Development of Experimental and Modelling Approaches to Characterize Noise Reduction Capability of Porous Materials

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Kai Huang, candidate for the degree of Doctor of Philosophy in Industrial Systems Engineering, has presented a thesis titled, Development of Experimental and Modelling Approaches to Characterize Noise Reduction Capability of Porous Materials, in an oral examination held on June 18, 2019. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

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ABSTRACT

Porous materials have been recognized as effective materials for noise reduction and noise control. It is also recognized that numerous inherent and external factors may affect the noise reduction properties of porous materials. The research of this dissertation aims to develop innovative experimental and modelling approaches to analyze the noise reduction capability of porous materials under different conditions and to study the main factors affecting the noise reduction capability of porous materials.

The impact of material age on noise reduction properties of porous materials is first studied, and a Nested Ensemble Filtering (NEF) approach is proposed for parameter estimation and uncertainty quantification in traffic noise emission from porous pavements. The proposed NEF method improves upon the ensemble Kalman filter (EnKF) method by incorporating sample importance resampling (SIR) procedures into the EnKF update process. Applying the proposed NEF method to traffic noise prediction on the Trans-Canada Highway in the City of Regina, the results indicate: (a) the NEF method provides accurate parameter estimation in the traffic noise prediction model; (b) the uncertainty in the traffic noise model can be significantly reduced and quantified through the proposed NEF approach; and (c) the unit noise emission for new porous pavement is significantly decreased in comparison with that of old pavement considered, regardless of the impacts of uncertainties.

In addition to porous material age, air density within pore structures also impacts acoustic properties of porous materials. Consequently, a series of experimental
investigations are conducted to investigate the effects of different levels of vacuum on the sound reduction and acoustic properties of porous materials. An innovative experiment would be designed to measure acoustic responses, such as sound intensities and corresponding frequencies, for various porous materials under different vacuum levels. The results indicate that applying even relatively low vacuum levels to porous materials has a significant effect on sound reduction. The sound absorption coefficients for various porous materials under different vacuum levels are further characterized through the statistical energy analysis (SEA) approach. It is anticipated that the research findings in this research may lead to the construction of effective sound reducing products for attenuating noise, increasing insertion loss or improving sound insulation.

In order to comprehensively evaluate the applicability of porous-structured noise control (PSNC) measures, a systematic evaluation framework is to be proposed to identify the most appropriate PSNC options under consideration of both internal and external factors. Such a framework is based on an inexact fuzzy integer chance constraint programming (IFICCP) approach to integrate the acoustic properties of each measure (i.e. reduction rate), unit cost, installation location and environmental tolerance into a general framework. Also, the IFICCP method can handle uncertainties expressed as fuzzy and interval numbers in the noise control system established with various porous materials. A number of decision alternatives have been obtained for each acceptable noise level and analyzed under various fuzzy confidence levels. They can potentially reflect complex tradeoffs among cost and properties of porous materials,
location, and environmental considerations, and further provide decision support to find the most desirable porous materials for noise reduction.
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DEDICATION

To my dear parents for their invaluable love and unconditional support throughout my graduate studies.

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CHAPTER 1  INTRODUCTION

1.1. Introduction

Urban noise pollution has gained considerable attention by researchers and engineers in recent years. The principal sources of urban noise pollution come from surface motor vehicles, aircrafts, trains and industrial sources (Stansfeld and Matheson, 2003). These noise sources expose millions of people to noise pollution and create not only annoyance, but also significant health consequences, including hearing loss, sleep disturbances, cardiovascular effects, and rising blood pressure. In addition, noise pollution presents significant economic costs with reduction in property values. Consequently, it is desirable to develop effective engineering practices for environmental noise control in urban communities. Developing such noise control strategies involves a number of areas including prediction of noise emission from various sources, characterization of noise reduction for various noise-reducing materials, and development of noise management strategies under multiple uncertainties.

Two of the key approaches to urban noise control lie in the utilization of porous materials and the optimization of their inherent and external properties for noise reduction. For example, traffic noise arises mainly from friction between road surface and vehicle tires, as well as vibration of exhaust systems and engines. As such, porous
materials used in pavement, tires and vehicle chassis are promising areas for noise reduction investigations. In addition, for residents living along major road systems, porous materials used in sound barrier walls and buildings (e.g. wall structures and windows) provide additional means for noise reduction. It is recognized that there are many inherent and external factors affecting the noise reduction properties of porous materials. Effects such as the type of material, porosity, material age, air density within the pores and location and orientation of the materials can have significant impacts on the noise reduction properties of porous materials.

In optimizing the properties of porous materials for noise reduction, noise prediction modeling is necessary to characterize the acoustic properties of the materials under different inherent and external conditions. For example, with respect to traffic noise, it is known that the noise level is influenced by various factors, such as the type of vehicle, engines, tires, and weather and road conditions. Prediction of traffic noise under different pavement conditions is desirable for aiding highway design or road enhancement (Steele, 2001; Huang et al., 2014). Also, characterization of road operation time on traffic noise emission is of great importance for road pavement using porous materials. However, due to the complexities of urban traffic systems, extensive uncertainties exist in the prediction of traffic noise, which also leads to great difficulties in quantitatively evaluating the impacts of pavement ages on noise emission. Effective approaches are desired to effectively quantify uncertainties in traffic noise prediction and further reveal the impacts of ages of porous pavement on traffic noise emission.
In addition to reliable prediction of noise emission from various sources, another major challenge for noise control is to characterize noise reduction effects for various materials and to further identify their potential for noise control under external conditions. Many materials have been studied to reveal their potential for noise reduction. Among them, porous materials such as polystyrene foam and nitrile butadiene rubber sheet have been widely used for noise reduction. Many studies have shown that the properties of the porous materials have a certain influence on transmission loss (TL), but whether external conditions, especially pressure or vacuum level in porous materials, have effects on TL, has not been found in this area. Consequently, it is necessary to study the effects of various porous materials on noise reduction under various external conditions (e.g. vacuum levels), and to provide support for seeking optimal noise reduction methods.

Appropriate engineering controls are strongly recommended to eliminate noise and diminish noise effects on workers and residents, since hearing loss is often permanent. However, how to choose appropriate engineering control measures for noise reduction is still a challenge since different noise reduction measures are usually associated with different costs. In addition, extensive uncertainties may exist in a noise control system, such as noise-reduction effects of different control measures, the unit cost of each measure, or acceptable noise levels of receptors. For instance, the unit cost of a noise control measure is rarely quantifiable by a single value, but may fluctuate within an interval due to the impact of socio-economic factors. These uncertainties amplify the complexity of the noise control system and are not reflected through traditional
optimization techniques. Consequently, inexact optimization models are desirable for helping decision makers make tradeoffs between system costs and noise control efficiencies under multiple uncertain conditions.

1.2. Objectives

Taking into consideration the aforementioned complexities in noise control practices as well as the application of porous materials to noise reduction, the objective of this research is to develop a series of experimental approaches and models for noise prediction and reduction under various complex conditions. The research tasks of the dissertation entail the following aspects:

(i) Characterization of the impact of age on the acoustic properties of porous materials. To that end, a novel Nested Ensemble Filtering (NEF) approach has been developed for parameter estimation and uncertainty quantification. This modeling approach has been experimentally validated on traffic noise data collected at various sites along highway systems in Regina;

(ii) Characterization of noise reduction properties of porous materials under various vacuum conditions. An innovative experimental setup has been created to generate different vacuum levels in different types of porous materials. The noise reduction properties of these porous materials under different vacuum levels and in response to different acoustic frequencies have been studied; and

(iii) Characterization of the impact of porous material location on noise reduction in urban communities whereby multiple noise sources and impacted communities may
exist. To address this problem, an Inexact Fuzzy Integer Chance Constraint Programming (IFICCP) approach has been developed to suitably account for the complexities in noise control within an urban environment. Such an approach provides an integrated cost-benefit approach to noise control.

1.3. Organization

The organization of this dissertation is as follows:

Chapter 2 provides a comprehensive literature review related to the application of porous materials in noise reduction as well as noise prediction and optimization techniques for noise control.

Chapter 3 presents modeling and experimental approaches for analyzing the impact of age on the acoustic properties of porous materials. A Nested Ensemble Filtering (NEF) model is described along with experimental procedures and results in the application of NEF to real-life traffic noise scenarios on road systems with different age conditions.

Chapter 4 presents experimental setup and results for characterizing noise reduction capabilities of porous materials under various vacuum conditions.

Chapter 5 presents analytical methodology for studying location of porous materials for noise reduction in a multi-source and multi-community setting. An Inexact Fuzzy
Integer Chance Constraint Programming (IFICCP) approach for noise control within an urban environment is described.

Chapter 6 concludes this thesis with a summary of the developed methods and illustrates recommendations for future research.
A number of studies have been proposed to address various concerns in noise control in urban areas. In order to provide reliable noise prediction under complex conditions, a number of uncertainty analysis methods have been applied to traffic noise prediction models. For example, previous research proposed by Peng and Mayorga developed probabilistic and fuzzy approaches for traffic noise prediction under uncertainty, in which the inputs (i.e., traffic volume, speed, and composition) of the traffic noise prediction model were represented by probability distributions (Peng and Mayorga, 2008; Huang et al., 2016). Gimenez and Gonzalez introduced a stochastic model for prediction of noise levels, in which noise level dynamics were represented through a Gaussian Ornstein-Uhlenbeck model (Gimenez and Gonzalez, 2009). Ramirez and Dominguez (2013) developed a stochastic dynamic traffic noise prediction model based on vehicle classes and their speed. Iannone et al. (2013) evaluated the influence of speed distributions in road traffic noise prediction. Huang et al. (2017) proposed the entropy-copula method to model the dependence between traffic volume and traffic noise on highways.

In addition, many studies have been proposed to characterize the mechanisms and features for noise absorption for different porous materials in terms of address noise reduction effects. For instance, Lee and Kim (2001) developed an approximate analysis method to solve sound transmission through structures lined with elastic porous materials. Bécot et al. (2011) examined the potential of using composite porous
materials to design robust noise control packages, in which a canonical plate/cavity system, excited with an internal acoustic source, is chosen to illustrate the potential of these materials for noise enclosures. de Rey et al. (2012) developed an empirical modelling of porous sound absorbing materials made of recycled foam made by ground polyurethane foam waste. Oliva and Hongisto (2013) proposed a study to evaluate the prediction accuracy of the sound absorption coefficient of seven published impedance prediction methods.

Great efforts were made to develop innovative optimization methods for noise control systems. For instance, Yeh et al. (2004) used genetic algorithms for optimizing the allocation and noise reduction measures of a multi-system noise system. Asawarungsaengkul and Nanthavanij (2006) proposed an analytical design procedure to determine optimal noise hazard control strategies for industrial facilities, in which six optimization models were developed and sequentially applied to select appropriate noise control measures without exceeding budgets. Zachary et al. (2010) developed a multi-impact optimization model to reduce aviation noise and emissions at Luxembourg’s Findel Airport. Prats et al. (2011) proposed a multi-objective optimization model for designing aircraft noise abatement strategies. Also, there are many other optimization models for identifying optimal noise control strategies (Waly and Sarker, 1998; King and Davis, 2003; Mun and Cho, 2009; Tokmechi, 2011). To address the uncertainties in noise control systems, Huang et al. (2013) introduced an interval binary programming (IBP) method for selection of control measures for noise reduction, in which the concepts of interval numbers and interval mathematical
programming were incorporated into a binary programming optimization framework.

Even though many studies have been reported for noise prediction, reduction and management, several challenges still needed to be addressed. For instance, previous studies on the uncertainty assessment in traffic noise predictions have focused on inputs, such as the probabilistic characteristics of road traffic flows (Huang, 2014). Few studies have been conducted on the parameter estimation and uncertainty quantification of traffic noise prediction models. Most studies mainly investigate the sound absorption properties for different porous materials, in which the influencing factors under consideration mainly include thickness, density and porosity of the chosen material. Limited studies have reported to reveal the compound effects of the materials’ properties and external factors on noise absorption and reduction. For noise management, extensive uncertainties may exist in a noise control system, which can hardly be reflected by traditional optimization approaches and, thus, may result in undesirable noise control measures.

In this dissertation, a series of experimental and modelling methods will be proposed to develop noise control measures using porous materials under complicated uncertainties. The obtained results of this research can provide scientific support for porous material-based noise control in terms of prediction, reduction, and effective management.
CHAPTER 3  CHARACTERIZING THE IMPACT OF POROUS PAVEMENT OPERATION TIME ON TRAFFIC NOISE EMISSION THROUGH A NESTED ENSEMBLE FILTERING APPROACH

3.1. Background

Material age is an important inherent property of porous materials that has significant impacts on their acoustic properties. This is particularly true for porous pavement materials used on roads. Through long term use, pavement properties such as pore structures and porosity are altered due to traffic and climate, as shown in Figure 3-1, leading to changes in associated noise emission patterns from traffic flow. To quantify the impact of age on the acoustic properties of porous materials, mathematical models that can accurately predict noise levels under different inherent and external conditions are used. In the past, ensemble Kalman filter (EnKF) and particle filter methods have been used for traffic noise prediction as related to porous pavement materials. Both methods are sequential Monte Carlo approaches for parameter estimation and suffer from an overshooting problem whereby estimated parameters take on negative or complex number values. When such states are reached, the algorithms terminate prematurely with erroneous results.
Figure 3-1. Comparison between (a) new pavement and (b) 2-year old pavement
In this dissertation, an extension of the EnKF and particle filter method is presented. This new model is termed the Nested Ensemble Filtering (NEF) method and is described in detail in this Chapter. NEF improves upon the EnKF method by incorporating a sample importance resampling (SIR) procedure into the EnKF update process. Compared to the EnKF method, the proposed NEF approach can avoid the overshooting problem in the EnKF update process. The proposed NEF method is validated through an experimental traffic noise prediction study on the Trans-Canada Highway in the City of Regina. Experimental results show improved noise prediction capabilities compared to existing statistical analysis methods. The proposed NEF method is effective in characterizing noise profile of porous materials under a variety of inherent conditions, with applicability in characterizing material aging effects demonstrated through the traffic noise prediction study.

3.2. Methodology

Uncertainty quantification methods such as ensemble Kalman filter (EnKF) and particle filter (PF) have attracted attention in various civil engineering fields. EnKF and PF, two typical sequential data assimilation (SDA) methods, can recursively quantify/correct states and parameters of a system model based on available observations. In a SDA process, the state evolution for a simulated system can be expressed as follows:

\[ x_t^f = h(x_{t-1}, u_t, \gamma) + \varepsilon_t \]  

(3-1)

where \( h \) is a transition function for system states from period \( t-1 \) to \( t \) under
consideration of model inputs $x_{t-1}^a$, $u_t$ and $\gamma$; $x_{t-1}^f$ is the posterior, also known as analyzed, estimation for state variable $x$ at $t-1$, which is obtained after correction based on the observation at $t-1$; $x_{t}^f$ is the priori, also known as forecasted, estimation for state variable $x$ at $t$; $\gamma$ represent the model parameters; and $\epsilon_t$ denotes the process noise.

Based on the forecasted states, the output from the system model can be obtained, which can be generally expressed as:

$$y_t^f = g(x_t^f, \gamma) + \tau_t$$

(3-2)

where $g$ is the output function for forecasted observations. $h(.)$ in Equation (3-1) and $h(.)$ in Equation (3-2) can be nonlinear. $\tau_t$ denotes the observation noise.

When new observations are obtained at period $t$, the priori state estimation $x_t^f$ is updated through assimilating the new observations into the system model. The essential principles for state correction are based on the Bayesian theorem, where the posterior distribution is for the current state for the observations, and is derived as follows:

$$p(x_t, y_t \mid y_{1:t}) = \frac{p(y_t \mid x_t, y_t)p(x_t, y_t \mid y_{1:t-1})}{p(y_t \mid y_{1:t-1})}$$

(3-3)

where $p(x_t, y_t \mid y_{1:t-1})$ denotes the prior distribution; $p(y_t \mid x_t, y_t)$ represents the likelihood function; $p(y_t \mid y_{1:t-1})$ is the normalizing constant. When the model is Markovian, the prior distribution $p(x_t, y_t \mid y_{1:t-1})$ can be obtained through the
Chapman-Kolmogorov equation:

\[ p(x_t, y_t | y_{t-1}) = \int p(x_t, y_t | x_{t-1}, y_{t-1}) p(x_{t-1}, y_{t-1} | y_{t-1}) dx_{t-1} dy_{t-1} \]  

(3-4)

Also, the value of \( p(y_t | y_{t-1}) \) is similarly estimated as follows:

\[ p(y_t | y_{t-1}) = \int p(y_t | x_t, y_t) p(x_t, y_t | y_{t-1}) dx_t dy_t \]  

(3-5)

The integrals of Equations (3-4) and (3-5) may be intractable, leading to difficulties in deriving the optimal solutions for Equation (3-3) (Plaze Guingla et al., 2013). Consequently, approximate methods such as EnKF and PF, are adopted to deal with the above issues.

EnKF and PF represent the probability density function (pdf) of the state as random samples. The major difference between the two methods lies in the recursive generation for approximating the pdf for the state (Weerts and El Serafy, 2006).

3.2.1. Ensemble Kalman Filter

The EnKF approach estimates the posterior distribution through the Bayesian analysis based on random samples. The random errors in EnKF are assumed to be Gaussian, while the associated error statistics are approximated by the Monte Carlo approach. Also, a Kalman gain matrix would be approximated based on the Monte Carlo approach for updating the state variables of the system model.

For a general stochastic dynamic model, we assume the state transition equations of
the model can be formulated as:

\[ x^f_{t+1,i} = h(x^a_{t,i}, u_{t,i}, \gamma^f_{t+1,i}) + \varepsilon_{t,i}, \quad i = 1, 2, \ldots, ne \]  \hspace{1cm} (3-6)

where \( ne \) denotes the ensemble size; \( x^f_{t+1,i} \) is the \( i \)th forecasted value of the state at \( t+1 \), \( x^a_{t,i} \) is the \( i \)th analyzed value of the state at \( t \), and superscripts \( f \) and \( a \) respectively denote the “forecasted” and “analyzed” values of the state; \( u_{t,i} \) is the \( i \)th input and \( \gamma^f_{t+1,i} \) is the \( i \)th forecasted parameter value. \( h \) denotes the state evolution of the system model structure and \( \varepsilon_{t,i} \) is a sample of the model error, which is assumed to be Gaussian with a zero mean and a covariance matrix of \( \Sigma^m_t \). The model parameters \( \gamma \) are also evaluated based on a random walk method as follows:

\[ \gamma^f_{t,i} = \gamma^a_{t-1,i} + \zeta_{t,i}, \quad \zeta_{t,i} \sim N(0, \Sigma^\theta_t) \]  \hspace{1cm} (3-7)

Also, the model equations corresponding to the observations are adopted to relate the states to the observation space, which can be formulated as:

\[ y^f_{t+1,i} = g(x^f_{t+1,i}, \gamma^f_{t+1,i}) + \tau^i_{t+1,i}, \quad \tau^i_{t+1,i} \sim N(0, \Sigma^\gamma_t) \]  \hspace{1cm} (3-8)

where \( y^f_{t+1,i} \) is the \( i \)th forecasted observation at \( t+1 \); \( g \) is the observation function; \( \tau_{t+1,i} \) means a sample from the Gaussian measurement error, which has a zero mean and a covariance matrix \( \Sigma^\gamma_t \). It is assumed the model and observation errors are uncorrelated, i.e., \( E[\varepsilon_t \tau_{t,i}^T] = 0 \). Based on the prediction (i.e. \( y^f_{t+1,i} \)), the posterior distributions for state \( x \) and parameter \( \gamma \) can be approximated through the Kalman update equations (DeChant and Moradkhani, 2012):

\[ x^a_{t+1,i} = x^f_{t+1,i} + K_{xy}[y_{t+1} + \sigma_{t+1,i} - y^f_{t+1,i}] \]  \hspace{1cm} (3-9)
\[ y_{t+1,i}^* = y_{t+1,i}^f + K_{yy} \left[ y_{t+1} + \sigma_{t+1,i}^f - y_{t+1,i} \right] \]  

where \( y_{t+1} \) denote the observation at period \( t + 1 \); \( \sigma_{t+1,i}^f \) denotes the \( i \)th sample of the observation error; \( K_{xy} \) and \( K_{yy} \) are the Kalman gains corresponding to state \( x \) and parameter \( \gamma \), respectively (DeChant and Moradkhani, 2012):

\[ K_{xy} = C_{xy} (C_{yy} + R_t)^{-1} \]  
\[ K_{yy} = C_{yy} (C_{yy} + R_t)^{-1} \]

Here, \( C_{xy} \) denotes the cross covariance between \( x_{t+1,i}^f \) and \( y_{t+1,i}^f \); \( C_{yy} \) denotes the cross covariance between \( y_{t+1,i}^f \) and \( y_{t+1,i}^f \); \( C_{yy} \) denotes the variance of the forecasted observation; \( R_t \) denotes the variance of the observation error at time \( t \).

### 3.2.2. Particle Filter

The PF, similar to the EnKF, is a sequential Monte Carlo method that approximates the posterior distributions of model states and parameters based on random samples. Compared with EnKF, the PF approach can relax the Gaussian error assumption required in EnKF, which makes the PF perform better than EnKF in some cases (Moradkhani et al., 2005; DeChant and Moradkhani, 2012). Consider \( ne \) as independent and identically distributed random variables \( x_{t,i} \sim p(x_t \mid y_{1:t}) \) for \( i = 1, 2, \ldots, ne \), the posterior pdf can be expressed by a discrete function based on the sequential importance sampling (SIS) method:

\[ p(x_t \mid y_{1:t}) = \sum_{i=1}^{ne} w_{t,i} \delta(x_t - x_{t,i}) \]  

(3-13)
where $w_{i,t}$ is the weight for the $i$th particle (i.e. sample), which would be updated and normalized when observations are available. $\delta$ denotes the Dirac delta function. When the system state is Markovian, the unnormalized weights (i.e. importance weights) for the particles can be updated based on Bayesian recursive expression:

$$w_{i,t}^n = w_{i,t}^f \cdot \frac{p(y_i \mid x_{i,t}^f, y_{t,i}^f) p(x_{i,t}^f \mid x_{t-1,i}^f, y_{t,i}^f)}{q(x_{i,t}^f \mid x_{t-1,i}^f, y_{t,i}^f, y_{t,i}^f)} \quad (3-14)$$

Based on Equation (3-14), when an appropriate proposal distribution (i.e. $q(x_{i,t}^f \mid x_{t-1,i}^f, y_{t,i}^f, y_{t,i}^f)$) is given, the importance weights can be sequentially updated. Consequently, the efficiency of PF would be significantly influenced by the choice of the proposal distribution. One of the most widely used proposal distributions is the transition prior function (Plaze Guingla et al., 2013):

$$q(x_{i,t}^f \mid x_{t-1,i}^f, y_{t,i}^f, y_{t,i}^f) = p(x_{i,t}^f \mid x_{i,t-1,i}^f, y_{t,i}^f) \quad (3-15)$$

Then Equation (3-14) can be simplified as:

$$w_{i,t}^n = w_{i,t}^f p(y_i \mid x_{i,t}^f, y_{t,i}^f) \quad (3-16)$$

The normalized form of the updated weights can be formulated as follows:

$$w_{i,t}^n = \frac{w_{i,t}^f p(y_i \mid x_{i,t}^f, y_{t,i}^f)}{\sum_{i=1}^{ne} w_{i,t}^f p(y_i \mid x_{i,t}^f, y_{t,i}^f)} \quad (3-17)$$

where $p(y_i \mid x_{i,t}^f, y_{t,i}^f)$ can be obtained from the posterior likelihood equation:

$$p(y_i \mid x_{i,t}^f, y_{t,i}^f) = \frac{L(y_i \mid x_{i,t}^f, y_{t,i}^f)}{\sum_{i=1}^{ne} L(y_i \mid x_{i,t}^f, y_{t,i}^f)} \quad (3-18)$$

$L(y_i \mid x_{i,t}^f, y_{t,i}^f)$ is the posterior likelihood function. If the Gaussian model error is to be used, the likelihood function can be expressed as:
For PF with SIS, one major limitation is particle depletion, which means that most particles would be discarded after a few iterations (time steps) because their importance weights are negligible (DeChant and Moradkhani, 2012). Consequently, sampling importance resampling (SIR) algorithms can be used to address the above issue, which would replace the particles with small importance weights by particles with large importance weights. In our study, the sampling importance resampling (SIR) approach proposed by Moradkhani et al. (2005) is used.

3.2.3. The Nested Ensemble Filtering Approach for Parameter Estimation and Uncertainty Quantification

In the state and parameter estimation process through EnKF, one of the main problems is overshooting, which means the parameters or states show abnormal values (e.g., negative or complex values) such that the data assimilation process cannot continue or incorrect parameter and state values are ultimately generated. Therefore, to overcome this problem, a Nested Ensemble Filtering (NEF) approach is proposed, in which the SIR procedures is integrated into the EnKF updating process to eliminate abnormal values. A full description of the NEF processes is illustrated in Figure 3-2.

1. Initialize the model. Sample \( ne \) initial states and parameters for the system model:
\(x_{t,i}, i = 1, 2, \ldots, ne, \ y_{t,i}, i = 1, 2, \ldots, ne, \ \gamma \in R^N\).

2. Assign a prior weight. Assign the particle with equal weights:

\[w_{t,i} = 1/ne\]

3. Forecast model states: Evolve the state variables and parameters forward through the model operator \(h\):

\[x^f_{t+1,i} = h(x^a_{t,i}, u_{t,i}, \gamma^f_{t+1,i}) + \epsilon_{t+1,i}, \ \epsilon_{t+1,i} \sim N(0, \Sigma_\epsilon), \ i = 1, 2, \ldots, ne\]

4. Forecast the observation. Use the observation operator \(g\) to transfer model state and parameters into observation space:

\[y^f_{t+1,i} = g(x^f_{t+1,i}, \gamma^f_{t+1,i}) + \tau_{t+1,i}, \ \tau_{t+1,i} \sim N(0, \Sigma_\tau), \ i = 1, 2, \ldots, ne\]

5. Correct parameters and states. Correct model parameters and states through the EnKF updating equations:

\[x^a_{t+1,i} = x^f_{t+1,i} + K_{xy}\{y_{t+1} + \sigma_{t+1,i} - y^f_{t+1,i}\}\]

\[\gamma^a_{t+1,i} = \gamma^f_{t+1,i} + K_{yx}\{y_{t+1} + \sigma_{t+1,i} - y^f_{t+1,i}\}\]

6. Estimate the likelihood:

\[L(y_{t+1} | x^a_{t+1,i}, \gamma^a_{t+1,i}) = \frac{1}{\sqrt{2\pi R_{t+1}}} \exp\left(-\frac{1}{2R_t}[y_{t+1} - g(x^a_{t+1,i}, \gamma^a_{t+1,i})]^2\right)\]

\[p(y_{t+1} | x^a_{t+1,i}, \gamma^a_{t+1,i}) = \frac{L(y_{t+1} | x^a_{t+1,i}, \gamma^a_{t+1,i})}{\sum_{i=1}^{ne} L(y_{t+1} | x^a_{t+1,i}, \gamma^a_{t+1,i})} = p(y_{t+1} - g(x^a_{t+1,i}, \gamma^a_{t+1,i}) | R_{t+1})\]

7. Obtain the updated weight for the analyzed ensemble values:

\[w^a_{t+1,i} = \frac{w^f_{t+1,i} \cdot p(y_{t+1} - g(x^a_{t+1,i}, \gamma^a_{t+1,i}) | R_{t+1})}{\sum_{i=1}^{ne} w^f_{t+1,i} \cdot p(y_{t+1} - g(x^a_{t+1,i}, \gamma^a_{t+1,i}) | R_{t+1})}\]

8. Sample importance resampling. Use the SIR approach proposed by Moradkhani et
al. (2005) to eliminate the abnormal samples, and replace the analyzed $x_{i+1,j}^a$, and $\theta_{i+1,j}^a$.

9. Evolve parameters to the next stage by the random walk method:

$$\gamma_{i+1,j}^f = \gamma_{i+1,j}^a + \xi_{i+1,j}, \quad \xi_{i+1,j} \sim N(0, \eta S(\gamma_{i+1,j}^a))$$

where $\eta$ is a hyper-parameter that determines the radius around each sample being explored; $S(\gamma_{i+1,j}^a)$ is the standard deviation of the analyzed ensemble values.

10. Check the stopping criterion. If measurement data are still available in the next stage, $t = t + 1$, and return to step 3; otherwise, stop.
Figure 3-2. The flow chart of the nested ensemble filtering method
3.3. Applications

3.3.1. Statement of Problem

The NEF method is applied to a real-life traffic noise prediction situation in the City of Regina, taking into account the age of the porous pavement material, to validate the efficacy of NEF. The City of Regina is located in the southern part of Saskatchewan, Canada, which can be reached by the Trans-Canada Highway in the west-east directions and four provincial highways from other directions. The city is also surrounded by a highway called the Ring Road, looping around the city's east side connecting Regina's east and northwest with the west side of the loop connected by Lewvan Drive (Saskatchewan Highways, 2006). Such highways are critical sources of traffic noise in most cities in Canada.

To evaluate the performance of traffic noise modeling under various road age conditions, three locations labeled A, B and C are chosen as noise monitoring sites, as shown in Figure 3-3. These sites are distributed along the Trans-Canada Highway (i.e. Ring Road), with a speed limit of 100 km/h (Huang, 2014). The major reason for us to choose these sites on the Trans-Canada Highway is that this road is one of the most important road in Canada, traveling through all ten provinces of Canada from the Pacific Ocean on the west to the Atlantic on the east. The three sites are close in proximity, hence experience similar traffic conditions. Site A is located along Assiniboine Avenue to Wascana Parkway in the city. This site has been repaved on October 4th 2013 after many years of use. At this site, we have collected noise data in
September 2013, which is considered to be an old pavement scenario and is denoted as $A_1$. Subsequently, we have collected noise data at Site A in October 2013, just after repaving. This data is considered to be a new pavement scenario and is denoted as $A_2$. Similarly, we have collected noise data at Site B in October 2013, which is located between Wascana Parkway to Assiniboine Avenue, just after the road is repaved in October 2013. Thus, the noise data at Site B is considered to be a new pavement scenario. Additionally, we have collected noise data at Site C in October 2013, located between Albert Street to Wascana Parkway. This data is considered to be an old pavement scenario since the road around this site is paved in the summer of 2012 (Huang, 2014).

As shown in Figure 3-3, the three sites have similar conditions in terms of the surrounding environment and road construction with no obvious noise reduction barriers or trees (Huang, 2014). Noise measurements at the three sites have taken over the course of about a month from September to October, 2013 in order to construct a traffic noise prediction model and to further analyze inherent model uncertainty.
Figure 3-3 Selection of the measuring sites.
3.3.2. Traffic Noise Emission Model

In noise studies, the sound spectra can be analyzed by several different types of weighting networks to generate the equivalent sound level for different objectives (Huang, 2014). At low noise levels, the “A” weighting networks have been widely used as the sound level parameter in noise studies (Huang, 2014). Thus, in this study, “A” weighted equivalent continuous sound levels (\(L_{Aeq}\)) are used to quantify the equivalent traffic noise levels.

In addition, traffic noise from vehicle streams show obvious variation over time subject to many different factors, such as traffic flow rates, vehicle speed, and weather conditions in the measurement. A time-averaged noise level computation is proposed to transform the fluctuating noise values in a time interval into a simple mean value. Even through the traffic flow conditions are different at all times, over a period of 1 hour, they may not fluctuate significantly. Consequently, a 1-hour time-averaged noise level \(L_{Aeq\, 1h}\) is used as a noise indicator in this research for traffic noise prediction and uncertainty quantification.

Previous studies indicate that the traffic noise intensity and the traffic flow volume have a logarithmic relationship (Rao and Rao, 1991; Singal, 2005; Agarwal and Swami, 2011). Consequently, an empirical traffic noise prediction model is employed as follows:

\[
L_{Aeq} = A \ln Q + B \quad (3-20)
\]
where $Q$ is the volume of the traffic flow; $A$ and $B$ are parameters based on the pavement and test conditions and can be determined by experiment. Moreover, based on Equation (3-20), the unit emission of traffic noise with respect to the traffic volume can be expressed by its derivative of traffic volume, which can be expressed as

$$\frac{dL_{eq}}{dQ} = \frac{A}{Q}$$

(3-21)

This equation can be generally used to evaluate noise emission effects for different pavement conditions and traffic volumes.

3.4. Result Analysis and Discussion

3.4.1. Parameter Estimation and Uncertainty Quantification of Traffic Noise Prediction Model in Scenario A

Site A is a special site along Assiniboine Ave to Wascana Pkwy. As discussed earlier, this site has been repaved on October 4th, 2013. At this site, we have collected traffic noise data in September 2013, which is considered to be an old pavement scenario and is denoted as $A_1$. After repaving, we have collected a new set of traffic noise data in October 2013. This data is considered to be a new pavement scenario and is denoted as $A_2$. These two groups of data are collected in two adjacent months; hence, the traffic conditions in these two months are assumed to be identical. The empirical traffic noise prediction model, expressed as Equation (3-20), is applied to Site A under old and new pavement conditions. Before the data assimilation process, initial ensembles are sampled from predefined intervals. As presented in Table 3-1, the ensembles of A and
B were uniformly sampled from predefined intervals. Figure (3-4a) presents the generated traffic noise prediction function based on these initial samples. In Figure 3-4, the green lines are generated based on the initial and final ensemble values of A and B; the red stars indicate the actual measurement and the red line displays the curve of Model (3-20). A and B are estimated through the maximum likelihood estimation method. As seen from Figure (3-4a), there is significant uncertainty in the noise prediction.

The uncertainty in the traffic noise prediction model can be significantly reduced based on the noise measurement in scenario A₁. As presented in Table 3-1, the mean
Table 3-1 Estimation results for the four scenarios

<table>
<thead>
<tr>
<th>Site</th>
<th>Initial</th>
<th>Final 1</th>
<th>Mean 1</th>
<th>MLE 1</th>
<th>Initial</th>
<th>Final 2</th>
<th>Mean 2</th>
<th>MLE 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>[0.1, 20]</td>
<td>[6.7, 7.2]</td>
<td>7.0</td>
<td>5.1</td>
<td>[-20, 50]</td>
<td>[10.5, 11.4]</td>
<td>10.8</td>
<td>23.4</td>
</tr>
<tr>
<td>B</td>
<td>[0.1, 20]</td>
<td>[4.5, 4.9]</td>
<td>4.7</td>
<td>5.2</td>
<td>[-20, 50]</td>
<td>[26.8, 30.4]</td>
<td>28.7</td>
<td>26.8</td>
</tr>
<tr>
<td>C</td>
<td>[0.1, 20]</td>
<td>[6.5, 6.8]</td>
<td>6.6</td>
<td>9.2</td>
<td>[-20, 50]</td>
<td>[26.9, 28.3]</td>
<td>27.6</td>
<td>10.1</td>
</tr>
</tbody>
</table>

note: (a) MLE = Maximum Likelihood Estimation
values of the updated coefficients are closer to their corresponding values obtained through the maximum likelihood estimation than they are to the initial coefficients. The standard deviations of the updated coefficients are reduced dramatically throughout the data assimilation process, and thus, the uncertainty of the coefficients has been greatly mitigated. Figure 3-5 depicts variations of coefficients A and B versus time. Significant uncertainty is found to be associated with the coefficients at an early stage of the assimilation process, though it is generally reduced as time progresses. Eventually, the uncertainty of the traffic noise prediction model with the updated coefficients is significantly reduced, as shown in Figure (3-4b). Figure 3-6 presents the comparison between the forecasted traffic noise prediction model with updated coefficients and the actual measurements. The predicted interval with a confidence level of 0.1 can cover most measurements at Site A under old pavement conditions.

The Pearson correlation coefficient ($R^2$) is employed to compare the performance of the proposed Nested Ensemble Filtering (NEF) method and the traditional maximum likelihood estimation (MLE) method. Since the traffic noise prediction model still contains some uncertainty after the data assimilation process, leading to uncertain forecasts for noise emission levels, the mean values of the uncertain forecasts are applied to calculate the $R^2$ values. As seen in Table 3-2, the NEF and MLE approaches perform well when estimating the unknown parameter in Model (3-20) at Site A with old pavement.
Figure 3-4. The initial and updated traffic noise prediction curves in scenario $A_1$. 
Figure 3-5. The variations of parameters A and B in Model (3-20) during the data assimilation process under scenario $A_1$. 
Figure 3-6. Comparison between the predictions and observations in scenario A₁
Table 3-2. Comparison of performance between NEF and MLE

<table>
<thead>
<tr>
<th>Site</th>
<th>R²</th>
<th>NEF</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A₁</td>
<td>0.9025</td>
<td>0.9025</td>
<td></td>
</tr>
<tr>
<td>A₂</td>
<td>0.7649</td>
<td>0.7639</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.7691</td>
<td>0.7699</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.8183</td>
<td>0.7646</td>
<td></td>
</tr>
</tbody>
</table>
3.4.2. Parameter Estimation and Uncertainty Quantification of Traffic Noise Prediction Model in Scenario A2

The measurement in scenario A2 is undertaken at Site A, as shown in Figure 3-3, just after the road at Site A has been repaved. Similar to the process in scenario A1, initial ensembles are sampled from predefined intervals (as presented in Table 3-1) for the model parameters, which lead to extensive uncertainties in model forecasts, as shown in Figure (3-7a). When measurements are available at Site A, the uncertainty in the model parameters (i.e., A and B) are reduced significantly (as shown in Figure (3-8)). Consequently, noise predictions by Model (3-20) can also be improved significantly, as seen in Figure (3-7b).

As seen from Figure 3-8, significant uncertainties exist in the coefficients of Model (3-20) at the early stage of the assimilation process. As more measurements become available, the uncertainties are dramatically reduced and eventually compressed within narrow intervals (i.e. [6.7, 7.2] for A and [10.5, 11.4] for B, as presented in Table 3-1). Figure 3-9 presents the comparison between the forecasts of the traffic noise prediction model with updated coefficients and the actual measurements. It indicates the predicted intervals can generally reflect the fluctuation of the actual noise emission levels under new pavement conditions.
Figure 3-7. The initial and updated traffic noise prediction curves in scenario $A_2$. 
Figure 3-8. The variations of parameters A and B in Model (3-20) during the data assimilation process in scenario A₂
Figure 3-9. Comparison between the predictions and observations in scenario A2
As presented in Table 3-1, the parameter values of A and B estimated by the nested ensemble filtering approach are quite different from those obtained through the maximum likelihood estimation method. However, from the values in Table 3-2, the NEF method performed slightly better than the MLE method, with the values of $R^2_{NEF}$ and $R^2_{MLE}$ being 0.7649 and 0.7639, respectively.

3.4.3. Parameter Estimation and Uncertainty Quantification of Traffic Noise Prediction Model in Scenario B

Scenario B corresponds to Site B, which is on the road from Wascana Pkwy to Assiniboine Ave, as depicted in Figure 3-3. Traffic noise data has been collected just after the road at Site B is repaved. Figure 3-10 presents the initial and final results of Model (3-20). There is great uncertainty in Model (3-20) initially, as indicated by the green lines in Figure (3-10a); such uncertainty is effectively reduced after data assimilation by NEF (i.e., green lines in Figure (3-10b)). During the data assimilation process, the uncertainties in parameters A and B are dramatically decreased, as shown in Figure 3-11. After the data assimilation process, the uncertainty of the traffic noise model can be quantified with the parameter values selected with the updated intervals (as stated in Table 3-1). Figure 3-12 shows the comparison between the predicted intervals and observations in scenario B, which suggests the forecasts can generally reflect the actual variations in noise emission levels.
Figure 3-10. The initial and updated traffic noise prediction curves in scenario B
Figure 3-11. The variations of parameters A and B in Model (3-20) during the data assimilation process under scenario B.
Figure 3-12. Comparison between the predictions and observations in scenario B
As seen from the green lines and red line in Figure (3-10b), the parameter values of Model (3-20) estimated from NEF are slightly different from those obtained from MLE. For example, the mean values of A and B obtained through NEF, as presented in Table 3-1, are 4.7 and 28.7, respectively, while the values generated through MLE are 5.2 and 26.8, respectively. Even though there are differences between the parameter values obtained through NEF and MLE, the performance of NEF, with the value of $R^2$ being 0.7691, is slightly worse than that of MLE (with an $R^2$ value of 0.7699).

### 3.4.4. Parameter Estimation and Uncertainty Quantification of Traffic Noise Prediction Model in Scenario C

Scenario C corresponds to Site C (from Albert St to Wascana Pkwy, as depicted in Figure 3-3), which is repaved in the summer of 2012. Traffic noise data has been collected in October 2013 and is considered as an old pavement scenario. Traffic flow at Sites B and C are in the same direction, opposite to the traffic flow direction at Site A. As old pavement data at Site B is unavailable, we have selected Site C to represent an old pavement scenario. Figure 3-13 presents the initial and final results of Model (3-20). The initial uncertainty in Model (3-20) (indicated by the green lines in Figure (3-13a)) is significantly reduced through the NEF process (presented by the green lines in Figure (3-13b)). The uncertainties in parameters A and B of Model (3-20) also decreases, as shown in Figure (3-14), during the data assimilation process, and the final values of A and B can be compressed within small intervals (presented in Table 3-1).
Figure 3-15 shows the comparison between the predicted intervals and observations in scenario C, indicating acceptable performance of NEF.

As seen from the green lines and red line in Figure (3-13b), the parameter values of Model (3-20) estimated from NEF are different from those obtained from MLE. As presented in Table 3-1, the mean values of A and B obtained through NEF are 6.6 and 27.6, respectively, while those values generated through MLE are 9.2 and 10.1, respectively. However, even though there are differences between the parameter values obtained through NEF and MLE, the performance of NEF, with the value of $R^2$ being 0.8183, is better than that of MLE (with an $R^2$ value of 0.7646).
Figure 3-13. The initial and updated traffic noise prediction curves in scenario C
Figure 3-14. The variations of parameters A and B in Model (3-20) during the data assimilation process under scenario C
Figure 3-15. Comparison between the predictions and observations in scenario C
3.4.5. Impact of Road Age on Noise Reduction for the Porous Road Pavement at Site A

In this study, we have collected related traffic flow and traffic noise data for two pavement conditions, the old and new pavement. Consequently, it is possible to further evaluate the impact of road age on the noise reduction for porous pavement. Moreover, according to the Equation (3-20), we can obtain the derivative to characterize the traffic noise emission with different pavement conditions and traffic volumes (i.e. Equation (3-21)).

Figure 3-16 describes the unit emission of traffic noise for different traffic volume for old and new pavements at Site A. It can be concluded that, for porous road pavement, the age of the pavement will pose significant effects for traffic noise emission. For certain traffic volume, new pavement would produce lower traffic noise than old pavement. This is particularly obvious for low traffic flow conditions. Moreover, uncertainties in the unit noise emission may be present due to inherent uncertain factors in traffic noise emissions. These uncertainties do not lead to apparent variation for unit noise emission and thus the unit noise emission of traffic noise from old pavement would still be higher than that from new pavement, as show in Figure 3-16(a).
3.5. Summary

(1) Acoustic properties of porous road pavement material are studied under different age conditions on the Trans-Canada Highway in the City of Regina. Four road scenarios have been considered: new (scenarios A₂ and B) and old (scenarios A₁ and C).
(2) A Nested Ensemble Filtering (NEF) approach has been advanced for parameter estimation and uncertainty quantification of traffic noise prediction models. It improves upon the ensemble Kalman filter (EnKF) method by incorporating the sample importance resampling (SIR) procedures into the EnKF update process. Compared to the EnKF method, the proposed NEF approach can avoid the overshooting problem (abnormal value, outside the predefined ranges or complex values, in parameter or state samples) in the EnKF update process.

(3) The proposed NEF approach has been applied to traffic noise prediction on data collected under new and old pavement scenarios at three different highway sites to evaluate the performance of the NEF approach in estimating unknown parameters and quantifying uncertainty in empirical traffic noise prediction models. The results demonstrate the applicability of the proposed methodology.

(4) Comparisons between the NEF approach and maximum likelihood estimation (MLE) method have been undertaken and the following results are apparent: (a) The NEF method performs better than MLE in most conditions, (b) the model parameters can be recursively corrected whenever a new measurement is available, and (c) the uncertainty in the traffic noise model can be significantly reduced and quantified through the proposed NEF approach.

(5) This study is a new attempt to improve upon the ensemble Kalman filter. Only an empirical traffic noise prediction model was applied to demonstrate the applicability
of the proposed NEF method. It is important that more real-world models (i.e., the Federal Highway Administration (FHWA) traffic noise model) be undertaken to demonstrate its practical applicability.
CHAPTER 4 CHARACTERIZATION OF NOISE REDUCTION CAPABILITIES OF POROUS MATERIALS UNDER VARIOUS VACUUM CONDITIONS

4.1. Background

With the ability to characterize noise profile of porous materials, an important practical next step is in determining the applicability of porous materials as noise reduction media. In the past, studies have focused on analyzing transmission loss (TL) properties of porous materials such as polystyrene foam and nitrile butadiene rubber sheet (Nechita and Năstac, 2018; Jiang et al., 2018). In their natural state, such porous materials consist of solid material scaffolding with air-filled pores. While air is an effective noise reduction medium compared to solids, it is well known that a more ideal noise reduction medium is vacuum since sound cannot be transmitted under full vacuum. In theory then, a porous material with vacuum pores would be a more effective noise reduction medium than one with air-filled pores. However, full vacuum condition is difficult to achieve in practice. While vacuum glass and other products can be found on the market, only a small amount of air can be extracted from the porous material without structural damage under atmospheric pressure. Given the promise of vacuum in porous material for noise reduction, however, a detailed study of vacuum level and pressure in porous materials on their transmission loss is warranted, which will serve to guide the design of optimal vacuum conditions in porous materials.
In this Chapter, a study of the effects of different vacuum conditions (via air extraction) in porous materials on sound reduction and transmission loss via systematic experimental investigations is presented. Four porous materials, created by enclosing either glass balls, polyethylene terephthalate sand (PET sand), polystyrene foam, nitrile butadiene rubber sheet (NBR sheet) or foaming concrete within a closed-double-container experimental instrument, is tested under various vacuum conditions. The Statistical Energy Analysis (SEA) approach is applied to reveal the associated noise absorption effects based on the experimental measurements. The obtained results can facilitate the identification and development of appropriate noise control measures with suitable porous material and optimized vacuum levels.

4.2. Experimental Design

4.2.1. Experimental Instrument

Many studies have shown material properties influence insertion loss (IL). However, whether external conditions such as pressure or vacuum in porous materials affects IL has not been determined in this area. This research studies the effects of various porous materials on noise reduction at various vacuum levels, and seeks to aid in development of optimal noise reduction methods.

The experiments conducted in this research utilize a set of custom-designed steel tube arrangement as shown in Figure 4-1. A microphone is placed inside the inner tube
which is hung under the cap of the outer tube through a wire connection. The tubes are not directly connected with each other. Figure 4-2 shows the experimental setup. The steel tube instrumentation is placed in an insulating box ((2) thick sound insulation) ensuring background noise has a minimal effect on the experiment. The laboratory background noise is about 60-70 dB and in the insulating box the background noise is only 18-25 dB. The box significantly reduces external interference and ensures the accuracy of the experimental results. A speaker (4) is placed under the instrument. A vacuum pump (3) is used to remove air from the instrument to achieve the required vacuum levels in the experiment. A microphone (7, CRY 2120U Sound Spectrum Analyzer and CRY 1084 1” Measurement Mic) is used to record the data of sound pressure level and frequency. The microphone is connected to a computer (1) for data recording. Table 4-1 shows the properties of the steel tube instrument. The thickness of this instrument is 0.3125 inch, which is strong enough to ensure the device is intact and does not deform under high vacuum levels. The sealing of the two tubes is enhanced by Vaseline to ensure the vacuum level can last enough for noise measurements.
### Table 4-1 Properties of the steel tubes instrument

<table>
<thead>
<tr>
<th></th>
<th>LARGE TUBE (mild steel pipe)</th>
<th>SMALL TUBE (316 stainless steel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>7.85 g/cm³</td>
<td>7.97 g/cm³</td>
</tr>
<tr>
<td>Length</td>
<td>12 inch</td>
<td>4 inch</td>
</tr>
<tr>
<td>OD</td>
<td>5.5 inch</td>
<td>1.875 inch</td>
</tr>
<tr>
<td>Thickness</td>
<td>0.3125 inch</td>
<td>0.145 inch</td>
</tr>
<tr>
<td>ID</td>
<td>4.375 inch</td>
<td>1.585 inch</td>
</tr>
<tr>
<td>CAP</td>
<td>6061 Aluminum</td>
<td>6061 Aluminum</td>
</tr>
<tr>
<td>Density</td>
<td>2.7 g/cm³</td>
<td>2.7 g/cm³</td>
</tr>
<tr>
<td>OD</td>
<td>6 inch</td>
<td>2.250 inch</td>
</tr>
<tr>
<td>Length</td>
<td>1.625 inch</td>
<td>1.250 inch</td>
</tr>
<tr>
<td>Thickness</td>
<td>0.625 inch</td>
<td>0.500 inch</td>
</tr>
<tr>
<td>Thread depth</td>
<td>1 inch</td>
<td>0.750 inch</td>
</tr>
</tbody>
</table>
The noise reduction rates with various porous materials are considered. Four kinds of materials are placed inside the steel tube apparatus to create four different types of porous materials, including glass ball, polyethylene terephthalate sand (PET sand), polystyrene foam, and nitrile butadiene rubber sheet (NBR sheet), as shown in Figure 4-3. The second consideration is the vacuum condition. Theoretically, it is impossible to transmit sound under full vacuum. In this experiment, a certain amount of air is pumped out from the porous materials, causing a decrease in air density, which is considered to be an increase in vacuum level. For instance, a 50% vacuum level means that half of the air in the porous material is pumped out. Varying amounts of air are extracted from the porous material under test to determine the impact of different vacuum levels on noise reduction in different types of porous media.

The speaker in the experimental setup generates pink noise, which is the most common noise in nature. Unlike white noise, which has the same amount of energy within equal frequency intervals, pink noise has the same amount of energy within every octave in frequency. Thus, the frequency spectrum of pink noise is linear on the logarithmic scale with equal power in proportionally wide bands. For example, pink noise has equal power in the frequency range from 40 to 60 Hz as in the 4000 to 6000 Hz band. Since humans hear in a proportional space, where a doubling of frequency (an octave) is perceived the same regardless of actual frequency (40-60 Hz is heard in the same interval and distance as 4000-6000 Hz), every octave contains the same amount of energy. Pink noise is often used as a reference signal in audio engineering and for acoustic testing. To the human ear, pink noise has a flat frequency response - "a very
pleasant noise".
Figure 4-1 Steel Tubes Instrument
Figure 4-2 Description of the experimental setup (1. Computer; 2. Insulation box; 3. Vacuum pump; 4. Speaker; 5. Outer tube; 6. Inner tube; 7. Microphone; 8. Porous material; 9. Meter)
4.2.2. Material Properties and Experimental Considerations

4.2.2.1 Material properties

Porous materials play a significant role in sound insulation. Materials can be divided into two major categories based on density, hard and soft materials. For example, stone, glass, and polyethylene terephthalate sand are hard materials, while cotton, polystyrene foam and nitrile butadiene rubber sheet are soft. Four materials are selected, including glass ball, polyethylene terephthalate sand (PET sand), polystyrene foam, and nitrile butadiene rubber sheet (NBR sheet). Different porous materials differ in noise transmission, and their acoustical properties impact the experimental results differently. Table 4-2 shows the properties of the selected porous materials as acoustic insulation materials between two tubes. Glass ball and PET sand are hard materials and Polystyrene foam and an NBR sheet are soft materials. The density of soft materials is very small (0.02 g/cm$^3$ and 0.045 g/cm$^3$ respectively), but the porosities (50% and 60% respectively) are greater than those of hard materials. Table 4-2 also shows E-Young's modulus, which is a physical quantity describing the ability of a solid material to resist deformation. The E-Young's modulus indicates the rigidity of the material. The larger the E-Young's modulus, the less likely it is to deform. Compared to soft materials, hard materials are less likely to deform.
Table 4-2. Properties of the selected porous media as filler material

<table>
<thead>
<tr>
<th>Material</th>
<th>Density (g/cm³)</th>
<th>Porosity (%)</th>
<th>E-Young's Modulus (GPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glass Ball</td>
<td>2.5</td>
<td>40</td>
<td>70</td>
</tr>
<tr>
<td>Polyethylene terephthalate Sand (PET Sand)</td>
<td>2.43</td>
<td>45</td>
<td>2.7</td>
</tr>
<tr>
<td>Polystyrene Foam</td>
<td>0.02</td>
<td>50</td>
<td>0.00475</td>
</tr>
<tr>
<td>Nitrile Butadiene Rubber Sheet (NBR Sheet)</td>
<td>0.045</td>
<td>60</td>
<td>0.001315</td>
</tr>
</tbody>
</table>
Figure 4-3. Selected porous media as filler material: (a) Glass balls; (b) PET sand; (c) Polystyrene foam; (d) NBR sheet
4.2.2.2. Calibration of instrument

Calibration is an important experimental step. Only calibrated instruments can generate accurate measurements. The calibration sensitivity in this experiment is 142.5mV/Pa. Figure 4-4 shows the experimental equipment. The CRY 2120U testing range is 25 dB to 130 dB, and the frequency range is between 20 Hz and 20 kHz. In the previous experiment, the background noise is approximately 18 dB. Here, the CRY 1087 is needed, which has one measurement microphone to collect the low-decibel sound. The testing range is 10 dB to 130 dB. A sound level calibrator CRY 5611 is used for calibration.
Figure 4-4. Experimental equipment: (a) CRY 2120U Sound Spectrum Analyzer; (b) CRY 1087 1” Measurement Mic; (c) CRY5611 Sound Level Calibrator
4.3. Model Development

4.3.1. Sound transmission loss

The concept of sound transmission loss is applied to reflect the sound reduction effect for various porous materials under various vacuum conditions. Consider a sound measurement instrument shown in Figure 4-5. The sound transmission loss can be calculated as:

\[ STL = L_1 - L_2 + 10 \log_{10} \frac{S}{A} \]  

(4-1)

where \( L_1 \) is the sound pressure level of the sound source, \( L_2 \) is the sound pressure level of the receiving microphone, and \( 10 \log_{10} \frac{S}{A} \) is correction for absorption. In terms of the experimental instrument shown in Figure 4-1, the absorption coefficient for the steel surface (denoted as \( \alpha \)), and for the \( i \)th surface, is:

\[ A_i = \alpha_i S_i \]  

(4-2)

So for a whole surface:

\[ A = \sum_{i=1}^{n} \alpha_i S_i \]  

(4-3)

\( S \) is the surface area of test specimen in m\(^2\) and \( A \) is the absorption of the specimen.

\( S \) is the surface of the small tube’s cap:

\[ S = \pi r^2 = 3.14 \times \left( \frac{0.05715}{2} \right)^2 = 0.00256521 \]  

(4-4)
Figure 4-5. Description of sound transmission loss test
\[ A = aS = 0.9 \times 0.00256521 = 0.002308689 \] (4-5)

\[ \frac{S}{A} = \frac{0.00256521}{0.002308689} = 1.11 \] (4-6)

So, \( 10\log_{10} \frac{S}{A} = 0.45323 \), and the correction for absorption is 0.45323.

**4.3.2. Development of sound transmission model**

The sound transmission process is simulated through a model constructed in Actran. The air layer model is created in Ansys, and meshed in Hypermesh with 3D PSolid elements. The acoustic propagation in fluids is governed by the propagation of acoustic waves which depend on mean flow quantities related to thermodynamic and material properties. The fluid properties include pressure (p), density (\( \rho \)), temperature (T), sound speed (c), enthalpy (h) and entropy (s). The finite element method is applied in Actran to address the radiated sound power and the diffuse incident pressure field. Also, the diffuse incident pressure field indicates the sound field in which the time average of the mean-square sound pressure is the same everywhere and the flow of acoustic energy in all directions is equally probable.
Figure 4-6 Plane structure mounted in a plane rigid baffle (Wang and Dai, 2018)
Radiated sound power can be formulated as a vibrating structure with radiating surface \( \Gamma \) located on the plane of a rigid baffle (Figure 4-6) (Wang and Dai, 2018):

\[
\Delta p\left(\vec{r}\right) + k^2 p\left(\vec{r}\right) = 0
\]

where \( p \) is the acoustic pressure, \( k \) is the wavenumber, and \( \vec{r} \) represents a point with coordinates \((x, y, z)\). The boundary conditions can be formulated as (Wang and Dai, 2018):

\[
\frac{\partial p}{\partial n} = \rho \omega^2 u_n \text{on } \Gamma
\]

and

\[
\frac{\partial \vec{p}}{\partial n} = 0 \text{ on } \Gamma_B
\]

where \( n \) denotes the inward normal direction, \( u_n \) is the related displacement component, and \( \Gamma_B \) denotes the boundary surface of the baffle.

Consider the coordinate system with a plane wave shown in Figure 4-7, the pressure field for a particular plane wave (index \( n \)), denoted as \( p_n \) can be denoted as \( p_n(r, t) \), where \( r(r, \theta, \varphi) \) indicates the vector position of the evaluation point and \( t \) is the time (Wang and Dai, 2018). Two given points are placed along axis 1. The first point (labeled as \( \zeta_1 \)) is located at the origin, while the second point (labeled as \( \zeta_2 \)) is located at coordinates \((r, 0, 0)\). If \( x_n(t) \) denotes the instantaneous pressure value at the origin for the considered plane wave then (Wang and Dai, 2018):

\[
x_n(t) = p_n(0, t)
\]
Figure 4-7. The coordinate system and a particular plane wave (Wang and Dai, 2018)
The pressure at location \( r \) along axis 1 is characterized by converting the spatial interval into an equivalent time interval (Wang and Dai, 2018):

\[
p_n(0, t) = p_n\left(0, t - \frac{r}{c} \cos \theta_n\right) = x_n\left(t - \frac{r}{c} \cos \theta_n\right)
\]  

(4-11)

The diffuse field pressure along axis 1 is represented by summing the effect of an infinite number of plane waves arriving from all directions (Wang and Dai, 2018):

\[
p(r, t) = \lim_{N \to \infty} \frac{1}{N} \sum_{n=1}^{N} p_n(r, t)
\]

(4-12)

Substitution of Equation (4-12) into Equation (4-11) obtains the following (Wang and Dai, 2018):

\[
p(r, t) = \lim_{N \to \infty} \frac{1}{N} \sum_{n=1}^{N} x_n\left(t - \frac{r}{c} \cos \theta_n\right)
\]

(4-13)

The incident diffuse sound power can be calculated with the relations between sound pressure and sound power.

4.3.3 Statistical Energy Analysis

Statistical Energy Analysis (SEA) has been widely used to predict sound transmission loss, radiation resistance and vibration amplitude of a partition (Crocker and Price, 1969). SEA consists of subdividing the system under study into coupled subsystems and analyzing the energy flow in the subsystems under the assumption that the energy flow between coupled systems is proportional to the modal energy difference between them (Taha, 2017). Two important acoustic phenomena are analyzed with SEA,
namely the resonant and non-resonant vibrations in a panel. When a sound wave impinges on a panel, the panel is forced to vibrate, producing non-resonant vibrations (Brekke, 1981). The non-resonant vibrations are reflected at the boundaries and standing waves are formed, which are called resonant vibrations (Brekke, 1981). It is assumed the non-resonant and resonant vibrations may be superimposed (Brekke, 1981). A number of studies have been reported to use the SEA approach for modelling sound transmission through complex structures (Brekke, 1981; Kenawy et al., 2005; Zhou and Crocker, 2010; Tageman, 2013). The major advantages of SEA are that it is applicable to structures that can be divided into subsystems coupled with a much simpler description. It predicts average sound and vibration levels, time and frequency averages, and averages within each subsystem (Tageman, 2013). Consequently, the SEA approach is adopted in the experiment to identify inherent noise reduction characteristics of various materials with different vacuum conditions.

Based on Figure 4-2, the noise transmission from the speaker to the microphone inside the inner tube can be simplified as a room-panel-cavity-panel-room system. The schematic figure is shown in Figure 4-8. In this figure, $W_i^{in}$ is the power input to subsystem $i$, $W_i^{diss}$ is the power dissipated by the subsystem $i$, and $W_{ij}$ shows the power transfer of power from Subsystem $i$ to Subsystem $j$. 
Figure 4-8. Schematic view of the sound transmission through the two-tube structure
Following the studies proposed by Price and Crocker (1970), Brekke (1981), and Kenawy et al., (2005), the resonant transmission loss of the room-panel-cavity-panel-room system in Figure 4-8 can be formulated as:

\[
TL_r = 20 \log(m_2 m_4) + 20 \log(d) + 50 \log(f) + 10 \log(\alpha_0) + 10 \log\left(\frac{1/2 L_c}{A_c}\right)
\]

\[-10 \log(\sigma_2 \sigma_3 \sigma_4) - 10 \log(f_{c2} f_{c4}) + 10 \log(\eta_2 \eta_4) - 40\]

In Equation (4-14), \(m_2\) and \(m_4\) are surface mass densities of outer and inner tubes, and \(m = \rho h\) where \(h\) is the thickness of tube and \(\rho\) is the density; \(d\) is the length of the cavity; \(f\) is the sound frequency; and \(f_{c2}\) and \(f_{c4}\) are the critical frequencies for the outer and inner tubes, which can be obtained from the following equation:

\[
f_c = \frac{c_0^2}{2\pi} \sqrt{\frac{12(1-\mu^2)m}{Eh^3}}
\]

where \(c_0\) is the sound speed, \(\mu\) is Poisson’s ratio, \(E\) is the Elastic Modulus, \(h\) is the thickness of the tube, and \(m\) is surface density. In addition, \(\alpha_0\) in Equation (4-14) denotes the normal incidence absorption coefficient. Its values can be assumed to be given as follows:

\[
10 \log \alpha_0 = \begin{cases} 
-10 \, dB, & d \geq 0.1 \, m \\
-3 \, dB, & d \leq 0.02 \, m \\
\text{Interpolation} & 0.02 \leq d \leq 0.1 
\end{cases}
\]

\(L_c\) in Equation (4-14) is the total boundary length of the tube and \(A_c\) is the area of the tube. \(\sigma_{mn}\) is the sound radiation factor from subsystem \(m\) to subsystem \(n\). Based on the studies by Price and Crocker (1969) and Brekke (1981), the radiation factor can be obtained as:
\[ \sigma = \begin{cases} 
\left(\lambda / \lambda_{H} / A_{H}\right)2(f / f_{c})g_{1}(f / f_{c}) + \left(L_{H} / \lambda_{H} / A_{H}\right)g_{2}(f / f_{c}), & f < f_{c} \\
(l_{1} / \lambda_{H})^{-1/2} + (l_{2} / \lambda_{H})^{1/2}, & f = f_{c} \\
(l-1 / f)^{-1/2}, & f > f_{c} 
\end{cases} \]  
\tag{4-17}

where

\[ g_{1}(f / f_{c}) = \begin{cases} 
\frac{(4/\pi^{4})(1-2\alpha^{2})}{\alpha(1-\alpha^{2})^{1/2}}, & f \leq \frac{1}{2} f_{c} \\
0, & f > \frac{1}{2} f_{c} 
\end{cases} \]  
\tag{4-18}

\[ g_{2}(f / f_{c}) = (2\pi)^{-2}\left\{(1-\alpha^{2})\ln[(1+\alpha)/\alpha] + 2\alpha\right\}/(1-\alpha^{2})^{3/2} \]  
\tag{4-19}

\[ \alpha = f / f_{c}^{1/2} \]  
\tag{4-20}

The parameters \( \eta_{2t}, \eta_{4t} \) in Equation (4-14) are the total loss factors for the outer and inner tubes, which can be denoted as follows:

\[ \eta_{2t} = \frac{2.2}{fT_{2}} \]  
\tag{4-21}

\[ \eta_{4t} = \frac{2.2}{fT_{4}} \]  
\tag{4-22}

where \( T_{2} \) and \( T_{4} \) are the reverberation times for subsystems 2 and 4. The reverberation time can be estimated as (Zhou and Crocker, 2010):

\[ T = \frac{0.161V}{\tau A_{S} + S\alpha_{3}} \]  
\tag{4-23}

where \( S \) is the total surface area of the receiving room, \( \alpha_{3} \) is the average absorption coefficient of the receiving room, \( V \) is the volume of the receiving room, \( A_{S} \) is the surface of the tube, and \( \tau \) is the sound transmission loss coefficient.
In addition to the resonant transmission, there is non-resonant transmission loss for the inner and outer tubes, which are obtained as:

\[ TL_{nr} = TL_{rand2} + TL_{rand4} + 20\log(d) - 10\log(f) + 10\log(\alpha_0) + 10\log\left(\frac{1/2L}{S}\right) + 48 \]  

(4-24)

where

\[ TL_{rand2} = TL_{20} + 10\log(0.23TL_{20}) \]  

(4-25)

\[ TL_{20} = 20\log fm_2 - 42 \]  

(4-26)

\[ TL_{rand4} = TL_{40} + 10\log(0.23TL_{40}) \]  

(4-27)

\[ TL_{40} = 20\log fm_4 - 42 \]  

(4-28)

Based on the resonant transmission and non-resonant transmission loss, the total transmission loss can be obtained for the system presented in Figure (4-8). However, the sound field in the cavity varies above and below the cut-off frequency \( f_d \) of the cavity, where

\[ f_d = \frac{c}{2d} \]  

(4-29)

\( c \) is the sound velocity and \( d \) is length of the cavity. When the sound frequency \( f \leq f_d \), the total transmission loss can be obtained as follows (Kenawy et al., 2005):

\[ TL = (2L_{\text{max}} + L_{\text{min}}) - 20\log \left[ 10^{\frac{L_{\text{max}}}{10}} + 10^{\frac{(L_{\text{max}} - T_{\text{nr}})}{10}} \right] \]  

(4-30)

where \( L_{\text{max}} \) and \( L_{\text{min}} \) are resonant transmission loss \( TL_r \), as denoted by Equation (4-14) or non-resonance transmission loss \( TL_{nr} \), denoted by Equation (4-23). For instance, if \( L_{\text{max}} = TL_r \), and \( L_{\text{min}} = TL_{nr} \), the total transmission loss can be expressed as:

\[ TL = (2TL_r + TL_{nr}) - 20\log \left[ 10^{\frac{TL_r}{10}} + 10^{\frac{(TL_r - TL_{nr})}{10}} \right] \]  

(4-31)
and

\[ \Delta L = TL_e - TL_{ar} \]  \hspace{1cm} (4-32)

When the sound frequency \( f > f_d \), the total transmission loss can be obtained as (Kenawy et al., 2005):

\[ TL = TL_2 + TL_4 + 10\log(d) + 10\log(\alpha_0) + 10\log\left(\frac{1/2L}{S_c}\right) + 3 \]  \hspace{1cm} (4-33)

where \( TL_2 \) and \( TL_4 \) are the transmission losses for two tubes and may be measured or calculated.
4.4. Results analysis

4.4.1. Experiment validation

In order to validate the applicability of the experimental instrument, comparisons between the transmission loss obtained through experimental measurements and the model simulation are conducted. The experimental transmission loss is calculated with the theoretical conversion formulas described in Section 4.3.1. The theoretical predictions for transmission loss are obtained through the theoretical model described in Section 4.3.2, which is built in Actran. Figure 4-9 shows the comparison of experimental and simulated average transmission loss under various vacuum conditions. The trend between the two is similar. The simulation values are obtained in an ideal state with the middle capacity filled with air. Due to the influence of the experimental conditions, the ideal state is difficult to achieve, and an order of magnitude difference occurs. Comparing the two trend lines, their slopes are very close in value at 1.1853 and 1.088, and their $R^2$ values are 0.9897 and 0.9547, respectively. There is a small difference between them. In this experiment, we want to identify the effect of vacuum level on noise reduction. This means that we will analyze the differences between TL of different vacuum conditions and the TL of normal condition. However, as shown Figure 4-9, the experimental TL and the simulation TL have similar trends. Thus, the experimental differences would be basically identical with the simulation differences. The accuracy and reliability of the experimental data can be obtained.
Figure 4-9 Comparison between average transmission loss of experiment and theoretical model
4.4.2. Experimental Measurements for Different Porous Materials under Various Vacuum Conditions

Five experimental conditions are considered, in which the space between the outer and inner tubes is filled with glass ball, polyethylene terephthalate sand (PET sand), polystyrene foam, nitrile butadiene rubber sheet (NBR sheet), or air. Five vacuum percentage levels i.e. 10%, 20%, 30%, 40%, and 50%, are considered in each experiment to reveal the effect of combining the porous materials and vacuum conditions on sound reduction. As we are interested in the impact of low vacuum conditions on noise reduction, vacuum levels above 50% have not been considered. Practically speaking, maintaining vacuum level above 50% for a sustained duration of time is difficult with the current experimental setup. In addition, to ensure the reliability of the proposed experiment, multiple testing would be conducted for each materials under each vacuum conditions and each test lasts 5 minutes. More than 10 thousand data will be produced for each condition. The average results will be employed for further characterization of the corresponding transmission loss.

During the experiments, the room temperature is kept at 20°C. Figure 4-10 presents the sound source spectrum, in which the high sound pressure levels (SPLs) occur at frequencies between 250 to 1300 Hz. The SPL slowly increases with frequency but remains less than 250 Hz. At high frequencies, the SPL gradually decreases with increasing frequency. The average SPL of the sound source is 113.5 dB.
There are higher SPL values for sound sources from low, medium, and high frequencies compared with empty tubes without vacuum. Figure 4-11 shows that the instrument itself has a good seal, reducing a large portion of the sound. The effect is particular obvious in the medium frequency range, resulting in a maximum reduction of 98.13 dB. Compared with the SPLs of the sound source and empty tubes, the sealed instrument can achieve a reduction of 51.92 dB.

Figure 4-12 presents the sound pressure level and spectrum of empty tubes. As the vacuum level increases, the SPL gradually decreases. The SPL is only 55.21 dB when the vacuum level reaches 50%. It can be seen from the spectrum diagram that the SPL with 50% vacuum level is lowest across the full sound frequency. In the spectrum diagram, the SPL at 125 Hz is at a maximum and the SPL gradually decreases with increasing frequency. Figure 4-13 shows the total insertion loss and the insertion loss attributed to different vacuum levels. The vacuum insertion loss is defined as the difference of the insertion loss under vacuum and the insertion loss under normal condition. For example, under 50% vacuum level, $\text{VIL}_{50\%} = \text{IL}_{50\%} - \text{IL}_{0\%} = 6.37$ dB. The overall insertion loss (IL) of the steel tube instrument is 52-58 dB under 10%-50% vacuum level. At vacuum levels of 40% and 50%, the vacuum insertion loss (VIL) is about 6 dB, making a contribution more than 10% of the total insertion loss. The optimal vacuum level is 10%, where it can reduce transmission by 3.08 dB. The IL at different frequencies under various vacuum levels is shown in Figure 4-14. In general, sound frequencies between 160 to 1600 Hz will have the highest IL. The peak IL occurs at 250 Hz. This pattern is applicable for nearly all vacuum levels. The difference in
SPL is compared in Figure 4-15 and Figure 4-16. There is significant reduction in the low frequency range. At 100 Hz, the reduction is 10.1 and 15 dB under 10% and 20% vacuum levels. At 125 Hz, the reduction is 14.8, 16.4 and 17 dB under 30%, 40% and 50% vacuum levels.
Figure 4-10. The spectrum of the sound source
Figure 4-11. The insertion loss contribution of the steel tubes instrument
Figure 4-12. (a) The sound pressure level and (b) The spectrum of empty tube under different vacuum level
Figure 4-13. (a) The vacuum insertion loss and (b) The insertion loss of empty tube under different vacuum level
Figure 4-14. The sound insertion loss contribution of empty tub
Figure 4-15 The difference of SPL under different vacuum level of empty tube
Figure 4-16 The difference of SPL in low, medium and high frequency ranges of empty tube
The glass ball insulating material is a hard material. Figure 4-17 indicates the sound pressure level and spectrum of the glass ball insulation in the instrument. As the degree of vacuum increases, the SPL gradually decreases. When the vacuum level reaches 50%, the SPL is only 57.9 dB. The SPL with a vacuum level of 50% reaches the lowest value at full frequency. As the frequency increases, the SPL is at a maximum value at 1600 Hz. In the high frequency range, the SPL gradually decreases as the frequency increases. With Figure 4-18, after filling with glass ball insulation, extracting a certain degree of vacuum can have a noise reduction effect. The overall insertion loss (IL) of this steel tube instrument is 50-56 dB under 10%-50% vacuum levels. The VIL is 3.29 dB at 10% vacuum level and 6.1 dB at 50% vacuum level. The optimal vacuum level for a tube filled with glass balls is 10% as it can reduce transmission by 3.29 dB. In Figure 4-19, IL reaches a maximum value at 50% vacuum level. The maximum value of IL at 250 Hz for glass ball insulation is the best noise reduction result, and the most effective noise reduction at 125 to 315 Hz. However, Figure 4-20 and Figure 4-21, indicate reduction in the low and medium frequency ranges. At 40 Hz, the reduction is 8.6, 10.1 and 16.4 dB under 10%, 20% and 30% vacuum levels, respectively. At 3150 Hz, the reduction is 14.2 and 14 dB under 40% and 50% vacuum levels.

Figure 4-22 shows the sound pressure levels and spectrum measured from the instrument filled with PET sand, another hard material. Since the solid transfers sound, and the PET sand is smaller than the glass balls, it has a larger area of contact with the instrument and can transmit more noise. Compared with the data from empty tubes, the SPL is greater under various vacuum levels. The SPL is 70.67 dB at atmospheric
pressure. However, the overall SPL still decreases as the vacuum level increases. In the spectrum diagram, the SPL at 1600 Hz is a maximum, and the SPL gradually decreases with increasing frequency in the high frequency range. Extracting a degree of vacuum after filling with PET sand can achieve a level of noise reduction as shown in Figure 4-23. Under 10% vacuum level, the VIL is 1.18 dB, and under 50% vacuum level, the VIL is 5.69 dB. The overall insertion loss (IL) of the steel tube instrument is 43-49 dB under 10%-50% vacuum levels. The optimal vacuum level is 20% of the tube when filled with PET sand and it can reduce transmission by 2.53 dB. The IL reached the maximum value in Figure 4-24 under 50% vacuum level. The maximum value of IL at 250 Hz is the best for noise reduction for PET sand. The frequency range for the most effective noise reduction is 160 to 315 Hz. There are obvious reduction effects in the low frequency range when comparing the SPLs in Figure 4-25 and Figure 4-26. At 100 Hz, the reduction is 5.2 dB under 10% vacuum level. At 315 Hz, the reduction is 6.2 and 10.4 dB under 20% and 30% vacuum levels. At 250 Hz, the reduction is 16.7 and 15.5 dB under 40% and 50% vacuum levels. The maximum values and effective ranges of the hard materials are similar.
Figure 4-17 (a) The sound pressure level and (b) The spectrum of glass ball under different vacuum level
Figure 4-18 (a) The vacuum insertion loss and (b) The insertion loss of glass ball under different vacuum level
Figure 4-19 The sound insertion loss contribution of glass ball
Figure 4-20 The difference of SPL under different vacuum level of glass ball
Figure 4-21 The difference of SPL in low, medium and high frequency ranges of glass ball
Figure 4-22 (a) The sound pressure level and (b) The spectrum of PET sand under different vacuum level
Figure 4-23 (a) The vacuum insertion loss and (b) The insertion loss of PET sand under different vacuum level.
Figure 4-24 The sound insertion loss contribution of PET sand
Figure 4-25 The difference of SPL under different vacuum level of PET sand
Figure 4-26 The difference of SPL in low, medium and high frequency ranges of PET sand.
Soft materials are also evaluated experimentally. The density of a soft material is very small and the porosity is very large, which has a large influence on the noise reduction effect. Figure 4-27 indicates the sound pressure level and spectrum with polystyrene foam in the instrument. Since the soft material itself has a good noise reduction effect, the SPL is smaller under various vacuum levels compared to empty tubes. The SPL is 45.49 dB without vacuum condition. As the degree of vacuum increases, SPL gradually decreases. When the vacuum level reaches 50%, the SPL has only 36.68 dB. It is apparent from the spectrum diagram that the overall SPL trend gradually decreases with increasing frequency. The SPL at 40 Hz reaches the maximum. Extracting a certain degree of air can achieve a good noise reduction effect when insulating with polystyrene foam as shown in Figure 4-28. The overall insertion loss (IL) of this steel tube instrument is 68-77 dB under 10%-50% vacuum levels. The VIL is 3.86 dB under 10% vacuum level and 8.81 dB under 50% vacuum level. In general, an increase in vacuum level will increase the contribution of the IL from vacuum. The optimum vacuum level is 10% of the tube filled with polystyrene foam, it can reduce transmission by 3.86 dB. The full frequency of IL in Figure 4-29 reaches a maximum value under 50% vacuum level. The maximum value of IL at 250 Hz is the best for noise reduction using polystyrene foam. Its most effective noise reduction frequency range is 160-1000 Hz. The low frequency range possesses an obvious noise reduction in Figure 4-30 and Figure 4-31. At 20 Hz, the reduction is 7.9 dB under 10% vacuum level and at 40 Hz, the reduction is 7.1, 11.3, 13.3 and 15.3 dB under 20%, 30%, 40% and 50% vacuum levels, respectively.
Another soft material under assessment is the NBR sheet. Figure 4-32 shows the sound pressure level and spectrum with the NBR sheet inserted in the instrument. Since the soft material itself has a good noise reduction effect, compared to the data of empty tubes, the SPL is smaller under various vacuum levels. The SPL is 38.82 dB at atmospheric pressure. Moreover, the overall SPL decreases as the vacuum level increases. The maximum value of SPL in the spectrum diagram occurs at 40 Hz and the overall trend for the SPL gradually decreases with increasing frequency. The overall trend of the SPL gradually decreases with increasing frequency. After inserting the NBR sheet and creating a vacuum level, one can achieve a good noise reduction effect as shown in Figure 4-33. The overall insertion loss (IL) of this steel tube instrument is 71-76 dB under 10%-50% vacuum levels. In comparison, the IL attributed to vacuum is relative low, which is less than 5 dB even for a 50% vacuum level. This may because the inherent noise reduction effect of the NBR sheet is quite large, leading to a small contribution from the vacuum. However, the effect on the noise reduction effect is not obvious under 10% and 20% vacuum levels. The optimum vacuum level is 50% when the tube is filled with PET sand where it reduces transmission by 4.39 dB. According to the data in Figure 4-34, soft materials have a significant effect on the reduction of low frequency noise. The maximum IL at 250 Hz for the empty tube is optimal for noise reduction. Its most effective noise reduction frequency range is 160-1600 Hz. This differs from hard material offering a better noise reduction effect for low-medium frequencies. Comparing Figure 4-35 and Figure 4-36 for differences in SPL, there are obvious reductions at low frequencies. At 31 Hz, the reduction is 9.6, 10, 10.4, 10.9 and 11.3 dB under 10%, 20%, 30%, 40% and 50%
vacuum levels, respectively.
Figure 4-27 (a) The sound pressure level and (b) The spectrum of polystyrene foam under different vacuum levels
Figure 4-28 (a) The vacuum insertion loss and (b) The insertion loss of polystyrene foam under different vacuum levels.
Figure 4-29 The sound insertion loss contribution of polystyrene foam
Figure 4-30 The difference of SPL under different vacuum level of polystyrene foam
Figure 4-31 The difference of SPL in low, medium and high frequency ranges of polystyrene foam
Figure 4-32 (a) The sound pressure level and (b) The spectrum of NBR sheet under different vacuum levels
Figure 4-33 (a) The vacuum insertion loss and (b) The insertion loss of NBR sheet under different vacuum levels
Figure 4-34 The sound insertion loss contribution of NBR sheet
Figure 4-35 The difference of SPL under different vacuum level of NBR sheet
Figure 4-36 The difference of SPL in low, medium and high frequency ranges of NBR sheet
Figure 4-37 presents the sound pressure level, vacuum insertion loss and insertion loss measurements for the five experimental conditions under various vacuum levels. Placing porous materials between the two tubes can generally reduce noise emission relative to air between the inner and outer tubes (empty condition), except for glass balls and PET sand. The noise reduction level is generally correlated with the vacuum level with high vacuum levels increasing sound reduction effects. Due to the solid transmission noise, insulating tubes with porous materials leads to lower VIL levels than empty tubes. In addition, the SPLs of hard material are higher than those obtained from empty tubes. The IL of hard material is lower than for empty tubes. More specifically, injecting polystyrene foam and using an NBR sheet will reduce more noise. This may be due to the high porosity of soft material, leading to more noise reflection and absorption.
Figure 4-37 The comparisons of sound pressure level, vacuum insertion loss and insertion loss
4.4.3. Characterization of sound reduction effects for porous materials under different vacuum conditions through SEA

The statistical energy analysis (SEA) approach is applied to establish the theoretical model described in Figure 4-8 for all the materials (i.e. air, glass balls, PET sand, polystyrene foam, and NBR sheet) and all vacuum conditions (i.e. 0%, 10%, 20%, 30%, 40%, and 50%) to further characterize the sound reduction effects for various porous materials under various vacuum conditions. Once the SEA model is established, the sound absorption coefficients, denoted as $\alpha_3$ in Equation (4-23) and based on the experimental measurements, can be estimated for various porous materials under vacuum conditions.

Figure 4-38 compares the predicted SEA transmission loss (TL) and experimental measurements for the empty condition under various vacuum conditions. The predictive TL agrees well with the measured TL at most sound frequencies, especially for sound frequencies from 20 to 315 Hz. The prediction from SEA fits the measurements quite well. The SEA may generate higher peak TL values than experimental measurements around 500 Hz and also produce an increasing TL trend for sound frequencies larger than 5000 Hz, which conflicts with the trend in the measurement data. However, such discrepancies would not affect the applicability of SEA for modelling the TL in the experiments. This is because: (1) in terms of noise affecting human health, the low and medium frequency noise are more difficult to eliminated. In this research, we have mainly analyzed the effect of vacuum conditions.
on the noise reduction of low and medium frequency noise. (2) From Figure 4-39(a), under high frequency, the sound absorption coefficient is relatively low, and the noise reduction effect of the vacuum condition on the high frequency noise is not obvious.

Figure 4-39 presents the average sound absorption coefficients for the empty cavity between the two tubes, in which Figure 4-39(a) shows the absorption coefficients for various sound frequencies, and Figure 4-39(b) gives the average absorption coefficient over the sound spectrum under various vacuum conditions. When the cavity between the tubes is empty (filled with air), the associated sound absorption coefficient is different for different sound frequencies and various vacuum levels. However, under various vacuum levels, the sound absorption coefficients show similar patterns. For all vacuum levels (i.e. 0%, 10%, 20%, 30%, 40%, and 50%), the empty cavity has the most significant reduction effect for sound around 1000 Hz, followed by the sound frequency around 50 and 250 Hz. In Figure 4-39(b) increasing the vacuum level in the empty cavity between the two tubes increases the absorption effects, especially when the vacuum level is larger than 30%.
Figure 4-38 Comparison of TL between prediction and experimental measurements for empty condition under different vacuum conditions
Figure 4-39 Sound absorption coefficients for the empty cavity between the two tubes (a) absorption coefficients for different frequencies, and (b) the average absorption coefficient
When the cavity between the two tubes is filled with porous materials, the sound reduction effects may change for different porous materials. Also, for the same insulating material, the sound reduction effect may also change under various vacuum conditions. When the cavity is filled with glass balls, the comparisons of TL from theoretical predictions of SEA and experimental measurements under selected vacuum levels are shown in Figure 4-40. The predictive TL agrees well with the measured TL at low sound frequencies, especially for sound frequencies from 20 to 200 Hz. However, the TL predictions from SEA are higher than the measurements for sounds around 300-400 Hz, where there is a predictive peak from SEA, but the peak is not exhibited in the measurement data. However, the SEA approach can be generally applicable for modelling the transmission loss for the experiments with the cavity filled with glass balls.

Based on the SEA, the sound absorption coefficient can be obtained for the glass balls in the cavity between the outer and inner tubes under various vacuum conditions, as shown in Figure 4-41. For one specific vacuum level (e.g. 0%, 10%, 20%, 30%, 40%, or 50%), the sound absorption coefficients for the glass balls are different for different sound frequencies, as shown in Figure 4 41(a). Moreover, at the same sound frequency, the vacuum levels also influence the corresponding sound reduction effect. However, as shown in Figure 4-41(a), the increase in vacuum level will significantly increase the sound reduction effect for the low frequency sound ranging from 25 to 80 Hz. Apparent sound reduction effects can also be observed for sound around 1000 Hz when vacuum is exerted on the tube. However, the variations in vacuum levels do not significantly
influence the sound reduction effect of the glass balls for sound around 1000 Hz. The sound reduction effect for the cavity filled with glass balls will increase for vacuum levels increasing from 0% to 30%, and then decrease for vacuum levels increasing from 30% to 50% as evident in Figure 4-41(b). The 40% and 50% vacuum levels lead to more sound reduction effects than the 10% and 20% vacuum levels. Such a phenomenon is mainly due to the different sound reduction effects of various vacuum conditions for sound at low frequencies.
Figure 4-40 Comparison of TL between prediction and experimental measurements for glass balls under different vacuum conditions
Figure 4-41 Sound absorption coefficients for the glass balls between the two tubes (a) absorption coefficients for different frequencies, and (b) the average absorption coefficient.
When the cavity between the two tubes is filled with PET sand, the experimental instrument may produce similar sound reduction patterns with the cavity filled with glass balls, as shown in Figure 4-40 and Figure 4-41. The SEA theoretical predictions for the cavity with PET sand show similar patterns under various vacuum conditions with the predictive TL values for the cavity filled with glass balls. Figure 4-42 shows a comparison of TL between the predictions and experimental measurements for PET sand under various vacuum conditions. The SEA approach can be applicable for modelling sound transmission for the experimental instrument filled with PET sand.

The sound absorption properties for the cavity filled with PET sand also show similar features with the properties for the cavity filled with glass balls. As shown in Figure 4-43(a), increasing the vacuum level leads to increased reduction effects for sound ranging from 25 to 80 Hz. The effects are significant for vacuum levels larger than 20%. The most significant reduction effect for the PET sand occurs at 40% vacuum level as shown in Figure 4-43(b). This may also attribute to the remarkable reduction efficiency for PET sand at this vacuum level.
Figure 4-42 Comparison of TL between prediction and experimental measurements for PET sand under different vacuum conditions
Figure 4-43 Sound absorption coefficients for the PET sand between the two tubes (a) absorption coefficients for different frequencies, and (b) the average absorption coefficient.
When the cavity between the two tubes is filled with soft porous materials, the associated sound reduction effects may show different features than the cavity filled with hard porous materials shown in Figure 4-40 to Figure 4-43. Figure 4-44 compares the TL prediction from SEA and the experimental TL measurements for the cavity filled with polystyrene foam under various vacuum conditions. The TL predictions at different sound frequencies capture the associated TL variations in the experiment under every selected vacuum level (i.e. 0%, 10%, 20%, 30% 40% and 50%). Even though small discrepancies at the TL peak area around 500 Hz and conflicted variation trends at high sound frequencies larger than 5000 Hz can be observed for TL predictions and experimental measurements, the theoretical model based on the SEA approach are applicable for modelling sound transmission in the experimental instrument under all the selected vacuum scenarios.

Based on the SEA, the sound absorption coefficient can be obtained for polystyrene foam in the cavity between the outer and inner tubes under various vacuum conditions, as shown in Figure 4-45. For a specific vacuum level (e.g. 0%, 10%, 20%, 30%, 40%, or 50%), the sound absorption coefficients for the polystyrene foam are different for different sound frequencies, as shown in Figure 4-45(a). At the same sound frequency, the vacuum levels also influence the corresponding sound reduction effect. As shown in Figure 4-45(a), the cavity filled with polystyrene foam will produce apparent sound reduction effects at low frequencies. The corresponding sound absorption coefficient shows a significant peak around 1000 Hz, and also two small peaks around 250 and 2000 Hz, respectively. When the vacuum condition is exerted on the cavity, the
associated sound reduction effect over the whole sound spectrum will change, especially at the three peaks of the absorption coefficient. For instance, a vacuum level of 40% will significantly increase the sound reduction effect at the peak region around 1000 Hz, while in comparison, a vacuum level of 50% will mainly enhance the sound reduction effect of the cavity with polystyrene foam at low sound frequencies and the two small sound reduction peaks at 250 Hz and 2000 Hz, respectively. Exertion of vacuum levels will increase the overall sound reduction effect for the cavity filled with polystyrene as shown in Figure 4-45(b). The highest average sound absorption can be obtained for the 50% vacuum level, followed by the 30% and 20% vacuum levels as shown in Figure 4-45(b).
Figure 4-44 Comparison of TL between prediction and experimental measurements for polystyrene foam under different vacuum conditions
Figure 4-45 Sound absorption coefficients for the polystyrene foam between the two tubes (a) absorption coefficients for different frequencies, and (b) the average absorption coefficient
When the cavity between the two tubes is filled with an NBR sheet, it may produce similar sound reduction patterns with the cavity filled with polystyrene foam as shown in Figure 4-44 and Figure 4-45. The theoretical predictions from SEA for the cavity with an NBR sheet also show similar patterns under various vacuum conditions with the predictive TL values shown in Figure 4-44. Figure 4-46 shows comparisons of TL between predictions and experimental measurements for an NBR sheet under various vacuum conditions. The SEA approach is applicable for modelling sound transmission for the experimental instrument filled with an NBR sheet.

Figure 4-47 presents the sound absorption coefficients for the NBR sheet between the two tubes under various vacuum conditions, in which Figure 4-47(a) exhibits the absorption coefficients for different sound frequencies, and Figure 4-47(b) provides the average absorption coefficient over the sound spectrum under various vacuum conditions. The cavity filled with an NBR sheet will reach its high sound reduction effects at around 1000 Hz, regardless of the vacuum conditions. It also has a peak reduction effect at around 250 Hz. The vacuum level will significantly influence the sound reduction effect for the cavity filled with an NBR sheet. For instance, a vacuum level of 50% will significantly increase the sound reduction effect at around 1000 Hz, while a 40% vacuum level will mainly increase the sound reduction effect of the cavity at the small peak region near 250 Hz. The most significant reduction effect for the NBR sheet occurs at the 50% vacuum level, as shown in Figure 4-47(b), followed by the reduction effect at vacuum levels of 40% and 10%. The vacuum level increases the overall sound absorption effect of the cavity filled with an NBR sheet as shown in
Figure 4-47(b), which agrees with the result for the polystyrene foam shown in Figure 4-47(b).
Figure 4-46 Comparison of TL between prediction and experimental measurements for NBR sheet under different vacuum conditions
Figure 4-47 Sound absorption coefficients for the NBR sheet between the two tubes (a) absorption coefficients for different frequencies, and (b) the average absorption coefficient.
4.4.3. Characterization of individual and compound effects of different factors on the overall sound reduction

Several parameters influence noise reduction effects for porous materials. When some vacuum levels are exerted on porous materials, the vacuum condition, associated with those inherent properties of the materials (e.g. porosity and density) create complex effects on the noise reduction for this material. Figure 4-48 shows the average sound reduction effect of various porous materials with various porosities and densities. A material with a high porosity rate has a high reduction effect. This would be especially apparent for some soft porous materials (i.e. Polystyrene foam and NBR sheet). According to the material density information in Figure 4-48(b), (i) soft porous materials have higher sound reduction effects than hard porous materials; (ii) for the same kind of porous materials (soft or hard), a higher density leads to a higher sound reduction effect. Figure 4-49 presents the sound reduction effects for various porous materials with various porosities and densities under several vacuum conditions. Similar to the normal condition, under a given vacuum level, the porous material with a high porosity leads to a high sound reduction effect; also, a material with high density has a high sound reduction effect for the same material. For one porous material, a high vacuum level will result into a high sound reduction rate.
Figure 4-48. Influences of porosity and density of porous materials on the sound reduction under normal condition (i.e. 0% vacuum)
Figure 4-49. Influences of porosity and density of porous materials on the sound reduction under different vacuum conditions
4.5. Experimental Results for Practical Construction Materials

In addition to the Glass balls, PET sand, Polystyrene foam and an NBR sheet used in the experiments, practical construction materials are tested in order to demonstrate the applicability of the research results for noise reduction. The building material—foaming concrete is further tested. The density of the foaming concrete, as shown in Figure 4-50, is very small and the porosity is very large, which may have great influence on the noise reduction effects under various vacuum conditions. Figure 4-51 indicates the sound pressure level and spectrum for foaming concrete filled in the instrument. Since the foaming concrete has a good noise reduction effect, compared to the data from empty tubes, the SPL is smaller under various vacuum levels. The SPL is 52.7 dB without vacuum. The SPL gradually decreases as the degree of vacuum increases. When the vacuum level reaches 50%, the SPL is only 46.02 dB. It can be understood from the spectrum diagram that the overall SPL trend gradually decreases with increasing frequency. The SPL reaches a maximum at 40 Hz. After filling with foaming concrete, extracting a certain degree of vacuum can achieve a good noise reduction effect as shown in Figure 4-52. The overall insertion loss (IL) of this steel tube instrument is 60-67 dB under 10%-50% vacuum levels. The IL is 1.31 dB under 10% vacuum level and 6.69 dB under 50% vacuum level. An increase in vacuum level will increase the contribution of the IL from vacuum. The optimal vacuum level is 30% of the tube filled with foaming concrete, as it can reduce transmission by 2.81 dB.

In Figure 4 53, the low frequency range of IL reaches a maximum value under 30% vacuum level. The maximum value of IL at 400 Hz for the foaming concrete is the best effect for noise reduction. In comparison, the IL in the medium to high
frequency ranges can reach a maximum value under 50% vacuum level. The maximum value of IL at 2500 Hz for the foaming concrete is the best effect for noise reduction. The most effective noise reduction frequency range is 30-60 Hz, 250-600 Hz, and 2000-4000 Hz. The low and medium frequency ranges in Figure 4-54 and Figure 4-55 show obvious reductions. At 4000 Hz, the reduction rates are 5.79 and 10.27 dB under 10% and 20% vacuum levels, respectively. At 315 Hz, the reduction rate is 12.3 dB at 30%. At 2000 Hz, the reduction rates are 14.45 and 15.59 dB under 40% and 50% vacuum levels.
Figure 4-50 The sample of foaming concrete
Figure 4-51 (a) The sound pressure level and (b) The spectrum of foaming concrete under different vacuum level
Figure 4-52 (a) The vacuum insertion loss and (b) The insertion loss of foaming concrete under different vacuum level.
Figure 4-53 The sound insertion loss contribution of foaming concrete
Figure 4-54 The difference of SPL under different vacuum level of foaming concrete
Figure 4-55 The difference of SPL in low, medium and high frequency ranges of foaming concrete
4.6. Summary

A novel experimental setup has been constructed to study the noise reduction effects of different porous materials at various vacuum levels. Porous material of varying density, porosity and E-Young’s modulus have been studied under different vacuum levels and frequency ranges. Sound pressure level, insertion loss and vacuum insertion loss are measured across a large set of experimental conditions. Based on the results of the research, the following can be concluded:

- Utilization of porous materials and applied vacuum in the material pores may effectively reduce noise for most of the porous materials utilized in the experiments. Considerably low vacuum level, such as 10% or 20% vacuum level in the porous materials may result in an optimal sound reduction effect for most of the porous materials utilized in the experiments.

- Different porous materials have different acoustic properties with respect to sound intensity and range of frequency, when applying vacuum in the materials.

- Capabilities of the porous materials are sensitive to the range of audible frequencies and frequency spectrums. This is significant for engineering applications.

- Each porous material used in the experiments has an optimal vacuum level for reducing sound intensity, among the vacuum levels implemented.

  - Empty tubes under 10% vacuum level, reduce transmission by 3.08 dB
  - Glass ball under 10% vacuum level, reduce transmission by 3.29 dB
  - PET sand under 20% vacuum level, reduce transmission by 2.53 dB
- Polystyrene foam under 10% vacuum level, reduce transmission by 3.86 dB
- An NBR sheet under 50% vacuum level, reduce transmission by 4.39 dB
- Foaming concrete under 30% vacuum level, reduce transmission by 5.40 dB

Comparing the results in the experimental groups, the foaming concrete is the best filler material among all the materials used. It is a building material while also being porous material. It has a supporting ability as a filling material under a degree of vacuum. A vacuum level of 30% on foaming concrete can lead to a noise reduction effect more than 5 dB.

- Comparison of experimental data shows the porous materials combined with vacuum can significantly reduce noise in the low and medium frequency ranges.
- The sound absorption coefficients obtained through SEA indicate soft porous materials (i.e. NBR sheet and polystyrene foam) between the two containers provide significant sound reduction effect around 1000 Hz, and the reduction effects are enhanced for increased vacuum levels. The hard porous materials (i.e. glass balls and PET sand) have sound reduction effects for sound at low frequencies.
- Softer materials, higher density and more porosity lead to higher sound reduction effects, and the vacuum conditions enhance the sound reduction effect for soft materials. Harder materials with higher density, possess higher sound reduction effects, and the vacuum condition also enhances the sound reduction effect. In comparison with hard materials, the soft materials seem to possess higher sound reduction effects.
The acoustic properties of porous materials under optimized vacuum levels are determined in this research. This contributes to the comprehension of the porous materials’ capabilities in noise mitigation when vacuum is applied to the materials. The research results may also lead to the construction of effective sound reducing products for abating noise, increasing insertion loss or improving sound insulation. The research results have a high industrial applicability.
CHAPTER 5 DEVELOPMENT OF A COMPREHENSIVE EVALUATION FRAMEWORK FOR POROUS STRUCTURE-BASED NOISE CONTROL MEASURES CONSIDERING BOTH INTERNAL AND EXTERNAL FACTORS

5.1. Background

In addition to material aging effects and the degree of vacuum levels studied in previous Chapters, the noise reduction capabilities of porous materials in real-life applications also depend heavily on their placement and orientation. For example, porous materials have been used for noise control measures (e.g. noise barriers along highways). Both inherent and external factors considered in the previous Chapters would be applicable to such materials. In addition, one crucial issue under consideration is how to localize the noise control materials to reduce the noise level to allowable tolerances for different receptors. For instance, when there are multiple communities impacted by noise sources, those communities far from the noise sources may merely require a small reduction rate since the sound would attenuate in the air, while those communities close to the noise sources would need intensive reduction rate. Consequently, effective approaches are required to characterize the most appropriate location of different noise control measures with different porous materials.
to achieve maximum reduction efficiency and minimum cost for the communities as a whole.

The amount of prevention measures (e.g. noise barriers, shelters) play an important role in noise control for controlling environmental, industrial and traffic noise. The noise control alternatives using porous materials are becoming more and more important in noise control applications. However, the applicability of porous-structure-based noise control (PSNC) measures is not merely influenced by their inherent acoustic properties (e.g. TL in Chapter 4), but also affected by the installation location, cost, as well as other environmental factors (e.g. allowable noise tolerance). For instance, the unit cost of porous materials is rarely quantifiable by a single value, but may fluctuate within an interval due to the impact of socio-economic factors. These uncertainties amplify the complexity of the noise control system and are not well reflected through previous optimization techniques. To address the uncertainties in noise control systems, Huang et al. (2013) introduced an interval binary programming (IBP) method for selection of control measures for noise reduction, in which the concepts of interval numbers and interval mathematical programming were incorporated into a binary programming optimization framework. Nevertheless, in IBP, all of the parameters were assumed to be expressed as intervals. This assumption may not be true since the uncertainty in the noise control system can be expressed in other formats (e.g. fuzzy and random variables). Specifically, the environmental guidelines and health impact criteria used in noise control are usually fuzzy in nature (Li et al., 2007). For example, if the noise abatement criteria are categorized into “strict”,

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“medium”, and “loose” levels, such linguistic information can be better quantified through fuzzy sets than intervals. But such fuzzy uncertainty are not well reflected through previous inexact optimization techniques.

Therefore, in order to comprehensively evaluate the applicability of the noise control measures, especially how the installation location and unit cost influence the selection of noise control alternatives, a comprehensive noise control evaluation model is proposed. Such a model is based on an innovative system analysis method named as Inexact Fuzzy Integer Chance Constraint Programming (IFICCP) approach, in which the acoustic properties of each measure (i.e. reduction rate), unit cost, installation location and environmental tolerance are integrated into a general framework. The proposed IFICCP has unique capability of reflect uncertainties expressed as intervals and fuzzy sets. The developed IFICCP approach combines the capability of interval programming and fuzzy chance constraint programming methods to address fuzzy and interval uncertainties in the noise control system. Based on the measures of possibility and necessity, the constraintes with fuzzy uncertainty are treated as fuzzy chance constraints. Under each fuzzy confidence level, interval solutions for binary variables will be analyzed and interpreted to provide useful decision alternatives for controlling noise from different sources, demonstrating the potential aplicability of the developed method.

5.2. Methodology

5.2.1 Interval Linear Programming (ILP)
Interval values are allowed to be incorporated into the optimization process in ILP.

All parameters and decision variables in a linear programming can be intervals (Huang et al., 1992).

Specifically, an ILP model can be defined as follows:

Max  \[ f^\pm = C^\pm X^\pm \]  \hspace{1cm} (5-1a)

Subject to:

\[ A^\pm X^\pm \leq B^\pm \]  \hspace{1cm} (5-1b)

\[ X^\pm \geq 0 \]  \hspace{1cm} (5-1c)

where \( A^\pm \in \{ R^\pm \}^{m \times n}, \ C^\pm \in \{ R^\pm \}^{1 \times n}, \ B^\pm \in \{ R^\pm \}^{m \times 1}, \ X^\pm \in \{ R^\pm \}^{n \times 1} \); \( R^\pm \) denotes a set of interval numbers; \( A^\pm = (a^\pm_{ij})_{m \times n} \), \( C^\pm = (c^\pm_1, c^\pm_2, \ldots, c^\pm_n) \), \( B^\pm = (b^\pm_1, b^\pm_2, \ldots, b^\pm_m)^T \) and \( X^\pm = (x^\pm_1, x^\pm_2, \ldots, x^\pm_n)^T \). An interval number \( (\alpha^\pm) \) is defined as (Huang et al., 1992):

\( \alpha^\pm = [\alpha^- \wedge, \alpha^+ \wedge] = \{ t \in \alpha \mid \alpha^- \leq t \leq \alpha^+ \} \).

An interactive solution algorithm named two-step-method (TSM) was proposed to solve the problem (Huang et al., 1992, 1995; Fan and Huang, 2013). Interval solutions can be obtained based on the analysis of detailed interrelationships between the parameters and variables and between the objective function and constraints. The main idea of TSM is to convert the original ILP model into two LP submodels corresponding to the lower and upper bounds of the objective-function value, respectively. For \( n \) interval coefficients \( c^\pm_j \) (\( j = 1, 2, \ldots, n \)) in the objective function, the former \( k \)
coefficients are assumed to be positive (i.e. \( c_j^+ \geq 0 \), for \( j = 1, 2, \ldots, k \)), and the latter (\( n - k \)) coefficients are negative (i.e. \( c_j^- \leq 0 \), for \( j = k+1, \ldots, n \)). Thus, the first submodel of model (5-1) correspond to \( f^+ \). It can be formulated as follows (assume that \( b_j^+ > 0 \) and \( f^+ \geq 0 \)):

\[
\text{Max } f^+ = \sum_{j=1}^{k} c_j^+ x_j^+ + \sum_{j=k+1}^{n} c_j^- x_j^-
\]

(5-2a)

Subject to:

\[
\begin{align*}
\sum_{j=1}^{k} a_{ij}^+ \text{Sign}(a_{ij}^+) x_j^+ + \sum_{j=k+1}^{n} a_{ij}^- \text{Sign}(a_{ij}^-) x_j^- & \leq b_i^+, \quad i = 1, 2, \ldots, m. \\
x_j^+ & \geq 0, \quad j = 1, 2, \ldots, k \\
x_j^- & \geq 0, \quad j = k+1, k+2, \ldots, n
\end{align*}
\]

(5-2b) (5-2c) (5-2d)

Solutions of \( x_{j_{\text{opt}}}^+ (j = 1, 2, \ldots, k) \) and \( x_{j_{\text{opt}}}^- (j = k+1, \ldots, n) \) can be obtained through solving submodel (5-2). Based on the solution for submodel (5-2), the submodel corresponding to the lower bound of equation (5-1a) can be formulated as follows:

\[
\text{Max } f^- = \sum_{j=1}^{k} c_j^- x_j^- + \sum_{j=k+1}^{n} c_j^+ x_j^+
\]

(5-3a)

subject to:

\[
\begin{align*}
\sum_{j=1}^{k} a_{ij}^+ \text{Sign}(a_{ij}^+) x_j^+ + \sum_{j=k+1}^{n} a_{ij}^- \text{Sign}(a_{ij}^-) x_j^- & \leq b_i^-, \quad i = 1, 2, \ldots, m. \\
0 & \leq x_j^- \leq x_{j_{\text{opt}}}^+, \quad j = 1, 2, \ldots, k. \\
x_j^+ & \geq x_{j_{\text{opt}}}^-, \quad j = k+1, k+2, \ldots, n
\end{align*}
\]

(5-3b) (5-3c) (5-3d)
From submodel (5-3), solutions for \( x_{j_{\text{opt}}}^- (j = 1, 2, \ldots, k) \) and \( x_{j_{\text{opt}}}^+ (j = k + 1, \ldots, n) \) can be obtained. Thus, the final solution of \( f_{\text{opt}}^\pm = [f_{\text{opt}}^-, f_{\text{opt}}^+] \) and \( x_{j_{\text{opt}}}^\pm = [x_{j_{\text{opt}}}^-, x_{j_{\text{opt}}}^+] \) can be obtained for model (5-1).

### 5.2.2. Fuzzy Chance Constraint Programming

Consider a fuzzy programming problem with ambiguous coefficients expressed as fuzzy sets, formulated as follows:

Max \( f = c \times X \) \hspace{1cm} (5-4a)

Subject to

\[ \tilde{A} \times X \leq \tilde{b} \] \hspace{1cm} (5-4b)

\[ X \geq 0 \] \hspace{1cm} (5-4c)

where \( c \in \{\tilde{R}\}^{n \times 1} \), \( X \in \{\tilde{R}\}^{m \times 1} \), \( \tilde{b} \in \{\tilde{R}\}^{m \times 1} \), \( \tilde{A} \in \{\tilde{R}\}^{m \times n} \); \( \tilde{R} \) denotes a set of fuzzy sets;

\[ c = (c_1, c_2, \ldots, c_n), \quad X^T = (x_1, x_2, \ldots, x_n), \quad b = (b_1, b_2, \ldots, b_m), \quad \tilde{A} = (\tilde{a}_{ij}), \quad \forall i \in m, \quad j \in n. \]

A fuzzy set \( \tilde{A} \) in \( X \) can be defined as \( \{x, \mu_{\tilde{A}}(x)\} : x \in X, \mu_{\tilde{A}}(x) : X \to [0, 1] \} \), where \( \mu_{\tilde{A}}(x) \) is the membership function or grade of membership (Zimmermann, 1985). The value of \( \mu_{\tilde{A}}(x) \) varies between 0 and 1, indicating the possibility of an element \( x \) belonging to \( \tilde{A} \). \( \mu_{\tilde{A}}(x) = 1 \) means that \( x \) definitely belongs to the fuzzy set \( \tilde{A} \), while \( \mu_{\tilde{A}}(x) = 0 \) denotes that \( x \) does not belong to \( \tilde{A} \). The closer \( \mu_{\tilde{A}}(x) \) is to 1, the more likely that \( x \) belongs to \( \tilde{A} \); conversely, the closer \( \mu_{\tilde{A}}(x) \) is to 0, the less likely \( x \) belongs to \( \tilde{A} \) (Zimmermann, 1985; Lai and Hwang, 1992).
To deal with the fuzzy constraints presented as Equations (5-4b), the measures of possibility and necessity were introduced to reflect the preferred confidence level of decision makers (Dubois and Prade, 1988; Inuiguchi and Ramik, 2000; Zhang et al., 2009). Suppose \( \tilde{a} \) and \( \tilde{b} \) be non-interactive fuzzy numbers with continuous membership function. For a confidence level \( \alpha \in [0, 1] \), then:

\[
\text{Pos}(a \geq b) = \sup \{ \min(\mu_a(x), \mu_b(y)) | x \geq y \} \geq \alpha \iff a_{\alpha}^R \geq b_{\alpha}^L \tag{5-5a}
\]

\[
\text{Nes}(a \geq b) = \inf \{ \max(1 - \mu_a(x), 1 - \mu_b(y)) | x \geq y \} \geq \alpha \iff a_{\alpha}^L \geq b_{\alpha}^R \tag{5-5b}
\]

where \( a_{\alpha}^L \) and \( a_{\alpha}^R \) are the lower and upper bound of the \( \alpha \)-cut of fuzzy number \( a \), respectively, and \( a_{\alpha}^L = \inf(x | x = \mu_a^{-1}(\alpha)) \), \( a_{\alpha}^R = \sup(x | x = \mu_a^{-1}(\alpha)) \); \( b_{\alpha}^L \) and \( b_{\alpha}^R \) are the lower and upper bounds of the \( \alpha \)-cut of fuzzy number \( \tilde{b} \), respectively.

Based on the measures of possibility and necessity, the concept of fuzzy chance constraint method was introduced to deal with the fuzzy constraint expressed as Equation (5-4b). According to a decision maker’s preference (optimistic or pessimistic), Model (5-4) can be transformed as (Xu et al., (2011)):

**Optimistic**

\[
\text{Max } f = c \times X \tag{5-6a}
\]

Subject to

\[
\text{Pos} \{ A \times X \leq \tilde{b} \} \geq \delta \tag{5-6b}
\]

\[
X \geq 0 \tag{5-6c}
\]
Pessimistic

Max \( f = c \times X \) \hspace{1cm} (5-7a)

Subject to

\[ N_{es}\{A \times X \leq \tilde{b}\} \geq \delta \] \hspace{1cm} (5-7b)

\( X \geq 0 \) \hspace{1cm} (5-7c)

### 5.2.3. Inexact Fuzzy Integer Chance Constraint Programming

In many real-world management problems, extensive uncertainties may exist and be expressed in various formats (e.g. fuzzy sets and interval numbers). Consequently, those multiple uncertainties expressed as different formats such as fuzzy and interval numbers are required to be well reflected in order to obtain robust decision alternatives. Specifically, involvement of some integer decision variables will also intensify the complexities of those system analysis. To address the above issues, this study will propose an innovative system analysis approach, named as inexact fuzzy integer chance constraint programming (IFICCP) method, to deal with various uncertainties as well as integer variables in an environmental noise control system. An IFICCP problem can formulated as follows:

Max \( f^+ = \sum_{j=1}^{n} c_j^+ x_j^+ \) \hspace{1cm} (5-8a)

Subject to
\[ \sum_{j=1}^{n} a_{ij}^- x_j^+ \leq b_i^-, i = 1, 2, ..., l \] (5-8b)

\[ \sum_{j=1}^{n} a_{ij}^+ x_j^+ \leq \tilde{b}_i, i = l+1, l+2, ..., m \] (5-8c)

\[ x_j^\pm = \text{interval continuous variables, } j = 1, 2, ..., p \ (p < n) \] (5-8d)

\[ x_j^\pm = \text{interval integer variables, } j = p+1, p+2, ..., n \] (5-8e)

\[ x_j^\pm \geq 0 \] (5-8f)

As presented in Section 2.1, the ILP problem can be solved by converting the original problem into two sub-problems corresponding to the upper and lower bounds of the objective function. Model (5-3), which is the sub-problem of the upper bound, corresponds to advantageous (optimistic) conditions, while Model (5-4) corresponds to the demanding (pessimistic) conditions (Huang et al., 1992; Fan et al., 2012; Fan and Huang, 2013). Models (5-6) and (5-7), in Section 2.2, correspond to optimistic and pessimistic conditions of Model (5-4). Consequently, an iterative two-step algorithm is proposed to integrate the two-step method for ILP (Huang et al., 1992; Fan et al., 2012), and the measures of fuzzy possibility and necessity to convert Model (5-8) into two sub-problems, corresponding to the optimistic and pessimistic conditions, respectively. The detailed solution process is presented as follows:

Optimistic

\[ \text{Max } f^+ = \sum_{j=1}^{k} c_j^+ x_j^+ + \sum_{j=k+1}^{n} c_j^- x_j^- \] (5-9a)

Subject to
\[
\sum_{j=1}^{k} a_{ij}^+ \text{Sign}(a_{ij}^+) x_j^+ + \sum_{j=k+1}^{n} a_{ij}^- \text{Sign}(a_{ij}^-) x_j^- \leq b_i^+, \; i = 1, 2, \ldots, l
\]  
(5-9b)

\[
\text{Pos}\{\sum_{j=1}^{k} a_{ij} x_j^+ + \sum_{j=k+1}^{n} a_{ij} x_j^- \leq \tilde{b}_i \} \geq \alpha, \; i = l + 1, l + 2, \ldots, m
\]  
(5-9c)

\[
x_j^\pm = \text{interval continuous variables, } j = 1, 2, \ldots, p \; (p < n)
\]  
(5-9d)

\[
x_j^\pm = \text{interval integer variables, } j = p + 1, p + 2, \ldots, n
\]  
(5-9e)

\[
x_j^+ \geq 0
\]  
(5-9f)

**Pessimistic**

\[
\text{Max} \; f^- = \sum_{j=1}^{k} c_j^- x_j^- + \sum_{j=k+1}^{n} c_j^+ x_j^+
\]  
(5-10a)

Subject to

\[
\sum_{j=1}^{k} a_{ij}^+ \text{Sign}(a_{ij}^+) x_j^+ + \sum_{j=k+1}^{n} a_{ij}^- \text{Sign}(a_{ij}^-) x_j^- \leq b_i^-
\]  
(5-10b)

\[
\text{Nes}\{\sum_{j=1}^{k} a_{ij} x_j^+ + \sum_{j=k+1}^{n} a_{ij} x_j^- \leq \tilde{b}_i \} \geq \alpha
\]  
(5-10c)

\[
0 \leq x_j^- \leq x_j^{\text{opt}}, \; j = 1, 2, \ldots, k.
\]  
(5-10d)

\[
x_j^+ \geq x_j^{\text{opt}}, \; j = k + 1, k + 2, \ldots, n.
\]  
(5-10e)

\[
x_j^\pm = \text{interval continuous variables, } j = 1, 2, \ldots, p \; (p < n)
\]  
(5-10f)

\[
x_j^\pm = \text{interval integer variables, } j = p + 1, p + 2, \ldots, n
\]  
(5-10g)

Model (5-8) can deal with fuzzy and interval uncertainties, in which fuzzy constraints can be treated based on possibility and necessity measures. Model (5-8) can be
converted into two submodels based on the two-step method for ILP proposed by Fan and Huang (2013), and the possibility and necessity measures. As expressed by Models (5-9) and (5-10), the optimistic submodel (i.e. Model (5-9)) corresponds to the upper bound of the objective function, with the fuzzy constraints treated by the possibility measure; while the pessimistic model (i.e. Model (5-10)) corresponds to the lower bound of the objective function, with fuzzy constraints treated by the necessity measure.

5.3. Case Study

5.3.1. Overview of the Study System

The applicability of the developed IFICCP approach is demonstrated through a hypothetical regional noise control problem based on representative cost and technical data from noise control system literatures. Figure 5-1 presents an illustration of a sample noise control system. In such a system, various noise sources (e.g. industrial factories) produce noise levels which pose health and economic costs to surrounding communities. Since the distances between communities and noise sources vary, different noise reduction rates may be necessary between different community and noise source pairs in order to satisfy noise tolerance levels at different communities.

Suppose there are I factories as noise sources, and K communities regarded as receivers. \( \text{ON}_i \) (dB) denote the original noise levels in the factories and \( \text{AN}_k \) (dB) represent the acceptable noise levels in the communities. The distance between factory \( i \) and
community $k$ is denoted as $D_{ik}$ (m). External noise control measures are required to reduce the noise received by the communities. There are a number of noise reduction approaches. However, due to the effectiveness of various porous materials in noise reduction, many noise control measures, such as sound barriers, are designed based on porous materials. Different porous materials, as shown in Chapter 4, usually have different acoustic properties, and thus lead to different noise reduction rates. Moreover, those porous materials also need various costs. In addition, for different communities with different distances to noise sources, it is required to identify appropriate noise control measures. Consequently, for a porous structure-based noise reduction system, how to identify the most appropriate PSNC strategies to reduce the excessive noise at emission sources would be influenced by a number of inherent (e.g. acoustic properties of porous materials) and external (e.g. cost, noise reduction requirement) factors, and thus be a challenge for decision makers.
Figure 5-1 The Study System
To address the above issue, a systematic approach based on the integer programming method can be employed to address this issue. Following the model developed by Huang et al., (2013), if there are $J$ (denoted as $j = 1, 2, \ldots, J$) PSNC options to control excessive noise from three factories (denoted as $i = 1, 2, 3$), and the noise-reduction effect is denoted as $RE_j$ (dB). The optimization model can be formulated as:

**Objective function**

$$\text{Min } TC = \sum_{i=1}^{I} \sum_{j=1}^{J} C_{ij} X_{ij}$$  \hspace{1cm} (5-11a)

where $C_{ij}$ ($$/B$$) represent the unit cost of each PSNC control measure; $X_{ij}$ denotes whether or not a noise-control is selected, in which $X_{ij} = 1$ meaning the $j^{th}$ noise control option would be conducted for factory $i$, and $X_{ij} = 0$ representing no control measure is required for factory $i$. Equation (5-11a) is the objective of the optimization model, which is to minimize the total noise-reduction cost ($TC$) for identifying effective noise-control measures under consideration of the received noise levels in communities no higher than the accepted levels.

**Constraints**

(1) Noise dispersion constraint

$$10\lg \left( \sum_{i=1}^{I} 10^{\left( \frac{ON_i - \frac{158.8D_k}{1000} \sum_{j=1}^{J} X_{ij} RE_j}{10} \right)} \right) \leq AN_k, \; k = 1, 2, \ldots, K$$  \hspace{1cm} (5-11b)

where $ON_i$ (dB) denote the original noise levels in the factories, $AN_k$ (dB) represent the acceptable noise levels in the communities, and $RE_j$ (dB) denote the noise-reduction effect of PSNC measure $j$. Equation (5-11b) means that noise received in
community $k$ should be no higher than the accepted level ($\text{AN}_k$). Noise reduction in the atmosphere is affected by a number of factors, including temperature and air pressure. However, in current study, the standard atmospheric condition is assumed, leading to a noise reduction rate of 158.8 dB per kilometer.

(2) Noise receptor constraint

$$ON_{(i1)} - \frac{158.8D_{(i1)k}}{1000} - \sum_{j=1}^{J} X_{(i1)jk} \text{RE}_j \leq ON_{(i2)} - \frac{158.8D_{(i2)k}}{1000} - \sum_{j=1}^{J} X_{(i2)jk} \text{RE}_j, (i1), (i2) = 1, 2, \ldots, I; k = 1, 2, \ldots, K$$

(5-11c)

Equation (5-11c) indicates the fact that longer distance leads to less noise effect. In Equation (5-11c), the distances between all the noise sources ($i = 1, 2, \ldots, I$) and community $k$ are expressed in a descending order, which are denoted as $D_{(i)k}$ ($i = 1, 2, \ldots, I1, i2, \ldots, I$), such that $D_{(i1)k} \geq D_{(i2)k}$.

(3) Technical constraint

$$\sum_{j=1}^{J} X_{ij} \leq 1, i = 1, 2, \ldots, I;$$

(5-11d)

$$X_{ij} = 0 \text{ or } 1, i = 1, 2, \ldots, I; j = 1, 2, 3, \ldots, J.$$  

(5-11e)

Equation (5-11d) indicates that no more than one of the $J$ scenarios will be implemented for the combination of factory $i$ and community $k$. Equation (5-11e) shows that $X_{ij}$ is a binary variable.

5.3.2. Inexact Fuzzy Integer Chance Constraint Programming Model for Noise
Control System

In practical noise control scenarios, many system parameters related to noise control systems such as the unit costs and noise-reduction effect of different control measures, and noise levels from different sources may not be determined as deterministic values. Most of them may present some levels of uncertainty. The quality of information that can be obtained for these uncertainties is usually not good enough to be presented as probability information. For example, the original noise levels for source 1 may vary over \([90, 92]\) dB, which means that the lowest level of the original noise from source 1 would be 90 dB and the highest level would be 92 dB. The noise abatement criteria (NAC), issued by FHWA, categorizes sound into five levels, with deterministic values. However, the limitation of the NAC with deterministic values is that, if the predicted sound level is reflected by uncertain values (e.g. interval numbers), the uncertain sound level should be transformed into deterministic values, in order to be compared with the NAC values. Also, as stated by Li et al. (2007), the environmental guidelines and health impact criteria are usually fuzzy in nature. In this study, the guidelines for the noise control criteria are categorized into three fuzzy sets, namely “strict”, “medium”, and “loose”. A questionnaire survey was conducted to collect data for establishing membership functions. Based on the considerations, interval parameters are introduced into the noise control optimization model framework to communicate uncertainties in \(C_{ij}\), \(ON_i\), and \(RE_j\) into the optimization process, while fuzzy NAC values are employed to reflect the inherent uncertainties in noise control guidelines. The proposed inexact fuzzy integer chance constraint programming (IFICCP) method can be applied to deal
with such a complicated problem with various uncertainties. The IFICCP model for the noise control optimization problem can be expressed as follows:

$$\text{Min } TC^z = \sum_{i=1}^{I} \sum_{j=1}^{J} C_{ij}^z X_{ij}^z$$  \hspace{1cm} (5-12a)$$

Subject to

$$10\log\left(\sum_{i=1}^{I} 10^{\left(\left\lfloor\frac{ON^z_{i} - \frac{158.8 I_{ik}}{1000} - \sum_{j=1}^{J} X_{ij}^z RE_j^z}{10}\right\rfloor\right)}\right) \leq AN_k \quad k = 1, 2, \ldots, K$$  \hspace{1cm} (5-12b)$$

$$ON_{(i1)}^z - \frac{158.8 D_{(i1)k}}{1000} - \sum_{j=1}^{J} X_{(i1)j}^z RE_{j}^z \leq ON_{(i2)}^z - \frac{158.8 D_{(i2)k}}{1000} - \sum_{j=1}^{J} X_{(i2)j}^z RE_{j}^z \quad (i1), (i2) = 1, 2, \ldots, I; k = 1, 2, \ldots, K$$  \hspace{1cm} (5-12c)$$

$$\sum_{j=1}^{J} X_{ij}^z \leq 1 \quad i = 1, 2, \ldots, I.$$  \hspace{1cm} (5-12d)$$

$$X_{ij}^z = [0, 1], [0, 0], [1, 0] \text{ or } [1, 1], i = 1, 2, \ldots, I, \text{ and } j = 1, 2, 3, \ldots, J.$$  \hspace{1cm} (5-12e)$$

Based on the two-step by Huang et al. (1995) and the possibility and necessity measures, Model (5-12) can be transformed to two-submodels as follows:

Sub-model 1

$$\text{Min } TC^- = \sum_{i=1}^{I} \sum_{j=1}^{J} C_{ij}^- X_{ij}^-$$  \hspace{1cm} (5-13a)$$

Subject to
\[
10 \lg \left\{ \sum_{j=1}^{J} 10^{\left[ \frac{ON_{ij} - 158.8D_{ik}}{1000} - \sum_{j=1}^{J} X_{ij} R E_{j}^{+} \right]/10} \right\} \leq (AN_{a}^{R})_{k}^{(p)}, \quad k = 1, 2, \ldots, K \quad (5-13b)
\]

\[
ON_{(i1)}^{+} - \frac{158.8D_{(i1)k}}{1000} - \sum_{j=1}^{J} X_{(i1)j} R E_{j}^{+} \leq ON_{(i2)}^{+} - \frac{158.8D_{(i2)k}}{1000} - \sum_{j=1}^{J} X_{(i2)j} R E_{j}^{+}, \quad (i1, i2) = 1, 2, \ldots, I; \quad k = 1, 2, \ldots, K \quad (5-13c)
\]

\[
\sum_{j=1}^{J} X_{ij}^{+} \leq 1, \quad i = 1, 2, \ldots, I. \quad (5-13d)
\]

\[
X_{ij}^{+} = 0 \text{ or } 1, \quad i = 1, 2, \ldots, I, \text{ and } j = 1, 2, 3, \ldots, J. \quad (5-13e)
\]

Sub-model 2

\[
\text{Min } TC^{+} = \sum_{i=1}^{I} \sum_{j=1}^{J} C_{ij}^{+} X_{ij}^{+} \quad (5-14a)
\]

Subject to

\[
10 \lg \left\{ \sum_{j=1}^{J} 10^{\left[ \frac{ON_{ij} - 158.8D_{ik}}{1000} - \sum_{j=1}^{J} X_{ij} R E_{j}^{+} \right]/10} \right\} \leq (AN_{l-a}^{L})_{k}^{(p)}, \quad k = 1, 2, \ldots, K \quad (5-14b)
\]

\[
ON_{(i1)}^{+} - \frac{158.8D_{(i1)k}}{1000} - \sum_{j=1}^{J} X_{(i1)j} R E_{j}^{+} \leq ON_{(i2)}^{+} - \frac{158.8D_{(i2)k}}{1000} - \sum_{j=1}^{J} X_{(i2)j} R E_{j}^{+}, \quad (i1, i2) = 1, 2, \ldots, I; \quad k = 1, 2, \ldots, K \quad (5-14c)
\]
\[
\sum_{j=1}^{J} X_{ij}^{+} \leq 1, \ i = 1, 2, \ldots, I. \tag{5-14d}
\]
\[
X_{ij}^{+} = 0 \text{ or } 1, i = 1, 2, \ldots, I, \text{ and } j = 1, 2, 3, \ldots, J. \tag{5-14e}
\]

### 5.4. Results Analysis

Table 5-1 shows the potential noise control measures, and their associated noise-reduction effects and unit costs. In this study, 11 control measures are considered for excessive noise control from different sources. The detailed control measures include Shelter, Wrapping, Resilience, Barrier, and their combinations, which are mainly constructed by porous materials. Samples for these control measures are shown in Figure 5-2. Nevertheless, this study is to develop an integrated evaluation framework to identify noise control strategies under consideration of various internal and external factors. Thus other control measures can also be evaluated by the proposed model. Different control measures produce different noise-reduction effects and also require different costs. As presented in Table 5-1, the combination of Shelter and Barrier produces the highest noise reduction effect, with the highest unit cost, while the measure of Resilience brings the lowest noise reduction effect and also costs the lowest unit expense. Due to various impact factors and system complexity, the original noise source levels are presented as interval values, which would be [87, 90], [91, 95], and [98, 100] dB from original noise sources 1, 2, and 3, respectively. Three scenarios are considered for acceptable noise levels in the two communities, namely “Strict”, “Medium”, and “Loose”. To reflect the uncertainty in the three linguistic criteria (i.e.
“Strict”, “Medium”, and “Loose”), the detailed noise levels for each criteria are presented as fuzzy sets, as shown in Table 5-2. All the acceptable levels under the three scenarios are presented as triangular fuzzy numbers. For example, the acceptable noise level for Community 1 under the “Strict” scenario is (53, 55, 57) dB, which means the strict acceptable noise level for Community 1 is about 55 dB, with 53 and 57 being its lower and upper bounds, respectively. Table 5-3 presents the distance from Noise Source $i$ to Community $k$. 
Figure 5-2. Sample figure of (a) noise shelter, (b) noise wrapping, (c) noise resilience, and (d) noise barrier
Table 5-1 Noise control measures for Factory $i$

<table>
<thead>
<tr>
<th>Options (j)</th>
<th>Noise control measures</th>
<th>$RE_j$(dB)</th>
<th>Cost for each scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Shelter</td>
<td>[14, 15]</td>
<td>[190, 210]</td>
</tr>
<tr>
<td>2</td>
<td>Wrapping</td>
<td>[12, 12.5]</td>
<td>[100, 110]</td>
</tr>
<tr>
<td>3</td>
<td>Resilience</td>
<td>[10, 12]</td>
<td>[55, 60]</td>
</tr>
<tr>
<td>4</td>
<td>Barrier</td>
<td>[17, 18.5]</td>
<td>[240, 260]</td>
</tr>
<tr>
<td>5</td>
<td>Equipment update</td>
<td>[28, 29]</td>
<td>[600, 650]</td>
</tr>
<tr>
<td>6</td>
<td>Shelter + resilience</td>
<td>[19, 20.5]</td>
<td>[260, 280]</td>
</tr>
<tr>
<td>7</td>
<td>Shelter + wrapping</td>
<td>[21, 22.5]</td>
<td>[320, 350]</td>
</tr>
<tr>
<td>8</td>
<td>Shelter + Barrier</td>
<td>[26.5, 27.5]</td>
<td>[520, 550]</td>
</tr>
<tr>
<td>9</td>
<td>Wrapping + Resilience</td>
<td>[15.5, 16.5]</td>
<td>[200, 220]</td>
</tr>
<tr>
<td>10</td>
<td>Wrapping + Barrier</td>
<td>[25, 26]</td>
<td>[400, 435]</td>
</tr>
<tr>
<td>11</td>
<td>Resilience + Barrier</td>
<td>[23, 24.5]</td>
<td>[350, 370]</td>
</tr>
</tbody>
</table>
Table 5-2 Acceptable noise levels of considered communities.

<table>
<thead>
<tr>
<th>Community</th>
<th>Strict level (dB)</th>
<th>Medium level (dB)</th>
<th>Loose level (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ($k = 1$)</td>
<td>(53.2, 55, 57)</td>
<td>(57, 59, 61)</td>
<td>(61, 63, 65)</td>
</tr>
<tr>
<td>2 ($k = 2$)</td>
<td>(51.2, 52, 54)</td>
<td>(54, 56, 58)</td>
<td>(57, 59, 61)</td>
</tr>
</tbody>
</table>

Table 5-3: Distance from the noise source $i$ to community $k$.

<table>
<thead>
<tr>
<th>Distance (m)</th>
<th>Noise source 1 ($i = 1$)</th>
<th>Noise source 2 ($i = 2$)</th>
<th>Noise source 3 ($i = 3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ($k = 1$)</td>
<td>150</td>
<td>200</td>
<td>120</td>
</tr>
<tr>
<td>2 ($k = 2$)</td>
<td>140</td>
<td>180</td>
<td>170</td>
</tr>
</tbody>
</table>
Table 5-4 presents the solutions obtained from the IFICCP model for noise abatement under the “Strict” scenario. Three predetermined confidence levels (denoted as $\alpha$) are selected to reflect the possibility of Constraint (5-12b). Different measures would be applied to different noise sources to mitigate the noise effect on residents in the communities, in which $[0,1]$ means one option will be applied under pessimistic condition while $[1,0]$ means one option will be applied under optimistic condition. For example, for one factory, the noise control measure may be different under different confidence levels. Under low confidence levels (i.e. $\alpha = 0.2$), option 6 (i.e. Shelter and Resilience) would be applied to control noise for factory 1 under the optimistic condition which corresponds to the lower bound of the objective-function value, while option 10 would be considered under the pessimistic condition. The differences in the choice of noise control measures under optimistic and pessimistic conditions is due to the differences of emphasis under the two conditions. The optimistic condition would predominately focus on the system cost while the conservative condition mainly considers the effect of noise reduction. Consequently, more powerful noise control measures (option 10 has a reduction rate of $[25, 26]$ dB with a unit cost of $[$400, 435$]) would be selected under pessimistic conditions while the control measure with less cost (option 6 has a reduction rate of $[19, 20.5]$ dB with a unit cost of $[$260, 280$]) would be chosen under optimistic conditions. For noise source 2, the noise control options would be similar with noise source 1. A less expensive option (i.e. option 3) would be applied under optimistic conditions while a more effective option (option 6) is to be used under conservative/pessimistic conditions. For noise source 3, option 10 (i.e. Wrapping and Barrier), which will cost less and has a lower efficiency, would be
used to control noise under optimistic conditions, while option 5 (i.e. Equipment Update), which is more expensive but more effective, would be applied under conservative conditions. However, as the confidence level increases, the possibility of the constraint (5-12b) would also increase, leading to more effective noise control measures to be employed. For example, when $\alpha = 0.5$, the control measures for the three noise sources under optimistic conditions would be option 4, 3, and 8 with a noise reduction rate of [17, 18.5], [10, 12], and [26.5, 27.5] dB, respectively. Similarly, the control measures under pessimistic conditions, when the confidence level is 0.5, are also more effective with higher costs than under a confidence level of 0.2. For the highest confidence level (i.e. $\alpha = 0.8$), the control measures under optimistic and pessimistic conditions would also be most effective, with highest total cost.
Table 5-4 the solutions from the IFICCP model under “Strict” scenario

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Scenario 2 (i.e. “Medium”) would allow normal standards for both communities, indicating medium acceptable noise levels being about 59 (i.e. (57, 59, and 61)) and 56 (i.e. (54, 56, and 58)) dB for Communities 1 and 2, respectively, as shown in Table 5-2. Since the noise level allowance increases, noise control measures with less reductions rates can be applied for noise control. Table 5-5 shows the solutions of noise control measures under the mid-acceptable level. For example, when noise from sources 1 and 2 is reduced by control measure 3 (with a reduction rate of [10, 12] dB), and noise from source 3 is reduced by control measure 6 (with a reduction rate of [25, 26] dB), the medium acceptable noise level for both communities can be satisfied under optimistic conditions for lower and normal confidence levels (i.e. \( \alpha = 0.2 \) and 0.5). For the noise reduction requirement under the confidence level of 0.8, the control measures for sources 2 and 3 are the same as their control measures (i.e. measure 3 for source 2 and measure 6 for source 3) under \( \alpha = 0.2 \) and 0.5; while source 1 would use control measure 2. In comparison, under the pessimistic conditions, the three noise sources can employ control measures 6, 9, 10 (with a reduction rate of [19, 20.5], [15.5, 16.5], and [25, 26]), respectively to meet the noise reduction requirement for both communities under the confidence levels of 0.5 and 0.8. When the confidence level is set to 0.2, the only difference between the control measures under this confidence level and those under the remaining two confidence levels is that noise source 1 would use option 9 to meet its noise reduction requirement.
Table 5-5 the solutions from the IFICCP model under “Medium” scenario

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In scenario 3, which implements the loosest standards in the two communities, the noise control measures with low reduction rates can be applied for the three noise sources to meet the noise reduction demands for the two communities. Under the optimistic conditions, the detailed control measures adopted by the three sources would not change significantly even though the confidence levels would vary. As presented in Table 6, noise sources 1 and 2 always use control measure 3 for the three selected confidence levels, while noise source 3 would adopt control measure 1 for the confidence levels of 0.2 and 0.5, and control measure 9 for the 0.8 confidence level. Conversely, under the pessimistic conditions, the noise control measures would vary extensively with the variation in the confidence level. Option 2 would be applied by sources 1 and 2, and option 7 would be applied by source 3 under a confidence level of 0.2. Options 9, 3 and 11 would be introduced to the three sources, respectively under $\alpha = 0.5$. Options 6, 2, and 7 would be employed under the highest confidence level.
Table 5-6: The solutions from the IFICCP model under “Loose” scenario

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Generally, uncertainties presented as fuzzy numbers and intervals in parameters can be incorporated into the IFICCP model process through the proposed modeling approach. Tables 5-4 to 5-6 also provide the total system cost from the IFICCP model under varying acceptable noise and confidence levels. The results suggest that different acceptable noise levels of two communities would lead to varied objective function values. Furthermore, under the same acceptable noise level, different confidence levels of the fuzzy chance constraints in the IFICCP model would generally lead to different system costs. The system cost would have an opposite tendency to that of the acceptable noise levels in two communities as shown in Figures 5-3 and 5-4. With a decrease in acceptable noise levels, more effective noise control measures would be required to meet the noise reduction demands, leading to an increase in the lower and upper bounds of the system cost. Meanwhile, the system cost has a consistent correlation with the confidence level of the fuzzy chance constraint, which means the lower and upper bounds of the system cost would generally increase with an increase in confidence levels. The lower-bound cost corresponds to advantageous conditions, while the upper-bound is associated with more demanding conditions, for a predetermined confidence interval. For example, under scenario 1, the system cost would be $[715, 1365]$ when the predetermined confidence level is 0.2 (i.e. $\alpha = 0.2$), indicating a system cost of $715 under advantageous/optimistic conditions and $1365 under demanding/pessimistic conditions. Moreover, the system cost would vary within $715 and $1365 as the model parameters vary within their lower and upper bounds. The lower bound of the system cost usually corresponds to the highest risk of violating the acceptable levels of two communities, while the upper bound of the system cost is
associated with the most conservative noise-reduction effect, leading to lowest risk but excessive expense. Therefore, the decision makers can make tradeoffs between system cost and violation risk of acceptable noise levels based on the solutions from the IFICCP model.
Figure 5-3. The lower bound of the total cost under different acceptable noise and confidence level
Figure 5-4. The upper bound of the total cost under different acceptable noise and confidence levels.
5.5. Discussion

In the current study, we have proposed a comprehensive evaluation framework for porous structure-based noise control measures under consideration of both internal and external factors. Such a framework is based on an Inexact Fuzzy Integer Chance Constraint Programming (IFICCP) approach to deal with interval and fuzziness in a regional noise control system. The innovation of the study is that a variety of internal (e.g. acoustic properties of porous materials) and external (e.g. cost, noise allowance) factors would be integrated into the framework to identify the most appropriate strategies. Moreover, the proposed IFICCP can allow the environmental guidelines of the acceptable noise levels to be presented as fuzzy sets. Such characterization is a meaningful representation of practical noise control optimization problems, since linguistic information from local residents or experts, which is easily expressed through fuzzy sets, can be introduced into the noise control process through the proposed IFICCP approach. Moreover, the fuzzy chance constraint programming method would be integrated into the ILP solution process, to provided decision alternatives under different fuzzy confidence levels. As shows in Tables 5-4 to 5-6, different noise control patterns would be obtained under different fuzzy confidence levels, if the acceptable noise criteria is predefined.

When the lower and upper bounds for the acceptable noise levels are only considered, Model (5-12) would be converted into an interval binary programming model, as developed by Huang et al. (2013). Table 5-7 shows the solutions obtained through the
IBP method. It indicates that the noise control patterns for different noise sources and acceptable noise level scenarios would be quite different from those obtained through the IFICCP approach. This is due to the fact that only the lower and upper bounds of acceptable noise levels are considered in the IBP model. In comparison, the fuzzy characteristic in the acceptable noise levels are introduced into the optimization process of IFICCP through the fuzzy chance constraint expressed by Equation (5-12b). Neglecting the inherent distributional information in the acceptable noise levels may lead to over conservative or optimistic control measures, which would result in high cost or high risk in adoption of noise control measures. Figure 5-5 compares the system costs obtained through the IFICCP and IBP approaches. The IBP model can only provide wide cost intervals for noise control under different acceptable noise levels. In comparison, the IFICCP model can provide multiple noise control measures and the associated system costs under various fuzzy confidence levels. Consequently, the solutions obtained with the IFICCP approach can provide better decision support for actual noise control than the IBP approach.
Table 5-7: The solutions from the IBP model under different criteria scenario

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Comparison between IFICCP and IBP

Figure 5.5. Comparison between system costs obtained through the IFICCP and IBP approaches
5.6. Summary

In this Chapter, we have taken a wholistic approach to the problem of noise reduction using porous materials by examining localization of multiple types of noise reduction measures in complex environments with multiple noise sources and impacted communities. Factors such as cost and efficacy of different noise reduction measures, relative location of communities and noise sources as well as fuzzy community noise requirements drive the engineering approach to one of optimization under fuzzy constraints. To that end, an Inexact Fuzzy Integer Chance Constraint Programming (IFICCP) approach is proposed to address interval and fuzziness in a regional noise control system.

As an extension of the interval binary programming (IBP) method proposed by Huang et al. (2013), IFICCP can explicitly address complexities and various uncertainties in a noise control system. Parameters in the IFICCP model can be expressed as fuzzy sets and intervals, and the uncertainties could be effectively incorporated within the model solution process. The possibility and necessity measures are adopted to deal with fuzzy uncertainty in the constraints. Two submodels corresponding to the lower and upper bounds of the objective-function value can be obtained by incorporating the possibility and necessity measures of fuzzy constraints into the two-step method proposed by Fan and Huang (2013), and interval solutions, under different confidence levels of fuzzy constraints, are then generated by sequentially solving the two submodels.
Results of the case study suggest potential noise control practices under different predefined confidence levels. Three acceptable noise levels have been considered in the case study, with each case being expressed as fuzzy sets. Under each acceptable noise level, a number of decision alternatives have been obtained corresponding to different confidence levels of the reduced noise satisfying the acceptable noise level. They reflect complex tradeoffs between environmental and economic considerations, as well as the decision makers’ attitudes toward noise control. High confidence levels indicate strong attitude in noise reduction, leading to high values for the lower and upper bounds of the system cost. For a predefined confidence level, higher operating costs (upper) will guarantee meeting the noise control standards, a desire to reduce the costs, however, would generally run into the risk of potentially violating the acceptable noise levels.

The proposed IFICCP method can deal with various uncertainties in noise control systems. Although the proposed method was applied to a simple noise control problem, the results suggest this approach is applicable to practical noise control problems associated with highly complex and uncertain information.
CHAPTER 6 CONCLUSION AND FUTURE WORK

6.1. Summary

Porous materials are being widely used for noise reduction in various engineering fields. However, a number of factors (both internal and external) may influence the performance of porous materials in noise reduction. In particular, material aging effects, types of materials, and vacuum levels are significant factors that impact the noise reduction capabilities of different porous materials. Prior methodologies in noise prediction suffer from algorithmic issues and fail to provide a systematic account of the impact of different inherent and external factors. Most significantly, prior works have seldomly investigated the impact of varying vacuum levels on the acoustic properties of different types of porous materials. In addition, for real-life urban noise control design, competing factors such as the cost of different noise control measures, their efficacy in noise reduction, as well as fuzzy noise tolerance levels of multiple surrounding communities call for a wholistic optimization approach that can account for multiple uncertainties. Therefore, this dissertation has proposed a set of experimental and modelling approaches for analyzing inherent and external factors on porous materials for noise reduction, including material aging, types of materials and vacuum levels. In addition, a wholistic optimization approach are developed for large scale noise reduction design. The analytical approach and proposed methodologies can provide decision support for noise prediction, noise reduction, and noise management.
6.2. Research Achievements and Contributions

The research presented in this dissertation advances the state of knowledge in noise reduction using porous materials in the following areas:

(i) The impact of material aging on the acoustic properties of porous pavement materials is studied experimentally on highway systems as well as cross-validated empirically with noise prediction models. As a part of this work, a novel Nested Ensemble Filtering (NEF) approach has been advanced as described in Chapter 3. The proposed NEF approach improves upon previous methods by incorporating sample importance resampling (SIR) procedures into the EnKF update process to enhance sample evolution efficiency and solve an overshoot problem inherent in the EnKF approach. In comparison with the maximum likelihood estimation (MLE) method, the NEF approach can (a) perform better than MLE in most conditions and (b) recursively correct the model parameters whenever new measurements are available. Based on this study, it has been found that the unit noise emission for new porous pavement is significantly decreased in comparison to that of the old pavement considered, regardless of the impacts of uncertainties (e.g. traffic volume).

(2) A systematic study of the effects of vacuum levels on acoustic insulation properties of different porous materials is conducted experimentally and described in Chapter 4. An innovative experimental setup is constructed to conduct a series of experiments.
whereby porous materials, including glass balls, PET sand, polystyrene foam, NBR sheet, and foaming concrete are tested for noise reduction under six vacuum conditions (i.e. 0%, 10%, 20%, 30%, 40%, and 50%). The statistical energy analysis (SEA) method has been adopted to investigate sound absorption properties of porous materials under selected vacuum levels across different audio frequencies. The results indicate that the utilization of vacuum levels on porous materials may effectively reduce noise for most porous materials utilized in the experiments. The sound absorption capabilities of the porous materials are sensitive to the range of audible frequencies and frequency spectrums of the materials. In particular, sound absorption coefficients obtained through SEA indicate that soft porous materials (e.g. NBR sheet and polystyrene foam) have a significant sound reduction effect for sound frequencies around 1000 Hz, and such reduction effects are enhanced for increased vacuum levels. The hard porous materials (e.g. glass balls and PET sand), on the other hand, have sound reduction effects for sound at low frequencies. These research results demonstrate the significant promise of applying vacuum levels to porous materials for noise reduction and opens the field for further research and industrial application. In addition, the real construction materials, namely foaming concrete, was also tested for noise reduction under different vacuum conditions, indicate great potentials for our results to related industries.

A holistic approach to noise reduction in complex environments is proposed in Chapter 5 that takes into account different cost and efficacy of noise reduction strategies (such as the use of the different types or porous materials) as well as fuzzy
noise tolerance demands. The complexity of a multiple noise source and multiple community noise reduction problem is captured through a comprehensive evaluation framework. Such a framework is able to reveal the most appropriate porous structure-based noise control measures through considering a variety of internal and external factors, such as the acoustic properties of porous materials and their costs. Moreover, the developed Inexact Fuzzy Integer Chance Constraint Programming (IFICCP) method within the framework can allow constraints to be expressed as fuzzy sets and intervals, thereby effectively incorporate uncertainties within the model solution process. Two submodels corresponding to the lower and upper bounds of the objective-function value can be obtained by incorporating the possibility and necessity measures of fuzzy constraints into a two-step method proposed by Fan and Huang (2013), and interval solutions under different confidence levels of fuzzy constraints can then be generated by solving the two submodels sequentially. The IFICCP approach provides an effective framework on appropriate noise control measure selection and suitable installation locations to systematically achieve noise reduction requirement with minimum costs. The possibility and necessity measures are adopted in the IFICCP to deal with fuzzy uncertainty in the constraints. Results of the case study suggest potential noise control practices under compound uncertainties and different predefined confidence levels. Specifically, the proposed framework cannot only localize different porous structure-based noise control measures, but also further identify their appropriate orientations.
6.2. Future work

The proposed Nested Ensemble Filtering (NEF) approach is a new attempt to improve upon the ensemble Kalman filter. In applying the NEF, an empirical traffic noise prediction model has been applied to demonstrate the applicability of the proposed NEF method. In the future, it is recommended that a more realistic traffic noise model, such as the Federal Highway Administration (FHWA) traffic noise model, is used to provide a richer set of traffic and road scenarios.

In order to further explore noise reduction effects of different materials, a wider range of porous materials comprising a mixture of soft and hard porous materials should be tested under different vacuum levels. The relationships between the acoustic properties of the porous materials and physical properties of the materials can be further investigated, focusing on the instrumentation used in the experimental study. Additional studies and developments concerning the theoretical relationships between the acoustic properties and vacuum levels may be conducted with a focus on the improvement of the existing insertion loss empirical formulas. Extensive collaboration with industrial sectors may be conducted to (i) test the noise reduction effects of practical construction materials under different vacuum conditions, and (ii) design innovative construction materials with high noise reduction effects based on experimental findings.

The proposed IFICCP method can incorporate various uncertainties in noise control
systems. In this dissertation, the proposed method has been applied to a simple hypothetical noise control problem. In the future, this approach may be extended to practical noise control problems associated with highly complex and uncertain information, which is not only able to localize different porous structured control measure, but also able to reveal their potential orientations.
PUBLICATIONS

In Ph.D program


In Master program


of Environmental Informatics, 2014, 24(2).


REFERENCES


programming for environmental decision making under uncertainty.

Engineering Optimization, 44(11), 1321-1336.


Structural design and sound absorption properties of nitrile butadiene rubber-polyurethane foam composites with stratified structure. Polymers, 10(9), 946.


62. Taha F.E., (2017). Theoretical predictions and experimental measurements of sound transmission through a flat plate and a cylindrical shell. MASc Thesis, Auburn University, Auburn, Alabama, US.


