Design of an end-to-end active noise control system in a partially enclosed sound field, such as a bedroom with an openable window, by applying the latest machine learning techniques

Introduction

This research aims to design an end-to-end active noise control system in a partially enclosed sound field, such as a bedroom with an openable window, by applying the latest machine learning techniques. Advancing active noise control systems would enable the widespread adoption of natural ventilation strategies in urban development by suppressing complex noise ingress. This could not only reduce the upfront and ongoing cost of urban development – which would leading to economic growth – but also provide a significant reduction in energy consumption, as natural ventilation will minimize the need for mechanical ventilation.

Society has become more aware of global warming and climate change as it accelerates due to excessive greenhouse gas emissions [1]. Global efforts are being made to make urban development sustainable [2]. This is critical, since in 2008 it was estimated that CO2 emissions from the operation of inhabited buildings accounted for almost 39% of the UK's total CO2 emissions [3].

Ventilation is a critical part of making a building habitable. Although mechanical ventilation is an easy method to achieve the desired design criteria, it is at the cost of a rise in carbon footprint [4] [5] [6]. Natural ventilation strategies are a much more cost effective and environmentally friendly solution, but their deployment is restricted in areas with excessive external noise levels [7] [8] [9].

Noise control will enable natural ventilation strategies to be deployed in noisy environments. Current noise control techniques used in the construction industry are limited. Passive noise control relies on additional infrastructure such as acoustic barriers or facade alterations. This could cause an increase in construction cost and impose restrictions on aesthetic design [10]. Active noise control has been well established as a field over the past three decades, but wider application of the technology has only just begun due to the advancement in complex algorithms, electroacoustics, and compute power [11]. The combination of greater computational power and highly complex algorithms provides the basis for active noise control to be advanced into popular use.

Machine learning has seen recent success in many areas including image classification [12] [13], object detection [14] [15], speech recognition
[16] and machine translation [17]. Neural networks are a particular class of algorithms that are driving many of these successes. They replace brittle systems composed of many hand-engineered components with a complete end-to-end solution that can efficiently learn from the vast amounts of data.

I therefore believe that the utilisation of end-to-end active noise control system to suppress noise breaking into buildings could be the revolutionary remedy to maximise natural ventilation in compacted cities. This could provide significant reductions in the cost of urban development, energy consumption, and hence climate change.

Preliminary Literature Review

For the past three decades, advancements in electroacoustic transducers and efficient adaptive algorithms have driven the study of active noise control (ANC) [18]. ANC is based upon the principle of superposition where destructive interference is achieved at a location by generating anti-phased signal with a secondary source to cancel out the signal from a primary source [19].

Frequency analysis has to be performed on the captured signal before an anti-phased signal is generated by the system.

Frequency analysis can either be performed by Fourier analysis or by passing the signal through a series of filters known as a filter bank [20]. The first consideration when constructing a filter bank is the type of filters to use as each have their pros and cons. Filtering in the time domain is done by operating convolutional filters which is known as impulse response (IR). Filters can generally be classified into Finite Impulse Response (FIR) or Infinite Impulse Response (IIR) [21].

FIR filters are fundamentally more stable since the filter is determined solely by convolving it with the input and can be constrained to have a linear phase response. Unlike FIR filters, the output of an IIR filter is determined by convolving with the input and combining it with the feedback of the previous output. This makes IIR more efficient than FIR at creating a sharp cutoff between the filtered in and out frequencies with a lower filter order. Thus, less computational load is required for IIR to achieve the equivalent magnitude characteristics as a FIR filter [22]. A disadvantage of IIR filters is the presence of nonlinear phase response which results in a distorted audio output [20]. IIR can also be numerically unstable if inappropriately designed [23].

Adaptive algorithms allow filters to adjust the impulse response to filter out the correlated signal in the input. They can adaptively track the signal under non-stationary conditions where statistics vary with time. These algorithms could be considered as primitive class of neural networks consisting of a single neuron and operating under the assumption of linearity. Adaptive algorithms can be categorised into two main families: Least Mean Squares (LMS) or Recursive Least Squares (RLS) algorithms [24] [25].

The fundamental principle of LMS algorithms is to mimic a desired filter by finding the filter coefficients that minimise the squared distance between the actual and predicted signals [26]. These filter coefficients are updated using stochastic gradient descent. The difference between the reference signal and the actual output is the error signal [24]. Conventional LMS algorithms can be highly sensitive to the input scale and they can be unstable due to the introduction of phase shift in the forward path [26]. Variations of conventional LMS algorithms have been developed to overcome these limitations [27]. Conversely, the RLS algorithm recursively finds the filter coefficients that reduce a weighted linear least squares cost function relating to the input signal [26]. The RLS algorithms are known for providing faster convergence rate but at a cost of increased computational complexity [26].

The specific choice of filter bank and adaptive algorithm also depends on the form of the ANC strategy. ANC strategies can be categorised as feedforward or feedback methods. Feedforward strategies could be used when reference signals are captured in proximity to the primary source. Conversely, feedback strategy could be used when the reference signal is not available directly [28]. Recent studies have also been undertaken on how hybrid feedforward-feedback can be applied to ANC [29].

Conventional signal processing and adaptive filter techniques have been successfully applied in ANC systems that target stationary noises such as aircraft or low frequency fan noise [28]. However, these systems are limited by the algorithms at their core that require the constant adaptation of filter coefficients based on a number of previous samples. In addition, adaptive filters are typically linear transformations and hence do not have sufficient power to model a highly nonlinear noise signal [30].

A neural network is a parameterized nonlinear system that learns a function based on the available data. This is typically done via supervised learning where the parameters are found using a variant of stochastic gradient descent that aims to iteratively find a minimum of a performance criterion or loss function [31]. Both speech recognition and noise suppression have been of interest to the telecommunications industry since at least 1952 [32]. Approaches utilising neural networks have recently gained tremendous attention due to their success in many areas, including both speech recognition and noise suppression [33] [34]. The models used today are now fully end-to-end, meaning they model the entire transformation from input to output, and replace previous systems made of complex hand-crafted processing pipelines. This developmental sequence has also occurred in hearing-aid technologies where noise cancelation is critical for speech intelligibility in noisy environments [35] [36]. Time-delayed neural networks, also known as convolutional neural networks [37], can be used to replace conventional adaptive filters [38] [39]. An early network architecture for noise cancellation was the Filtered-X Backpropagation Neural Network (FXBPNN) [40]. Through simulation experiments, methods have proven to be effective compared to conventional algorithms. Further laboratory experiments are still required since simulations are unable to accurately model the entire noise in the system [41] [42].

There is a recent breakthrough of ANC application in construction industry where a system has been applied to window configurations in order to increase the facade's sound insulation properties. However, these types of systems impose restrictions on the architectural design and facade alterations are required to achieve a global noise reduction within the room [43] [44].

The complexity of the normal modes within a large enclosure has made global control active noise cancellation challenging [45]. The classical normal-mode theory is found to be incomplete and an additional term representing the direct radiation from the source must be added [46].
Multi-channel ANC system has also been applied to a three-dimensional enclosure. The required number and location of both loudspeakers and microphones were examined to achieve global control within the room. Experiments were carried out to compare different ANC adaptive algorithms [47]. All ANC algorithms provide significant noise reduction for periodic engine noises with feedforward structure being a more viable approach for broadband cancellation. Feedback structures could only achieve narrowband noise rejection due to waterbed effect [47].

A successful noise suppression system can also be achieved by confining noise energy in a region, making global suppression inside a room nonessential [48]. A vibro-acoustic coupling system via active wave control method has been studied to generate a quiet zone [48] . The application of localised noise suppression has been extended to sound field control where two or more 'sound field zones' are created in the same space with little to no interference between programmes [49] [50]. Localised noise suppression was also developed to tackle low frequency snoring noise [51]. The experiment established that this ANC system could be improved by placing error microphones close to the ears of KEMAR, representing a bed partner [51]. Virtual sensing techniques could be the critical solution for many practical and applications that have to place error sensors away from the desired control locations [51].

Two types of algorithm have been developed for virtual sensing ANC; spatially fixed and moving virtual sensing algorithms [52]. The first type requires offline training to calibrate virtual sensors from physical sensors before deploying them [53]. It is highly dependent on the accuracy of the offline training and is sensitive to change in the environment and placement of the physical sensors [52]. The moving virtual sensing algorithms generate a virtual microphone capable of tracking a virtual location that is moving through the sound field [54]. These algorithms do not need offline training to create the system model, and are thus more flexible in their application [52].

Omnidirectional loudspeakers are used for conventional noise cancellation. Recently, interest in designing an ANC system using highly directional sound sources has increased [55]. A directional secondary source can be used to attenuate primary noise to achieve focused noise control at a localised quiet zone with little spill over outside this area [56]. One shortfall of highly directional loudspeakers would be their inability to control lower frequencies due to poorer frequency response at lower frequency range [57].

Research Questions

The following research questions have been considered in order to understand how neural networks can be used to process a complex nonlinear noise signal. The end-to-end system will be used to create an active noise control system that generates a localised stationary quiet zone by suppressing noise ingress from an open window using directional loudspeakers within a bedroom:

Can wave-based techniques be used to simulate a 3D localised noise suppression quiet zone using directional speakers to control noise ingress from an open window into a bedroom?

Can an end-to-end deep learning approach be used to replace conventional adaptive virtual sensing techniques, such as the FXLMS and FSLMS algorithms, and implement a nonlinear active noise control system?

Can the simulated stationary localised quiet zone system be physically implemented via an end-to-end deep learning approach with directional speakers to control the noise ingress from an open window into a bedroom?

Methodology

In the acoustic domain, acoustic wave equation theories will be reviewed [58]. This will lead to the exploration of different wave-based techniques. For frequency-domain techniques, both finite element method (FEM) and boundary element method (BEM) can be used to establish the characteristics of the noise ingress sound energy through an open aperture in the facade with 3D simulations [59] [60]. This is built upon the research carried out by Bhan Lam et al., where 2D FEM simulations were used to establish the physical limits on the performance of active noise control through open windows [61]. For time-domain techniques, finite difference time domain (FDTD) can also be used to calculate room sound fields via impulse response [62]. Further research on other acoustic techniques will be covered to discover approaches to quantify the source directionality of an open window and ways to simulate a partially enclosed sound field [63] [64]. Strategy on the quantity and location of sensors and actuators will be based upon the findings of the room acoustic assessment [65]. Directional secondary source, such as parametric array loudspeakers, can be used as a method to generate noise suppression at the designated control points [66] [67] [68].

In the electrical domain, model-based approach will first be used to design the active noise control system [18]. This will establish the relationship between all the necessary components and identify exactly which part(s) can be replaced by the proposed end-to-end system. Convolutional and recurrent neural network architectures will be considered [69]. This platform will allow the algorithm to perform sequence to sequence translation, where the output sequence is a spectrogram. The limited available dataset is currently foreseen to be one of the limitations. The audio dataset from Urbansound8K will be used as a source for supervised training [70]. This dataset equates to approximately eight hours which is likely not enough to model environmental noise. Further investigation will be performed to find available datasets, evaluate techniques for data augmentation, and investigate techniques to generate data such as those used by autonomous driving companies [71]. A simulation experiment will be conducted to compare the performance between FXLMS, FSLMS, and the end-to-end algorithm. The performance indicators will include, attenuation, latency, and algorithmic efficiency as part of the assessment.

An experiment will be performed to validate the finalised configuration of the designed ANC system. The experiment can be carried out in an anechoic chamber with a built-in openable sash window on a temporary bedroom. The interior finish and the ANC system will be replicating the simulated configuration with KEMAR rest horizontally on a bed representing the receptor. Lastly, a primary loudspeaker will be placed outside the temporary bedroom facing directly to the sash window, generating the urban noises for the experiment. Conclusions will be drawn to compare between the experiment measurement and the simulated results.

Significance & Contribution

This study will be a significant step towards the widespread deployment of active noise control in the building industry. The development of complex algorithms for active noise control will be addressed by incorporating the latest techniques in machine learning. The laboratory experiment will provide the evaluation opportunity to assess the real-world performance of the designed localised active noise suppression system in comparison to the simulation experiments. This study will be a source of valuable information for further study.

Proposed Programme

	Year 1			Year 2			Year 3		
Scope of Work	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
Research of Acoustic Theory Framework & Methodology									
ANC Model-based Approach Design									
Acoustic Domain Simulation									
Research of Electrical Theory Framework & Methodology									
Conventional Algorithms Replication									
Neural Network Architectural Design									
Electrical Domain Simulation Experiment									
ANC Components Procurement & Assembly									
Literature Review Write Up									
Documentation on Acoustic Domain Simulation									
Documentation on Electrical Domain Simulation									

Methodology Write Up									
ANC Laboratory Experimentation									
Documentation on Laboratory Experimentation									
Analysis Write Up									
Thesis Review									
Final Review									

References

Rodney Boyd, Nicholas Stern, Bob Ward, “What will global annual emissions of greenhouse gases be in 2030, and will they be consistent with avoiding global warming of more than 2°C?”, The ESRC Centre for Climate Change Economics and Policy (CCCEP), and The Grantham Research Institute on Climate Change and the Environment, London, 2015.

Diana Reckien, Monica Salvia, Oliver Heidrich,..., Richard Dawson, “How are cities planning to respond to climate change? Assessment of local climate plans from 885 cities in the EU-28”, Journal of Cleaner Production, vol. 191, pp. 207-219, 2018.

E. &. I. Department for Business, “Estimating the Amount of Co2 Emissions that the Construction Industry can Influence, Supporting material for the Low Carbon Construction IGT Report”, [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/31737/10-13 16-estimating-co2-emissions-supporting-low-carbon-igt-report.pdf. [Accessed 10 February 2019].

P. Wargocki, “The Effects of Ventilation in Homes on Health”, International Journal of Ventilation, vol. 12, no. 2, pp. 101-118, 2013.

CIBSE, “TM59 Design methodology for the assessment of overheating risk in homes”, May 2017. [Online]. Available: https://www.cibse.org/knowledge/knowledge-items/detail?id=a0q0O00000DVrTdQAL. [Accessed 10 February 2019].

J. E. Janssen, “The History of Ventilation and Temperature Control”, Ashrae Journal, vol. 41, pp. 48 - 70, 1999.

O. Seppänen, “Ventilation, Energy and Indoor Air Quality”, in Indoor Air 2002, Helsinki, 2002.

A. Chilton, A. Long, D. Trew, J. Harvie-Clark, J. Healey, M. Hyden, N. Conlan, S.Turner, Acoustics Ventilation and Overheating, Residential Design Guide, Croydon: Association of Noise Consultants, 2018.

T. B. S. Institution, “Guidance on sound insulation and noise reduction for buildings”, BS 8233:2014, p. 26, February 2014.

“Innovative Noise Mitigation Designs and Measures”, Environmental Protection Department, The Government of the Hong Kong Special Administrative Region, [Online]. Available: https://www.epd.gov.hk/epd/Innovative/greeny/eng/. [Accessed 25 02 2019].

Xiaojun Qiu, Jing Lu, Jie Pan, “A new era for applications of active noise control”, in Inter Noise, Melbourne, 2014.

Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, “ImageNet Classification with deep convolutional neural network”, in 25th International Conference on Neural Information Processing Systems, Lake Tahoe, Nevada, 2012.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich, “Going deeper with convolutions”, Google Inc., 2014.

Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, Alexander C.Berg, “SSD: Single Shot MultiBox Detector”, UNC Chapel Hill, Zoox Inc., Google Inc., University of Michigan, Ann-Arbor, 2016.

Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi, “You Only Look Once: Unified, Real-Time Object Detection”, University of Washington, Allen Institute for AI, Facebook AI Research, 2016.

Dario Amodei, Sundaram Ananthanarayanan, ... , Zhenyao Zhu, “Deep Speech 2: End-to-End Speech Recognition in English and Mandarin”, in 33rd International Conference on Machine Learning, New York, 2016.

Yonghu Wu, Mike Schuster,..., Macduff Hughes, Jeffrey Dean, “Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation”, Google Brain, 2016.

S. J. Elliott, Signal Processing for Active Control, London: Academic Press, 2000.

Sen M. Kuo, Woon-Seng Gan, Kevin Kuo, “Active noise control: Open problems and challenges”, in Green Circuits and Systems (ICGCS), China, 2010.

J. M. Kates, Digital Hearing Aids, Oxford: Plural Publishing, 2008.

L. R. Rabiner, J.F. Kaiser, O. Herrmann, and M. T. Dolan, “Some Comparisons Between FIR and IIR Digital Filters”, The Bell System Technical Journal, vol. 53, no. 2, pp. 305 - 331, 1973.

R. a. Losada, “Digital Filters with MATLAB”, The Mathwork, INC, 2008.

H. Dillon, Hearing Aids, Stuttgart: Thieme, 2012.

S. O. Haykin, Neural Networks and Learning Machines: a Comprehensive Foundation, Canada: Pearson, 2008.

A. Singh, “Adaptive Noise Cancellation”, Netaji Subhas Institute of Technology, 2001.

Jyoti Dhiman, Shadab Ahmad, Kuldeep Guila, “Comparison between Adaptive filter Algorithms (LMS, NLMS, and RLS)”, International Journal of Science, Engineering and Technology Research (IJSETR), vol. 2, no. 5, pp. 1100 - 1103, 2013.

Colin Hansen, Scott Snyder, Xiaojun Qiu, Laura Brooks, Danielle Moreau, Active Control of Noise and Vibration, CRC Press, 2012.

Giovanni L. Sicuranza, Alberto Carini, “Nonlinear multichannel active noise control using partial updates”, in Acoustics, Speech, and Signal Processing, 1988. ICASPP-88, 1988 International Conference on, Volume:3, USA, 2005.

A.D. Streeter, L.R. Ray, R.D. Collier, “Hybrid feedforward-feedback active noise control”, in Proceedings of the 2004 American Control Conference, Boston, 2005.

P. B. Suman, “Noise Cancellation using Adaptive Filters Algorithms”, International Journal of Engineering Research and General Science , vol. 3, no. 4, pp. 263-267, 2015.

Dorf, Richard C, Jose C. Principe, The Electrical Engineering Handbook, Boca Raton: CRC Press LLC, 2000.

K. H. Davis, R. Biddulph, and S. Balashek, “Automatic Recognition of Spoken Digits”, The Journal of the Acoustical Society of America, vol. 24, no. 6, pp. 637 - 642, 1952.

Andrew L. <ass, Quoc V. Le, Tyler M. O'Neil, Oriol Vinyals, Patrick Nguyen, Andrew Y. Ng, “Recurrent Neural Network for Noise Reduction in Robust ASR”, in INTERSPEECH, 2012.

Yong Xu, Jun Du, Li-Rong Dai, and Chin-Hui Lee, “A regression Approach to Speech Enhancement Based on Deep Neural Networks”, IEEE Transactions on Audio, Speech and Language Processing, vol. 23, no. 1, pp.
7-19, 2015.

Ying-Hui Lai, Yu Tsao, Xugang Lu, Fei Chen, Yu-Ting Su, Kuang-Chao Chen, Yu-Shuan Chen, Li-Ching Chen, Lieber Po-Hung Li, Chin-Hui Lee, “Deep Learning-Based Noise Reduction Approach to Improve Speech Intelligibility for Cochlear Implant Recipients”, Ear and Hearing, vol. 39, no. 4, pp. 795-809, 2018.

Mahmoud Keshavari, Tobias Goehring, Hustin Zakis, Richard E. Turner, and Brian C. J. Moore, “Use of a Deep Recurrent Neural Network to Reduce Wind Noise: Effects on Judged Speech Intelligibility and Sound Quality”, Trends in Hearing, vol. 22, pp. 1-12, 2018.

Yanmin Qian, Mengxiao Bi, Tian Tan, Kai Yu, “Very Deep Convolutional Neural Networks for Noise Robust Speech Recognition”, IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 24, no. 12, pp. 2263 - 2276, 2016.

Youichi Tsuyama, Yataka Maeda, “Active Noise Control Using Neural Network with the Simultaneous Perturbation Learning Rule”, in 41st SICE Annual Conference, Osaka, 2002.

Shubhra Dixit, Deepak Nagaria, “Neural Network Implementation of Least-Mean-Square Adaptive Noise Cancellation”, in International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Ghaziabad, 2014.

Snyder, Scott D., and Nobuo Tanaka, “Active Control of vibration using a neural network”, IEEE transactions on neural networks, vol. 6, no. 4, pp. 819-828, 1995.

Seyed Amir Hoseini Sabzevari, Majid Moavenian, “Application of reinforcement learning for active noise control”, Turkish Journal of Electrical Engineering & Computer Sciences, vol. 25, pp. 2606-

2613, 2017.
T. Krukowicz, “Active Noise Control Algorithm Based on a Neural Network and Nonlinear Input-Output System Identification Model”, Archives of Acoustics, vol. 35, no. 2, pp. 191-202, 2010.
Christian Carme, Olivier Schevin, Clement Romeroqski, and Julien Clavard, “Active noise control applied to open windows”, in Inter Noise, Hamburg, 2016.
Chuang Shi, Tatsuya Murao, Dongyuan Shi, Bhan Lam, and Woo-Seng Gan, “Open loop active control of noise through open windows”, in 172nd Meeting of the Acoustical Society of America, Honolulu, Hawaii, 2016.
D. Guicking, “ Active Control of Sound and Vibration - Fundamentals - State of the Art”, Festschrift DPI, no. Universit¨atsverlag, pp. 1-32, 2007.
D.-Y. Maa, “Sound Field in a Room and Its Active Noise Control”, Applied Acoustics, vol. 41, pp. 133-126, 1994.
M. R. Bai, Z. Lin, “Active Noise Cancellation for a Three-Dimensional Enclosure by Using Multiple-Channel Adaptive Control and H∞ Control”, Journal of Vibration and Acoustics, vol. 120, no. 4, pp. 958 - 964, 1998.
Motoya Watanabe, Hiroyuki Iwamoto, Nobuo Tanaka, “Active noise reduction of a coupled rectangular cavity using active wave control”, in Inter Noise, Melbourne, 2014.
Jon Francombe, Philip Coleman,... Jan Abildgaard Pedersen, “Perceptually optimised loudspeaker selection for the creation of personal sound zones”, in Audio Engineering Society: 52nd International Conference: Sound Field Control - Engineering and Perception, Guildford, 2013.
Olik, Marek; Francombe, Jon; Coleman, Philip; Jackson, Philip J. B.; Olsen, Martin; Møller, Martin; Mason, Russell; Bech, Søren, “A Comparative Performance Study of Sound Zoning Methods in a Reflective Environment”, in 52nd International Conference: Sound Field Control - Engineering and Perception , Guildford, 2013.
S.R. Chakravarthy, S.M. Kuo, “Application of Active Noise Control for Reducing Snore”, in IEEE International Conference on Acoustics Speech and Signal Processing, Toulouse, 2006.

Yoshinobu Kajikawa, Woon-Seng Gan, and Sen M.Kuo, “Recent advances on active noise control: open issues and innovative applications”, APSIPA Transactions on Signal and Information Processing, vol. 1, no. 3, pp. 1 - 21, 2012.
J. Garcia-Bonito, S. J. Elliott, and C. C. Boucher, “Generation of zones of quiet using a virtual microphone arrangement”, The Journal of the Acoustical Society of America , vol. 101, no. 6, p. 3498 – 3516, 1997.
Danielle Moreau, Ben Cazzolato, Antony Zander, and Cornelis Petersen, “A Review of Virtual Sensing Algorithms for Active Noise Control”, Algorithms, vol. 1, no. 2, pp. 69 - 99, 2008.
Nobuo Tanaka, and Motoki Tanaka, “Active noise control using a steerable parametric array loudspeaker”, The Journal of the Acoustical Society of America, vol. 127, no. 6, pp. 3526-3537, 2010.
Nobuo Tanakaa, and Motoki Tanaka, “Mathematically trivial control of sound using a parametric beam focusing source”, The Journal of the Acoustical Society of America, vol. 129, no. 1, pp. 165 - 172, 2011.
Woon-Seng Gan, Ee-Leng Tan, and Sen M. Kuo, “Audio projection: directional sound and its application in immersive communication”, IEEE Signal Processing Magazine, vol. 28, no. 1, pp. 43 - 57, 2011.
Lawrence E. Kinsler, Austin R. Frey, Alan B. Coppens, James V. Sanders, Fundamentals of Acoustics 4th Edition, New York: John Wiley & Sons, Inc, 2000.
L. L. Thompson, “A review of finite-element methods for time-harmonic acoustics”, The Journal of the Acoustical Society of America, vol. 119, no. 3, pp. 1315-1330, 2005.
Alexander H., D. Cheng, Daisy T. Cheng, “Heritage and early history of the boundary element method”,
Engineering Analysis with Boundary Elements, vol. 29, no. 3, pp. 268 - 302, 2005.

Bhan Lam, Stephen Elliott, Jordan Cheers, Woo-Seng Gan, “Physical limits on the performance of active noise control through open windows”, Applied Acoustics, vol. 137, no. 1, pp. 9 - 17, 2018.

Shinichi Sakamoto, Ayumi Ushiyama, Hiroshi Nagatomo, “Numerical analysis of sound propagation in rooms using the finite difference time domain method”, The Journal of the Acoustical Society of America , vol. 120, no. 5, p. 3008, 2006.

A. Southern, D.T. Murphy, “Low Complexity Directional Sound Sources for Finite Difference Time Domain Room Acoustic Models”, in 126th AES Convention, Munich, 2009.

Y.-H. Kim, Sound Propagation: An Impedance Based Approach, New York: John Wiley & Sons, 2010.

Philip Coleman, Philip J. B. Jackson, Marek Olik, “Numerical Optimization of Loudspeaker Configuration for Sound Zone Reproduction”, in The 21st International Congress on Sound and Vibration, Beijing, 2014.

Nobuo Tanaka, and Motoki Tanaka, “Active noise control using a steerable parametric array loudspeaker”,
Journal of the Acoustical Society of America, vol. 127, no. 6, pp. 3526 - 3557, 2010.

J. L. S. Bellin and R. T. Beyer, “Experimental Investigation of an End-Fire Array”, The Journal of the Acoustical Society of America , vol. 34, no. 8, pp. 1051 - 1054, 1962.

J. Naze and S. Tjøtta, “Nonlinear Interaction of Two Sound Beams”, The Journal of the Acoustical Society of America, vol. 37, no. 1, pp. 174 - 175, 1965.

Oord, Aaron van den, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu., “Wavenet: A generative model for raw audio”, Google DeepMind, London, 2016.

Justin Salamon, Christopher Jacoby, and Juan Pablo Bello, “Urban Sound Datasets”, UrbanSound8K, [Online]. Available: https://urbansounddataset.weebly.com/urbansound8k.html. [Accessed 27 02 2019].

Justin Salamon and Juan Pablo Bello, “Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification”, 28 11 2016. [Online]. Available: https://arxiv.org/pdf/1608.04363.pdf. [Accessed 27 02 2019].