Plans for the Assimilation of Cloud-Affected Infrared Soundings at the Met Office

Ed Pavelin and Stephen English
Met Office, Exeter, UK

Abstract
A practical approach to the assimilation of cloud-affected infrared radiances is proposed. The technique is best suited to advanced infrared sounders such as AIRS and IASI. Radiances are first pre-processed by a one-dimensional variational analysis (1D-Var) scheme, where cloud parameters (cloud top pressure and effective cloud fraction) are retrieved simultaneously with atmospheric profile variables. The retrieved cloud parameters are then passed to a variational data assimilation system, where they are used to constrain the radiative transfer in the assimilation of a reduced set of channels. The channel selection is chosen to reduce the sensitivity to errors in the forward modelling of radiation originating below the cloud top. The performance of this technique is explored by means of a 1D-Var study using simulated measurements. It is demonstrated that the technique has the potential to allow the use of a significant proportion of cloud-affected infrared sounding measurements, possibly bringing valuable benefits to an operational NWP system.

Introduction
The assimilation of radiances from AIRS at the Met Office has been shown to make a significant positive impact on forecast accuracy (e.g. Cameron et al., 2005). However, AIRS radiances are not currently exploited in cloudy conditions. This is particularly significant because soundings in cloudy regions are expected to have a large impact on forecast accuracy, due to the meteorologically sensitive nature of such areas (McNally, 2002). On average, around 70% of the globe is covered by cloud (Wylie and Menzel, 1999). In this context it is clear that the desire to gain the maximum benefit from current and future advanced IR sounders drives an urgent requirement for methods of assimilating cloudy IR radiances.

In the absence of prior information on the cloud field, the direct assimilation of cloud-affected radiances by 4-dimensional variational analysis (4D-Var) requires an observation operator containing a sufficiently accurate representation of cloud effects and an NWP model capable of accurately forecasting or diagnosing cloud on the scales that affect individual satellite fields of view (Chevallier et al., 2004). Such capabilities are beyond the scope of current global NWP systems. The problem of assimilating cloudy IR soundings is side-stepped at most NWP centres by rejecting fields of view or individual channels that are thought to be cloud-affected. The most conservative approach involves simply rejecting all fields of view deemed to possibly contain cloud, based on a cloud test carried out before the beginning of the assimilation cycle. This is the method that has been used at the Met Office (English et al., 1999). Some centres retain cloudy soundings but reject all channels which are thought to be cloud-affected (McNally and Watts, 2003). These methods are far from optimal, since only a small proportion of the available soundings is being exploited. New techniques are required to assimilate a significant proportion of cloud-affected radiances, which should lead to a large increase in the volume of infrared soundings available for assimilation, and a corresponding improvement in NWP skill.
If the properties of the cloud within the satellite field of view are known (or can be estimated), then this information can be used by the radiative transfer model within the data assimilation system, allowing the direct assimilation of the cloud-affected radiances. However, it is not obvious how accurately the cloud properties need to be known in order to gain a ‘useful’ (from an NWP perspective) improvement in the analysis compared with the background.

In this paper we assess the feasibility of assimilating infrared radiances in cloudy areas using simple retrieved cloud parameters to constrain the radiative transfer calculations in the assimilation process. The cloud parameters are retrieved using 1-dimensional variational analysis (1D-Var). We present the results of a simulation study using synthetic AIRS measurements to investigate the performance of such an assimilation system. Simplified data assimilation experiments are also carried out within a 1D-Var framework.

**Estimation of cloud parameters**

**One-dimensional variational analysis**

Cloud parameters are commonly retrieved from infrared soundings using techniques such as CO$_2$ slicing and the minimum residual method (Eyre and Menzel, 1989). However, it has been shown (Eyre, 1989) that a 1-D variational retrieval of cloud parameters produces cloud parameters which are more accurate than those retrieved by these schemes because the cloud parameters are retrieved simultaneously with the temperature and humidity profiles.

In the Met Office operational NWP system, satellite radiances are subjected to an initial 1D-Var processing stage before being passed to the 4D-Var data assimilation system, and it would seem logical to include the retrieval of cloud parameters in this process. For the purposes of this study, 1D-Var cloud parameter retrievals are carried out on simulated AIRS data using a stand-alone 1D-Var package (the NWP SAF Met Office 1D-Var).

The 1D-Var analysis described here is based on the Bayesian optimal estimation techniques described by Rodgers (2000). We reach an estimate of the atmospheric state vector, $\mathbf{x}$, consistent with the observations, $\mathbf{y}$, and any prior knowledge of the background state $\mathbf{x}_0$ by minimising the cost function

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_0)^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}_0) + (\mathbf{y} - \mathbf{y}(\mathbf{x}))^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}(\mathbf{x})),$$

where $\mathbf{R}$ is the measurement error covariance matrix (including forward model errors), $\mathbf{B}$ is the background error covariance matrix, superscript $^T$ indicates matrix transpose, superscript $^{-1}$ indicates matrix inverse, and $\mathbf{y}(\mathbf{x})$ represents the forward-modelled radiances corresponding to the atmospheric state $\mathbf{x}$. The 1D-Var retrieval code used in this study was configured to use a Marquardt-Levenberg minimisation algorithm, which has been found to be the most suitable for non-linear problems (Rodgers, 2000).

The state vector in this case consists of temperature on 43 levels between 0.1 and 1013 hPa (corresponding to the fixed pressure levels used by RTTOV), specific humidity on the lowest 26 levels (122–1013 hPa), surface air temperature, skin temperature, surface humidity, cloud top pressure and effective cloud fraction.
Representation of cloud in the forward model

The forward model used in the 1D-Var analysis is the RTTOV fast model (Matricardi et al., 2004). This model contains a simplistic representation of the effect of clouds on top-of-atmosphere infrared radiances. Clouds are assumed to be single-layer black bodies of negligible depth. Each field of view may contain a given fractional coverage of cloud at a given cloud-top pressure. The cloud-affected radiance \( R_{\text{cld}} \) is calculated as follows:

\[
R_{\text{cld}} = (1 - N_e) R_{\text{clr}} + N_e R_{\text{ovc}}(p_c) \, ,
\]

where \( R_{\text{clr}} \) is the clear-sky component of the radiance, \( R_{\text{ovc}} \) is the contribution to the radiance from the top of an opaque cloud layer, \( p_c \) is the cloud-top pressure, and \( N_e \) is the effective cloud fraction. The effective cloud fraction is defined as the product of the geometrical cloud fraction, \( N \), and the cloud emissivity, \( \varepsilon \), assuming the emissivity is independent of wavelength. \( N_e \) therefore represents the combined effects of variable cloud fraction and emissivity.

Cloud parameter first guess

In this work no prior cloud information is provided to the 1D-Var algorithm. Although the NWP model may, in some situations, be able to provide useful cloud information that could be used in 1D-Var, the error characteristics of the model cloud field are difficult to define. In addition, it is not always clear how the properties of the clouds represented in the model are related to the two cloud parameters retrieved by the 1D-Var. Consequently, the background error covariances for the cloud parameters in the 1D-Var are assumed to be very large, so that the cloud parameters in the background vector are effectively ignored.

Due to the highly non-linear nature of the cloudy 1D-Var problem, it is necessary to initialise the minimisation with as good a first guess as possible. In this work we use a first guess derived using the minimum residual method described by Eyre and Menzel (1989). Using this technique we arrive at estimates of the cloud top pressure and effective cloud fraction by minimising the difference between measured and forward-modelled cloudy radiances, using nine AIRS channels.

Simulation study framework

In this study we make use of a set of 13495 NWP model profiles derived from the ECMWF ERA-40 re-analysis (Chevallier, 2001). This profile dataset is designed to sample a diverse range of atmospheric states, seasons and geographical locations. The dataset contains profiles of temperature, humidity, ozone, cloud liquid water content, cloud ice water content and cloud fraction on 60 fixed pressure levels, as well as surface temperature, surface humidity, skin temperature and surface properties. This profile dataset is used as the basis for simulations of AIRS brightness temperatures and NWP background profiles described in the following sections.

Simulated AIRS brightness temperatures

We use the RTTOV radiative transfer model to perform simulations of AIRS infrared brightness temperatures. The brightness temperatures are simulated using an extended version of RTTOV 8.5 with full cloudy radiative transfer (RTTOVCLD; see Saunders et al., 2005). This model makes use of the cloud liquid water and ice profiles present in the NWP profile dataset. The simulated brightness temperatures therefore contain effects consistent with realistic cloud profiles which may have mixed-phase and multi-layer characteristics. For each atmospheric profile in the ECMWF dataset, a set of
324 brightness temperatures (out of a total of 2378 AIRS channels) has been simulated. This corresponds to the subset of AIRS channels routinely distributed to NWP centres by NOAA-NESDIS.

Random measurement errors were added to the brightness temperatures, based on the measurement error covariance matrix \((R)\) used in the operational assimilation of AIRS data at the Met Office. The simulated errors are Gaussian, unbiased, independent of scene temperature and uncorrelated between channels.

**Simulated NWP model background profiles**
In order to perform the 1D-Var analysis, background estimates of the atmospheric state are required. For each member of the sampled profile dataset, a corresponding simulated NWP forecast profile was generated. The background profiles were generated by adding simulated forecast errors to the original model profiles which are consistent with a forecast error covariance matrix \((B)\). The forecast error covariance matrix is intended to be representative of 6-hour forecast errors and covariances in temperature and humidity. Background profiles were generated for temperature, humidity, surface temperature, surface humidity and skin temperature. No attempt was made to simulate background values of the cloud parameters, since we are assuming an absence of prior knowledge of these variables.

**Cloud parameter retrievals results**
5811 simulated soundings over the sea were passed for retrieval. Soundings over land and sea ice were omitted because these are not currently assimilated in the Met Office operational NWP system due to uncertainties in the surface emissivity for these surface types. A sub-set of 92 channels was chosen for use in the 1D-Var minimisation. The channels were chosen by selecting the channels that most reduced the analysis error covariance in a range of different atmospheric scenarios (Rodgers, 1998).

In total, 5433 of the 1D-Var cloud retrievals converged within 10 iterations (93.5%). The majority converged within 3 or 4 iterations. Profiles that did not converge within 10 iterations were rejected. The convergence test was based on the value of the cost function and its normalised gradient.

**Simulated cloudy radiance assimilation**
The main focus of this study involves the use of the cloud parameters retrieved by 1D-Var \((p_c\) and \(N_c)\) in a simulated data assimilation process. For simplicity, the assimilation is carried out in one dimension only, in contrast to the full 4-dimensional variational analysis carried out in the Met Office operational NWP system.

**1D-Var assimilation method**
A 1D-Var analysis was carried out with the cloud parameters fixed to those values retrieved in the first (cloud retrieval) 1D-Var stage. Of the 5811 simulated AIRS observations over sea, only the 5433 observations which converged in the cloudy 1D-Var analysis were passed for 1D-Var assimilation. No other observation types were included in the analysis. In total, 5393 of these observations converged (92.8% of all observations).

**Analysis results using 92 channels**
Figure 1 shows the mean errors in the analysed and background profiles of temperature and water vapour compared with the ‘truth’ (i.e. the original ECMWF model profile interpolated onto 43 levels).
The 1D-Var analysis was carried out using the same set of 92 channels used in the cloud parameter retrievals. The analyses have been divided into three groups: high cloud cases (defined as cases with retrieved cloud top above 500 hPa), mid-level cloud cases (500—800 hPa) and low cloud cases (below 800 hPa).

**Figure 1:** Mean analysis error profiles resulting from the 1D-Var analysis of all cloudy profiles. The thick lines represent root-mean-square deviations from the truth; the thin lines show mean biases. The solid lines show the analysis, and the dashed lines show the background. (a), (b): High cloud cases; (c), (d): mid-level cloud cases; (e), (f): low cloud cases.
It is clear that there are large biases present in the analysed profiles of both humidity and temperature. Only in the low cloud case can the mean biases be considered to be within acceptable limits. The profiles of RMS errors shown in Figure 1 indicate that the analyses are worse than the background for high cloud cases, except for upper-tropospheric humidity, which is slightly improved above 300 hPa. The error profiles for mid-level cloud cases show that the RMS error in the analysis is improved with respect to the background above the cloud top for both temperature and humidity; however, there are significant biases (especially in temperature), and the RMS errors are worse than the background below the cloud top. For low cloud cases the temperature analysis is of a good quality, showing improvement over the background temperature profile both in terms of RMS error and bias. The low cloud humidity analysis, however, is worse than the background below the cloud top.

The increased biases and RMS errors discussed above are most likely caused by the over-simplified cloud model employed by the 1D-Var cloud retrieval scheme, as well as errors in the 1D-Var cloud parameter retrievals. The majority of cloud situations inevitably differ from the simple single-layer black-body cloud assumption to some extent, and if we are to use retrieved cloud parameters to assimilate cloudy radiances in this manner we require a means of overcoming this limitation.

**Channel selection**

Ideally we would wish to choose soundings to assimilate that have cloud properties approximately consistent with a single-layer grey cloud model based on some prior knowledge of the cloud structure—e.g. a multi-layer cloud detection scheme. However, in the present implementation no prior cloud information is available (apart from a simple test for the presence of cloud). Therefore in order to reduce the errors described above to an acceptable level, we have chosen to filter the channel selection used in the 1D-Var assimilation to remove channels with a high sensitivity to temperature below the retrieved cloud top. In this way we hope to remove those channels most likely to be poorly modelled by the RTTOV single-layer grey cloud scheme.

The channel selection was performed automatically as follows: first, the RTTOV pressure level corresponding to the retrieved cloud top is identified. The temperature Jacobians for each channel are examined, and any channel with more than 10% of its total integrated value below the cloud top is flagged for rejection. The threshold of 10% was determined empirically to give the best trade-off between reduced bias and increased RMS error. The channel selection procedure is carried out for each sounding individually. It can either be performed using the result of the RTTOV Jacobian calculation from the last iteration of the cloud retrieval, or from the first RTTOV call of the assimilation cycle. In this way, the channel selection itself does not require any additional radiative transfer calculations.

Figure 2 shows example temperature Jacobians for one case with low cloud, one with mid-level cloud, and one with high cloud. Note that the Jacobians are allowed to “tail off” below the cloud top. In this way we hope to retain radiance information originating from the cloud top whilst rejecting most of the information transmitted from below in cases of semi-transparent, multi-layer cloud (since such cloud is more difficult to accurately represent in RTTOV, and the cloud retrievals have been shown to be relatively poor in these cases). In the sample high cloud case shown, only 6 channels out of 94 are retained after channel selection. In the mid-level and low cloud cases, 39 and 84 channels are retained respectively.
Results of 1D-Var assimilation with cloudy channel selection

Figure 3 shows the results of the 1D-Var analysis using a reduced set of channels, based on the retrieved cloud top pressure as described in the previous section. The analyses are again divided into high, mid-level, and low cloud cases. It is clear that the biases in temperature and water vapour are much reduced compared to the analysis using all 92 channels (Figure 1). There is still a small negative bias in water vapour in the tropopause region (around 200 hPa). This is because a proportion of the randomly-perturbed background humidity profiles are super-saturated in this region, whereas supersaturation is penalised by the 1D-Var algorithm.
The RMS errors shown in Figure 3 indicate that, on average, there is useful temperature and humidity information being retrieved from the cloudy soundings in high, mid-level, and low cloud cases. The RMS temperature analysis errors are smaller than the RMS background errors down to below 800 hPa in the high and mid-level cloud cases. In the low cloud cases, the cloudy soundings are contributing temperature information to the analysis all the way to the surface.
As a point of reference, the 1D-Var analysis has been repeated using clear-sky radiances, with cloud parameter retrieval switched off. This analysis represents a ‘best case’ scenario, and is useful for comparison with the results of the cloudy analysis. The mean error profiles for the clear-sky analyses are shown in Figure 4. As expected, the clear-sky analysis performs better than the cloudy case. However, especially in the low cloud case, the difference between the RMS errors of the cloudy analysis and background are of comparable magnitude to those in the clear sky case, albeit with slightly degraded performance below the cloud top. In the mid-level and high cloud cases the difference between the cloudy and clear analyses is more obvious, but it appears that the assimilation of mid-level cloud cases may still bring significant benefits. The amount of information gained from the high cloud cases is small however, and it is possible that such soundings will not make a significant contribution to an operational analysis.

Figure 4: Mean analysis error profiles resulting from the 1D-Var analysis of all clear sky profiles, with cloud parameter retrieval switched off. The thick lines represent root-mean-square deviations from the truth; the thin lines show mean biases. The solid lines show the analysis, and the dashed lines show the background.

**Discussion**

The results in the previous section have shown that the 1D-Var assimilation of cloudy radiances using fixed cloud parameters can lead to improvements over the background in RMS errors of temperature and humidity. This is extremely encouraging, and leads us to anticipate that significant benefits to NWP accuracy might be obtained by implementing this technique in an operational context.

The analysis is expected to perform best for cases of shallow layer cloud and high cloud fractions. It would be extremely useful if such cases could be detected and singled out for 1D-Var analysis. In practice, however, we do not currently have suitable prior information on the vertical distribution of cloud. Therefore, for an initial implementation it is proposed that the automatic channel selection technique be used to eliminate channels sensitive below the cloud top. If, in the future, a method can be developed to identify cases of single layer cloud, it may be possible to relax the channel filtering criterion in these cases. For example, multi-layer cloud detection may be possible using a combination of microwave and infrared sounding data.

**Conclusions**

We have performed a simulation study to assess the feasibility of the assimilation of cloud-affected infrared radiances using retrieved cloud parameters as fixed constraints. The cloud parameters, cloud
top pressure and effective cloud fraction, are retrieved by 1D-Var analysis. For the purposes of the simulation study, the retrieved cloud parameters were then passed to a second 1D-Var minimisation to simulate the assimilation of cloud-affected radiances.

It was found that the 1D-Var assimilation of the cloud-affected radiances using fixed cloud parameters performed poorly for mid-level and high cloud cases when the full selection of 92 channels were used. It is likely that this is due to a combination of errors in the cloud parameter retrievals and, more importantly, the presence of multi-layer cloud, which is not represented by the 1D-Var forward model used here.

In order to overcome the limitations of the cloudy forward model and reduce the analysis errors to an acceptable level, a simple method was developed to exclude channels sensitive to temperature below the cloud top. Only those channels were chosen whose temperature Jacobians had 90% or more of their integrated amplitude above the retrieved cloud top. In this way, the sensitivity to multi-layer cloud is greatly reduced.

Using the reduced channel selection, the 1D-Var assimilation was found to perform well. Useful information appears to be gained even in high cloud cases. In cases of low cloud, the cloudy analysis resulted in an improvement in RMS temperature and humidity errors comparable to that resulting from the assimilation of clear sky radiances. Significant benefits are also observed from the inclusion of mid-level cloud cases. The inclusion of soundings with high cloud, although not detrimental to the analysis, may be of less value.

It is proposed that the technique described here be implemented for real AIRS data in the Met Office operational 4D-Var data assimilation system. The results of the trials of this system will be described in a future paper.

References


