Automatic checking of observations at ECMWF
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Observations are essential for numerical weather prediction (NWP) systems. They are used by the data assimilation system to produce the best estimate of the initial conditions (the analysis). The quality of the analysis and the subsequent forecasts depend, amongst other factors, on the quality and availability of observations. A reliable monitoring system is therefore needed for early detection of observational data issues that can potentially degrade the quality of the analysis. The steady increase in data volumes makes it difficult to rely solely on manual checking procedures.

In 2008, ECMWF started to use an automatic data checking system to trigger warnings if there are sudden changes in the quality or availability of the data actively assimilated by the ECMWF four-dimensional variational data assimilation system (4DVAR). The checking system was initially limited to satellite observations, but last year it was extended to cover in-situ measurements. More recently, the system has been complemented with an automatic checking of persistent quality improvements of in-situ data that are blacklisted (not used because of previously poor or unknown data quality) in the Integrated Forecasting System (IFS), for potential future use in the analysis.

In this article a brief description of the automated checking process is first provided. It is followed by a description of the system configuration for satellite and in-situ observations. Thoughts about the potential of the system to improve the data assimilation and model diagnostics are then discussed. The concluding section presents the status of the system validation and the on-going work to improve it.

Automatic checking process

For each set of observations, selected statistical quantities (e.g. number of observations, bias correction, mean bias-corrected innovations (i.e. observation minus background) and analysis departures) are checked against an expected range. An appropriate alert message is generated if statistics are outside the specified limits. A severity level (‘slightly’, ‘considerably’, ‘severely’ or ‘severely persistent’) is then assigned to each message depending on how far statistics are from the expected values. The automatic checking uses two kinds of ranges: soft and hard limits (see Figure 1 and Box A).

Soft limits are designed to detect sudden changes in statistics, whilst hard limits are used to detect slow drifts in statistics. The automatic alarm system uses an ‘ignore’ facility to filter out warnings for data with known problems (e.g. expected outages or orbital manoeuvres). For each alert message (apart for data missing events) the alarm system generates a relatively long time series providing a comprehensive view of the time evolution of the various statistical quantities (e.g. innovations, counts and bias correction). When a problem is detected, the system includes the number of times the same issue has been detected during the past ten days (see Figure 2).

Alert messages are sent by email to subscribed users (mainly from within ECMWF with the exception of few external users) according to their registered preferences (i.e. data types of interest and levels of severity needed). The warnings are also published on the ECMWF monitoring web pages, which have public access (http://www.ecmwf.int/forecasts/see-our-forecasts/medium-range-forecast-charts/monitoring-observing-system). To help with follow-up investigations, warnings are archived in a relational events database allowing conditional extraction of alerts (e.g. to find possible links with forecast busts or weather events). The events database is currently not publically available.

The automated checking system is designed for ECMWF internal use. Results are based on feedback information from the ECMWF data assimilation system and therefore they reflect ECMWF’s data usage. Alerts published on the ECMWF website are provided for information on an as-is basis. This information can potentially be used by other NWP centres as additional information that can be compared to their own monitoring.
Automated checking system limits

Soft limits
Soft limits are updated automatically using statistics from the last twenty days (the last two days and extremes are excluded during this process). The soft limits are calculated as:

\[
\text{upper soft limit} = \text{mean} + A \times \text{stdev} \\
\text{lower soft limit} = \text{mean} - A \times \text{stdev}
\]

where \(\text{stdev}\) is the standard deviation. In the current configuration \(A\) is set to 5.

Hard limits
The hard limits are estimated during the process of adding new data to the alarm system. They are adjusted occasionally when a drift is noticed or during IFS upgrades. The hard limits are updated manually when needed.

Severity levels
The classification into 'slightly', 'considerably', 'severely' and 'severely persistent' depends on the expected variability and is as follows.

- **Slightly**: outside \(\pm 5\) \(\text{stdev}\) from the mean.
- **Considerably**: outside \(\pm 7.5\) \(\text{stdev}\) from the mean.
- **Severely**: outside \(\pm 10\) \(\text{stdev}\) from the mean.
- **Severely persistent**: Severe problems occurring frequently during the past 10 days.

Figure 1 Example of an alert for ATMS Channel 9 produced at 12 UTC on 19 April 2013.

Figure 2 Example of an automatic alert message for ATMS Channel 9 triggered at 12 UTC on 19 April 2013.
Lunar intrusion event

On 19 April 2013, the automatic checking system triggered severe warnings for several NPP/ATMS channels. The alerts were caused by a sudden sharp increase in the innovations standard deviation (see the plot below for ATMS channel 9 innovations covering 09 to 21 UTC on 19 April 2013) due to the moon intrusion into the ATMS field of view used for the calibration of the instrument.

To filter out contaminated data, ECMWF was relying on the Quality Control flags provided with the data. The algorithm used to detect and flag moon intrusion events was evolving at the time. It has now reached a level of maturity allowing the detection and flagging of most moon intrusion events.

Table 1

<table>
<thead>
<tr>
<th>Data Types</th>
<th>Statistical quantities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiances</td>
<td>• Data counts</td>
</tr>
<tr>
<td></td>
<td>• Average of innovations</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of innovations</td>
</tr>
<tr>
<td></td>
<td>• Bias correction</td>
</tr>
<tr>
<td>AMVs</td>
<td>• Data counts</td>
</tr>
<tr>
<td></td>
<td>• Average of innovations</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of innovations</td>
</tr>
<tr>
<td></td>
<td>• Average pressure (pressure of the assigned height)</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of pressure</td>
</tr>
<tr>
<td>Scatterometer (wind speed)</td>
<td>• Data counts</td>
</tr>
<tr>
<td></td>
<td>• Average of innovations for the best ambiguity</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of innovations for the best ambiguity</td>
</tr>
<tr>
<td>Ozone</td>
<td>• Data counts</td>
</tr>
<tr>
<td></td>
<td>• Average of innovations</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of innovations</td>
</tr>
<tr>
<td></td>
<td>• Bias correction</td>
</tr>
<tr>
<td>GPS Radio Occultation</td>
<td>• Data counts</td>
</tr>
<tr>
<td></td>
<td>• Average of normalized innovations</td>
</tr>
<tr>
<td></td>
<td>• Standard deviation of normalized innovations</td>
</tr>
</tbody>
</table>

Alarm system for satellite data

For satellite data, potential quality and availability issues are mainly related to the instrument, ground segment or telecommunication problems. As the same satellite instrument covers a large area, any quality issues affect the assimilation on a large, often global scale which makes it especially important to detect such issues as quickly as possible. For satellite data, we check separately global statistics from each satellite, instrument, channel, parameter and statistical quantities. The only exceptions to this are the Atmospheric Motion Vectors (AMVs), which are averaged over the total vertical column. The system offers the flexibility to add new statistical quantities. The current setup is summarized in Table 1.

An example of an alert is given in Figures 1 and 2, showing a sudden increase in the standard deviations of innovations for a channel on ATMS that is used to retrieve profiles of atmospheric temperature and moisture. Further investigation showed that this was caused by temporary calibration problems: for certain parts of some orbits, the moon entered the space view used for the calibration of the instrument, leading to incorrectly calibrated observations (see Box B). Flagging of such data was subsequently introduced in the ECMWF system, and the data providers also updated their processing to mitigate such problems.
Alarm system for in-situ measurements

Unlike satellite observations, in-situ measurement issues are typically specific to each individual station. However, on some occasions widespread issues might be caused by data routing problems, significant weather events, model errors or data assimilation issues. To cover both aspects, the automatic data checking system has been extended to perform two kinds of automatic check.

Individual stations

For each assimilation cycle, the system checks the quality of available stations based on the estimated Probability of Gross Error (PGE), the mean and root-mean-square of innovations and bias correction. The parameters checked are the temperature, pressure, specific humidity, relative humidity and wind vector difference. PGE values are provided directly by the 4DVAR for all 'used' data. The automatic system calculates the percentage of in-situ reports with PGE above a pre-defined threshold (currently 0.75). It then triggers a warning if this percentage is high or if there are significant changes in the other statistical quantities. The system performs the same check over a period of ten days. Any such issues are flagged as ‘severely persistent’.

Main data types over a number of pre-defined geographical areas.

This component of the system detects widespread issues. It follows the same method as applied for satellite data but with an additional test comparing the standard deviation of innovations and analysis departures. Such a test is important to highlight areas and situations where the model or the analysis is not performing well. One analysis-related example is the intermittent widespread rejection of surface pressure observations over Europe in 2012 (see Figure 3 and Box C). The system currently monitors data from:

- Nine predefined geographical areas: North America, Europe, North Atlantic, Asia, South Pacific, South America, Africa and Indian Ocean. It offers the flexibility to add new geographical areas.
- Ten data types: SYNOP, METAR, SHIP, AMDAR, ACARS, AIREP, TEMP, PILOT, DRIBU and PROFILERS.

Automatic detection of improvements

Currently in-situ measurements are added to a blacklist when affected by frequent quality issues. Removing improved measurements from the blacklist requires an assessment of their behavior (e.g. using monthly values of the root-mean-square of innovations). These statistics are checked against fixed values ignoring the dependency of departures on geographical areas and significant weather events.

To make the procedure automatic and efficient, the data checking system has been extended to detect persistent improvement in the quality using a PGE-like quantity. For each flagged station, the system produces a time series plot that will help in making the final decision. The plot includes the estimated PGE, mean and root-mean-square of innovations, data counts and spread of the Ensemble of Data Assimilations (EDA).

Figure 3 Left: Statistics for SYNOP surface pressure over Europe: standard deviations of first-guess departure [stddev(fg_depar)] and analysis departure [stddev(an_depar)] along with hard and soft limits and observation count. Right: surface pressure observations with low variational quality control weight for a 12-hour 4DVAR ‘delayed cut-off data assimilation’ cycle in February 2012.
Potential for model performance monitoring

The automatic data checking system was primarily designed to detect data-related issues. However, since the quality assessment is mainly based on innovations, there is a potential to detect situations where the forecast model or the data assimilation itself has weaknesses. This can be the case in the following situations.

• The system triggers alerts for independent satellites/instruments that provide similar observations of the atmosphere. Large departures associated with independent data suggest that the forecast model is not able to fully capture the phenomena being observed. With the increase in satellite data sources, there is a potential to improve the diagnostics of the model and data assimilation algorithms. As an example, on many occasions the system triggered alerts associated with microwave and infrared satellite upper-stratospheric channels. These alerts were caused by sudden stratospheric warming episodes where the initial rapid circulation changes were not well captured by the model, leading to larger than usual differences between the model first-guess field and the observations.

• Widespread warnings affecting in-situ measurements (apart from availability issues) are likely to be related to the forecast model or the data assimilation (see example in Figure 3).

• Individual warnings occurring in the vicinity of dynamic atmospheric situations need to be investigated. They can potentially point to model or data assimilation issues (e.g. a weather system moving too slowly in the model).

Alarm system validation and future developments

For the last two years, the automatic alarm system has been running operationally at ECMWF. Although the results are not being verified objectively, the alarm system has reached a good level of maturity allowing the detection of almost all severe data quality issues (according to the daily data monitoring and other external notifications). However, the system still produces many ‘slight’ warnings that are related to small changes in statistics. Such warnings are still being distributed to internal users to keep track of all data-related changes. The system is performing well by keeping the rate of ‘severe’ false alarms to a very low level.

The system is fully automatic in detecting issues but at the moment it does not act automatically on any other component of the data assimilation. The results from the system are used to manually update the blacklist, but in future some kind of semi-automatic updating of the blacklist might be possible.

Work is on-going to improve the reliability of the system and explore further its potential for improving the daily monitoring of the operational data assimilation and forecasting system at ECMWF.