Stratigraphic attenuation (Q) effects in heavy oilfield VSP data

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ABSTRACT

As an extension of work on near-field Q-factor recovery we apply Q(z)-inversion by forward modeling to VSP model data generated from Ross Lake well-logs applying a multi-interface Sommerfeld integral algorithm. An intrinsic Q(z) model is derived from Ross Lake P-wave velocities by applying an empirical equation. When computing swept-Q forward models with the same Sommerfeld algorithm as is used for generating the VSP model data the sum of squared differences show minima at the correct intrinsic Q-values; velocities and densities are assumed to be known in these forward model computations. Applying a Golden-Section-Search algorithm for computational efficiency leads to a local-minimum problem at some depths which is solved by adding a local-minimum search extension. For this ideal noise free model situation intrinsic Q-factor recovery is very successful.

INTRODUCTION

In our quest for *intrinsic attenuation* we have to determine and remove the effects of *stratigraphic attenuation* because these two types of attenuation can be of the same order of magnitude (Haase and Stewart, 2007). Our best efforts thus far attempt spectral normalization with less than satisfactory results (Haase, 2009). The approach taken in our 2009 Report is the modelling of *stratigraphic attenuation* with a multi-interface Sommerfeld integral because spherical waves and multi-interface models describe the earth's response to seismic waves more accurately than plane waves can; multiples and reverberations can be modelled in a stack of layers and with a Sommerfeld integral we introduce near-field, far-field and geometrical spreading. We use the same modelling method for our current study, but generate a more realistic Q-model based on Waters's (1978) empirical equation.

The procedure described in this study is developed from a near-field inversion algorithm introduced in a companion Report (Haase and Stewart, 2010). Both, model VSP data and the forward model, are computed by a multi-interface Sommerfeld integral from the Ross Lake velocity and density logs; the Q-model is assumed to be known only for the model VSP data computation.

Q-MODEL GENERATION

In our previous stratigraphic Q investigation (Haase and Stewart, 2009) a constant intrinsic Q-factor of 100 is assumed. One of the few things that are quite certain in seismology is a non-constant Q-factor. Waters (1978) introduced an empirical equation linking Q-factors and velocities; his equation is based on field-data observations from the (probably softer) sediments of Texas. Nonetheless, this equation is a better starting point than to assume constant Q and we adapt it to our purposes as follows

$$Q_{z-\Delta z} = Q_z \left[\frac{\mathrm{V}_{z-\Delta z}}{\mathrm{V}_z}\right]^2 . \tag{1}$$

Figure 1 shows our Ross Lake well-log information and we use the P-wave velocity as input to Equation 1. When assuming Q=100 in the constant velocity region below the well-bottom (that is below about 1150m) we can use Equation 1 to compute the velocity dependent Q-model plotted in Figure 2. VSP model data traces are obtained from our multi-interface Sommerfeld integral by using the velocity/density information of Figure 1 and the Q(z)-model of Figure 2 as input parameters.

Q-ESTIMATION FOR THE ROSS LAKE VSP MODEL

In this section we are attempting to match the VSP model data generated previously by suitable forward models. As is also done in the Report on inhomogeneous near-field effects on Q-estimation (Haase and Stewart, 2010) we again assume that velocities and densities are given and Q-factors are the only unknowns. The *summed differences* approach that is successfully employed for the inhomogeneous near-field situation is more error-prone with increasing depths and eventually fails altogether. The main reason for introducing *summed differences* is computational efficiency and there are other ways of pursuing that objective. For now, we return to exhaustive Q-searches to determine if the minimum of the *sum-of-squared-differences* can pinpoint a desired model Q. The results for three of these searches at different depth levels are displayed in Figure 3; for all searches there is a pronounced minimum at the correct Q-factor. It would be easy to pick the minimum following an exhaustive search, but what can be done to reduce the computational burden?

We adopt a "*golden section search*" procedure from Numerical Recipes (reference???) which is touted to find the *minimum* with the fewest number of function evaluations when three starting points are given that bracket the desired *minimum*. For the starting point search we begin at Q=10 and add points at Q=20 and at Q=30: if the *sum of squares* at Q=20 is less than both neighbors then we found the bracket; if the *sum of squares* at Q=20 is not less than both neighbors we add a new point $Q_{new}=Q_{last}+10$ and repeat the three point test and so on till a bracket is found. The result of applying this procedure to all depth levels is given in Figure 4. For a model study, these estimation errors are unacceptable. The worst error at z=856m is +27%. To investigate the cause of error, we compute exhaustive Q-sweeps once more, this time for the three depth levels in Figure 4 where the worst errors occur, and plot them in Figure 5. Inspection of Figure 5 reveals a multitude of local minima and presumably this is where the minimum search stopped prematurely. What is required in the above procedure is the addition of a local-minimum-test: following every golden section search the neighborhood within a predetermined search-radius of the present minimum is tested for an improved minimum. If an improvement is found the golden section search is repeated for a new minimum and so on until there is no improvement within the search radius of the last minimum. When applying this augmented search technique to all depth levels the Q-estimates of Figure 6 are obtained. The departure between augmented-search-Q(z) and model-Q(z) must be less than the curve width in Figure 6. When computing and plotting the actual Q-estimation errors Figure 7 results. Considering that, firstly, we know the exact velocities/densities and, secondly, there is no seismic noise in our model data, this Q-estimation result is not too surprising. The real test lies with the real VSP data.

The frequency range for our *sum-of-squared-differences* computation is 1.5Hz to 80Hz. What is the sensitivity of these sums with respect to the low frequency limit? Figure 8 shows the *sums of squares* computed with various low frequency limits. For a smaller bandwidth fewer squares are summed and we should expect smaller sums which is exactly what Figure 8 demonstrates. Most encouraging is the fact that the minimum location is independent of the low frequency limit; for this ideal VSP model data situation Q-estimates appear to be independent of bandwidth at least to some extent.

CONCLUSIONS

In this study we employ Ross Lake well-logs to generate an intrinsic Q(z) model and VSP model data. To compute intrinsic model Q-factors from P-wave velocities an empirical equation suggested by Waters (1978) is used. VSP model data is obtained from a multi-interface Sommerfeld integral when well-logs and intrinsic Q(z) are introduced as input parameters; this model data combines the effects of intrinsic attenuation [Q(z)] and stratigraphic attenuation and we attempt to implicitly quantify and remove the effects of stratigraphic attenuation in order to recover intrinsic attenuation [Q(z)]. Assuming that velocities and densities are known we generate forward models for an exhaustive Q-factor search employing the same Sommerfeld integral approach as above. Sums of squared differences between VSP model data and forward models show a pronounced minimum at the correct model intrinsic Q(z) when plotted against the Q-sweep. For computational efficiency we apply a Golden-Section-Search algorithm (GSS) gleaned from Numerical Recipes. Occasionally this GSS algorithm finds a local minimum which we escape by testing within a prescribed search radius and repeating GSS if found necessary. With this multiple GSS technique Q-inversion is very successful because VSP model data and forward models are generated with the same Sommerfeld algorithm and the data is noise free. It will be interesting to test this inversion approach with real VSP data when velocities and densities are not exactly known and seismic noise is present.

ACKNOWLEDGEMENTS

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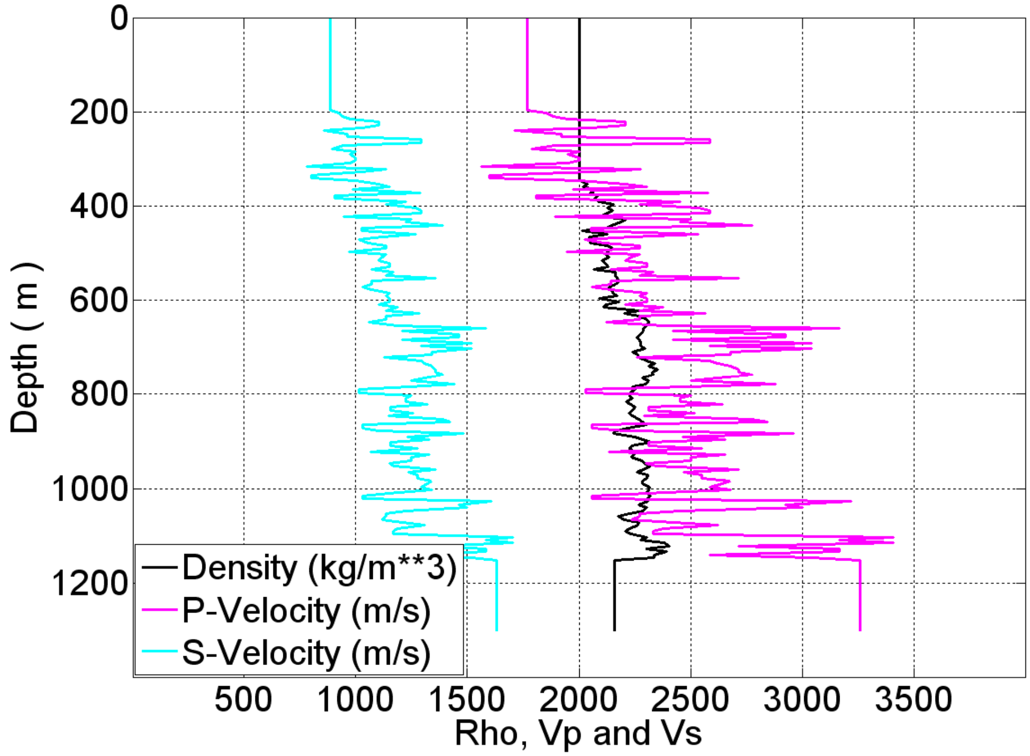

FIG.1. Ross Lake velocities and density.

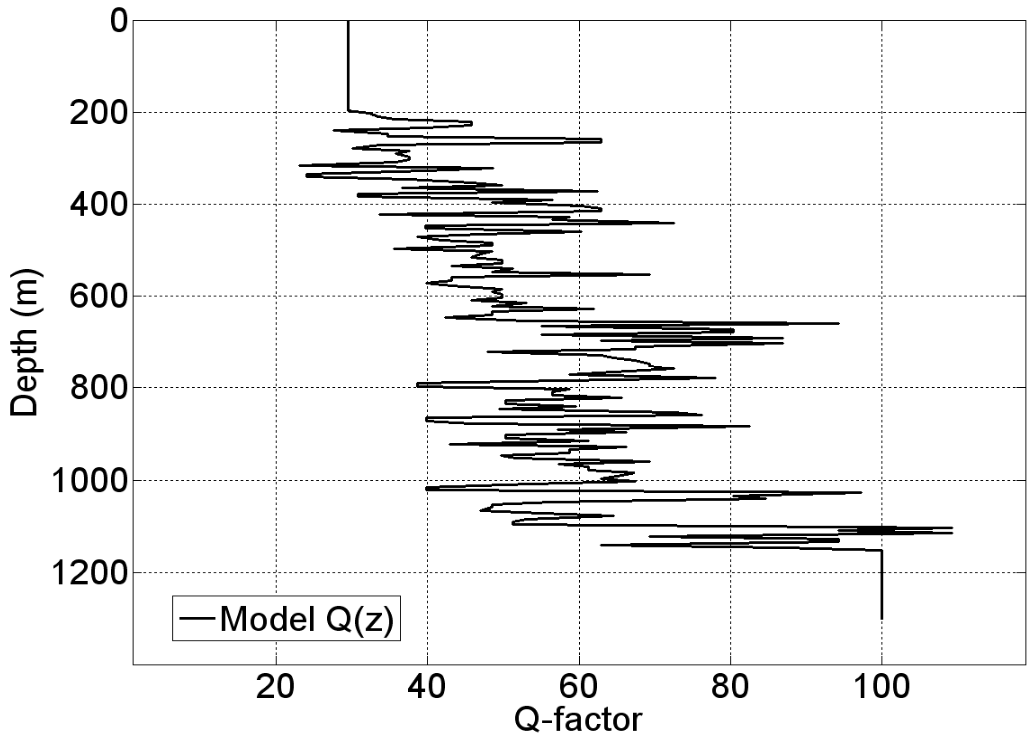

FIG.2. Q-model generated from Ross Lake P-wave velocities using Waters's equation.

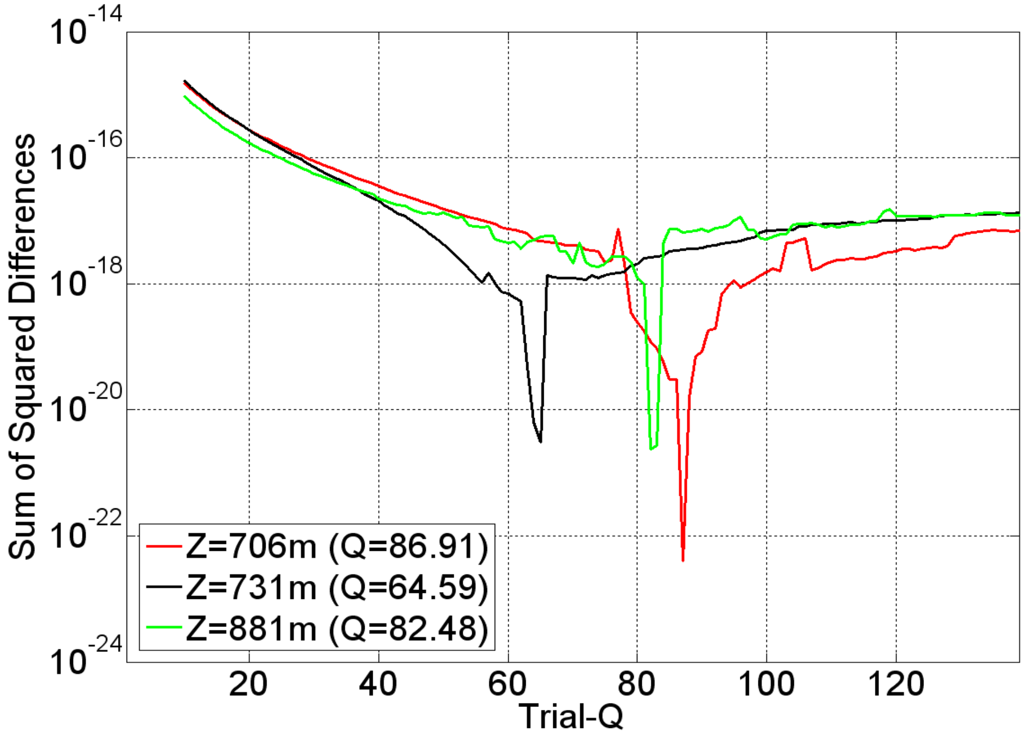

FIG.3. Exhaustive Q search results.

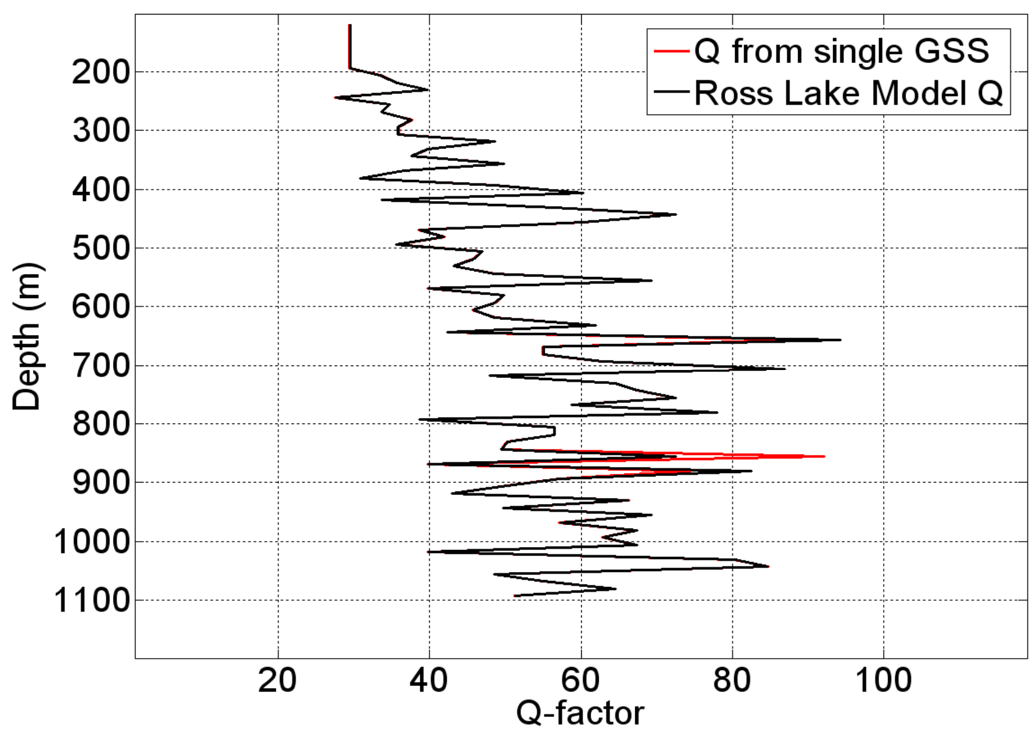

FIG.4. Q versus depth from Golden Section Search compared to Ross Lake model Q.

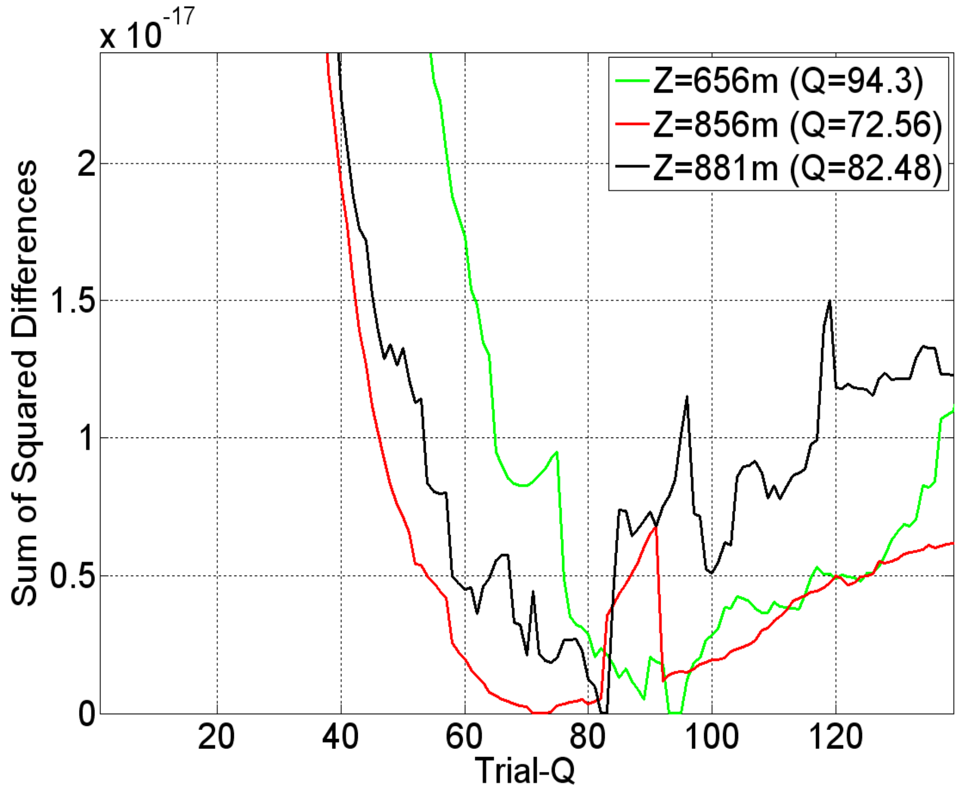

FIG.5. Exhaustive Q search results at estimation error locations.

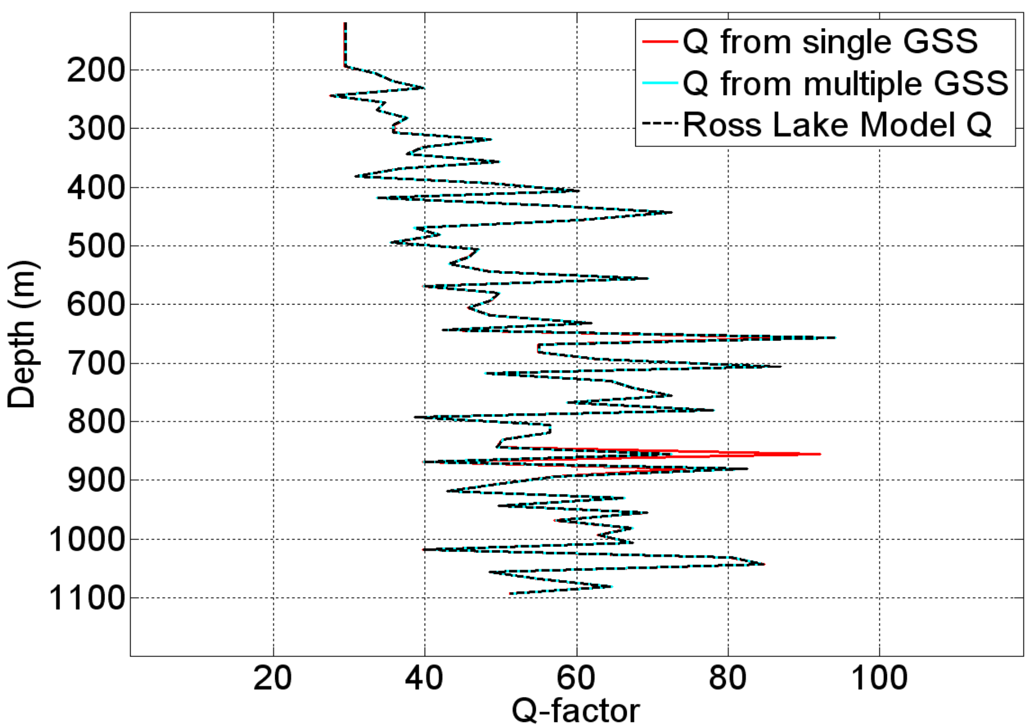

FIG.6. Q versus depth from augmented Golden Section Search compared to Figure 4.

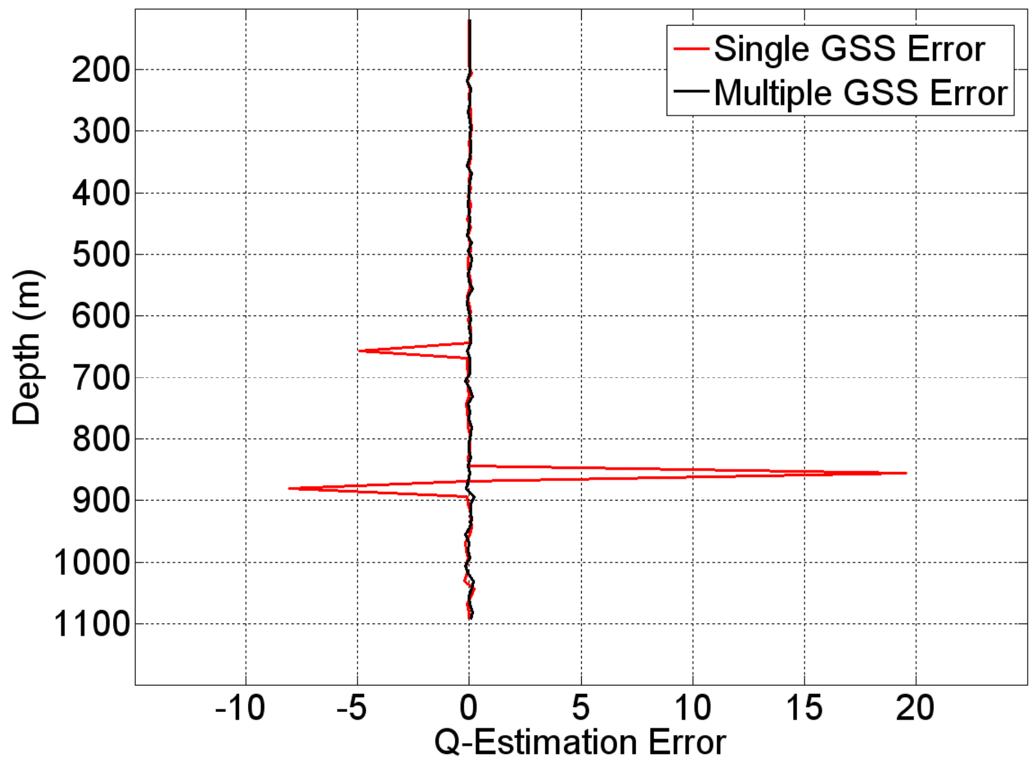

FIG.7. Ross Lake Q-estimation error following Golden Section Search.

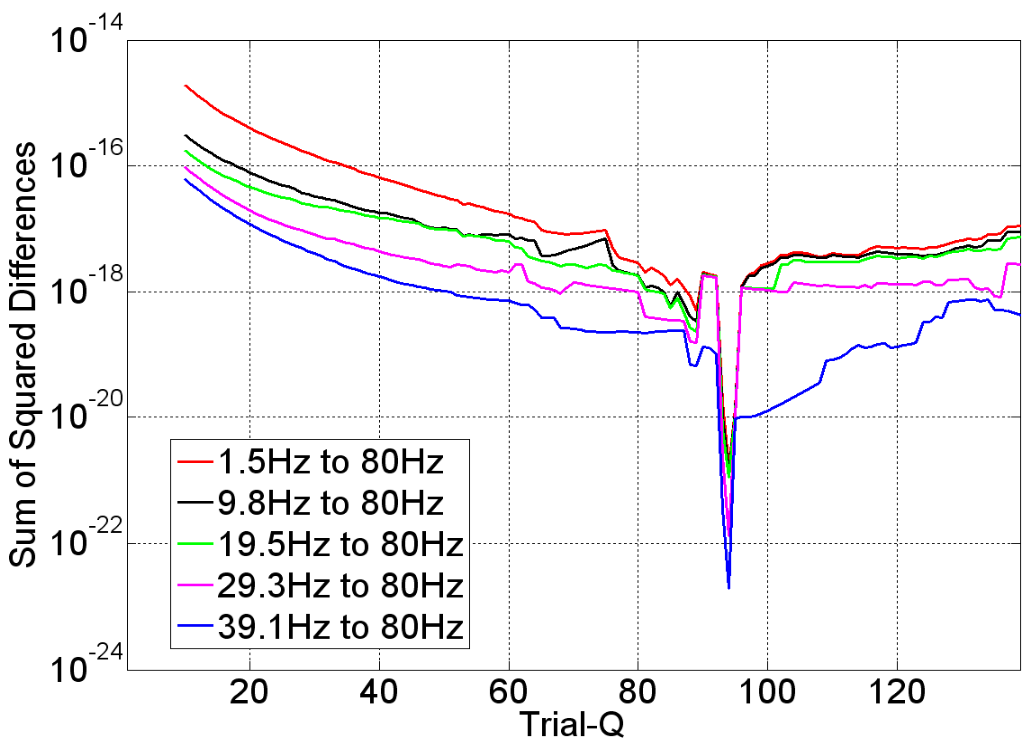

FIG.8. Bandwidth dependence of *sums-of-squared-differences* at Z=656m (Q=94.3).