SHEAR-WAVE VELOCITY MODELING BY INVERSION OF MICROSEISMIC HORIZONTAL-TO-VERTICAL SPECTRAL RATIO

Sahar RAHPEYMA¹, Benedikt HALLDORSSON²,³, Birgir HRAFNKEISSLSON⁴, Orhan POLAT⁵

ABSTRACT

The shear-wave velocity (Vₛ) model is a key parameter in many geotechnical and earthquake engineering applications. The Vₛ profile can be retrieved either using invasive or non-invasive techniques. Although the non-invasive methods provide useful and cost-efficient alternatives, the inversion problems are highly nonlinear and can be influenced by non-uniqueness solution which mainly result in high level of uncertainties. In this study, a method for estimating the Vₛ profile of subsoil structure has been proposed based on the inversion of the observed microseismic Horizontal-to-Vertical (H/V) spectrum. The inversion scheme is set up in the context of the Bayesian framework using Markov chain Monte Carlo (MCMC) technique with Metropolis steps in order to explore the space of model parameters and find the best fitting family of subsoil properties along with their associated uncertainties. The theoretical H/V spectrum are calculated through body-wave approximation as a reliable estimate for subsoil structure of the sedimentary layers overlaying the half-space. The proposed technique has been assessed using microseismic recordings from a nominated station from IzmirNet, Turkey. Due to the lack of geological information to constrain the inversion and to get a reliable resolution of layering we implement a blind test for the number of layers in the model to systematically investigate the optimal model parametrization. More importantly however, they provide us with a quantitative estimate of the certainty that we have in the inversion results, which has important implications for the use of indirectly derived velocity profiles for the purpose of modeling site response for earthquake engineering applications.

Keywords: shear-wave velocity; inversion; Bayesian approach; Markov chain Monte Carlo; Uncertainty; Non-uniqueness problem

1. INTRODUCTION

One of the most remarkable lessons learned from the historical catastrophic earthquakes such as Michoacan earthquake (Mexico City, 1985) and Loma Prieta earthquake (Northern California, 1999) is that geological characteristics and subsoil structural effects, known as site effects, can significantly change site response and resulting damage distribution even over short distances. The estimate of site effect is, therefore, one of the critical components for any seismic hazard mitigation. In geotechnical as well as engineering applications, shear-wave velocity (Vₛ) is the most common indicator of the soil dynamic properties to characterize the site conditions. Estimation of the Vₛ model has been accomplished using a variety of either invasive (e.g. down-hole or cross-holes seismic surveys) or non-invasive (e.g. surface-wave or body-wave approaches, and refraction-reflection analyzes) processing tools. The
classical in-situ methods commonly use borehole drilling to determine detailed and accurate information of the soil properties with reasonable resolution between closely spaced boreholes (Kramer 1996). However, invasive methods are known to be rather expensive and time consuming to amass the measurements across the whole area under study. Hence, these approaches are primarily recommended in projects of relevant importance. Contrary to the in-situ measurements, the non-invasive techniques have long been recognized as cost-efficient and practical alternatives to obtain the subsoil \( V_s \) structure. To a large extent, ground motion recordings comprise important information of the subsoil characteristics, therefore, utilizing different theoretical and numerical algorithms considering wave propagation have been largely developed for soil profiling. In particular, surface-wave analysis founded on inversion of the dispersion curves are becoming more common (Aki 1957; Arai and Tokimatsu 2004, 2005; Castellaro and Mulargia 2009; Bard et al. 2010; Socco et al. 2010). Nonetheless, data processing and inversion of the experimental data using the surface-wave methods are usually computationally intensive in comparison to the invasive techniques besides result can be intensely influenced by prior assumptions (Scherbaum et al. 2003; Molnar et al. 2010; Garofalo et al. 2016a, b). On the other hand, surface-wave inversion is characterized as non-linear and ill-posed problem which can strongly affect the obtained results (Luke et al. 2003; Scherbaum et al. 2003; Foti et al. 2009; Teague and Cox 2016). These drawbacks can cause certain level of ambiguity in the obtained \( V_s \) profile.

Arai and Tokimatsu (2004, 2005) and Herak (2008) successfully applied microseismic Horizontal-to-Vertical Spectral Ratio (HVSR) method to estimate \( V_s \) profile. The HVSR technique also known as Nakamura’s method is a well-known and practical alternative which reliably characterizes resonance phenomena (Nogoshi and Igarashi 1970; Nakamura 1989, 2008). It has been well investigated that the shape of the amplification (HVSR) curve is a representative of the velocity contrast between soil layers (Nakamura 2000, 2008) and the frequency associated to the maximum amplitude of the HVSR curve shows the fundamental frequency of the subsoil structure (Nakamura 2000, 2008). The basic statement of the HVSR technique is that the vertical component of the ground motion in cases where the soil stratigraphy is flat and horizontal is supposed to be free of any kind of influence related to the site conditions at the recording site. Nevertheless, there are different physical interpretations for the fundamental concepts of the Nakamura’s technique. The critical debate over the underlying theory of Nakamura’s method focused on the hypothesis that the obtained spectral ratio is determined by whether body-waves, approaching vertically the surface (Herak 2008; Nakamura 2008), or surface-waves, Rayleigh and Love waves with relevant upper modes (Arai and Tokimatsu 2004, 2005; Lunedei and Albarello 2010). However, the numerical comparison of different interpretations revealed that the surface-wave approach presents more reliable results for frequencies larger than fundamental resonance frequency of the sedimentary layer over the bedrock; whereas, the body-wave approach provides more consistent results around the fundamental frequency (Albarello and Lunedei 2010). Despite a wide debate over different concepts, by and large the HVSR method is considered as a practical tool to obtain the \( V_s \) profile.

Therefore, in this paper we aim to model the \( V_s \) profile by inverting the experimental microseismic HVSR. We set up our inversion problem based on the Bayesian framework to improve our understanding of the model parametrization as well as the associated uncertainties. The theoretical HVSR technique obtained based on the body-wave approximations is applied to a benchmark/test station with microseismic recordings to verify the efficiency of the proposed approach. We use the microseismic data recorded at a nominated station from IzmirNet collocated in Izmir Bay region, Turkey (Polat et al. 2009). A Markov-Chain Monte Carlo (MCMC) algorithm with Metropolis steps is considered to simulate the posterior distribution of the unknown model parameters. The convergence diagnostics of the MCMC algorithm are also applied to find the most reliable \( V_s \) model beneath the nominated station. Although there are still many sources of uncertainties, such as lack of good prior information and extremely simplifying assumptions about the ground structure, the results are in good agreement with available geological information. The results of this research will improve our understanding of the site characteristics and provide significant information for many earthquake engineering applications.
2. GEOLOGICAL SETTINGS

In 2008, a small aperture local seismic network, IzmirNet, consists of 16 stations (see Figure 1) was established across the Izmir Bay (Polat et al. 2009). The Aegean region in western extremities of Turkey is known as one of the seven geographical regions of Turkey and one of the most seismically active region of the Eastern Mediterranean region. Izmir, the capital of the Aegean region of Turkey, is known as one of the most populated with dense industrial infrastructures in the country. Historically, this region has a prominent seismic risk due to its large and growing population and key infrastructures which are surrounded by active faults. Figure 1 shows the distribution of IzmirNet stations across the Izmir Gulf (Polat et al. 2009; Gok and Polat 2014). As can be seen in Figure 1, the majority of the settlements (industrial and populated areas) are collocated on top of Quaternary alluvial deposits around the Gulf of Izmir. Other prominent units are Miocene-aged sandstones, mudstones, andesitic volcanic, and Paleocene limestones (Polat et al. 2009, 2012; Gok and Polat 2014). It is worth mentioning that the unconsolidated deposits in the Izmir basin can significantly change the propagation of ground motions to the surface; hence, the assessment of seismic hazard for the Izmir region is an imperative issue. It has been reported that the Quaternary sediments and cretaceous flysch are the main units near the Balcova area, with a sedimentary fill up to 180 m.

![Figure 1. Location of IzmirNet array (filled triangles) on geology of Izmir and simplified geological features. YM: Yamanlar mountain, IF: Izmir Fault, KFZ: Karsiyaka Fault Zone, OTFZ: Orhanli-Tuzla Fault Zone, SFZ: Seferihisar Fault Zone (Gok and Polat 2014). The insert figure on bottom left shows the observed HVSR form microseismic measurements with a Konno and Ohmachi smoothing coefficient B=20 for BYN station.](image)

3. DATA PROCESSING

A continuous microseismic recordings of a minimum 30-minute duration and sampled at 100 sps (samples per second) were recorded at IzmirNet stations. All stations are free-field and equipped with three-component CMG-5TD accelerographs (Guralp Systems, Reading, UK) with CMG-5T force balance accelerometer and built-in 24-bit AD converter for data acquisition (Polat et al. 2009). An asymmetric digital subscriber line (ADSL) system controls the stations and downloads real-time continuous data. At each station, a minimum 15 minutes of microseismic measurements were recorded at the sampling rate of 100 Hz. The data processing to obtain the HVSR at each site was performed using GEOPSY software in the following routine: the data was filtered between 0.20 and 25 Hz by a band-pass 4 poles Butterworth filter after the mean and a linear trend were removed; then each component of the recorded signal was windowed in a time series of 30 second length without overlapping; use cosine taper 5% and for each time window Fast Fourier Transform (FFT) was calculated and smoothed using Konno and Ohmachi logarithmic window function, B = 20 (Konno and Ohmachi 1998). For each time window of 30 second length, the spectral ratio between the root-mean square average spectrums of two horizontal components over the spectrum of the vertical component
was calculated and, finally, the station representative average HVSR and the standard deviation were computed and plotted as a function of frequency. This approach is also the recommended method by SESAME (i.e. Site EffectS assessment using Ambient Excitations; Bard and SESAME-Team 2005) and is the most commonly used method for HVSR analyses. In this study, we selected station BYN located on soft soil in the eastern part of Izmir Bay with a clear fundamental frequency peak at $0.7 - 0.8$. As can be seen in the insert figure at bottom left in Figure 1, the HVSR curve at station BYN has a predominant frequency at $\sim 0.76$ Hz. The HVSR characteristics for BYN station suggests that the soil column acts as a single layer on top of a high impedance contrast between layers, where strong amplification and frequency dependent resonance are known to occur.

4. MODELING SETUP

4.1 Bayesian statistical inference

In this study we implement Bayesian approach with the aim of providing a constructive framework for making inference on different soil properties in the light of the observations. In the context of the Bayes theorem, the unknown model parameters are assumed to be random variables and assigned prior probability distribution logically defined based on available information or a priori subjective beliefs (Congdon 2014; Gelman et al. 2014). As it is shown in Equation (1), the prior information about the model parameters will be updated by conditioning on the observed data with respect to the underlying probability model.

$$\pi(\theta | y) \propto \pi(\theta) \pi(y | \theta)$$

where, $\pi(\theta | y)$ is the joint posterior distribution of the model parameters, $\theta$ (which represents soil properties), given the derived theoretical transfer function of the subsoil as data, $y$, requires information about the sampling distribution $\pi(y | \theta)$ and also a sensible assumption about the prior distribution $\pi(\theta)$ if exist. In this regard, the obtained posterior distribution integrates updated knowledge on model parameters considering knowledge found from the observed data. In order to numerically approximate posterior density function of model parameters, a Markov Chain Monte Carlo (MCMC) algorithm, is employed (Gelman and Rubin 1992; Smith and Roberts 1993; Gilks 2005). MCMC is basically applicable to almost any Bayesian modeling and is a general algorithm for simulating independent Markov chains which has a desired target density. This procedure is mainly carried out using the Gibbs sampling framework (Geman and Geman 1984; Casella and George 1992) and the Metropolis algorithm (Metropolis et al. 1953) as an updating strategy which tracks adaptation of a random walk in parameters space to define the acceptance or rejection of the samples to converge to the specified target distribution. The following steps summarize the applied MCMC in this study to sample the posterior density of $\theta$:

Step 1: Initialize the MCMC process with preliminary estimates of parameters $\theta^0$.

Step 2: At step $k$ sample a proposal value $\theta^* \| y$ from a given proposal density (e.g. in this study normal distribution is used) with mean $\theta^{k-1}$.

Step 3: Calculate the ratio

$$\alpha = \min \left\{ 1, \frac{\pi(\theta^* | y)}{\pi(\theta^{k-1} | y)} \right\}$$

Step 4: Sample $u_k$ from uniform density on $[0,1]$. Accept or reject the proposed values of $\theta$ according to:

$$\theta^k = \begin{cases} 
\theta^{k-1} & \text{if } \alpha \leq u_k \\
\theta^* & \text{if } \alpha > u_k 
\end{cases}$$
In other words, if the state transition leads to higher probability value than the previous state, the proposed value is accepted, but if the transition produces a lower probability, then the proposed value is only accepted with a probability of $\alpha$.

**Step 5:** Run the MCMC algorithm with the updated estimates and repeat steps 2-4.

**Step 6:** Obtain posterior summaries for model parameters $\theta$ using their posterior samples.

### 4.2 Bayesian convergence diagnostics

In this study, we use three different convergence diagnostics to assess the convergence of multiple MCMC chains. First, visual inspection can expose bad mixing of Markov chains or chaotic behavior of separate chains. Secondly, the Gelman-Rubin statistics (Gelman and Rubin 1992) by relying on the within-chain variance to the between-chain variance tests whether the chains all converge to the same posterior distribution. Large values ($>1.10$) of Gelman-Rubin test indicates that simulated chains have not converged to the target density. Finally, the autocorrelation plots evaluate the exist dependency between successive samples within each Markov chain.

### 4.3 Inversion strategy

We implement the theoretical HVSR obtained based on the transfer functions of a set of horizontally stratified, linearly elastic layers overlaying half-space excited by vertically incident proposed by Tsai (1970). The parametrization of the theoretical HVSR is based on the assumptions of 1-D layered models consisting of a stack of homogenous linear elastic layers over a half-space (read Albarello and Lunedei, 2010 for more details and comparison). Hence, subsoil physical properties such as thickness ($H$), density ($\rho$), shear-wave velocity ($V_s$), compressional velocity ($V_p$), and elastic properties for S- and P-waves ($Q_s$ and $Q_p$) are considered as model parameters.

Trial inversion using all model parameters revealed that due to the non-uniqueness results and large trade-off between parameters the model cannot converge reliably. We observed that thickness and S-wave velocity are the most influential and correlated variables. Therefore, we set model parameter $\theta = (H, V_s)$ and fix the rest of parameters with the aim at better convergence. It has been also proven that the theoretical transfer function chiefly depends on S-wave velocity and depth of the subsoil and negligibly on the other soil properties (Foti et al. 2009; Molnar et al. 2010). Therefore, in this study, $\theta = (H, V_s)$ are assumed to be unknown and the rest of parameters are defined as fixed parameters and their values can be approximated on the basis of available geological information.

At each iteration $k$ of the MCMC process, the unknown variables are drawn, as input for theoretical HVSR, from a normal distribution centered at an adaptive mean (i.e., the latest accepted value) value and pre-defined standard deviation for each layer over all chains as can be seen in Equation (4):

$$\theta_{p,l}^k \sim N\left(\theta_{p,l}^{k-1}, \sigma_{\theta_{p,l}}^2\right)$$

where subscripts $p = 1,2$ and $l = 1,\ldots,L$ indicate the model parameters indicator $\theta = (H, V_s)$ and the layer, respectively. The standard deviation, $\sigma_{\theta_{p,l}}$, is defined based on 5% of the mean value of the model parameters. For each model parameter at each layer, the lower ($\theta_{p,l}^L$) and upper ($\theta_{p,l}^U$) bounds are chosen reasonably to avoid the inversion stick into a wrong convergence track due to the trade-off between model parameters; however, the boundaries should be wide enough to allow the data to determine the S-wave velocity profile parameters ($\theta_{p,l}^L \leq \theta_{p,l} \leq \theta_{p,l}^U$). The initial values of the model parameters, which are used to produce the initial theoretical HVSR, are instinctive approximations.

The Bayesian framework requires specifying prior probabilities for all model parameters and a likelihood function (see Equation (1)). Due to the lack of precise information about the subsoil structure, the prior probability density function of each parameter is chosen as a uniform probability density functions on the interval $\theta_{p,l}^L \leq \theta_{p,l} \leq \theta_{p,l}^U$, such that

$$\pi(\theta_{p,l}) = \begin{cases} 1, & \theta_{p,l}^L \leq \theta_{p,l} \leq \theta_{p,l}^U \\ 0, & \text{otherwise} \end{cases}$$

Equation (5)
And the joint prior probability density function for all the model parameters in $\theta$ is the product of the individual prior densities. It is assumed that the probability density function of the spectral amplitudes $HVSR_i$ (i.e., $y_i$) in each frequency bin $f_i$ with $i = 1, \ldots, I$ (I is the total number of frequency bins) is lognormal with parameters $\mu_{HV}(f_i)$ and $\sigma_{HV}^2(f_i)$, i.e., the expected value and the variance of log($HVSR_i$). So, the probability density function for each $y_i$ within frequency bin $i$ is given by Equation (6):

$$
\pi(y_i|\theta) \sim LN\left(y_i \mid \mu_{HV}(f_i), \sigma_{HV}^2(f_i)\right)
$$

A practical issue influencing convergence to an unbiased estimate include deleting early samples of the Markov chain, commonly referred to as “burn-in” (a burn-in length of at least 25% of total samples is applied here). We run many sets of combination with different number of layers, various prior assumptions and initial values, number of iterations, number of chains, and burn-in sample size to find the most consistent results. All chains would be analyzed together after simulating the desired number of iterations by removing burn-in part.

5. RESULTS AND DISCUSSION

The clear peak in the observed HVSR (black curve in Figure 2(a)) at the nominated station indicates that the fundamental mode of the subsoil structure is linked to a strong enough velocity contrast within depth. Theoretically, we can assume the simplest subsoil structure with a single predominant frequency as a sedimentary column sits on top of a hard layer (bedrock). Figure 2(a) shows the observed (black curve) and the initial theoretical (blue curve) HVSR model obtained based on the initial assumption of $V_s$ profile (blue curve in Figure 2(b)). It should be noted that we invert the observed HVSR over the nominated range of frequencies defined around the fundamental frequency (gray area in Figure 2(a)). It may be argued that at relatively high frequency, no HVSR peak associated to a shallow stratigraphic horizon can be observed; thus, the basic requirement for the proposed procedure to concentrate around the fundamental mode could be satisfied. Furthermore, in the seismic microzonation practice, attention has generally only been paid to the main resonance frequency, which is the largest HVSR peak, while other stable humps and troughs in the curve were not considered.

A grid search of the MCMC initiated with a starting model whose parameters are randomly perturbed within the bounds defined $[\theta_1, \theta_U]$ results in posterior probability distribution of the model parameters (magenta curve in Figure 2(a-b)).

As can be seen in Figure 2(a), the initial model is considered to be different from the observed HVSR.
Furthermore, we assumed a wide range of model parameters space (0.30 and 1.5 times of the initial model parameter values as lower and upper boundaries) with small jumping steps (0.05 times of model parameters values at each iteration) which let the synthetic models converge to the highest probability ratio obtained by sampled model parameters. According to the available geological/geostuctural data, BYN station sits directly on top of an alluvial deposit layer of around 180 − 200 meter depth. It is explicit in Figure 2(b) that for a single-layer model the mean posterior of sedimentary layer thickness over the half-space is estimated around 200 m with ~50 m of standard deviation that is in very good agreement with available information.

Although with a single-layer subsoil structure we could quantitatively estimate model parameters' characteristics, the key question is that to what extent a detailed $V_s$ profile can be extracted from the recorded data? It is noteworthy that due to complexity of the subsoil structure, non-linearity of the model, and non-uniqueness solution for the inversion process, it is likely that a single-layer model cannot precisely capture the subsoil structure. In soil properties inversion problems, defining enough parameters (e.g. number of layers, fixed or dynamic model parameters) is essentially critical to estimate a proper resolution for layering and parametrization. Adopting not enough parameters can conspicuously result in under-fitting the data, biasing parameter estimation and under-estimating the associated uncertainties. In contrast, considering too many parameters can over-fit the data result in under-determined parameters and excessive variations of parameters (Molnar et al. 2010). In this study, with the aim to determine the most probable subsoil parametrization with reasonable resolution, initially, a single-layer model is considered (as shown in Figure 2) and through gradually increasing the number of stack layers over the half-space the posterior distributions of the model parameters acknowledge to what extent the current subsoil structure is informative (i.e., a uniform posterior distribution of model parameter is non-informative). We conduct a blind test over the number of layers to consistently investigate the best resolution of model parametrization. Therefore, we continue adding the number of layers as far as the posterior distributions of model parameters do not provide any consistent information. The effect of increasing the number of layers is shown in Figure 3 the marginal posterior probability distributions of a five-layer model over bedrock parameters for $H$ and $V_s$ by illustrating.

![Figure 3](image-url)

**Figure 3.** (a) The observed, initial, and posterior theoretical HVSR model obtained from Bayesian MCMC inversion for a 5-layer subsoil structure at BYN station, Turkey; (b) S-wave velocity profile for the initial (blue) and posterior (magenta) model; (c) Correlation matrix of posterior samples of model parameters; (d) posterior histograms for thickness ($H$) and S-wave velocity ($V_s$).
We used a Gibbs sampler with Metropolis steps for total iteration of $N_T = 20,000$ through $N_C = 20$ parallel chains, and $N_B = 5,000$ burn-in samples which in total creates $300,000$ random samples across the nominated range of frequency between $0.6$ to $1.0$ Hz (gray area in Figure 3(a) around the fundamental frequency). The initial HVSR model (blue HVSR curve) and the final HVSR model (magenta HVSR curve) obtained based on the posterior mean values of soil properties (thickness and S-wave velocity) in addition to the associated $V_s$ profiles are shown in Figure 3(a) and Figure 3(b), respectively.

The convergence of the obtained model parameters is evaluated by controlling the traceplots of the Markov chains, calculating the Gelman–Rubin ($\hat{R}$) statistic for all parameters. As a reference, the point estimates of the $\hat{R}$ statistics should be between $1.00 - 1.10$ for all parameters. The obtained $\hat{R}$ for the models are at each layer is in the acceptance range. Moreover, the dependence between successive samples of the Markov chain is assessed using the autocorrelation from lag 1 to 50 which is obtained with the sample correlation. It should be noted that due to the predefined boundary for model parameters the autocorrelation is naturally higher than what we expected. However, considering thinning factor of 5 can help to decrease the autocorrelation.

As can be seen in Figure 3(a-b), although the initial $V_s$ profile and HVSR model behaves differently, the posterior model fits the observed HVSR very well and the estimated depth of the sedimentary layer over the half-space is around $180 - 190$ meter. Figure 3(c) illustrates the matric correlation and evaluate the correlation between posterior model parameters. Contrary to the relatively high correlation for a single-layer subsoil structure (cf. $\sim$80% in Figure 3(c)), the correlation between model parameters of a multi-level subsoil structure is not large ($\sim \pm 30 - 40\%$). The negative and positive correlation can be observed between thicknesses and S-wave velocities of layers. The posterior histograms of thickness and S-wave velocity for each layer are shown in Figure 3(d). As can be seen the obtained posterior distributions of specifically thickness are weakly informative with large uncertainties for deeper layers comparing to the shallower layers.

One of the main obstacles embedded in the $V_s$ model inversion strategies is the non-uniqueness solutions that is mainly related to the ill-posed mathematical formulation. In other words, the HVSR inversion process suffers from trade-off between the S-wave velocity and layer thickness and therefore may not be very reliable in terms of absolute velocity-depth values (Scherbaum et al. 2003). In general, the higher uncertainty for deeper layers reflects the non-unique nature of the inverse problem. This phenomenon can be observed in Figure 4 where different soil structures and stack layers result in the same theoretical HVSR. However, we investigated that increasing the number of parallel chains can reasonably results in better convergence due to expansion of the input parameters combinations and considering as much as possible potential synthetic HVSR models. In this regard, within the MCMC grid search all perturbations start around different initial parameters values. Hence, the determined $V_s$ profiles with this approach and the associated uncertainties would be reliable.

![Figure 4. non-uniqueness solutions; (a) theoretical HVSR and (b) associated $V_s$ profiles obtained by posterior mean values of model parameters using different layering.](image)
In order to confirm the efficiency of the inversion results is finding the predominant frequency from posterior simulations of model parameters we calculate the natural frequency of the soil, \( f_n \), using the harmonic average defined in Equation (7):

\[
\frac{2n - 1}{4 \sum_{i=1}^{L} \left( \frac{h_i}{V_{s,i}} \right)}
\]  

(7)

where \( n \) is the mode number, \( h_i \) is the thickness and \( V_{s,i} \) is the shear-wave velocity for the \( i^{th} \) soil layer, and \( L \) refers to the number of layers overlaying the half-space. The estimated mean posterior predominant frequency \( f_0 \) for a five-layer subsoil structure over half-space estimated in Figure 3 for station BYN is 0.63 Hz with the posterior 95% interval of 0.58 – 0.72 Hz which is in approximately good agreement with the experimental fundamental frequency of 0.70 Hz.

6. CONCLUSION

In this study, we proposed and then evaluated a Bayesian inversion framework to invert the experimental microseismic HVSR at a nominated station of the IzmirNet located in Izmir Bay (Turkey) to obtain the most-probable \( V_s \) profile. Applying Bayesian inversion technique resulted in posterior probability density of the subsoil geophysical model parameters along with the associated uncertainties. We implemented a Markov chain Monte Carlo (MCMC) algorithm with Metropolis steps to systematically search the model parameters space. Different configurations of the subsoil structure were examined in order to find the most-likely subsoil S-wave velocity structure as well as the related uncertainties for model parameters (thickness and S-wave velocity for each layer). An informative resolution of the subsoil layering was determined by progressively increasing the number of subsoil layers and assessing the posterior probability distribution of the model parameters. The validation and convergence of the posterior samples were examined using traceplots visualizing, Gelman-Rubin statistics, and the autocorrelation plots. The analysis revealed that the final \( V_s \) model is very sensitive to the initial assumptions and the inversion process can easily be biased by wrong choices in terms of model parameterization which can guide the final solution into either local minima or mal-functioning of modeling. The obtained \( V_s \) profile for the nominated station is in good agreement with the available geological information. In addition, the obtained fundamental frequency using the mean posterior values of the model parameters from each layer (0.63 Hz) is in the same range as the observed fundamental frequency from the site effect estimation (0.70 Hz). As this is a non-linear inversion problem, we suggest that using the Bayesian inference by MCMC algorithms for posterior simulation can point out important inter-parameter relations (trade-off) and also irregular non-Gaussian distributions which would otherwise lead to faulty conclusions when treated through simple linear regressions.

7. ACKNOWLEDGMENTS

This work was supported by the Icelandic Centre for Research (Grant of Excellence no. 141261-051/52/53), the University of Iceland Research Fund, and a Doctoral grant from Eimskip Fund of the University of Iceland.

8. REFERENCES


Bard PY, SESAME-Team (2005). Guidelines for the implementation of the H/V spectral ratio technique on ambient vibrations: measurements, processing, and interpretations. SESAME European research project. SESAME European research project.


