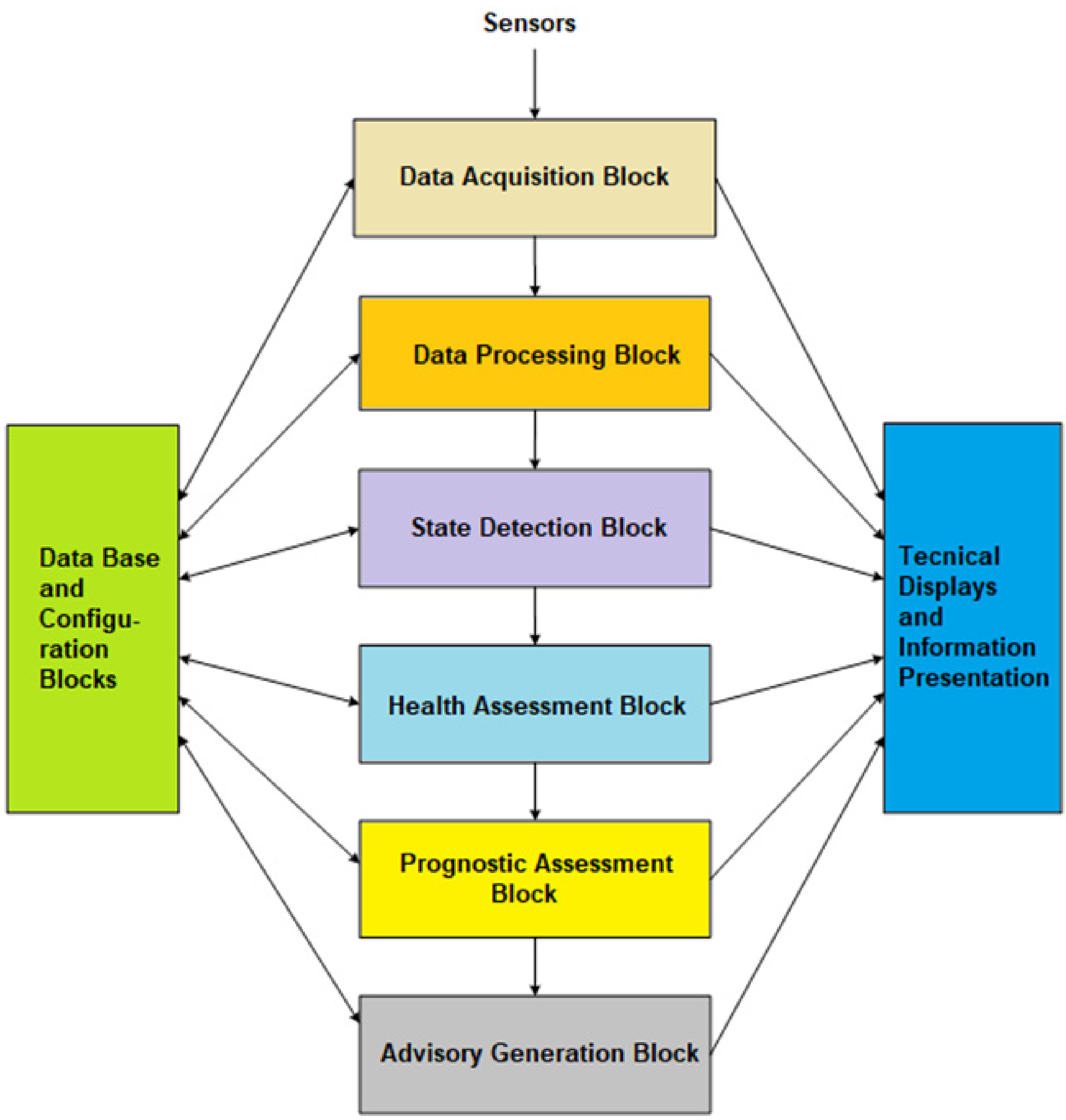

Fig. 1. Block diagram of information flows according to ISO 13374-1: 2003.

major repairs according to the actual condition of machinery and equipment.

- **Proactive maintenance**, which is associated with establishing the root causes of damage of the technical unit and application of proactive actions to eliminate or minimise them.

PREDICTIVE MAINTENANCE STANDARDS

Several international standards are related to predictive maintenance. The standard [5] of Sweden SS-EN 13306, 2001 defines the basic concepts in this field, such as preventive and predictive maintenance, degradation, etc. They are given below:

- Condition based maintenance and condition monitoring and/or parameters and follow-up.

- Predictive maintenance based on the condition performed because of a forecast obtained from the analysis and evaluation of significant parameters of element degradation.

- Degradation - an irreversible process in one or more characteristics of an element over time or with use or due to an external cause.

The international standard ISO 13374-1: 2003 [6] specifies the basic requirements for open source software for state-based maintenance. In Fig.1 the scheme for data processing and the blocks included in the information flow is shown. The diagram shows that the standard fully complies with predictive maintenance due to the presence of a prediction unit.

The main blocks in the information flow are:

- Data Acquisition (DA) block;
- Data processing block (DP) block;
- State Detection Block (SD);
- Health assessment (HA) block,
- Prognostic Assessment (PA) block;
- Advisory Generation (AG) block.

Additional blocks are the external systems block, blocks for data archiving and configuration and the block for technical displays and presentation of information.

The international standard ISO 13381-1: 2004 [7] is aimed at forecasting. It gives the following definition of forecast. The forecast is an estimate of the time to failure and the risk of one or more existing and future failures and is usually intuitive and based on experience. The prognosis is effective for failures and failures with known age-related or progressively deteriorating characteristics, the simplest of which is linear.

According to [8], the Condition-Based Maintenance (CBM) process contains three main stages:

1. Data Acquisition (DA). The main functions are related to the process of collecting and storing information coming from the facility under maintenance. The incoming data are mainly of two types:

- Events Data;
- Condition Monitoring Data.

Event data contains information about what happened to a facility: damage, repair, whether there were preventive maintenance actions, etc. Most often, these data are entered manually, which predisposes to the influence of the subjective factor.

The monitoring data from the observations of the condition of the facility contain measurements related to the current condition of the facility. Most often, they enter automatically, and in some cases, this information is entered manually into the CBM information system, which is again a cause of subjective errors.

2. Signal Processing (SP). The first step involves the primary processing of signals, which includes filtering incoming signals and eliminating gross errors when entering information manually, and it is possible that errors in incoming information are caused by sensor failure. The next step in signal processing is signal analysis. The choice of model, algorithm or tool used for data analysis depends primarily on the nature of the incoming data. Incoming data can be classified into three main groups:

- Data (values) collected in a certain period as unit values of certain variables.

- Data having a waveform. These data are collected as temporary sequences of values. The most common such data are vibration data, acoustic signals and others. The main three categories of waveform data analysis are:

- *Time-domain analysis*. Calculate mean value, maximum value, intervals between maxima, standard deviations and others. Modern approaches include the application of autoregressive models (AR) and autoregressive models with a moving average (ARMA).

- *Frequency-domain analysis*. They are based on the conversion of signals in the frequency domain. The advantage of these methods over time domain analysis is the ability to identify and isolate certain frequency components of interest. The most commonly used method is spectral analysis of signals by means of fast Fourier transform.

- *Time-frequency analysis*. It is developed for non-stationary processes having a wave character.

- Data collected over a period as multi-dimensional values. For example, infrared thermography.

3. Maintenance decision support. This stage involves the use of:

Diagnosis. Statistical approaches, model-based approaches and artificial intelligence approaches are most often used to diagnose equipment. The most commonly used are artificial neural networks and expert systems. Other artificial intelligence techniques used for diagnostics are fuzzy logic-based systems, neuro-fuzzy systems, and evolving systems.

Prognosis. The most commonly used approach is based on previous developments and the current state to predict how much time is left before failures occur. The time remaining until a failure occurs is called “Remaining Useful Life (RUL)”, “Remaining Useful Life” or “Remaining Useful Life”. Another approach is to predict the probability that the facility will operate without failure during a certain subsequent time interval or until the next inspection. This type of prognosis is used in a small number of literature sources.

Forecasting with maintenance policies. The purpose of forecasting is to provide decision support for maintenance actions. The main idea of this approach is to optimize the maintenance policy in accordance with certain criteria such as risk, price, reliability and suitability.

The considered standards and approaches, as well as the processes for signal and data processing in predictive maintenance systems are the basis for the development of software systems and platforms for predictive diagnostics and maintenance of technological equipment.

PREDICTIVE DIAGNOSTICS SOFTWARE SYSTEMS

One of the most common software systems in the field of predictive support is the open system architecture for support based on the state [9, 10], known as the Open System Architecture for Condition-Based Maintenance (OSA-CBM). It is a software platform for managing communications related to the monitoring and diagnostics of various machines and systems. OSA-CBM offers a component-based distributed approach effectively to integrate all data collection; to manage processes and to forecast and make decisions about the maintenance of machinery or equipment. The purpose of OSA-CBM is to standardize the data and message exchange protocol. The effect of this is faster technological development and easy modernization of software (CBM) components, expanding the number of suppliers of such components, which in turn leads to lower prices of the final software. However, the greatest benefit of OSA-CBM is in the process of maintenance and connectivity (unification of interfaces) between all levels/layers of components.

The OSA-CBM architecture consists of seven (Fig. 2) generalized functional layers/levels:

1. Data Acquisition layer;
2. Data Processing and Manipulation layer;

3. State Detection layer,
4. Health Assessment layer,
5. Prognostics Assessment layer;
6. Advisory Generation or Decision Making layer;
7. Presentation layer for presentation of results and decisions.

The layers correspond to the blocks describing the information flows in standard ISO 13374-1: 2003. Only the first five layers are implemented in the OSA-CBM architecture. The decision layer is too specific for each predictive support system and needs to be developed further. Each of the first five layers contains three interfaces: for data, for configuration and for explanations.

The data interface describes the data related to a specific event. The configuration interface contains information about the configuration of the individual module/layer, and the explanation interface includes information about the specific

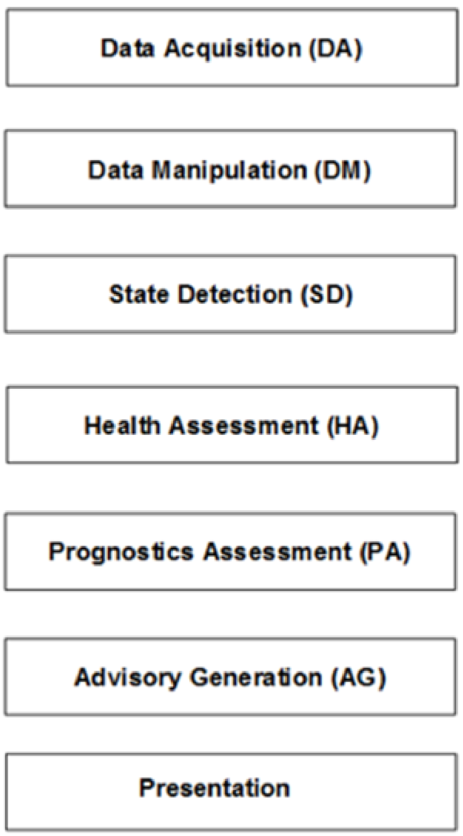

Fig. 2. Layers of OSA-CBM.

device (sensor, etc.) and its setting. This interface is optional for the upper levels.

The last Presentation layer visualizing the results can have interfaces not only to the sixth layer, but also to the others, depending on the specific program implementation.

Each of the interfaces, respectively the data with which it manipulates, are described by XML schemas, which ensures reliability in the exchange and validation of data. The team that developed OSA-CBM initially focused its efforts on the implementation of software components in each of the layers through CORBA, COM/DCOM technologies and the use of synchronous communications. The latest developments and versions of OSA-CBM are focused on the use of Java RMI platforms, Microsoft .NET and programming languages Java, C ++, and C #, as well as the use of WEB-services and asynchronous communications.

When generating the hollow software code for each level / layer, the UML language and its diagrams are used. Through software products such as Rational Rose, Borland Together UML diagrams automatically can be translated into one of the listed above programming languages. Thus, it is possible for component programmers for different layers of OSA-CBM to use different programming languages without interfering with communication between levels, as the latter use XML schemas to describe data and interfaces.

Based on OSA-CBM, a system of forecasting system [11] and management (monitoring) of the "health" of the facilities (Prognostic and Health Management/Monitoring (PHM) system) has been developed. It intended for vehicle monitoring. Because the system is distributed one, the principles of multi-agent systems are also used in it.

Another software platform implementing OSA-CBM is the MIMOSA (Machinery Information Management Open System Alliance) platform. It adds standardized requirements for communication with databases - CRIS

(Common Relational Information Schema). CRIS defines a relational schema database with machine maintenance information. MIMOSA [12] standardizes and defines interfaces for communications between modules, building a layer / layer of OSA-CBM layers. In fact, the original idea for standardizing MIMOSA's interlayer communications and interfaces was further developed and enriched with the OSA-CBM platform in standardizing interlayer interfaces. Both platforms use UML to describe interfaces and XML schemas when describing data and layer configuration.

The software platforms analysed above can integrate in their layers newly created software with the corresponding functionality or ready-made components from CBM program libraries. When creating new software for OSA-CBM and MIMOSA layers, in addition to programming knowledge and expertise in the field of the developed system for predictive support, as well communication between software developers and relevant experts are required.

So far, OSA-CBM and MIMOSA have been used for predictive maintenance in ship systems, heavy machinery, industrial processes and aircraft, such as civil and military helicopters.

The CBMvision software system [13] based on MIMOSA offers on-line wireless communication with the sensors mounted on the monitored objects. The information from the sensors connected to the objects with rotating parts is transmitted to a specialized diagnostic server. It performs filtering and data processing and diagnostics and forecasting of the monitored equipment/objects. The information from the server is archived in a database, according to the schemes of CRIS MIMOSA and is replicated to the cloud (cloud computing) from where it is accessible through WEB-clients.

ReliaSoft [13] has developed a range of software products for simulation, analysis, predictive diagnostics and maintenance of technological equipment. Such are the Lambda Predict, RENO, RCM ++ software products, which are based on various prediction standards used in cases where there is no data on the reliability of a given facility. This is done in order to identify potential areas of damage and thus extend the period of use of the equipment. The software products support prediction of the degree of failure, prediction of the average time between faults (failures), based on the following prediction standards ISO 13374-1:2003, MIL-HDBK-217, (MIL-217), Bellcore, Telcordia and NSWC for prediction of mechanical damage.

Based on the MIMOSA and OSA-CBM GE Intelligent Platforms offers the SmartShield predictive diagnostics and support software platform [15]. The product includes predictive damage analysis of facilities used in the production of electricity, such as turbines, electricity and gas generators or equipment in refineries and oilrig

In [18, 19] the software system for predictive maintenance of technological equipment that complies with the standard ISO 13374-1: 2003 is proposed. The system based on software platform MicroStrategy Analytics [20, 21], using its rich capabilities for data visualizations, reports and analysis, accessible to many users through a web interface, through different types of browsers, mobile and stationary devices. It applied for predicting the state of the Peirce-Smith converters in metallurgy on the base of different methods as Monte Carlo, Case-Based Reasoning [22, 23], etc.

New generation predictive maintenance systems are integrated in Product Lifecycle Management (PLM) systems and in Computerized maintenance management software (CMMS). Systems. The Product Lifecycle Management systems [16] (Fig. 3) are oriented to process business operations and data (different events) produced by technical units or products during they whole lifecycle. The lifecycle includes phases as Beginning of Life (BOL), Middle of Life (MOL) and End of Life (EOL) where BOL is related to the manufacturing of the product, MOL is related to the of usage and operation of the product and EOL means the time when the product is replaced with new one and the old one goes to recycling. The predictive maintenance in PLM system is related to the MOL phase but can be used to BOL phase when new product is designed. It can be used, as well in EOL phase when feedback is provided to the designers in order to modify or better the next generation of the same product.

The difference between PLM systems and the systems discussed above are that PLM ones are definitely Web and Cloud oriented and are based on information and knowledge obtained from the smart sensor devices (product embedded information devices) integrated in new generation products or equipment known as smart or intelligent products. The intelligent products include web services for accessing collected data (events, states, faults), local or distributed memory, number of services supporting monitoring, prognosis and prediction processes, services for planning maintenance actions, as well an appropriate communication infrastructure (standard or mobile network).

Computerized maintenance management software systems (CMMS) are oriented to big enterprises with large amount of different types of equipment and units. These systems support large number of the maintenance activities and processes related to work order management, automated maintenance scheduling, repair parts and supplies tracking, custom reports, purchasing, preventive and/or predictive maintenance, etc. Most CMMS [24] support preventive maintenance activities

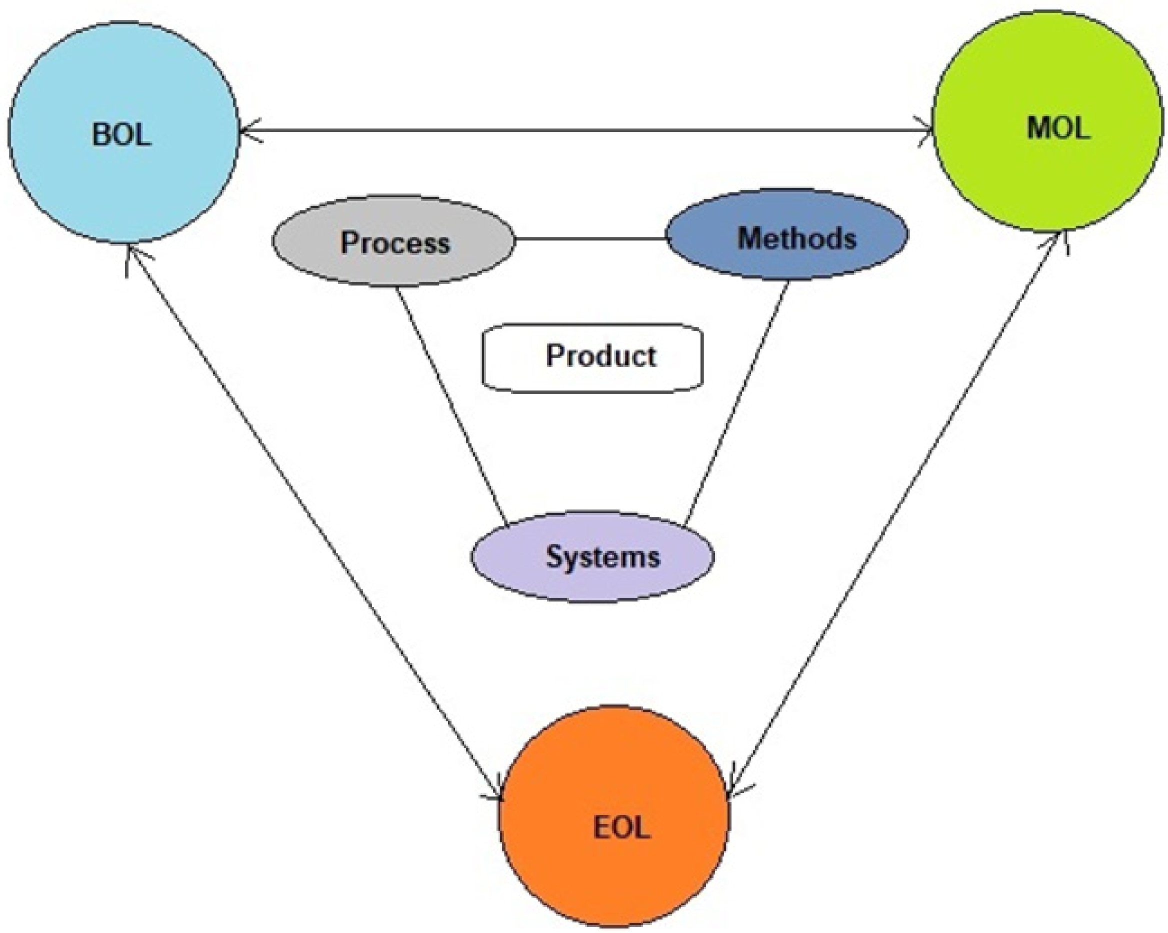

Fig. 3. Product Lifecycle Management System.

(Fiix Software, eMaint CMMS, Hippo CMMS, Q Ware CMMS, Maintenance Connection), other systems support predictive ones (Senseye PdM, Asset Essentials, Limble CMMS). In some CMMS the PLM systems are integrated, so in these cases the predictive maintenance activities are a part of PLM services.

CONCLUSIONS

The report discusses the basic standards for predictive maintenance of technological equipment. The non-commercial software platforms OSA-CBR and MIMOSA analysed, as well as a number of commercial frameworks for predictive support.

The advantages of open source software OSA-CBR and MIMOSA are that it is open to expand and add new or existing components in its various architectural layers.

These platforms are open to upgrades with robust management components, agent-based systems, case-based reasoning, decision-making, and more.

The main disadvantage of these platforms is that the development of specific applications requires excellent programming knowledge and expertise in the specific industry or technological field for which the software for predictive support is intended.

Commercial software products offer turnkey solutions for predictive maintenance of specific facilities or classes of equipment in specific areas of industry. Many of them are flexible and reconfigurable in terms of their settings. At the same time, they offer mobile solutions for access to the data of the monitored objects and flexibility in making decisions for their maintenance, especially since these decisions are based on the experience gained by companies as a result of continuous monitoring in the specific subject area.

A disadvantage of commercial systems is the inability to add new functionality and components due to lack of access to software code.

The analysis made in the report is dictated by the formulation of requirements for the development of own software for predictive maintenance of technological equipment.

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