CONCEPTUAL ARCHITECTURE FOR IMPARTING AI WITH OLFACTION: INTEGRATION OF ELECTRONIC NOSES, AROMA GENERATORS AND LLM

Aldeniz Rashidov, Fatme Rashidova*

Technical University of Gabrovo, Gabrovo,
Bulgaria

* Corresponding Author, e-mail: aldeniz@tugab.bg

Abstract: This paper proposes a conceptual architecture to integrate olfaction into AI using an electronic nose, an odor generator, and large language models like ChatGPT. The electronic nose detects odors via chemical sensors, while the aroma generator reproduces similar scents remotely. Large language models enhance real-time system calibration and provide a natural language interface, addressing issues like signal standardization, sensor calibration, and data interpretation. Potential applications span industry, medicine, VR/AR, and e-commerce. The outlined workflow and challenges pave the way for prototyping and real-world testing to redefine AI's interaction with the physical and digital worlds.

Key words: artificial intelligence, electronic nose, large language models, machine learning, aromatic generators.

1. INTRODUCTION

The sense of smell is one of the most subtle and complex human senses, playing a key role in many areas of human activity, from food and cosmetics to medical diagnostics and security systems, and the ability to "digitize" smells (simultaneously capture, analyze and transmit) opens up new horizons for innovative applications and research - for example, clever detection of spoiled food, personalized scent offerings in online sales, or even virtual reality travel where smells complement vision and hearing.

Parallel to the fast development of the Internet of Things (IoT) and modern Large Language Models (LLMs) such as ChatGPT and Copilot, which could process sensor data, offer natural-language descriptions of detected odors, and accept calibration commands, interest in digital olfaction continues to grow and open up a wide range of new applications - automated recognition of sets of chemical signals coming from an electronic nose; describing scents through dialogue ("That smells like citrus with hints of clove"); two-way interaction with the user to specify or calibrate the sense of smell ("Do you want a weaker or stronger cinnamon note?").

Today, a variety of electronic noses (e-noses) are being developed that integrate multiple gas and chemical sensors to detect volatile organic compounds, as well as aroma generators (diffusers) widely used to enrich the air with certain scents [1-3]. Despite the success of machine learning and deep learning for odor classification, attempts to merge electronic noses with LLM for dialog interpretation and odor calibration remain limited [4-7].

There are projects focused on either scent recognition or scent dispersion, but no comprehensive solutions exist that cover the full cycle - from capture to remote reproduction, utilize LLMs for natural language interface and analysis, and offer a standardized format for encoding and decoding scent data.

Filling these gaps could lead to the creation of fully integrated AI digital olfaction systems, where an electronic nose detects the scent, an LLM recognizes and describes (or calibrates) it, and a scent generator reproduces a similar scent at a remote location.

Such a solution has great practical value in industry (accelerated quality inspection), medicine (early diagnosis by breath odor), virtual reality and augmented reality (VR/AR) environments (more complete immersion) and e-commerce (virtual "sniffing" of products). Such an approach would change the way humanity interacts with the digital world, bringing us one step closer to a complete cyber-physical reality.

While electronic noses, diffusers, and AI language models have all been advanced individually, a complete solution that both captures and reproduces scents with a conversational interface has not yet been developed.

This study aims to propose a conceptual architecture for an integrated solution – a full cycle from odor capture to reproduction, based on an electronic nose, an aroma generator and an LLM.

In this regard, the main tasks are related to the presentation of a common architecture and logical sequence between the components (electronic nose, LLM and aroma generator), the identification of key challenges, and the formulation of next steps for real experiments and tests to validate the proposed concept under practical conditions.

2. CONCEPTUAL ARCHITECTURE FOR GIVING AI OLFACTION

Figure 1 shows a conceptual flowchart of the integrated solution that gives AI the ability to do full digital olfaction - from capturing and analyzing real odors to reproducing them at a remote point. The schematic illustrates how the e-nose, based on multiple sensors, collects odor data that is passed through layers for pre-processing and classification. The resulting information is processed by a LLM, which provides the AI with the ability to "sense" and describe odors in user-understandable language, as well as accept natural-language commands to calibrate or modify scents.

The second main part of the flowchart reflects the aroma generator (diffuser/dispenser) which, guided by the LLM's instructions, mixes the necessary essences to reproduce a similar aroma in real time. The user (or another kind of feedback system) can give new instructions for fine-tuning the smell ("sweeter", "less minty", etc.) that feed back to the language model. This closes the two-way process - "smell - analyze - transmit - reproduce - feedback" - that is the basis of the concept of AI olfaction imparting.

A more detailed description of the main components of the flowchart, their functionality and role in the integrated process follows:

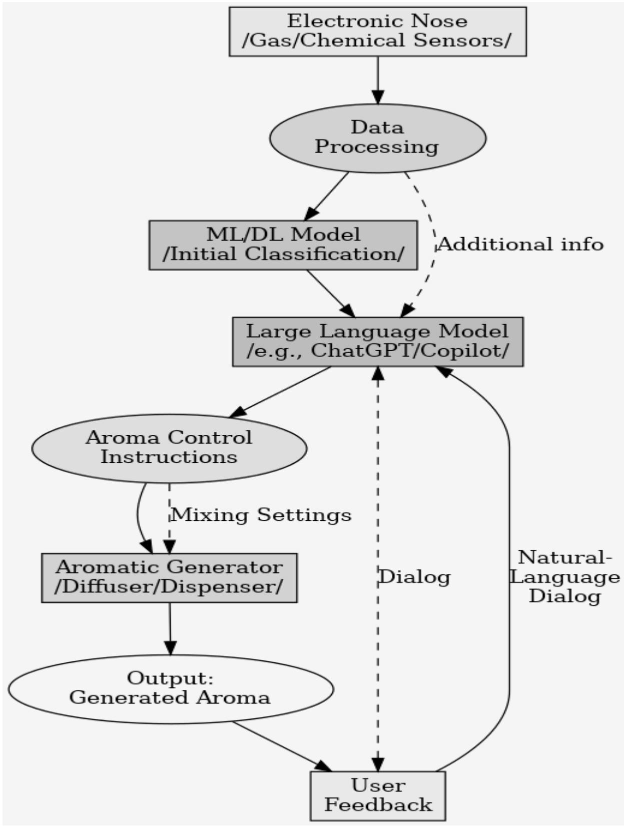

Figure 1. A conceptual flowchart of the integrated solution

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2.1. Electronic nose

The electronic nose is the first point of contact between the physical environment and the AI system. It collects information about volatile organic compounds (VOCs) from the environment - critical for any olfaction-related application. By using different types of sensors, the e-nose can provide a unique "scent fingerprint" for each specific odor. This fingerprint is the basis on which subsequent data processing and classification is performed. The e-nose converts the analogue signals generated on contact with the VOC into digital data that the system can process. The data is transmitted to the AI system via standardized communication protocols (e.g. Wi-Fi, Bluetooth), providing a real-time flow of information.

The e-nose data are used to train and fine-tune Machine Learning / Deep Learning (ML/DL) models that classify and interpret odors. This allows the AI, through the large language models, to get better at describing and reproducing specific scents. Sensory data undergoes pre-processing and is analyzed by the AI in real time, allowing for rapid recognition of scents and adaptation of reproduction according to dynamic environmental conditions.

Choosing sensors that cover a wide range of VOCs allows the system to capture a more diverse range of odors, minimizing false positives and improving classification accuracy. To maintain the accuracy of the measurements, the e-nose must be periodically calibrated with known standard fragrances. Software algorithms to dynamically adapt the calibration in real time, according to environmental conditions, also contribute to the reliability of the system. The use of filtering algorithms that remove background noise and unnecessary information from the sensor data is recommended.

To avoid information loss and increase processing speed, it is necessary to provide secure and standardized communication between the e-nose and the next layers in the architecture (data processing, ML/DL model and LLM).

The electronic nose functions as a gateway to the system, providing primary sensor data for subsequent processing. It is a critical part of the architecture's input chain - without reliable and accurate odor sensing, the entire system could not operate efficiently. The e-nose data is passed to processing and machine learning layers where it is used for classification and management. Therefore, the quality and accuracy of the e-nose data directly affects the performance of the entire AI-assisted olfactory process.

An exemplary electronic nose can be implemented using a Raspberry Pi combined with a set of MQ series gas sensors (e.g., MQ-2, MQ-3, MQ-135) and additional Figaro or TGS sensors, tailored to the specific aromas to be captured [1, 8]. This configuration collects sensor data in real-time and transfers it to the AI system via standard communication interfaces (e.g., Wi-Fi, Bluetooth), enabling seamless integration with large language models and other AI components. The data undergoes processing and machine learning, after which the AI interprets and manages the process. Instructions are generated to control the aroma generator, which reproduces the aromas through a diffuser or dispenser, completing the workflow.

2.2. Data processing

This component is responsible for filtering, normalizing, and extracting relevant features from the raw sensor data collected by the electronic nose. Data processing is used to prepare the input information before it is analyzed by the ML/DL models and the LLM. This includes background noise removal, data normalization, and extraction of key features needed for accurate odor classification. The processed data is fed to the next stage, ML/DL model pre-classification, which improves the accuracy and efficiency of the system, allowing the AI to better understand the environment.

A software platform such as Python, which combines scientific computing and machine learning libraries, can be used to implement this component. For example, using the SciPy library, a digital filter (e.g. Butterworth filter) can be applied to the raw signals from the sensors to remove background noise and unwanted interference. Using scikit-learn or NumPy, normalization can be performed by standardizing the data over a range

[0,1], which ensures comparability of measurements from different sensors. Through dimensionality reduction techniques such as Principal Component Analysis or other methods, key features that characterize odor can be extracted. These features serve as input to the ML/DL models.

2.3. ML/DL model (Preliminary classification)

This component is responsible for the initial classification of the processed sensor data. Once the data from the electronic nose passes through the processing phase, it is fed to the ML/DL model. Using pre-trained machine or deep learning algorithms (e.g., neural networks such as CNN or MLP), the model analyzes the extracted features and classifies the specific odors [9]. Here, the sensory features are transformed into more explicit labels (e.g. "coffee", "citrus", etc.). The model can apply noise reduction and feature optimization techniques, which increases the classification accuracy. The classification results - probability scores or labels of detected odors - are passed to the large language model for further interpretation and interaction.

The use of large and diverse training datasets improves the generalizability of the model. It can be periodically retrained or adapted for new smells and conditions, allowing the AI to improve over time.

A software platform such as TensorFlow with Keras API [10] can be used to build the ML/DL model. Using this platform, a neural network including several layers (Dense and Dropout) is created for classification. The network is trained on a preprocessed dataset containing extracted features from different odors. The training process involves minimizing the error between the predicted classes and the actual labels. After training, the model can accept new input data from the processed sensors and classify the odors with high accuracy, providing the results for subsequent interpretation by the LLM.

2.4. Large Language Model

Once the ML/DL model performs the pre-classification, the data is passed to the LLM, which plays a key role in the interpretation and management of the process. The LLM takes the results from the ML/DL model and converts them into human-readable descriptions of the odors - for example, "This smells like citrus with hints of clove". Unlike traditional ML models, LLMs enhance real-time odor calibration by interpreting ambiguous sensor patterns through contextual understanding and user feedback, enabling adaptive adjustments that better reflect subjective scent perceptions. The model dialogues with the user, accepts natural language commands ("Make scent stronger", "Add minty notes") and interprets them to optimize system settings. Based on interpretation and feedback, the LLM generates instructions for the aroma generator that optimizes odor reproduction. LLM uses adaptive dialogue strategies to understand the context and nuances of the user's commands. For example, after a series of interactions, the model can learn that the user prefers lighter or more intense aromas depending on the situation and automatically adjusts the reproduction parameters accordingly. Working as a bridge between data processing and physical reproduction, the LLM coordinates communication between the ML/DL layer and the scent generator, providing a smooth and interactive process for imparting scent to the AI.

Example implementation of LLM usage:

- Through an LLM-based chat or voice interface platform (e.g. ChatGPT), users can interact with the system. They submit descriptions of desired aroma changes, to which the LLM responds with clear instructions.
- The LLM is deployed in a cloud service or on-premises environment where it receives input from the ML/DL module. Through text processing API, LLM can accept results such as "probabilistic aroma: citrus with hints of clove" and generate responses and instructions.

To explain more clearly how the system works step by step, a brief description of the workflow representing the sequence of interactions between the ML/DL model, the LLM, the user and the aroma generator follows:

- The ML/DL model sends a classification result to the LLM.
- LLM converts this result into human understandable expression and sends it to the user or uses it to automatically generate instructions.
- The user can adjust or refine their preferences via a text/voice interface.
- LLM interprets these commands and generates specific instructions for the aroma generator.

2.5. Aromatic generator

The odor generator is the physical device that reproduces odors based on the digital instructions provided by the LLM. It converts the commands for mixing and adjusting fragrances into specific odor reproduction by controlling the amount and proportions of fragrance essences released [11].

The aroma generator receives control commands from the LLM. These instructions determine which essences to use, in what proportions and at what intensity to reproduce the desired smell. The device contains reservoirs with specific aroma essences (e.g. citrus, mint, clove). Based on the instructions received, the aroma generator mixes the essences in appropriate proportions to create the desired aroma. Through built-in diffusion or evaporation techniques, the generator releases mixtures of essences into the environment. This can be done by ventilation, heating or other mechanisms that ensure even distribution of the aroma.

The aroma generator is connected to the LLM or control component that sends instructions. This can be done via local communication (e.g., via a serial port or GPIO pins on the Raspberry Pi) or via a network connection if the device is compatible with IoT protocols. The generator works in close conjunction with the LLM, receiving updated instructions based on user feedback or changes in the surrounding environment. This allows dynamic aroma tuning in real time.

To accurately reproduce odors, the generator must have high control over the dosage and mixing of the different aroma essences. The reservoirs and mechanical parts of the generator require periodic maintenance to maintain the quality of the fragrances released.

For example, an aroma generator can be implemented by a combination of a microcontroller (Raspberry Pi or Arduino) that controls a diffuser equipped with reservoirs for different aroma essences (such as citrus, mint, clove, etc.).

The control module receives instructions from the LLM that determine which essences to use and in what proportions. It operates valves or pumps that control the flow of different aroma essences from the reservoirs. With appropriate mixing, the essences are fed to the diffuser, which, through evaporation or ventilation techniques, evenly distributes the fragrance into the environment. Adjustment and mixing instructions are generated in real time by the LLM based on feedback and ongoing data analysis, allowing for dynamic adaptation of aromas.

2.6. User interface

The user interface (UI) provides the link between the user and the LLM, allowing two-way communication via text or voice commands. The user gives instructions, for example "Increase aroma intensity" or "Add a hint of mint", and the interface sends these commands to ChatGPT, which interprets the commands and generates the appropriate instructions for the system.

The UI implementation can be implemented through a web application that uses the ChatGPT API to process text commands and generate responses. For voice interaction, a voice recognition application can be integrated that converts voice commands into text inputs for ChatGPT. Alternatively, technologies such as Google Assistant or Alexa can be used in conjunction with ChatGPT to enable user interaction via real-time voice commands. This implementation provides an interactive interaction where the system adapts its behavior based on the user's commands and preferences. The interface provides two-way communication - the user submits commands, and the system returns responses.

2.7. Feedback and adaptation

This component provides dynamic adaptation of the system based on user or environmental feedback. After the aroma is reproduced, the user can give feedback on the desired result (e.g. "Make the aroma stronger" or "Reduce the citrus note"). This information is used by the AI system to automatically adjust the settings of the aroma generator. The system uses real-time feedback to update the proportions of essences used and the intensity of the fragrance. User commands can be stored and used for subsequent retraining of the ML/DL models, improving the accuracy and customization of the system over time.

Feedback can be implemented via text or voice commands given by the user via the UI. Once the user submits a command, such as "Add more vanilla", the system analyzes that command using ChatGPT and sends updated instructions to the aroma generator. In addition, the system can record these commands in a database and use the accumulated information to adapt the ML/DL model and improve future recognition of similar requests.

3. AI SCENT IMPARTING SYSTEM WORKFLOW

This section describes the workflow of the integrated system that imparts olfaction to AI by capturing, analyzing, describing, and reproducing odors (Fig. 2). The main idea is to demonstrate how the individual components - electronic nose, processing module, ML/DL model, LLM and aroma generator - interact with each other to provide a complete solution.

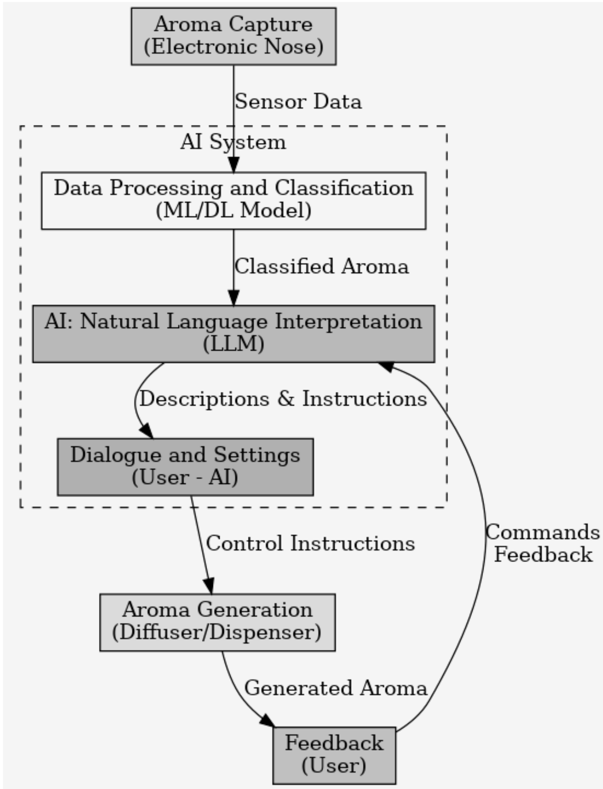

Figure 2. Block schema of the AI olfaction imparting system workflow

The workflow follows a logical sequence of steps, starting with the capture of odors from the physical environment and ending with feedback that allows the system to adapt and improve:

- *Capturing aroma.* The e-nose detects volatiles and generates sensory signals containing odor composition data, which is transmitted to the processing module.
- *Processing and base classification.* Sensor data undergoes preprocessing that includes filtering, normalization, and key feature extraction. The processed data is then fed to the ML/DL model which performs baseline classification and recognizes the specific odor. The result can be a single categorical class or multiple probabilities for different scents.
- *Natural language description.* The classification result is passed to the LLM, which can interpret and describe it in words. For example, if the classified fragrance contains notes of citrus and vanilla, the LLM may generate a description such as "This is a bittersweet fragrance with predominant citrus notes and light vanilla".
- *Dialogue and settings.* The user interacts with the system via text or voice commands and can ask questions or instructions to change the aroma. For example, the user can say, "Increase the intensity of the citrus note" or "Make

the aroma sweeter." The LLM interprets these commands and generates instructions to adjust or calibrate the parameters. In addition to the logical sequence between the components, it is especially important to note the importance of parallel work between the ML/DL model and the LLM. This parallel processing allows the system to reduce the response time when analyzing and describing aromas, providing a more intuitive and smooth interaction with the user. For example, while the ML/DL model performs basic classification of odors, the LLM can pre-process text descriptions or analyze previous user commands. This not only improves the efficiency of the system but also increases the ability to adapt to different contexts and user preferences.

- *Reproduction.* Once the system processes the commands, the aroma generator receives the control instructions and mixes the appropriate base essences to reproduce the desired aroma. The fragrance can be released directly into the environment for immediate use or encapsulated for remote application.
- *Feedback.* The user evaluates the result and gives feedback to the system, such as "The aroma is too weak" or "Add more vanilla". The LLM accepts this feedback and generates new instructions to further calibrate the parameters, allowing the system to adapt and optimize its behavior in real time.

4. IDENTIFYING KEY CHALLENGES

The full integration of an electronic nose, LLM and aroma generators into a complete solution poses a few challenges. The main difficulty stems from the need to accurately capture, classify, interpret, and reproduce aromas, which require robustness and precision of all components in the system. Furthermore, providing an intuitive and efficient natural language interface for user interaction and dynamically adapting the system to changing conditions in real time is key to its successful implementation.

The following is an overview of the main challenges that need to be overcome to create a fully functional and reliable AI olfaction system:

- *Sensor calibration.* For the system to be effective, it is necessary for the electronic nose to provide reliable and accurate data for a variety of odors. A major challenge here is sensor calibration, which must account for external factors such as temperature, humidity, and VOC concentration. Developing automated algorithms for real-time calibration is critical for system robustness.
- *Odor classification model.* ML/DL models used for odor classification require large and diverse training datasets. Collecting such data is challenging as different odors may have very similar characteristics. Furthermore, the ML/DL model needs to be adaptive to be able to recognize novel or unknown odors.
- *Natural language interface.* Interacting with the user through natural language is an essential part of the system. For the interface to be effective, the LLM must be trained on specific scenarios related to odors. The main challenge here is to ensure accuracy in command interpretation and correct instruction generation for the scent generator.
- *Synchronization of components.* The smooth operation of the system depends on the synchronization of the individual modules - the electronic nose, the

ML/DL model, the LLM and the aroma generator. Any delay or mismatch in communication between these components may result in incorrect aroma reproduction. It is therefore necessary to ensure fast and stable communication through standardized protocols.

- *Personalization and adaptation.* The system must be able to adapt to the individual preferences of the user. This includes not only the correct recognition of scents, but also the ability to learn from feedback and optimize odor reproduction. The main challenge here is developing personalization algorithms that adapt over time based on the data collected.

5. NEXT STEPS FOR REAL EXPERIMENTS AND TESTS

To validate the proposed concept and verify the effectiveness of the system in practical conditions, it is necessary to proceed to building a physical prototype and conducting a series of experiments. The main objective at this stage is to establish whether the system can capture and reproduce odors with high accuracy, provide intuitive user interaction and adapt its behavior based on feedback.

Following are the basic steps for implementing and testing the system:

- *Prototype creation.* The first step is to create a physical prototype of the system, including an electronic nose connected to an AI system that controls the aroma generator. This prototype will allow testing the core functionality, from capturing odors to reproducing them.
- *Training data collection.* A large and diverse dataset of different odors is needed to serve for training and retraining ML/DL models and LLM. This includes both raw sensor data and user-generated textual descriptions of odors.
- *Testing and validation.* Conduct controlled experiments where the system will be subjected to different conditions to verify the accuracy of odor capture and reproduction. Validation will be carried out by comparison between perceived and generated odors, and by evaluation by users who will interact with the system.
- *Optimization and upskilling.* Based on the results of the experiments, the system will be optimized, and the models will be retrained to increase the accuracy and efficiency of the processes.

The concept of imparting AI with olfaction opens new challenges in many areas of research and industry. In industry, digital olfactory systems could be integrated into production lines to monitor product quality, especially in the food industry, where aromas play a key role in consumer perception of products. In medicine, such systems could be used to diagnose diseases by analyzing volatile organic compounds in patients' breath. This is particularly important for the early detection of diseases such as diabetes, lung infections and even some types of cancer. In the context of VR/AR, digital olfactory could significantly enrich consumer experience by adding aromatic sensations to visual and auditory components. The application of the technology in e-commerce also has significant potential – customers could virtually "smell" products before purchasing.

Despite the wide range of applications, the realization of this concept requires overcoming certain technical challenges, including calibrating the sensors, ensuring accurate odor classification, and ensuring an effective natural language interface. In this context, developing prototypes and conducting experiments are critical steps to validate the idea in practical conditions.

7. CONCLUSION

This research proposes conceptual architecture for the integration of electronic noses, odor generators, and LLMs to give AI the ability to capture and reproduce odors. The system encompasses the entire process - from capturing real scents through an electronic nose, processing sensory data with machine learning, interpreting the results through an LLM to managing the scent generator that reproduces the odor. Users can interact with the system through natural language commands, allowing dynamic adaptation and customization of the scents reproduced.

The proposed solution provides significant benefits, including modularity that facilitates integration with IoT and AI platforms, and adaptability, allowing real-time changes to aromas based on user feedback. The wide range of possible applications includes industrial quality control, early medical diagnostics, virtual and augmented reality, and personalized e-commerce.

Despite these advantages, the system also faces some challenges, including the need for precise sensor calibration, large and diverse datasets for training the models, and achieving high accuracy in aroma reproduction. Overcoming these challenges is essential to improve the system and successfully deploy it in real-world settings.

Future system development may focus on improving sensor technologies, optimizing machine learning models, and expanding LLM capabilities for more accurate aroma interpretation. Implementing prototypes and conducting experiments in real environments will enable validation of the proposed concept and contribute to its further refinement. In successfully overcoming these obstacles, the system has the potential to change the way AI interacts with the physical world and to offer a new generation of digital technologies enriched with olfactory sensations.

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Information about the authors:

Aldeniz Rashidov is an Associate Professor at the Technical University of Gabrovo, Bulgaria, where he serves as the Director of the Center for Electronic and Distance Learning and Head of the Information Assurance Sector. His scientific interests include internet-based systems, industrial networks, databases, cyber-physical systems, and the application of artificial intelligence in research. Rashidov is the author of over 100 scientific publications and a Senior Member of IEEE, actively participating in the IEEE Computer Society and IEEE RAS.

Fatme Rashidova is a Chief Assistant Professor at the Technical University of Gabrovo, Bulgaria, where she is a member of the Department of Automation, Information, and Control Systems. Her research interests focus on multi-criteria decision-making, academic timetabling, and the development of optimization models and algorithms. She is the author of over 25 scientific publications and a member of IEEE, the world's largest professional engineering organization.

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