Automatic characterisation of ground surfaces from in situ measurements

Guillaume Dutilleux and David Ecotiere

Lab. Régional des Ponts et Chaussées, 11, rue Jean Mentelin, BP 9, 67035 Strasbourg Cedex 2, France
guillaume.dutilleux@equipement.gouv.fr

The study of long term performance of road pavements requires to access to the evolution of the intrinsic parameters of theses surfaces, like resistivity or tortuosity. In long range sound propagation as well, it is well know that ground absorption is time-varying. The understanding of this variation is an important issue. In both application cases, non-destructive measurement methods are required. The present contribution focuses on the 2-parameter model of Delany and Bazley for outdoor surfaces and the 4-parameter one of Hamet and Bérengier for porous road pavements. It is shown that for both models the automatic identification from *in situ* measurements is possible. For the 2-parameter model the identification is based on a suitable cost function. The complexity of the function is low enough for a resolution by exhaustive search. It turns out that, for a large set of ground samples, the cost function is convex. Therefore the resolution can be done quite efficiently by classical gradient descent methods. Regarding the 4-parameter mode, although the cost function is no longer convex, the resolution can be performed using a global optimization tool, like an evolutionary algorithm.

1 Introduction

The acoustic behavior of road surfaces depends on intrinsic parameters like porosity or tortuosity. The access to these parameters is a key to understand the progressive degradation of the acoustic performance of road surfaces, and drainage pavements in particular. Outdoor sound propagation models are often based on models for boundary conditions that also depends on intrinsic parameters in the case of natural soils.

Directly determining these parameters is difficult outside the laboratory, because it requires a complex apparatus. On the other hand, laboratory measurement imply to collect samples. This is not always suitable, especially when sampling is to be repeated over time, as it is the case in the study of the long term performance of road surfaces. In addition, the required sample area for certain laboratory tests may be large. In the case of road surfaces, sampling requires to work on the road with evident safety issues. Finally a recurring difficulty of sampling is to obtain a sample that corresponds to the material *in situ*, especially with granular materials. Therefore, it is of interest to find a way to estimate intrinsic parameters from *in situ* measurements.

The models of materials considered here provide absorption characterizing parameters like the impedance, the complex reflection coefficient or the absorption coefficient. They depend on a limited number of intrinsic parameters, typically 2 to 6. Several non-destructive methods for the measurement of the acoustic absorption are available. For instance, the ISO 13472-1 standard is dedicated to measurements on road surfaces [5]. For natural soils, the acoustics group of Laboratoire Central des Ponts et Chaussées uses a method based on transfer function measurements between two microphones. In both cases, the current practice to obtain intrinsic parameters is to use such measurement results and to perform a visual adjustment of the parameters. To this end, the operator uses a software program with a graphical user interface. He(She) tunes the parameters with scrollbars, so that the model matches the measurement. When the number of parameters and/or the number of measurement increases, this procedure tends to be tiresome. Moreover, this way of determination can be relatively operator-dependent.

We present here two attempts to identify the intrinsic parameters from acoustic measurements. In both cases an inverse approach is used. Section 2 describes the models to identify. Section 3 describes the propagation model involved in the forward model needed in the inverse problem resolution. Section 4 presents the automatic identification of the Delany and Bazley model in the case of a grass-covered ground. The optimization results are compared with the classical visual optimization. Section 5 explores the possibility of the identification of the model by Hamet and Bérengier on a porous pavement by the clonal selection algorithm.

2 Models for acoustic absorption

2.1 Delany and Bazley

The Delany and Bazley model is a semi-empirical model of porous materials. It gives the expression of the acoustic impedance Z_∞ and the wave number κ in the ground [7] :

$$Z_\infty = \rho c \left(1 + 9.08 \left(\frac{f}{\sigma} \right)^{-0.754} + 11.9\jmath \left(\frac{f}{\sigma} \right)^{-0.732} \right) \tag{1}$$

$$\kappa = k \left(1 + 10.8 \left(\frac{f}{\sigma} \right)^{-0.7} + 10.3\jmath \left(\frac{f}{\sigma} \right)^{-0.595} \right) \tag{2}$$

where ρ is the density of air, c is the speed of sound in air, k is the wavenumber in air, σ is the specific flow resistivity of the material, $\jmath^2 = -1$ and f is the frequency. In the case of a material with infinite thickness, σ is the only intrinsic parameter Z depends on. In practice, one obtains a better adjustment assuming a porous layer of finite thickness e. The thickness correction is expressed as follows :

$$Z = Z_\infty \coth \kappa e \tag{3}$$

Therefore, the unknowns are the specific flow resistivity σ and thickness e.

2.2 Hamet and Bérengier

Hamet and Bérengier designed a phenomenological model dedicated to porous pavements [6]. As the previous model, it defines the acoustic impedance and the wavenumber in the material of semi-infinite thickness :

$$Z_\infty = \rho c \frac{1}{\Omega} \sqrt{\frac{K}{\gamma}} \frac{\sqrt{1 - \jmath \dfrac{f_\mu}{f}}}{\sqrt{1 - \left(1 - \dfrac{1}{\gamma}\right) \dfrac{1}{1 - \jmath \dfrac{f_\theta}{f}}}} \tag{4}$$

$$\kappa = \frac{2\pi f}{c}\sqrt{K\gamma}\sqrt{1-\jmath\frac{f_\mu}{f}}\sqrt{1-\left(1-\frac{1}{\gamma}\right)\frac{1}{1-\jmath\frac{f_\theta}{f}}} \quad (5)$$

where Ω is the porosity, K the tortuosity, γ the adiabatic constant. The parameters f_μ and f_θ are respectively the viscous and thermal dependences

$$f_\mu = \frac{1}{2\pi}\frac{R_s}{\rho}\frac{\Omega}{K} \quad (6)$$

$$f_\theta = \frac{1}{2\pi}\frac{R_s}{\rho}\frac{1}{N_{pr}} \quad (7)$$

where R_s is the specific flow resistivity and N_{pr} is the Prandtl's number. As for the previous model, the finite thickness correction as in Eq. 3 is applied. To sum up, the unknowns here are R_s, e, Ω and K.

3 Model for propagation

The identification requires a model for sound propagation. Propagation over a flat impedance plane in an homogeneous atmosphere is assumed. Rudnick's model is used [4]. For a point source and a receiver i the pressure is given by

$$p_i = \frac{e^{\jmath k R_{di}}}{R_{di}} + Q_i \frac{e^{\jmath k R_{ri}}}{R_{ri}} \quad (8)$$

R_{di} (resp. R_{ri}) is the length of the direct (resp. reflected path) between source and receiver i. Q_i is the complex reflexion coefficient in spherical waves corresponding to the reflected path i. Q is related to the complex reflection coefficient in plane waves R_p by

$$Q = R_p + (1-R_p)F(w) \quad (9)$$

w is the so-called numerical distance defined by

$$w = \jmath\frac{2kR_r}{(1-R_p)^2\sin^2\theta}\left(\frac{\rho c}{Z}\right)^2\left(1-\frac{k^2}{\kappa^2}\sin^2\theta\right) \quad (10)$$

where θ is the angle of incidence and

$$F(w) = 1 + 2\jmath w^{1/2}e^{-w}\int_{-\jmath w^{1/2}}^{\infty} e^{-u^2}du \quad (11)$$

R_p is related to the acoustic impedance Z by

$$R_p = \frac{Z\cos\theta - \rho c}{Z\cos\theta + \rho c} \quad (12)$$

In one of the following applications the absorption coefficient $\alpha = 1 - \|Q\|^2$ shall be used.

4 Identification of a grass-covered ground

The most often used model for a grass-covered ground is the Delany and Bazley one with finite thickness correction. Both parameters are obtained here from transfer function measurements between 2 microphones under the geometry used by LCPC.

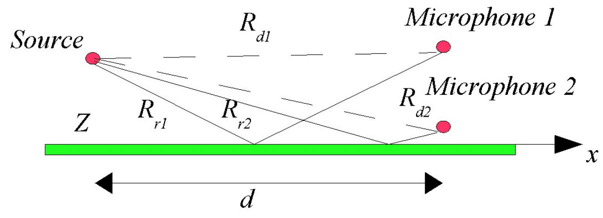

Figure 1: Experimental setup for the transfer function measurement

The experimental setup consists of a source located at a known height and 2 microphones at 2 different heights as shown in figure 1

The parameters we search for are obtained by a minimization of the cost function defined in the interval [100 Hz, 1 kHz]

$$C(\sigma, e) = \sum_{f=100Hz}^{f=1kHz}\left[\partial_f \Delta L_{computed} - \partial_f \Delta L_{measured}\right]^2 \quad (13)$$

ΔL is the difference between spectra for microphones 1 and 2. The cost function C is based on the derivative of ΔL with respect to frequency (∂f). ΔL can be measured - $\Delta L_{measured}$, and also be expressed theoretically :

$$\Delta L_{computed} = 20\log_{10}\frac{p_1}{p_2} \quad (14)$$

where p_1 and p_2 are computed as in Eq.8. The derivative in 18 is computed by finite difference.

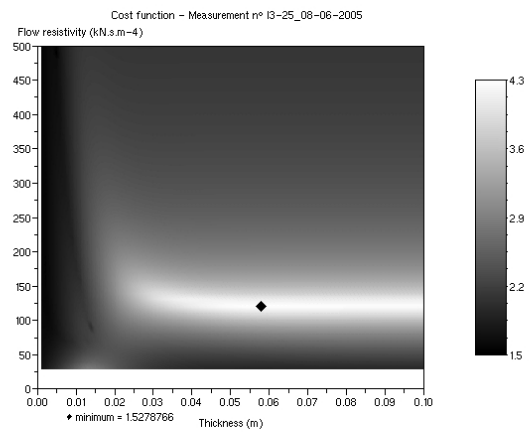

Figure 2: Typical cost function with respect to σ and e. The black spot locates the minimum.

With the current computers, the computation speed allows to perform an exhaustive computation of the values of the cost function on a fine enough grid over the parameter space as shown on figure 2. The global minimum of this function gives the optimal values of σ and e associated to the measurements performed (Cf. figure 3 for an illustration of the adjustment between model and measurement.

A validation of the automatic procedure described here has been performed. The automatically optimized values for the specific flow resistivity and thickness are

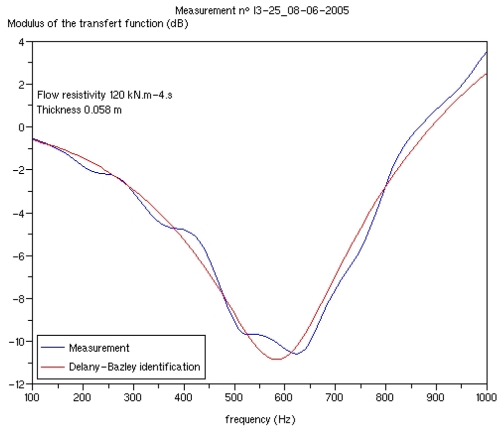

Figure 3: Magnitude of the transfer functions measured (blue) and computed from automatically optimized values of σ and e

compared to the ones obtained from the visual method by 4 different experienced operators at LCPC. The comparison has been done for 10 measurements taken out of a large experimental campaign on outdoor sound propagation organized in 2005 [3]. Figure 4 shows the results obtained by both methods with the standard deviation of the visual method. A good agreement is observed between both methods. However, the automatic method tends to give slightly lower values of σ than the visual one. The determination is likely to be frequency-dependent.

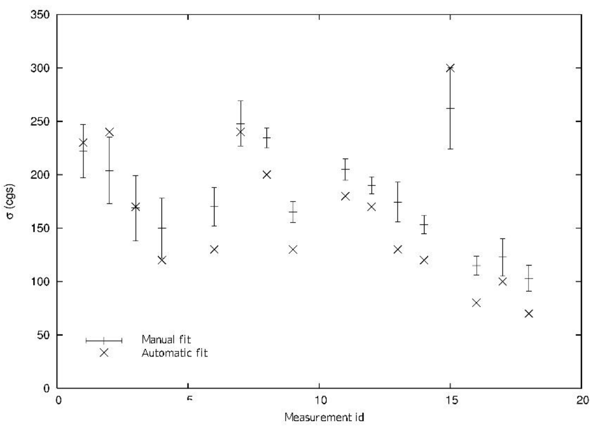

Figure 4: Comparison of the specific flow resistivity obtained by visual adjustment, +/- 1 standard-deviation, and obtained automatically

5 Identification of porous pavements

The identification was performed on the ISO 13472-1 compliant absorption coefficient measurements performed in june 2005 on the test tracks of LCPC Nantes (France), by personnel of the acoustics group of LCPC. The data is provided as $\alpha_{measured}(f)$ in narrow bands with a frequency resolution of 8 Hz. The frequency resolution must be as high as possible in order to allow a fine tuning of the model on the measurements.

For such a material the model chosen is of course the one by Hamet and Bérengier. The geometry of the ISO 13472-1 normal incidence measurement is simulated using Rudnick's formulation for the propagation over an homogeneous impedance plane. This gives an expression for $\alpha_{Hamet}(\sigma, \Omega, K, e, f)$, *i.e.* the modeled absorption coefficient.

The cost function to minimize C is the sum of two terms A and L . A, named *a priori*, judges the validity of the parameter set. One considers that a parameter set is valid if it is located in the hypervolume defined by $100 \leq \sigma \leq 70000$, $1 \leq K \leq 10$, $0 \leq \Omega \leq 0.5$ and $0.02 \leq e \leq 0.5$. In this domain, the *a priori* equals 0. Outside, a quadratic penalty V is applied. It is defined in Eq. 15. It is defined as the absolute value of the distance to the closest boundary of the hypervolume.

$$V_i(x) = \begin{cases} (x - x_{i,min})^2 & x < x_{i,min} \\ 0 & x_{i,min} \leq x \leq x_{i,max} \\ (x - x_{i,max})^2 & x > x_{i,max} \end{cases} \quad (15)$$

One can then define A as

$$A(\sigma, K, \Omega, e) = V_\sigma(\sigma) + V_K(K) + V_\Omega(\Omega) + V_e(e) \quad (16)$$

The second term of the cost function is called likelihood. The likelihood is a measure of the adequation of the model to experiment, such as in 17 :

$$L(\sigma, K, \Omega, e) = \sum_{f=f_{min}}^{f=f_{max}} D\left(\alpha_{Hamet}(f) - \alpha_{measured}(f)\right) \quad (17)$$

where several choices are possible for the likelihood term and for D. Three possibilities haves been studied. The first one is a least-squares adjustment on the whole frequency range of ISO 13472-1, *i.e.* from the third-octave 250 Hz to the 4000 Hz one. The second one is restricted to the range [200,2000] Hz. This choice takes into account that most of the energy of road traffic noise is in the low range of the spectrum. Therefore, a fine tuning in this range is more relevant than a tuning over the whole frequency range. In order to reduce the weight of outliers, a criterion based on the median in [200,2000] Hz range was also tested. The second formulation i.e.

$$L(\sigma, K, \Omega, e) = \sum_{f=200}^{f=2000} \left[\alpha_{Hamet}(f) - \alpha_{measured}(f)\right]^2 \quad (18)$$

led to the best results.

Whatever the formulation chosen for the likelihood term is, the cost function is not convex over the search space investigated. Therefore, the cost function must be processed with a global optimization algorithm. An evolution strategy (ES) and a clonal section (CS) have been applied to this non convex optimization problem. It is beyond the scope of this paper to present this algorithms. They both belong to the class of biologic metaheuristics. The quite classical ES draws its principles from the theory of evolution. For more details on ES, the reader shall refer to [1]. The more recent CS is inspired by the operation of the vertebrate immune system. The CS algorithm is presented in detail in [2]. It

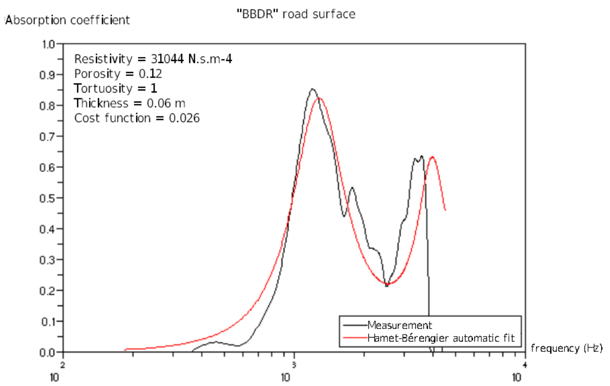

Figure 5: Automatic identification of the Hamet's model by the clonal selection algorithm

was chosen because it performs very well on hard optimization problems. The global form is used here [2].

In order to compare both algorithms, one has performed 10 successive optimizations with each algorithm on a given measurement. The maximum number of evaluations of the cost function was set to 10000. This allows for an objective comparison of algorithms that manipulate populations of candidate solutions and whose demographies are different. CS appears to give the much better solutions with better reproducibility. A typical result is shown on 5. The identification is good until the 2500 Hz third-octave band.

6 Conclusion

In the case of the automatic identification of the model by Delany and Bazley, the model is simple enough for an optimization by exhaustive search. However, the shape of the cost function suggests the classical gradient descent method is usable, starting from initial values close to the maximum thickness values. This would improve the quality of the minimum and accelerate the computation so that the determination of the parameters of interest can be done in real-time. An *a posteriori* check of the quality of the optimum is always possible. The small bias between visual an automatic identification is likely to originate in the translation of the expert rules of visual identification in a cost function.

The clonal selection algorithm gives promising results on the automatic identification of the model by Hamet and Bérengier from measurements of the absorption coefficient at normal incidence for the 250 to 2000 third-octave bands. For higher frequencies, the adjustment is not satisfactory and this point must be investigated. The discrepancies may come from measurement artefacts or the ability of the model to describe accurately the behavior of the material.As such, the identification by inverse approach leads to an *acoustically equivalent* material acceptable on the main frequency range of road traffic noise. A comparison with direct methods is necessary before stating that the intrinsic parameters obtained correspond to the ones of the material under test. Unfortunately, this comparisons appears to be difficult, because laboratory measurement do not work well on highly resistive and irregular materials like road pavements.

References

[1] Thomas Bäck. *Evolutionary algorithms in theory and practice - Evolution Strategies - Evolutionary Programming - Genetic Algorithms.* Oxford University Press, 1996.

[2] L.N. de Castro and F.J. von Zuben. Learning and optimization using the clonal selection principle. *IEEE Transactions on Evolutionary Computation*, 6(3):239–251, 2002.

[3] Junker F., Gauvreau B., Cremezi-Charlet C., Ecotière D. Gérault C., Blanc-Benon Ph., and Cotté B. Classification de l'influence relative des paramètres physiques affectant les conditions de propagation à grande distance : campagne expérimentale de lannemezan. In *Actes du 8ème Congrès Français d'Acoustique*, Tours, France, August 2005.

[4] Rudnick I. The propagation of an acoustic wave along a boundary. *J. Acoust. Soc. Am.*, 19(3):348–356, 1947.

[5] ISO/TC43/SC1. *ISO 13472-1 Acoustics – Measurement of sound absorption properties of road surfaces in situ – Part 1: Extended surface method.* ISO, 2002.

[6] Hamet J.F. and Bérengier M. Acoustical characteristics of porous pavements : a new phenomenological model. In *Proc. Inter-noise*, pages 641–646, Leuven, Belgique, August 1993.

[7] Delany M.E. and Bazley E.N. Acoustical properties of fibrous absorbent materials. *Appl. Acoust.*, 3:105–116, 1970.