

DATA-DRIVEN TENSOR PRODUCT POLYTYPIC BASED MODEL FOR ENVIRONMENTAL NOISE MONITORING

Author(s) / Szerző(k):

Darwish Sultan
University of Debrecen (Hungary)

Zairi Housseem
University of Debrecen (Hungary)

Dénes Kocsis (Ph.D.)
University of Debrecen (Hungary)

E-mail:

housseem.zairi.hr6587@gmail.com

Cite: Sultan, Darwish; Housseem, Zairi and Kocsis, Dénes (2025): Data-driven Tensor Product Polytypic Based Model for Environmental Noise Monitoring. *Mesterséges Intelligencia – interdiszciplináris folyóirat*, VII. évf. 2025/2. szám. 45-55.

Idézés: Doi: <https://www.doi.org/10.35406/MI.2025.2.45>



This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

EP / EE: Ethics Permission / Etikai engedély: KFS/2025/MI0009

Reviewers: Anonymous reviewers / Anonim lektorok:

- Lektorok:**
1. Anonymous reviewer (Ph.D.) / Anonim lektor (Ph.D.)
 2. Anonymous reviewer (Ph.D.) / Anonim lektor (Ph.D.)
 3. Anonymous reviewer (Ph.D.) / Anonim lektor (Ph.D.)
 4. Anonymous reviewer (Ph.D.) / Anonim lektor (Ph.D.)

Abstract

This paper presents a compact matlab-based workflow for acquiring, organizing, and analyzing urban environmental noise data with a strict spatiotemporal structure. Multi-station sound pressure level (SPL) measurements are organized into a three-dimensional tensor, unfolded into a two-dimensional matrix, and analyzed using singular value decomposition (SVD) to extract dominant spatial and temporal patterns. Two lightweight normalization schemes cumulative normalized output (CNO) and separated normalized noise nodes (SNNN) are introduced to support low-rank reconstruction, anomaly detection, and decision-making. A case study conducted in Debrecen, Hungary, over an eight-week period (daily averages) demonstrates the effectiveness of the proposed methodology by revealing clear weekly patterns and midweek noise anomalies. The framework is scalable to dense sensor networks and can be integrated into smart city dashboards, offering a robust foundation for adaptive urban planning and real-time environmental noise management.

Keywords: Environmental noise; MATLAB; tensor data; singular value decomposition; smart city monitoring

Discipline: Environmental Engineering

AbsztraktADATVEZÉRELT TENZORSZORZAT-POLITÍPUS ALAPÚ MODELL
KÖRNYEZETI ZAJMONITOROZÁSHOZ

Ez a tanulmány egy kompakt, MATLAB-alapú munkafolyamatot mutat be a városi környezeti zajadatok szigorú tér-időbeli struktúrában történő gyűjtésére, rendszerezésére és elemzésére. A több mérőállomáson végzett hangnyomásszint (SPL) mérések háromdimenziós tenzorba kerülnek szervezésre, majd kétdimenziós mátrixba kifejtve szingulárisérték-felbontással (SVD) kerülnek elemzésre a domináns térbeli és időbeli mintázatok feltárása érdekében. A tanulmány két könnyűsúlyú normalizálási eljárást vezet be – a kumulatív normalizált kimenetet (CNO) és a szétválasztott normalizált zajcsomópontokat (SNNN) –, amelyek támogatják az alacsony rangú rekonstrukciót, az anomáliadetektálást és a döntéstámogatást. Egy esettanulmány, amelyet Debrecenben végeztek egy nyolchetes időszak alatt (napi átlagértékekkel), igazolja a javasolt módszertan hatékonyságát azáltal, hogy jól elkülönülő heti mintázatokot és a hét közepére jellemző zajanomáliákat tár fel. A keretrendszer skálázható sűrű szenzorhálózatokra, és integrálható okosváros-irányítópultokba, így robosztus alapot nyújt az adaptív várostervezéshez és a valós idejű környezeti zajkezeléshez.

Kulcsszavak: környezeti zaj; MATLAB; tenzoradatok; szingulárisérték-felbontás; okosváros-monitorozás

Diszciplína: környezetmérnöki tudomány

Environmental noise has become a pressing public health issue, particularly in densely populated urban areas where rapid population growth and infrastructure development contribute to rising noise levels. Extended exposure to high noise levels is associated with a variety of health problems, ranging from hearing loss to cardiovascular issues, as well as cognitive and sleep-related disturbances, making noise pollution a critical environmental and societal challenge (Basner et al., 2014; Sheikhmozafari et al., 2025; Chen et al., 2023). Traditional noise mapping approaches often rely on sparse, static measurements that capture only limited snapshots of the acoustic environment. Classical statistical techniques, such as linear or multiple regression models, are valued for their simplicity and low computational demands (Maulud & Abdulazeez, 2020). However, they struggle to capture the complex and dynamic spatiotemporal patterns of urban noise and tend to perform poorly when datasets are missing or irregular (Chen et al., 2015; Ahmed & Raihan, 2024).

The increasing deployment of real-time sensor networks and Internet of Things (IoT) based platforms has significantly improved the capacity for continuous acoustic monitoring and high-resolution data collection (Gunatilaka et al., 2025; Banaras & Nasir, 2025). While these systems generate valuable datasets, they also introduce challenges related to storage, processing, and interpretation. Addressing these challenges requires advanced analytical approaches that can efficiently model large-scale spatiotemporal

data while maintaining interpretability and scalability.

Recent advances in machine learning (ML) and artificial intelligence (AI) have been applied to environmental noise prediction and classification, often outperforming traditional statistical methods (Ali et al., 2022). Techniques such as neural networks and clustering algorithms provide powerful tools for uncovering hidden patterns, but they typically require extensive computational resources and large labeled datasets. Moreover, their “black-box” nature limits transparency, making it difficult for urban planners and policymakers to interpret and act on the results (Ali et al., 2022; Albaji et al., 2022; Szandala, 2023). A tensor-based framework offers an effective solution by organizing environmental data in a multidimensional form, allowing both spatial and temporal relationships to be retained. Spatiotemporal tensor decomposition methods, such as those based on Singular Value Decomposition (SVD), enable simultaneous data reduction, pattern extraction, and noise filtering, offering both computational efficiency and interpretability (Sudár et al., 2025; Auddy et al., 2024). Prior research on fuzzy modeling and rule-based reduction has also demonstrated the value of simplifying complex decision-making systems, which aligns closely with the goals of the present study (K & M. B, 2024; Jin et al., 2019; Dénes & Baranyi, 2000). Building on these concepts, this paper introduces a data-driven tensor product polytypic framework developed in MATLAB for urban noise monitoring and analysis. In the proposed

methodology, raw Sound Pressure Level (SPL) data collected from multiple monitoring stations are structured into a three-dimensional tensor. The tensor is then unfolded into a two-dimensional matrix and processed using SVD to reveal dominant spatiotemporal structures. This approach supports low-rank approximations, temporal modeling, and anomaly detection while remaining computationally efficient and interpretable. To validate the framework, a case study was conducted in Debrecen, Hungary. Over an eight-week period, the system successfully identified consistent weekly acoustic cycles and midweek anomalies with high precision. These results highlight the potential of the proposed framework as a decision-support tool for smart urban planning, adaptive noise regulation, and real-time environmental management systems.

Methodology

This section presents a systematic methodology for analyzing environmental noise using a 3D tensor-based approach in MATLAB. Earlier works concentrated on the straightforward reduction of heuristically generated rule bases.

The methodology aims to transform raw monitoring data into actionable insights by employing signal processing, mathematical modeling and visualization techniques.

Data Structure and Collection. Environmental noise levels were recorded using a network of fixed monitoring stations distributed across various urban zones. The collected data comprises daily average Sound Pressure

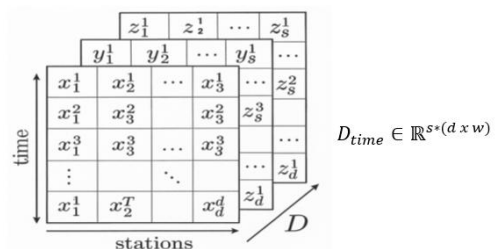
Levels (SPL) measured in decibels (dB), organized in a 3D tensor format to capture spatiotemporal dynamics:

- Spatial axis (s): Stations (e.g., $s = 12$)
- Temporal axis (d): Days of the week (Monday to Sunday, $d = 7$)
- Week index (w): Weekly observations (e.g., $w = 8$)

The tensor encapsulates the average SPL at each station (i), on each day (j), during each week (k).

Tensor Flattening and Matrix Construction. To facilitate decomposition techniques like SVD, the 3D tensor is unfolded into a 2D matrix: each row represents a monitoring station, and each column a specific day across all weeks. Example: the resulting tensor \mathcal{D} has a shape of $(12 \times 7 \times 8)$, corresponding to 12 stations, 7 days per week, and 8 weeks. The tensor is then reshaped into a matrix \mathbf{D}_{time} of shape (12×56) , preserving the spatial resolution while flattening the temporal dimensions for easier linear algebra processing (Figure 1).

Figure 1. Tensor-to-matrix unfolding for SVD analysis.



Singular Value Decomposition (SVD). SVD is applied to the flattened matrix:

$$D_{\text{time}} = U \cdot \Sigma \cdot V^T$$

Left singular vectors (spatial patterns)

Diagonal matrix of singular values

Right singular vectors (temporal patterns)

This factorization isolates the dominant modes of variation in noise across space and time.

Temporal Weight Function Extraction. Once the singular value decomposition (SVD) is performed on the unfolded noise matrix, the resulting right singular matrix contains vectors that represent the temporal modes of noise variation.

To analyze temporal behavior, the first two right singular vectors are selected. These vectors are transformed into weight functions:

$$\omega_1(S_a) = V_1(S_a)$$

$$\omega_2(S_a) = V_2(S_a)$$

Where $S_a \in [1, d \cdot w]$ represents a specific time index combining day and week. These temporal weight functions serve the following roles:

ω_1 Captures baseline trends in the noise profile, such as weekly periodicity and stable daily cycles.

ω_2 Captures secondary oscillations, reflecting more nuanced variations, such as day-to-day anomalies or mid-week disturbances.

In the case study conducted over May and June, these functions revealed:

ω_1 highlighted a repetitive weekday/week-end pattern, particularly peaking during workdays and dropping during weekends.

ω_2 emphasized periodic deviations, suggesting the presence of irregular local activities or transient noise sources (e.g., construction, traffic surges).

Together, these extracted functions provide the temporal structure necessary for downstream modeling and enable the decomposition of noise evolution into interpretable components.

Normalization Techniques. To enhance interpretability and robustness, two normalization techniques are integrated:

- Cumulative Normalized Output (CNO), which highlights long-term temporal trends and recurring daily patterns.

- Separated Normalized Noise Nodes (SNNN), which isolates short-term irregularities and high-intensity noise events.

Noise Pattern Modeling. The normalized weight functions are combined linearly to model the SPL signal: Where and control the contribution of each mode.

Model examples: Raw SVD; CNO; SNNN

Pattern Recognition and Decision Support. The extracted models support various practical applications:

- Recurring Pattern Detection: Identifying weekday-weekend cycles or seasonal effects.

- Anomaly Detection: Spotting unexpected events or deviations.

- Classification: Grouping days by similar noise behavior.

- Urban Noise Mitigation: Locating high-risk zones and optimal intervention times.

- Policy Evaluation: Measuring the impact of noise control strategies.

- Smart City Integration: Enabling real-time monitoring and alerts.

This methodology offers a comprehensive and scalable framework for environmental noise analysis using advanced signal decomposition in MATLAB.

Each model serves a specific purpose: trend extraction, anomaly detection, or signal reconstruction

Results And Discussion

Case Study: Station-Based Noise Analysis

To demonstrate the practical application of the proposed methodology, a case study was conducted using data from a single noise monitoring station situated in central Debrecen, Hungary. The location was chosen based on its suitable positioning and consistent recording performance.

The study covers the months of May and June (2025), totaling eight weeks. This duration enables identification of both transient acoustic disturbances and recurring weekly sound patterns. Data analyzed consisted of daily average sound pressure levels (SPLs), measured in A-weighted decibels (dB(A)), processed using the entire 3D noise analysis pipeline: tensor construction, matrix flattening, singular value decomposition (SVD), normalization, and temporal modeling.

This case study validates the methodology's ability to:

- Capture temporal dynamics
- Detect Anomalies
- Generate decision-supporting insights into noise management

Data Collection

The dataset originates from one Class 1 SV 307A noise monitoring station and covers 8 weeks (May-June), with a daily resolution. The structured format was a 3D tensor, reshaped into a 2D matrix for analysis (Table 1).

Table 1. Daily average SPL readings over 8 weeks [dB(A)]

Day	Week							
	W1	W2	W3	W4	W5	W6	W7	W8
Monday	54.9	53.3	52.0	52.3	53.2	55.4	56.9	56.9
Tuesday	54.5	53.2	53.5	51.4	54.6	56.4	53.4	56.2
Wednesday	55.1	52.9	54.6	53.6	55.3	55.4	55.5	53.1
Thursday	53.4	52.1	53.7	52.4	54.3	58.2	55.4	54.9
Friday	50.8	54.8	51.9	56.3	55.4	55.8	55.1	53.5
Saturday	50.4	55.2	51.6	52.3	53.6	51.7	52.9	52.5
Sunday	52.3	49.6	51.8	50.5	52.0	51.9	51.7	50.4

Results from MATLAB Simulation

Tensor Reshaping:

- Decomposition: SVD yields dominant vectors
- Normalization: Applied via CNO and SNNN methods

Model Outputs:

Raw model:

$$SP_{\text{mas}}(sa) = 233 \cdot w_1(sa) + 6 \cdot 10^{-14} \cdot w_2(sa)$$

CNO model:

$$SP_{\text{mac}}(sa) = 44 \cdot w_1^{\text{cno}}(sa) + 60 \cdot w_2^{\text{cno}}(sa)$$

SNNN model:

$$SP_{\text{snnn}}(sa) = \alpha \cdot w_1^{\text{snnn}}(sa) + \beta \cdot w_2^{\text{snnn}}(sa)$$

Key Insights:

- Weekly cycles and anomalies confirmed
- CNO: Emphasizes long-term structure
- SNNN: Highlights daily variability

Table 2 shows model errors, and Figure 2 summarizes the weekly normalization comparisons.

Table 2. Model errors per week

Week	ER_snnn	ER_cno
1	$1.56e^{-13}$	$2.13e^{-14}$
...
8	$9.94e^{-14}$	$1.42e^{-14}$

Multi-Week Analysis

To better interpret temporal dynamics, average normalized curves (Figure 3) were computed for three periods: Weeks 1–4, Weeks 5–8, and Weeks 1–8. Both CNO and SNNN methods were used to construct representative sound profiles by linearly combining the first two temporal weight functions.

CNO curves highlighted smooth, long-term trends across days and weeks.

SNNN curves emphasized short-term variability and anomalies.

Key Patterns Identified:

- Midweek Peaks (Day 3 – Wednesday): Recurrent noise spikes linked to increased midweek activity.

- Weekend Calm (Days 6–7 – Saturday & Sunday): Notable decrease in noise, reflecting reduced urban activity.

These patterns remained consistent across all time segments, validating the reliability of both normalization approaches in capturing meaningful temporal structures in environmental noise.

Figure 2. Weekly normalization comparisons (CNO vs. SNNN)

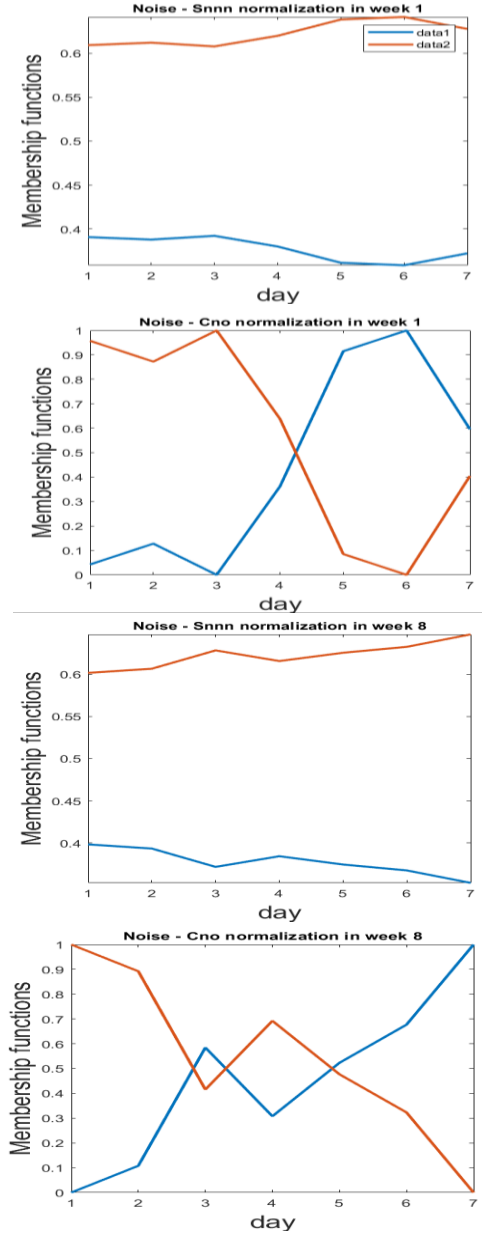


Figure 3. Average normalized values (W1–W8)

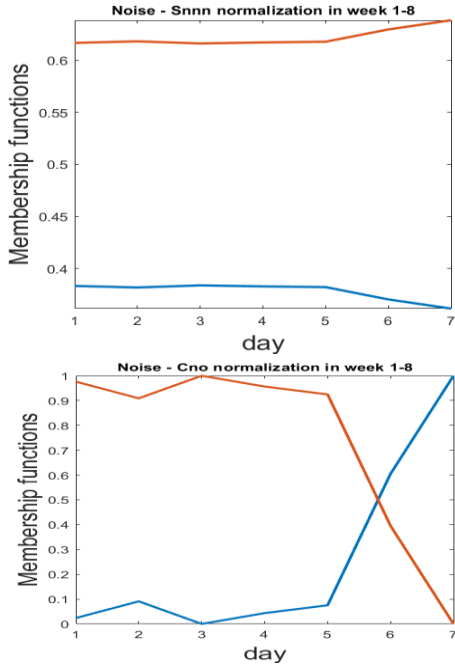
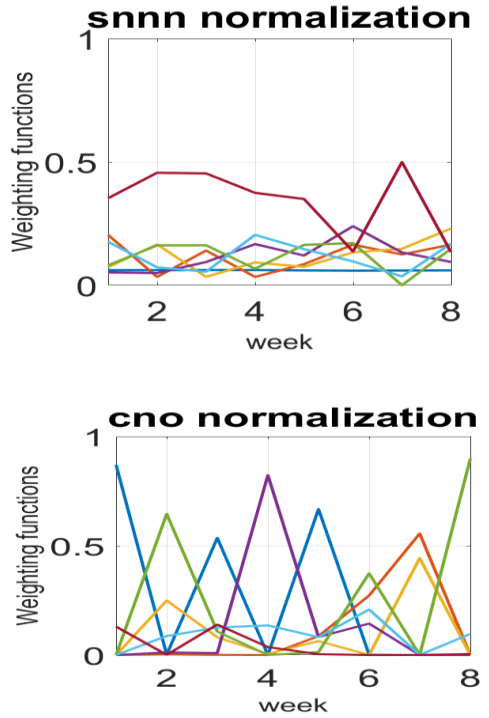


Figure 4. Normalized weighting functions



Weighting Function Identification

- SNNN: A dominant dark red curve models ambient noise trends best.
- CNO: The blue curve models peak midweek noise.

The normalized weighting functions can be seen in Figure 4.

Spatio-Temporal Surface Analysis

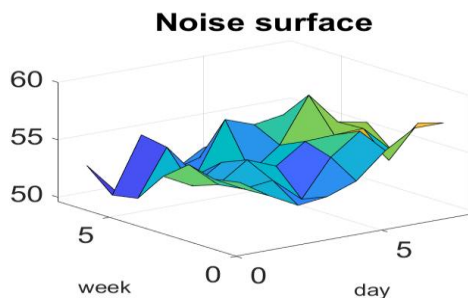
3D noise surface reveals (Figure 5):

- Midweek noise ridges
- Weekend valleys

SNNN: One dominant component

CNO: Chaotic peaks (local events)

Figure 5. Noise surface – 3D



To sum up, SNNN normalization provides a stable reference for ambient noise modeling, while CNO captures short-term noise disturbances (Table 3). These insights are essential for adaptive urban noise mitigation strategies.

Table 3. Summary of findings

Feature	SNNN	CNO
Pattern	Smooth, stable	Fragmented, volatile
Dominance	One major component	Multiple transient peaks
Usefulness	Long-term modeling	Local disturbance detection

Analysis and Interpretation

The MATLAB-based analysis of environmental noise data yielded several key insights into the temporal and structural behavior of urban sound patterns:

- **Dominance of a principal component:** The first singular value consistently captured more than 90% of the total variance, indicating the presence of a dominant and repetitive trend in the noise data. This component reflects the regular weekly rhythm of urban noise, with identifiable high and low cycles.
- **Secondary mode differentiation:** The second singular mode introduced moderate fluctuations, corresponding to behavioral transitions between weekdays and weekends. These shifts illustrate the natural alternation between high-activity (workdays) and low-activity (weekend) environments.
- **Temporal consistency and weekly structure:** The reconstructed SPmac surface model

demonstrated a stable weekly pattern across multiple weeks, with systematic noise peaks observed midweek (especially on day 3 or 4) and significant declines toward the weekend, confirming earlier statistical observations.

- **Detection of local noise anomalies:** The SNNN normalization model revealed distinct outlier contributions, associated with short-duration, high-intensity noise events. These include likely causes such as traffic congestion, public events, or construction, and were clearly identifiable due to the sharp concentration in the weighting and SC (spatial-temporal concentration) maps. **Model stability and interpretability:** While CNO normalization revealed highly chaotic and scattered contributions, SNNN normalization exhibited structured, dominant components — particularly one that aligned strongly with weekend silence. This confirms that silence modeling offers more stable and interpretable structures than raw noise amplitude.

These outcomes demonstrate the effectiveness of combining singular value decomposition (SVD), spatio-temporal modeling, and normalized weighting functions for extracting meaningful information from raw environmental data. The results are not only statistically robust, but also operationally relevant for practical noise monitoring and control systems.

Conclusion

The analysis of environmental noise data over eight consecutive weeks has highlighted the structured, cyclical nature of the examined

urban soundscape, with consistent patterns of midweek noise surges and weekend calm. Using advanced matrix decomposition techniques and membership function normalization (CNO and SNNN), the study successfully:

- Isolated week-specific anomalies and spikes, and
- Revealed a clear weekly acoustic rhythm.

Among the models, SNNN normalization proved the most effective in revealing structured, interpretable ambient noise patterns, while CNO normalization emphasized the irregular and reactive nature of noise events.

This methodological framework offers a valuable foundation for:

- Early-warning systems for noise pollution,
- Urban acoustic planning,
- Policy-driven interventions targeting specific temporal windows of noise vulnerability.

In sum, the work demonstrates that noise monitoring can go beyond raw decibel levels toward intelligent pattern recognition, strategic mitigation, and sustainable sound management in modern urban environments.

References

- Ahmed, I., & Raihan, A. S. (2024). *Spatiotemporal Data Analysis: A Review of Techniques, Applications, and Emerging Challenges BT – Multimodal and Tensor Data Analytics for Industrial Systems Improvement* (N. Gaw, P. M. Pardalos, & M. R. Gahrooei (eds.); pp. 125–166). Springer International Publishing. Doi: https://doi.org/10.1007/978-3-031-53092-0_7
- Albaji, A. O., Rashid, R. B. A., Sarijari, M. A. Bin, Salam, Z. Bin, Hamid, S. Z. A., & Ali, Y. H. (2022). *A Machine Learning for Environmental Noise Monitoring and Classification Using Matlab*. June 2024, 194–217. Doi: <https://doi.org/10.5281/zenodo.6640773>
- Ali, Y. H., Rashid, R. A., & Hamid, S. Z. A. (2022). A machine learning for environmental noise classification in smart cities. *Indonesian Journal of Electrical Engineering and Computer Science*, 25(3), 1777–1786. Doi: <https://doi.org/10.11591/ijeecs.v25.i3.pp1777-1786>
- Auddy, A., Xia, D., & Yuan, M. (2024). *Tensor Methods in High Dimensional Data Analysis: Opportunities and Challenges*. 1–38. Opened: 01.12.2025. URL: <http://arxiv.org/abs/2405.18412>
- Banaras, F., & Nasir, W. (2025). *Real-Time IoT-Based Monitoring of Mechanical Systems Using Acoustic and Vibration Data*. Opened: 01.12.2025. URL: <https://www.researchgate.net/publication/389338528>
- Basner, M., Babisch, W., Davis, A., Brink, M., Clark, C., Janssen, S., & Stansfeld, S. (2014). Auditory and non-auditory effects of noise on health. *The Lancet*, 383(9925), 1325–1332. Doi: [https://doi.org/10.1016/S0140-6736\(13\)61613-X](https://doi.org/10.1016/S0140-6736(13)61613-X)

- Chen, X. C., Faghmous, J. H., Khandelwal, A., & Kumar, V. (2015). Clustering dynamic spatio-temporal patterns in the presence of noise and missing data. *IJCAI International Joint Conference on Artificial Intelligence*, 2015-Janua(Ijcai), 2575–2581.
- Chen, X., Liu, M., Zuo, L., Wu, X., Chen, M., Li, X., An, T., Chen, L., Xu, W., Peng, S., Chen, H., Liang, X., & Hao, G. (2023). Environmental noise exposure and health outcomes: an umbrella review of systematic reviews and meta-analysis. *European Journal of Public Health*, 33(4), 725–731. Doi: <https://doi.org/10.1093/eurpub/ckad044>
- Dénes, I., & Baranyi, P. (2000). Inverse Model of DC-DC Converters. *IFAC Proceedings Volumes*, 33(28), 147–152. Doi: [https://doi.org/10.1016/s1474-6670\(17\)36825-8](https://doi.org/10.1016/s1474-6670(17)36825-8)
- Gunatilaka, D., Sawangphol, W., Charoenritthitham, T., Kanjanapoo, T., Burasotikul, T., & Pongprasit, K. (2025). An acoustic sensing system for noise monitoring and source identification using transfer learning. *Expert Systems With Applications*, 299(PB), 130014. Doi: <https://doi.org/10.1016/j.eswa.2025.130014>
- Jin, Y., Cao, W., Wu, M., & Yuan, Y. (2019). Accurate fuzzy predictive models through complexity reduction based on decision of needed fuzzy rules. *Neurocomputing*, 323, 344–351. Doi: <https://doi.org/10.1016/j.neucom.2018.10.010>
- K, N., & M. B, M. K. (2024). Fuzzy rule based classifier model for evidence based clinical decision support systems. *Intelligent Systems with Applications*, 22(May), 200393. Doi: <https://doi.org/10.1016/j.iswa.2024.200393>
- Maulud, D., & Abdulazeez, A. M. (2020). A Review on Linear Regression Comprehensive in Machine Learning. *Journal of Applied Science and Technology Trends*, 1(2 SE-Standard Journal Issues), 140–147. Doi: <https://doi.org/10.38094/jastt1457>
- Sheikhmozafari, M. J., Omari Shekaftik, S., Fasih Ramandi, F., Monazzam Esmaeelpour, M. R., & Biganeh, J. (2025). A review of the studies investigating the effects of noise exposure on humans from 2017 to 2022: Trends and knowledge gaps. *Noise Mapping*, 12(1). Doi: <https://doi.org/10.1515/noise-2025-0015>
- Sudár, A., Berki, B., & Horváth, I. (2025). Fuzzy model-based analysis of user feedback for product development insights. *Heliyon*, 11(12), e43537. Doi: <https://doi.org/10.1016/j.heliyon.2025.e43537>
- Szandala, T. (2023). Unlocking the black box of CNNs: Visualising the decision-making process with PRISM. *Information Sciences*, 642(May), 119162. doi: <https://doi.org/10.1016/j.ins.2023.119162>