Hybrid Monitoring of Offshore Compression Systems

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Abstract: In this work a hybrid methodology based on statistical approach and phenomenological modeling was developed aiming the monitoring of the performance of compression equipment in an offshore oil platform. A rigorous model was employed in order to estimate thermodynamic based values of the performance of the compression system, given by the polytropic efficiency and head. Residuals were generated by comparing the model values with the ones which were calculated from manufacturer's curves using process data (suction and discharge pressures and temperatures, turbine rotation and suction flow). Even though the monitoring technique developed is essentially multivariable and dynamic, the results are displayed using typical univariate process control charts, providing a friendly interface for the operator and allowing the clear detection of process faults.

Keywords: process models, monitored control systems, fault detection and diagnosis, compressors.

1 INTRODUCTION

Oil and gas production can be a potentially hazardous activity due to flammability of the substances involved combined with the stringent operational conditions of the process. Equipment failure can potentially cause leaks, fires or even explosions, resulting in loss of life, invested money, profit and production (Natarajan & Srinivasan, 2010).

In oil and gas facilities, the compression system requires a high level of equipment availability, and therefore faults that could result in the shutdown of the system should be eliminated (Carnero, 2002). According to Eriksson (2010), the value of increasing production related to the gas injection is approximately US$2 million per day, and the difference between planned and non-planned shutdowns is roughly US$60 million. These facts justify the need for an enhanced monitoring system for the gas compression system, contributing to reduce risks and losses and to raise equipment reliability.

The goal of this paper is to develop a methodology to monitor a real compression system located in an offshore production facility. The more general objective is to help maintenance and monitoring personnel improve equipment reliability, thus reducing the undesirable consequences of equipment failures.

The literature related to compression system monitoring is scarce. Kacprzynski *et al.* (2001) suggested an approach based on compression efficiency using simplified models to monitor the compression efficiency and predict performance degradation due to deposition of salt. Eriksson (2010) proposed a predictive monitoring based on models to a pilot submarine compression system. In this work, the monitored variables were actuators, level sensors, anti-surge controllers, voltaic systems, process systems variables and structural vibrations. In addition, inferences were made for the compression system efficiency and pump efficiency.

Rotem *et al.* (2000) used an approach combining phenomenological models and Principal Component Analysis (PCA) to monitor an ethylene compressor. In their work, a simplified compression model was used, obtaining a linear and parameterized expression. The residuals between the predicted and measured discharge pressure and temperature were employed in the monitoring and fault identification of the system, applying PCA using a metric proposed by Wachs and Lewin (1998).

In general, the offshore compression system monitoring is based on alarm limits: trip high, high high, high, low, low low, trip low. These limits are based on the experience of the compression systems monitoring staff. When a certain limit is achieved, the monitoring system warns the engineering and maintenance team.

In this paper, a hybrid methodology based on statistical approach and the residuals from phenomenological and empirical models is proposed for monitoring offshore compression system. The application of different statistical monitoring approaches to this methodology is also evaluated.

Phenomenological models require specific knowledge about the physical process, the relevant theories about the monitored system, and the application of mass, energy and momentum conservation laws, as well as state equations (Venkatasubramanian et al., 2003a). This type of methodology makes use of the residuals to verify the consistency of process measurements and mathematical model inferences (Peng et al., 2010). These approaches have the advantage of being applicable to systems with different operating conditions. No further knowledge about the correlations between process variables is needed.

Quality control was one of the first attempts to monitor process changes on-line. The control charts of Shewhart (Shewhart, 1931) were introduced in 1931. Later, Page (1954) developed the Cumulative Sum Control Charts (CUSUM), followed by Roberts´s (1959) proposal of Exponentially Weighted Moving Average (EWMA).

Quality control charts were initially developed for process quality control; however, it has also been extensively applied to fault detection problems (Montgomery, 1994; 2008). These charts are based on the principle that a process that is subject to natural variability will remain statistically under control when the process variables are near a target value (Montgomery, 1994; 2008). Therefore, by constantly monitoring the process, abnormal events can be detected. If the causes of the abnormal events are diagnosed and the problems are corrected, the process should return to normal operation (Venkatasubramanian et al., 2003b). The advantages of these approaches are their simplicity and speed of detection, which allow for applicability in on-line monitoring systems. Among the disadvantages is the assumption that the "in control" process presents a random variation around a steady-state, being this variation described by a normal distribution error, with independent and identically distributed values (Montgomery, 1994; 2008).

The proposed hybrid strategy aims at combining the advantages of the physical models and the simplicity of the quality control statistical models. Two types of models are used: (1) rigorous thermodynamic models, which provide the thermodynamic efficiency and polytropic head and (2) empirical models based on the compressor curves provided by the equipment manufacturer, from which the theoretical efficiency and polytropic head are calculated. The residuals between thermodynamic and theoretical models are obtained and used in control charts.

This article is subdivided in: four sections. Section 1 presents the objective of the work. The methodology is explained in Section 2, while Sections 3 and 4 present the results and the conclusions, respectively.

2 METHODOLOGY

The application of hybrid strategies based on phenomenological and statistical models is proposed here. In order to test this methodology, the following previous steps were applied to the case of compressor monitoring of a real Brazilian offshore platform:

- Process characterization
- Development of a phenomenological model
- Inferences from datasheets

2.1.1 Process Characterization

In this step, information about the description of the compression process of the platform and the available instrumentation was obtained from the piping and instrument diagram, shown in Figure 1.

The first compression stage contains the following equipments: suction vessel, turbine, compressor and cooler (Figure 1). The control system includes: anti-surge control, level control (suction vessel), capacity control and temperature control (cooler). The available on-line measurements are the level of the suction vessel, suction flow, pressures and temperatures, discharge pressure and temperatures, as well as the rotation of the turbine and temperature after the cooler.

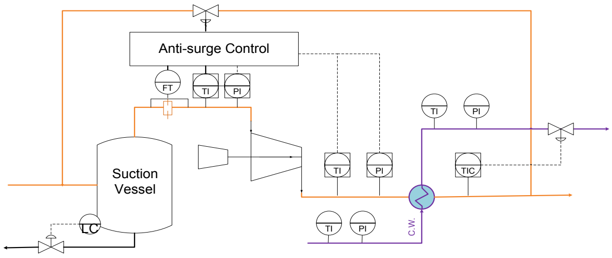

Fig. 1. Simplified Diagram of the first compression stage of the platform.

2.1.2 Development of the phenomenological model

In order to simplify the approach, only the model of the compressor was considered in order to focus on performance parameters as polytropic efficiency and head.

The model of the compressor was implemented on the Environment for Modeling, Simulation, and Optimization – EMSO, developed by Soares and Secchi (2003). The compressor model was based on Botros (1994). The model was validated using PETROBRAS Process Simulator PETROX and process data.

2.1.3 Inferences from datasheets

As the polytropic efficiency and head cannot be measured directly, they were inferred from the compressor manufacturer's curves (empirical model), given the measurements of suction volumetric flow rate and turbine rotation.

2.1.4 Proposed Algorithm

The proposed monitoring/fault detection algorithm can be seen in Figure 2.

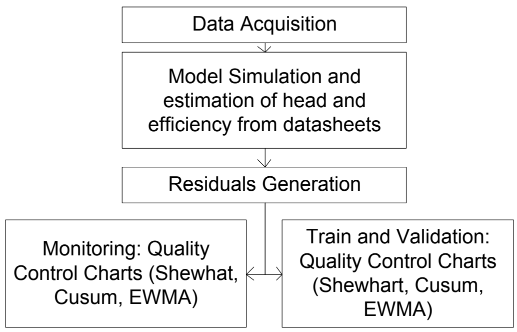

Fig. 2. Hybrid approach to monitoring and fault detection.

As shown in Figure 2, the proposed algorithm includes a data acquisition step, followed by phenomenological and empirical models simulation. The residuals are then calculated, and monitored through the selected quality control charts. The parameters for the charts are previously estimated using a training data set.

2.1.5 Data Acquisition

The following compressor data was collected: suction flow rate, pressure and temperature, discharge pressure and temperature, and rotation of the turbine.

2.1.6 Model Simulation and estimation of head and efficiency from datasheets

The phenomenological compressor model is simulated in EMSO and the performance variables (thermodynamic polytropic efficiency and head) are calculated.

The estimated polytropic head and efficiency are obtained from datasheets, that is, from the curves provided by the compressor manufacturer.

2.1.7 Residuals Generation

The thermodynamic and estimated polytropic efficiencies and heads are collected for a training period and normalized, and the residuals between these amounts are calculated.

In the validation phase, the thermodynamic and the estimated polytropic efficiencies and heads are normalized according to the respective standard deviations and means of the training data set. The residuals between the thermodynamic data and the measured data are then calculated and the statistical quality control charts are applied.

2.1.8 Quality Control Charts

During the training phase, the quality control charts (Shewhart, CUSUM and EWMA) are applied to the training data considered to be “in control”, and (upper, lower and target) control limits are calculated according to the chosen level of significance.

Then during the validation phase, the quality control charts are applied to the monitoring data having as thresholds the statistics previously obtained from the training data.

3 RESULTS

The proposed algorithm was tested on a set of real data from an oil & gas production platform.

3.1.1 Data Acquisition

Following the proposed procedure, data related to suction pressure, suction temperature, suction flow, discharge temperature, discharge pressure and turbine rotations were acquired for a period of time and are displayed in Figs. 3-5.

According to the data displayed in Figure 3, a large oscillation in suction pressure after 600 min can be noticed, which could indicate either lack of control in the process or a change in the operating condition. Figures 3-5 also show that the process variables are in a dynamic state to which traditional quality control charts could not be directly applied if variable observations (instead of residuals) were directly used.

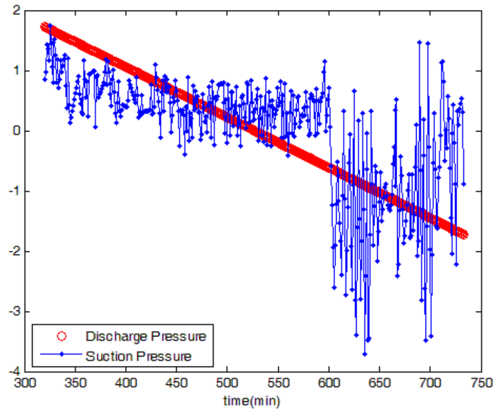

Fig. 3. Normalized suction and discharge pressure.

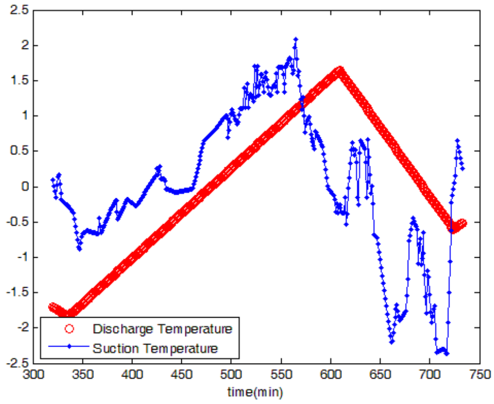

Fig. 4. Normalized suction and discharge temperature.

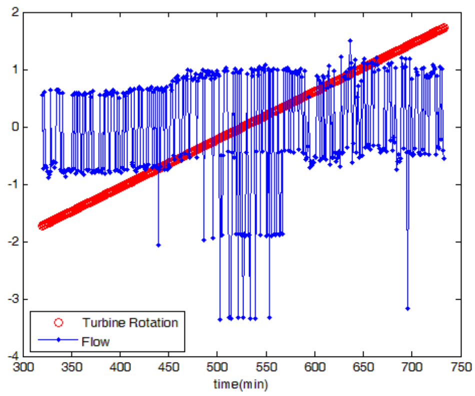

Fig. 5. Normalized data of flow rate and turbine rotation.

Figure 5 presents the normalized data of suction flow rate and turbine rotation. These data are of particular importance, since the polytropic efficiency and head estimated from datasheet are functions of flow rate and turbine rotation. According to this figure, the turbine rotation grows linearly, while the suction flow has increased oscillations between times 470 min and 570 min. The acquired data points were split into a training (from time 320 min to 420 min) and a validation data set (from time 420 min on).

3.1.2 *Model Simulation and estimation of the head and efficiency from datasheets*

The thermodynamic and estimated polytropic efficiencies and heads are presented in Figure 6. These values were obtained by using the measured pressures, temperatures, flow rate, and turbine rotation.

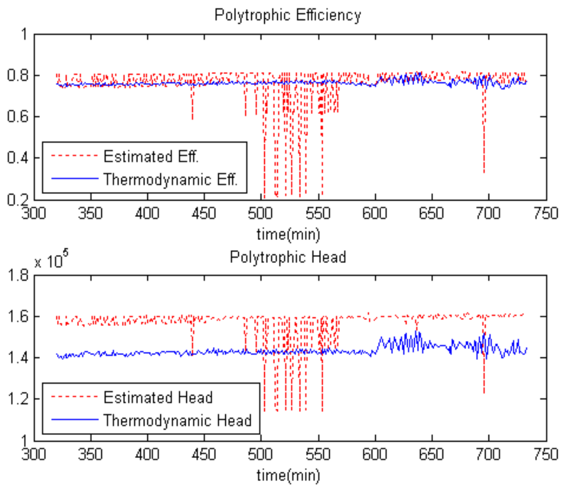

Fig. 6. Thermodynamic and estimated polytropic efficiency and head.

3.1.3 *Residuals Generation*

The residuals between the estimated and thermodynamic efficiencies and heads are displayed in Figure 7.

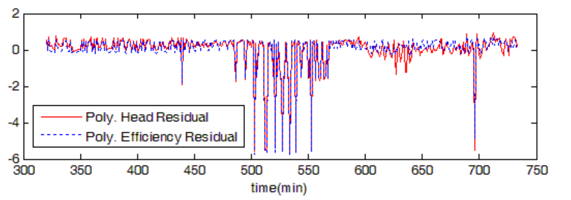

Fig. 7. Residuals between thermodynamic and estimated polytropic efficiencies and heads.

According to Figure 7, the residuals from both the polytropic efficiency and head identified the increased oscillations caused by suction flow (from time 470 min to 570 min). However, only the residuals from the polytropic head identified the oscillations resulting from the suction pressure changes (from time 600 min to 650 min, from 670 min to 700 min, and from 710 min until the end). This could be explained by the fact that suction flow rate variation was propagated into the estimated polytropic efficiency calculations. Therefore the oscillations that occurred in thermodynamic efficiency were not apparent in the residual calculations.

For this reason, data were normalized before the residuals calculation was performed (Equation 1).

$$z = \frac{x-\bar{x}}{\sigma} \qquad (1)$$

Where $\bar{x}$ is the mean of the training data and σ is the standard deviation.

The results from normalizing polytropic efficiency and head as well as the residuals of the normalized data above can be seen in Figure 8.

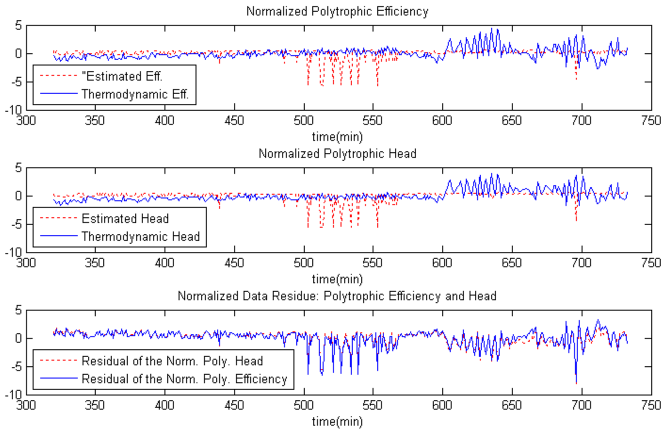

Fig. 8. Normalized polytropic efficiency and head and their residuals.

By normalizing these variables as in Figure 8, both the flow rate and suction pressure oscillations (from time 470 min to 570 min; and from time 600 min to 650 min, 670 min to 700 min and 710 min on, respectively) can be identified by either the residuals of the normalized heads, or by the residuals of normalized efficiencies.

3.1.4 *Quality Control Charts*

3.1.5 *Shewhart Chart for individual measures*

The Shewhart Charts for individual measurements were applied to the residuals of the normalized efficiencies. Figure 9 shows the training data set and the control limits were based on two and three standard deviations of the training data (95% and 99.73% probability interval).

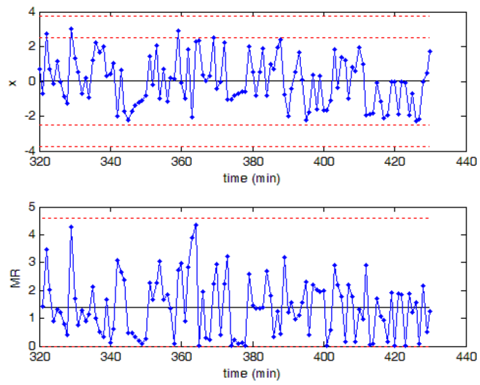

Fig. 9. Shewhart Charts for training data set of the residuals of normalized efficiency.

Figure 10 displays the Shewhart chart for the validation data set. The Shewhart chart was based on individual measurements (i.e., no replicates are used). In that figure, it is possible to identify data points that lie outside of the three standard deviation region, which includes the region of increased oscillation in flow (from time 470 min to 570 min), as well as the region of suction pressure instabilities (from time 600 min to 650 min, 670 min to 700 min and 710 min on). Both X(individual chart) and MR (moving range chart) identified those intervals as out-of-control regions.

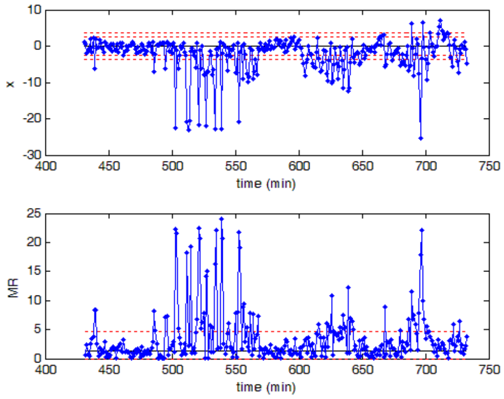

Fig. 10. Shewhart Charts for the validation data set of the residuals of normalized efficiency.

Residuals of the normalized polytropic head were also trainned with Shewhart charts. The results can be seen in Figures 11 (training data) and 12 (validation data).

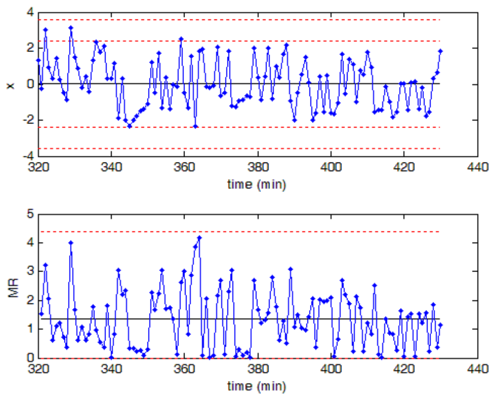

Fig. 11. Shewhart Charts (training) of residuals of normalized heads.

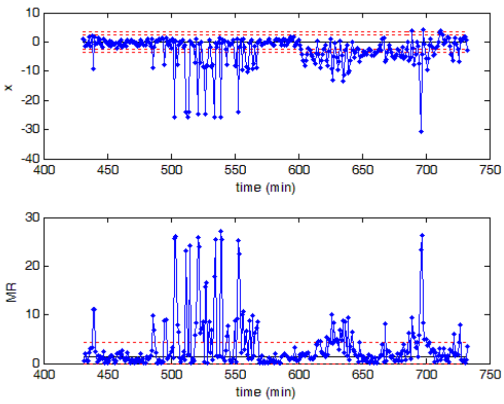

Fig. 12. Shewhart Charts (validation) of residuals of normalized heads.

The regions identified as out-of-control according to the polytropic head residuals (Figure 12) were identical to those found in the control charts of the polytropic efficiency validation.

3.1.6 Cumulative Sum Charts (CUSUM)

The CUSUM methodology uses the unilateral (positive C^+ and negative C^-) sums of deviations to the target value, being able to detect trends of change of operating points. When the unilateral cumulative sum presents a value higher or lower than a certain limit, it is said that the process is out-of-control. The control limits are also based on three standard deviations of the training data (99.73% probability interval).

The results obtained by monitoring the residuals of the normalized polytropic efficiency and polytropic head are presented below.

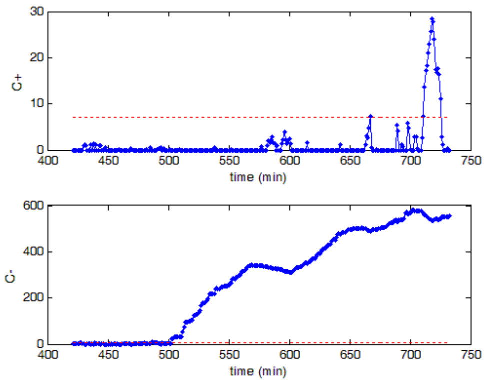

Fig. 13. CUSUM Chart of normalized efficiency residuals for the validation data set.

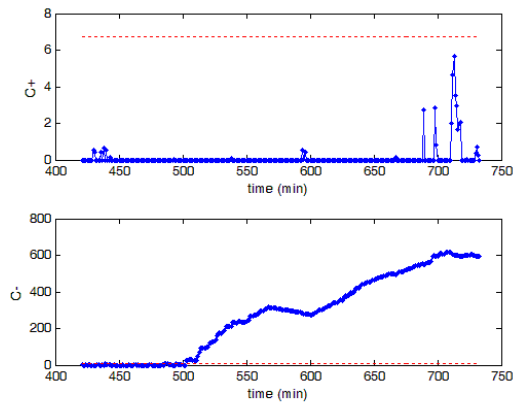

Fig. 14. CUSUM Chart of normalized head residuals for the validation data set.

According to the C^-statistic (Figures 13 and 14), there is a downward trend of the mean after time 510 min, followed by process stabilization around a new mean value (around time 570 min). Towards the end of the monitoring period, the efficiency residuals indicated a rising trend, as indicated by the C^+ statistic in Figure 13.

3.1.7 Exponentially Weighted Moving Average Charts (EWMA)

EWMA methodology was also applied to the residuals of the normalized polytropic efficiencies and heads. The upper- and lower control limits were based on three standard deviations of the training data (99.73% probability interval). If the monitored data is outside of these limits this may be an indication that it is out of control. The results of monitoring the residuals of normalized efficiency and head are shown in Figures 15 and 16.

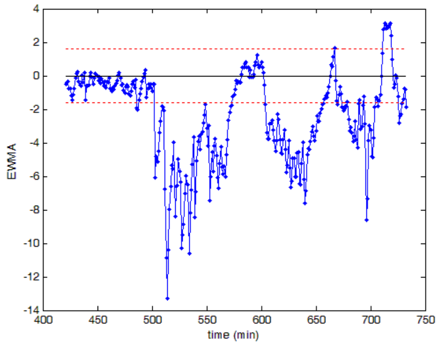

Fig. 15. EWMA chart for validation of the residuals of normalized efficiencies.

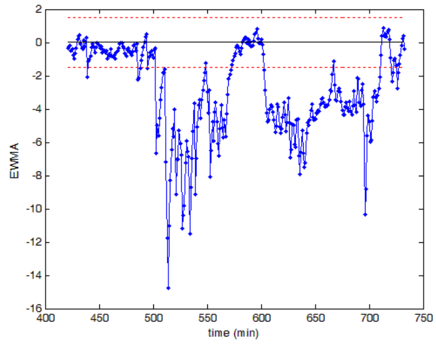

Fig. 16. EWMA chart for validation of the residuals of normalized heads.

These results show several violations of the lower limit (LSL) after 500 min due to flow instabilities, returning to normal operation at 580 min. At 600 min there is another series of violations of the lower limits (this time, due to suction pressure instabilities). In the normalized efficiency residuals there is a violation of the upper limits (USL) after 600 min.

4 CONCLUSION

This paper presented a hybrid methodology for fault detection and process monitoring based on phenomenological models and quality control charts. The main contribution of this work was the multivariable monitoring using simple univariate quality control charts combined with the power of phenomenological models.

Tests of this methodology were made with dynamic real data of a Brazilian offshore platform. The results obtained were consistent with the train and validation data applied.

Shewhart, CUSUM and EWMA charts were able to identify process operation out of the train limits, indicating that the operation might be out of control, and also were able to identify operations zones under the control limits, even with the data under dynamic conditions. Despite its simplicity and easy interpretation, the Shewhart chart showed sufficient sensibility to identify out of control regions.

Other data analysis can also be applied in this methodology, such as Partial Least Square and Principal Component Analysis investigated in Zyngier *et al.* (2012).

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