SOUND LEVEL CONTROL FOR AIR HANDLING UNITS

Ralph KRAUSE, Thomas OPPELT, Christian FRIEBE,
Leopold MODRAKOWSKI, Karsten HACKESCHMIDT

*Institut für Luft- und Kältetechnik Gemeinnützige Gesellschaft mbH,
Bertolt-Brecht-Allee 20, 01309 Dresden, Germany*

SUMMARY

A control algorithm for Air Conditioning Units (ACUs) is presented. The core of the algorithm is a machine-learning-trained algorithm which distinguishes between different acoustical situations in a room and adjusts the air volume flow of the ACU. The algorithm classifies the microphone-recorded sound in a room into one-person-presentation (SCL 0) and multiple-persons-conversation (SCL 1). The algorithm was trained with real-class sound-recordings and applied to a virtual ACU providing this room with supply air. The supply air has direct impact on the CO_2-concenctration in this room and therefore on the comfort of the occupants. This paper presents the outcomes of this algorithm and provides an outlook on the application of it.

INTRODUCTION

Providing clean air is an important function of Air Conditioning Units (ACUs) in indoor rooms. The amount of clean air required in a room depends on the number of people present. Especially under pandemic conditions, sufficient ventilation of the occupied rooms is of great importance [1, 2, 3].

However, experience shows that these ACUs are often found to be a source of noise [4]. The noise pressure level often significantly exceeds 40 dB(A), especially for small indoor units [5, 6]. The recommendation for the permissible sound pressure level (SPL) in classrooms is between 30 and 40 dB(A) maximum [7, 2, 8]. Therefore, ACUs are often powered down to reduce the noise level and to increase intelligibility. As a result, the provision of fresh air is no longer sufficiently ensured. Intelligibility is an important parameter especially in rooms where conversation is essential.

The control of ACUs regarding the noise emission in order to achieve a low noise level and good intelligibility could help to counteract the problem. One important parameter of such a control mechanism is the detection of the presence of conversation in a room. Therefore, Voice Activity Detection (VAD) or Speech Activity Detection is a common method in order to achieve this. VAD has been a subject of continuous research projects for several years. One early adaption is the suggestion of Rabiner *et al.* [9] to detect speech within a background noise to keep data amount at minimum, e.g. in telecommunication systems. Thasni *et al.* [10] compared different algorithms and parameters. The introduction of artificial intelligence (AI) and deep learning algorithms (DL) into the topic yield further potential for improvement [11, 12, 13].

In general, it can be assumed that the noise caused by ACUs increases with increasing air volume flow. Consequently, the noise emission can also be reduced by reducing the air volume flow. Controls are already known that hide the noise level caused by the ACU behind the noise level in the room by simply reducing the air volume flow [14]. However, this type of control very often leads to the problem that the necessary air exchange in the room is no longer guaranteed.

An approach to simultaneously improve intelligibility and achieve a good fresh air rate is presented in the following section. A deep learning algorithm is applied to real-life sound records to distinguish between different acoustical situations. The result of this algorithm is utilized in a simulation to examine the effect on the CO_2 concentration in a room with occupants (the source of CO_2) and an ACU.

APPROACH

Within this paper the application focuses on everyday school life. The approach of the acoustic control is based on the idea that there are different situations in a class room. The situations differ in terms of noise acceptance. For example, during a direct conversation between teacher and student, it is crucial to avoid disturbing background noise that could deteriorate intelligibility. In contrast, when there are several simultaneous conversations over short distances (e.g. during group work), a significantly higher noise level can be accepted.

For the control of the ACU, one of the strategies as presented in Table 1 can be chosen. Controlling the fresh air volume flow according to CO_2 concentration is mandatory to ensure the air exchange required by hygienic reasons, but causes acoustic disturbance. Therefore, the control according to the sound pressure level (SPL) is the typical application. Without further measures in addition to one of the two mentioned strategies, either the SPL is too high or the air exchange rate is too low. By controlling the ACU according to the sound classification (SCL), the disadvantages of the previous control strategies can be almost completely eliminated. The required air exchange is ensured while establishing an acceptable noise level. A well-designed ACU with a state-of-the-art low noise emission is essential.

Table 1: priority of controlling the volume flow of the air handling unit to avoid noise disturbance

Strategy	Parameter	Note
1	CO_2 concentration	necessary for air exchange rate concerning the hygienic need, leads often to perturbing noise emission
2	sound pressure level (SPL)	the ACU noise level is suppressed below the speech level by at least 10 dB at any time, can lead to high CO_2 concentration
3	sound classification (SCL)	dynamically establish the maximum possible volume flow rate for the specific situation with acceptable noise emission

To verify the approach, an acoustic control simulation is performed. The objective of this simulation is the validation and the optimisation of the correlation between the fresh-air delivery-rate and the noise-level. The parameter of verification is the CO_2 concentration of the investigated room. The CO_2 concentrations are separated into three different classes (see Table 2).

Table 2: air quality categories (AQC) and description thereof

Air Quality Category (AQC)	Description	CO_2 in ppm
1	"green" level: "good", low concentration	< 1000
2	"yellow" level: "moderate", acceptable.	1000 - 1250
3	"red" level: "poor", inacceptable, to be avoided	> 1250

MEASUREMENT SETUP AND DATA AQUISITION

Previously published - analyses (e.g. Kemp *et al.* [15]) do not provide sufficient information and data. Therefore, an audio recording was recorded in a class during a real school day. The audio recording is the basis for performing the sound detection and the acoustic control simulation described in the next sections.

Two microphones were used to record the sound. Both were placed in the classroom at 1 m above floor level, one in the front near the blackboard and the other one in the back. Figure 1 shows the arrangement.

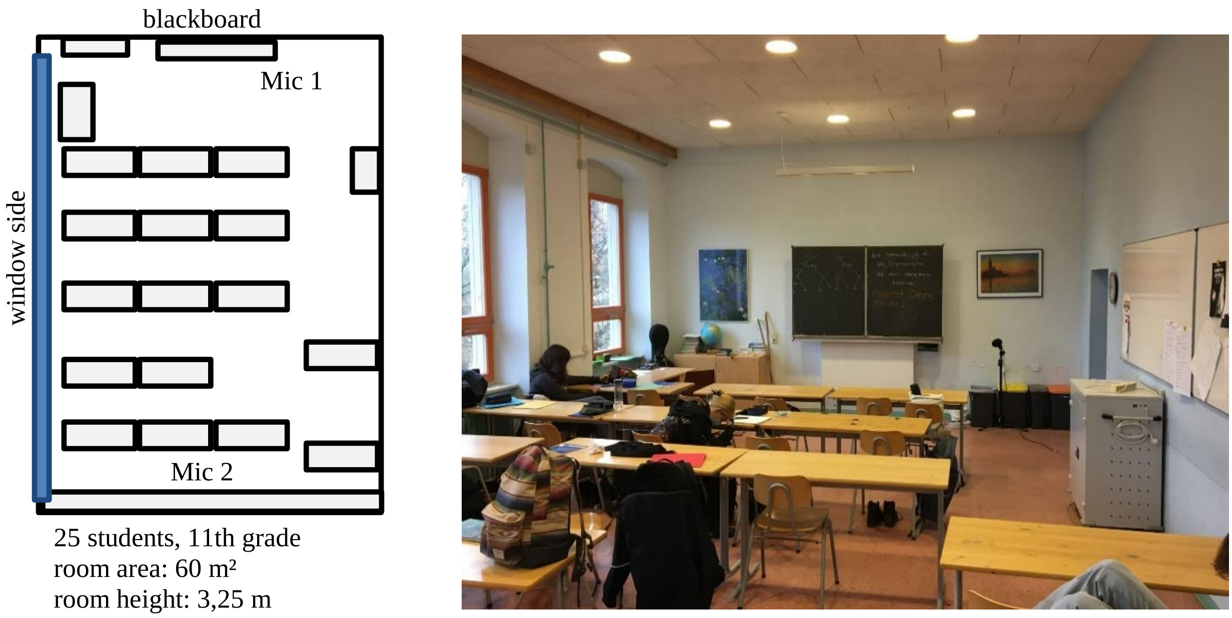

Figure 1: classroom used for the sound recording, floor plan with positions of the microphones (left) and interior view (right)

The audio file was recorded for about 90 minutes (two lessens including breaks). The sound record was first analysed manually and divided into parts with specific sound characteristics. Next, a sound classification (SCL) ranging from 0 to 3 has been assigned to every specific sound characteristic (see Table 3). These SCLs represent certain acoustic characteristics and inherit different acoustic requirements (see Table 4).

Table 3: sound recording during a real class

Sound characteristic	Description	Recording time	Sound classification (SCL)
Lecture	Single person is talking – direct communication across the entire room	12:43	0
Lecture and background noise	Single person is talking and murmuring in the background – direct communication across the entire room	9:34	
Discussion	Single persons are talking alternately – direct communication across the entire room	7:04	
Discussion and background noise	Single persons are talking alternately and murmuring in the background – direct communication across the entire room	13:33	
Team discussion	Several students are talking simultaneously – direct	43:05	1
Silence	No speech intelligibility – no direct communication	0:56	2
Others	Short ambient noises – door, chairs	04:25	3
	Audio playback from technical devices	35:16	

Table 4: sound classification (SCL) and description thereof

Sound classification (SCL)	Description	Acoustic requirement
0	Single person speaking	high
1	More than one person speaking simultaneously	low (high noise acceptance)
2	Silence, SPL below 35 dB(A)	medium
3	No conversation but background noise	medium

SOUND CLASSIFICATION AND MACHINE LEARNING ALGORITHM

In the first stage of the development, a machine learning algorithm was trained which distinguishes between two classes (binary classification):

- Class 0: single person talking (might be different people one after the other, but not simultaneously), e.g. teacher talking to students; representing SCL 0 in Table 4
- Class 1: several people talking simultaneously, e.g. groups of students talking in group discussion, representing SCL 1 in Table 4

A common method for audio classification is the application of convolutional neural networks (CNN) which are used intensively in the field of image classification [16]. At first, the audio clips are converted into images, e.g. spectrograms showing the frequency in mel-scale [17, 18]. In the next step, these images are fed into a CNN for training, validation, testing or productive application.

The classroom audio files belonging to class 0 or 1 were split into clips with a length of 5 s with an overlap of 2 s. This leads to 829 clips for class 0 for each microphone and 826 clips for class 1. For one half of the clips, the records of microphone 1 were chosen and for the other half the records of microphone 2; the same clip was never used from both microphones. Thus, the data available for training, validation and testing consist of 1655 files with a length of 5 s each. For these clips, normalised mel spectrograms were generated as shown in Figure 2.

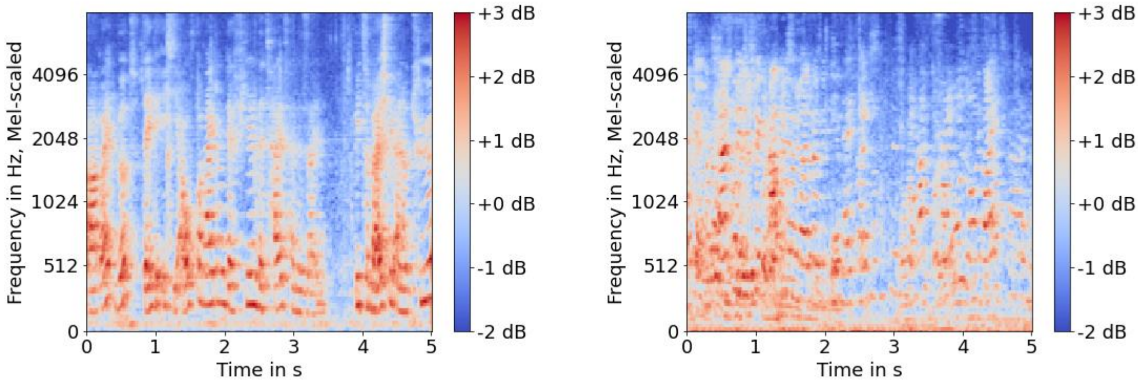

Figure 2: Mel spectrograms (normalised), left: single person talking (class 0), right: several people talking simultaneously (class 1)

80 % of the colored spectrograms were fed into a CNN model created with Keras [19], 20 % were kept for validation. The network contains three convolutional layers with normalization and max pooling layers [20] and was trained from scratch with the Adam optimizer [21]. An important finding during the model-development was the fact that the learning rate (a hyperparameter which controls how much the model may change within each iteration step) has to be very low, e.g. 1E-5. With higher learning rates, overfitting of the model was detected which leads to a poor generalization.

The final model assigns the correct sound classes with an accuracy of 98 % in the training process. In the validation process with data not shown to the CNN during training, 88 % are classified correctly. These first results are very convincing against the backdrop of quite few training data in this first approach. The reached accuracy shows that the machine-learning-based classification of the acoustical situation in a room is feasible. At the next stage, the model will be extended to more classes and increased training data.

The trained model was applied for classifying the complete classroom records with a time step of 5 s. Figure 3 illustrates the obtained result in comparison to the "true" classification by human (which is not always deterministic for short-term situations). It is obvious that the longer periods (which are important for controlling) are detected very well. From the total time with classes 0 and 1, 84 % were classified correctly with respect to the human classification.

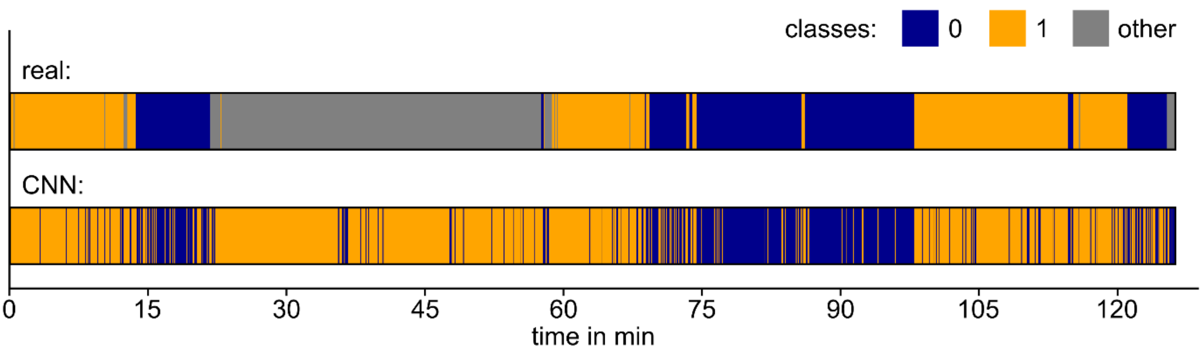

Figure 3: Real acoustical situations (classes) during classroom records compared to classification by CNN with time step of 5 s; CNN only distinguishes between classes 0 (single person talking) and 1 (several people talking simultaneously)

ACOUSTIC CONTROL SIMULATION

The acoustic control simulation is performed on the basis of the control strategy and the SCL. The calculated CO_2 concentration in the classroom is used to evaluate the control strategy according to the defined AQC (see Table 2).

The classroom for the simulation corresponds to the room parameters in Figure 1. It is assumed that

- one person emits 15 litres CO_2 per hour,
- an ACU with a supply air of 325, 650, 850 m³/h (reduced, normal, increased volume flow) is installed,
- the CO_2 concentration of supply air is 450 ppm
- the class starts with an initial CO_2 concentration of 800 ppm and
- a full-mixed ventilation scheme exists.

To achieve good air quality under the described boundary conditions, the ACU must operate with a volume flow of 650 m³/h. This keeps the CO_2 concentration under 1000 ppm while 25 students are present.

The analysis is applied to the second of both 45-min classes (70 min to 115 min in Figure 3). The corresponding SPLs are presented in Figure 4. Here, the blue curve represents the SPL of the recorded noise in the class and the AQC is represented by the background colour. The strategies how to operate the ACU (Table 1) are applied virtually and result in a specific course of the CO_2 concentration and hence the obtained AQC-levels.

The red line indicates the calculated CO_2 concentration applying Strategy 1. The supply air volume flow rate is constant over time and adapted to the load of the CO_2 emission (in proportion to the number of students).

In order to achieve acceptable noise emissions of the ACU, the performance of the ACU was virtually adapted according to Strategy 2 (if the SPL exceeds the criteria of the acoustic requirements the ACU's operation level will be lowered). This results in an adapted course of the CO_2 concentration, which is represented by the yellow line.

The third attempt is the application of Strategy 3. The SCLs as presented in Figure 3 ("real") are transferred to ACU-performance. This results in a CO_2 concentration course according to the green line in Figure 4. While at Strategy 1 the ACU is at constant, normal performance and the ACU at Strategy 2 works in normal and reduced mode at silent room conditions, Strategy 3 allows an increased operation mode if the SCLs allow a higher sound emission (according to Table 4, the acoustic requirements for SCL 1 are defined as low).

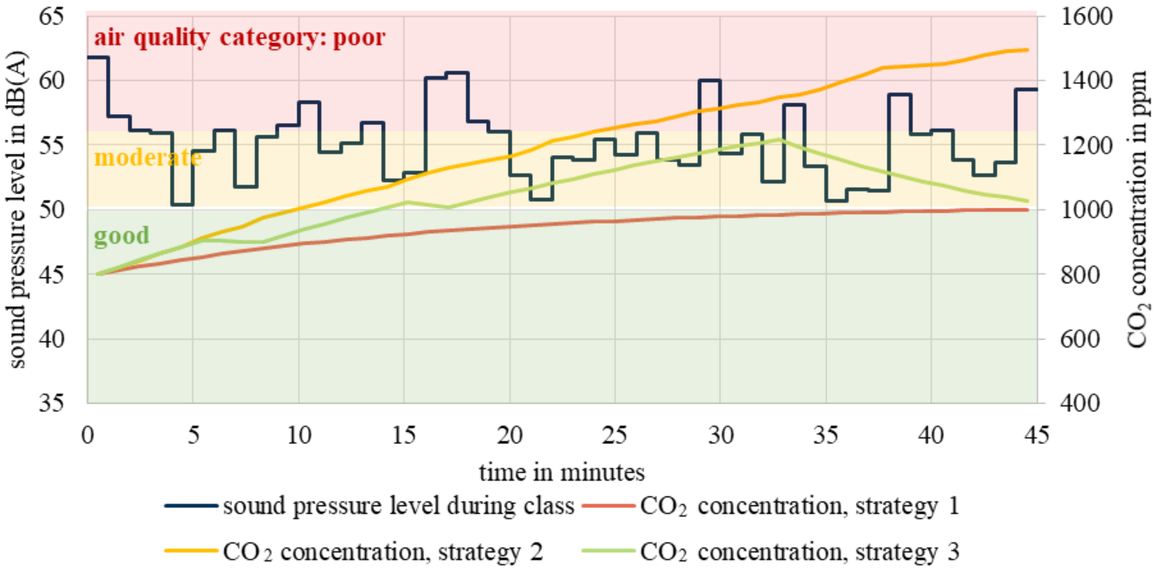

Figure 4: sound pressure level (SPL) and CO_2 concentration in the timeline for second class

The results of the calculation are summarized in Table 5. The table represents each strategy's acoustic impact at the occupants and the resulting AQC (in minutes during the class) and the maximum CO_2 level.

Table 5: comparison of the effect of the control strategy on acoustic and air quality

Strategy	acoustically disturbing	AQC in minutes			CO_2 max
		1 ("good")	2 ("moderate")	3 ("poor")	
1	yes	45	0	0	1.000
2	no	9	15	21	1.500
3	no	13	32	0	1.218

SUMMARY, CONCLUSIONS AND OUTLOOK

In this paper, the method and application of an acoustic control system for air conditioning units (ACUs) is explained. The system comprises at least one microphone and an algorithm to set the ACU's fan speed at a value that fits both, the needed air volume flow rate and the noise level acceptance.

The authors acknowledge that, at best, an ACU is already installed to meet noise criteria even at maximum airflow. But the experience shows that very often ACUs leads to disturbing noise, even if they are newly installed. Under these circumstances, the application of such an algorithm will be beneficial in terms of capital cost, changing room usage and occupants' comfort.

Depending upon the defined sound classification (SCL) and the air quality category (AQC), the supply air volume rate is adjusted in order to meet the acoustic requirements. The decision algorithm is a deep learning algorithm trained with sound records taken in a real class at a high school. The trained algorithm is capable to distinguish between one-person-presentation (SCL 0) and multiple-person-conversation (SCL 1). Surveys at schools supported the assumption that at SCL 0 it is crucial to avoid noise from ACUs and that at SCL 1 it is permitted to increase the sound emission resulting from a higher ACU-performance.

Three strategies of ACU operation were investigated. Strategy 1 operates the ACU at performance level with 640 m^3/h to ensure a good air quality, whilst Strategy 2 reduces the volume flow rate from normal to a reduced flow rate (325 m^3/h) when the sound pressure level in the room is low.

Contrary to this strategies, Strategy 3 operates the ACU in three levels of 325 m^3/h, 650 m^3/h and 850 m^3/h. The decisions of the volume flow rate (and the sound emission, respectively) depends upon the classified voice activity (SCL).

The air volume flow rate of the supply air has a direct impact on the CO_2 concentration in the room. The CO_2 concentrations correspond to defined AQCs, which represent the occupants' comfort in terms of the air quality.

Strategy 1 has the lowest CO_2 concentration and the best AQC, respectively. However, the noise emission of the ACU is not acceptable to the occupants. Strategy 2 bypasses the noise problem at the cost of the AQC. Strategy 3 performs well in terms of AQC and SPL. The noise emission is acceptable and the AQC is below 3.

In the future, a more detailed classification is necessary for a better definition of the acoustic requirement. But in this early state of the development, it is reduced to four SCLs and three levels for acoustic requirements.

The results obtained with this approach can be transferred to other room types and situations.

ACKNOWLEDGEMENTS

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LIST OF ABBREVATIONS

ACU	Air Conditioning Unit		DL	Deep Learning
AI	Artificial Intelligence		SCL	Sound Classification
AQC	Air Quality Category		SPL	Sound Pressure Level
CNN	Convolutional Neural Network		VAD	Voice Activity Detection

REFERENCES

[1] *Anforderungen an Lüftung und Luftreinigung zur Reduktion des Infektionsrisikos über den Luftweg AHA + Lüftung*. Fachverband Gebäude- Klima e.V. **2021**

[2] *AMEV 140: Hinweise zur Planung und Ausführung von Raumlufttechnischen Anlagen für öffentliche Gebäude*. Bundesministerium des Innern, für Bau und Heimat (BMI) **2018**

[3] *VDI 6022 Blatt 1 2018-01: Raumlufttechnik, Raumluftqualität - Hygieneanforderungen an raumlufttechnische Anlagen und Geräte (VDI-Lüftungsregeln)*. Verein deutscher Ingenieure **2018**

[4] Krause R. *Unterscheidungsmerkmale von Raumluftreinigungsgeräten, Ergebnisse aus Laboruntersuchungen*. In: Förderverein Gebäude- und Klimatechnik e.V. **2021**

[5] Krause R, Friebe C, Heidenreich R. *Application of Mobile Air Cleaning Devices in daily school routines*. **2021**;

[6] Friebe, C.; Krause, R.; Heidenreich, R.; Holfeld, S.; Rosenbaum, H.; Hackeschmidt, K. & Grüttner, R. *Test Procedures of Mobile Air Cleaning Devices -First Experiences and Results*. **2021**;

[7] *DIN EN 13779 Lüftung von Nichtwohngebäuden –Allgemeine Grundlagen und Anforderungen für Lüftungs- undKlimaanlagen und Raumkühlsysteme*. Deutsches Institut für Normung **2007**

[8] *DIN EN 15251:2012-12 Eingangsparameter für das Raumklima zur Auslegung und Bewertung der Energieeffizienz von Gebäuden - Raumluftqualität, Temperatur, Licht und Akustik*. Deutsches Institut für Normung **2012**

[9] Rabiner LR, Sambur MR. *An Algorithm for Determining the Endpoints of Isolated Utterances*. Bell System Technical Journal **1975**; 54: 297–315, doi:https://doi.org/10.1002/j.1538-7305.1975.tb02840.x

[10] Thasni N, Surendran S, T S. *Voice Activity Detection*. In: 1st National conference on systems, environment and energy. Government Engineering College, Kannur, Kerala **2013**

[11] Takialddin A smadi, Handam A. *Artificial Neural Networks for Voice Activity Detection Technology*. Journal of Advanced Sciences and Engineering Technologies **2022**; 5: 23–31, doi:10.32441/jaset.05.01.03

[12] Jassim WA, Harte N. *Voice Activity Detection Using Neurograms*. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). **2018**

[13] Lehner B, Widmer G, Sonnleitner R. *Improving voice activity detection in movies*. In: Proc. Interspeech 2015. **2015**

[14] Coleman R.L., Edmonds D.E., Lind S.J., Meredith D.E.J. *System and Method for Controlling HVAC Equipment so as to obtain a desired range of Sound Pressure Level and/or Sound Power Level*. **2015**;

[15] Kemp A., Delecrode C., Guida H., Ribeiro A. & Cardoso A. *Sound pressure level in a municipal preschool*. International Archives of Otorhinolaryngology **2013**; 17: 196–201, doi:10.7162/S1809-97772013000200013

[16] Piczak KJ. *Environmental sound classification with convolutional neural networks*. In: 2015 IEEE International Workshop on Machine Learning for Signal Processing, Boston, USA. **2015**

[17] Subhransu Sekhar Dash BKP C. Lakshmi Swagatam Das (ed.). *Artificial Intelligence and Evolutionary Computations in Engineering Systems*. Springer Nature **2020**

[18] Stowell D, Plumbley MD. *Automatic large-scale classification ofbird sounds is strongly improved byunsupervised feature learning*. PeerJ 2:e488 2014;, doi:10.7717/peerj.488

[19] Keras. *https://keras.io/*. **2022**;

[20] Atienza R. *Advanced Deep Learning with Keras*. Packt Publishing Ltd **2018**

[21] Kingma DP, Ba J. *Adam: A Method for Stochastic Optimization*. In: 3rd International Conference for Learning Representations, San Diego. **2015**

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