Collaborative Industrial Internet of Things for Noise Mapping

YE LIU, LEI SHU, ZHIQIANG HUO,
KIM-FUNG TSANG,
and GERHARD P. HANCKE

Exposure to environmental noise has harmful effects on human health for both physiological and mental aspects, such as annoyance, sleep disorders, cardiovascular disease, or even permanent hearing impairment. This problem is further exacerbated in industrial environments, where millions of workers are exposed to occupational noise. Therefore, noise mapping is essential and the first step to solving noise-pollution problem.

However, both sound-level meter (SLM)-based measurement and computational model-based simulation, the two main

Digital Object Identifier 10.1109/MIE.2020.3040162
Date of current version: 19 February 2021

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noise-mapping approaches at present, have their own limitations. To promote the development of noise-mapping techniques, this article presents the framework of the collaborative Industrial Internet of Things (IIoT) for next-generation noise mapping, especially in industrial parks. Moreover, other potential applications beyond noise mapping for smart factories are listed. Finally, fundamental issues and suggestions for future research are discussed in detail.

The Challenges of Noise Pollution

Noise pollution, behind air pollution, has risen to the second-most common environmental cause of public health problems, especially in industrial environments where workers are exposed to hazardous occupational noise in their workplaces. Long-term exposure to noise, as has been reported [1], has negative impacts on human physiological, mental, and physical health. Like humans, animals and plants are also negatively affected by noise pollution [2]. For example, cows and chickens reared in a noisy environment undergo a sharp decline in the production of milk and eggs, respectively. Also, since noise changes the behavior of wild animals, the dispersal of plant seeds is hampered [3].

Figure 1 illustrates the types of noise pollution, which, based on measurement and sound sources, can be classified into three broad categories:

- *Occupational noise*: This deals with the various noises employees are exposed to during their working time. Occupational noise is generated by industrial machinery in power generation, product fabrication, processing, and assembly sections, which significantly affects industrial workers.
- *Environmental noise*: This relates to unwanted sound that occurs from either outside or indoors [4]. The major sources of environmental noise include transportation activities, construction sites, and public social activities. Transportation is the leading source of noise pollution in urban areas, as road-traffic density has gradually increased. Construction activities (e.g., building construction, road maintenance, and land excavation) affect not only workers but also bystanders. Moreover, public announcement systems and loud talking, including entertainment, all contribute to environmental noise in a public place. A taxonomy for noise pollution in urban areas and the UrbanSound data set have been presented in [5], which are helpful for environmental noise mapping. Although the sound-pressure levels of environmental noise are not very high, the noise is often intensely annoying and extremely affects our daily lives.
- *Product noise*: Finally, acoustic noise is produced through heavy machinery, electric vehicles [6]–[8], data centers, and other appliances when they are in operation. Therefore, it is necessary to measure product noise to reduce its level to meet standards and regulatory requirements.

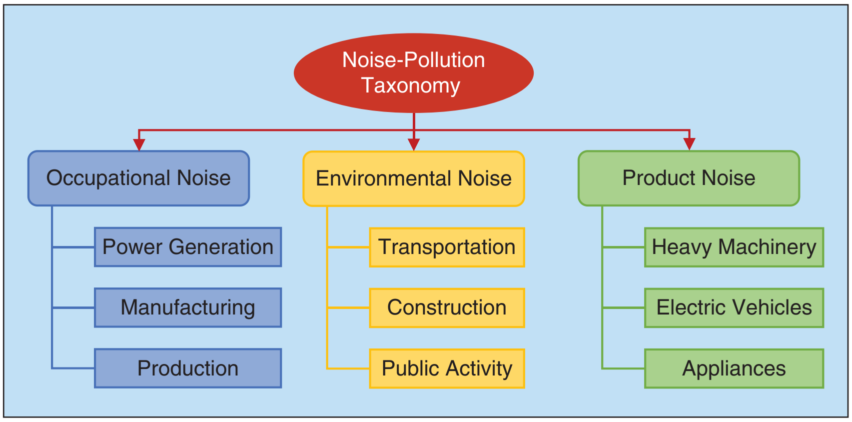

FIGURE 1 – The types of noise pollution based on the purposes of measurement and sound sources.

In 2002, a strategic noise-mapping action was initially established through the Environmental Noise Directive 2002/49/EC [9] when the European Union (EU) realized noise pollution would become a threat to the public health-care systems and even the economy of Europe [10]. All member states are required to publish their noise maps every five years, along with noise-management action plans. The first three rounds of the strategic noise-mapping action were completed in 2007, 2012, and 2017, respectively, and it is currently in the fourth round. The motivation for noise mapping lies in the following three aspects:

- Due to the substantial negative impacts on human health, the ecological environment, and the national economy, noise pollution becomes a major problem for many developed and developing countries.
- It is challenging to solve the noise-pollution problem since environmental noise is invisible, dynamic, and generated by different kinds of activities.
- With many tens of millions of people moving to urban areas, their activities cause a sharp increase in environmental noise. As a result, it becomes more challenging to ensure a sustainable environment for a smart city due to the trend of metropolitan expansion.

Overview

Today's Noise-Mapping Approaches

The most common instruments for noise monitoring are professional SLMs that are capable of measuring

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sound-pressure levels directly and performing frequency analysis. The SLM-based measurement is suitable for small-scale product-noise analysis. However, the approach is labor intensive, time consuming, and cost prohibitive when it comes to large-scale measuring for occupational and environmental noise.

An alternative is model-based noise computation, which has mainly been used to generate noise maps over the past years. This approach not only computes the sound-pressure level but also evaluates the performance of noise-reduction actions in advance. Differing from real-world noise measurement, the principle of computational model-based noise mapping is based on exploiting the acoustic emission behavior of noise sources and sound propagation characteristics to assess noise pollution.

Figure 2 illustrates the model-based noise-computation basic work process, which involves input, processing, and map generation. In the first step, it is necessary to load data regarding the sound source and environment characteristics from geographical information systems and third-party databases. The sound-source characteristics are used for estimating noise emission from industrial production, transportation activities, and so forth. Also, the propagation attenuation of noise at the receptor is calculated through environmental characteristics.

After finishing data input, noise exposure is estimated based on computational models in the second step. A comprehensive review of computational models for traffic noise was conducted in [12] and [13], where the authors gave a detailed introduction of popular traffic noise models and presented a critical analysis in terms of different technical attributes, such as sound propagation, source emissions, and geometrical divergence. Based on this valuable work,

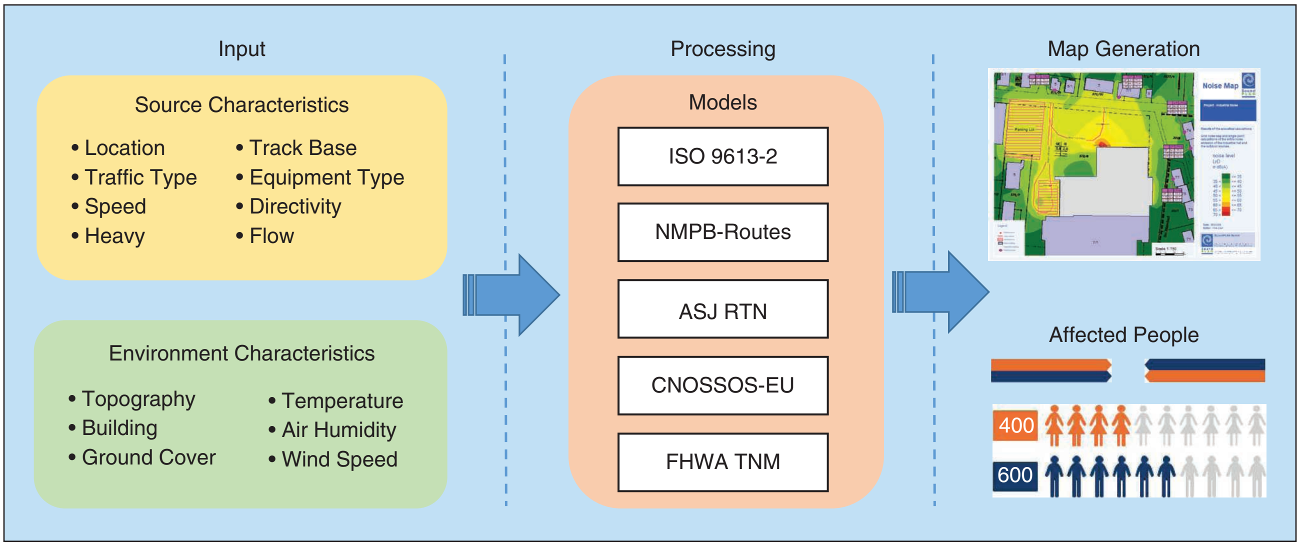

FIGURE 2 – The basic work process of computational model-based noise mapping [11]. ASJ-RTN: Acoustical Society of Japan Road Traffic Noise Model; FHWA TNM: Federal Highway Administration Traffic Noise Model; NMPB-Routes: Nouvelle Méthode de Prévision du Bruit des Routes.

TABLE 1 – POPULAR NOISE COMPUTATIONAL MODELS AND SUPPORTING APPLICATION SCENARIOS.

			APPLICATION SCENARIOS				
MODEL	YEAR	PUBLISHER	ROAD TRAFFIC	RAILWAY	AIRCRAFT	INDUSTRIAL SITE	WIND TURBINE
ISO 9613-2	1996	ISO				✓	
HARMONOISE/IMAGINE	2005	EU	✓	✓	✓	✓	
Nord2000	2006	Nordic countries	✓	✓			✓
NMPB-Routes-2008	2008	France	✓	✓		✓	
ASJ-RTN model	2013	Japan	✓				
CNOSSOS-EU	2015	EU	✓	✓	✓	✓	
FHWA TNM	2017	United States	✓				

ASJ-RTN: Acoustical Society of Japan Road Traffic Noise Model; FHWA TNM: Federal Highway Administration Traffic Noise Model; ISO: International Organization for Standardization; NMPB-Routes-2008: Nouvelle Méthode de Prévision du Bruit des Routes.

we present a discussion from the point of view of the application scenarios they can support.

Table 1 shows the popular noise computational models and their supporting application scenarios. The International Organization for Standardization (ISO) published the ISO 9613-2 model, which presents an empirical method to calculate sound propagation attenuation in the outdoor environment. Although the approximate results are not accurate enough, the ISO 9613-2 model is simple and easy to program using software tools. The model was also recommended in Directive 2002/49/EC for assessing industrial noise for first-round strategic noise mapping.

Since then, many noise models have been developed. For example, the HARMONOISE project [14] was supported by the EU framework program to develop reliable methods to assess environmental noise from road traffic and railways. The IMAGINE project extended its use to industrial scenarios and aircraft. The Nord2000 model was applied in Nordic countries to estimate road and railway noise. This method is also used for wind farm noise assessment in recent years. Other classical models include the Nouvelle Méthode de Prévision du Bruit des Routes (NMPB-Routes-2008) [15], Acoustical Society of Japan Road Traffic Noise Model [16], and Federal Highway Administration Traffic Noise Model.

However, diversification causes inconsistent noise maps. To address this problem, the European Commission has been offering to develop a common approach for noise assessment since 2009. As a result, the Common Noise Assessment Methods in Europe (CNOSSOS-EU) model was published in 2015, and then Directive 2015/996/EC specified that all members should apply the CNOSSOS-EU model to generate strategic noise maps beginning in 2019.

In the third step, noise maps are generated in graphical and numerical formats. Many commercial software tools, such as Predictor-LimA, CadnaA, SoundPLAN [11], and noise3D, can carry out these complicated tasks automatically. Apart from commercial software, researchers have been proposing open source tools for academia to study environmental noise [17], [18]. NoiseModelling [19] is open source software that calculates traffic noise using the NMPB-Route-2008 method. An industrial sound-source application is also available in the NoiseModelling tool. Also, the opeNoise is another free tool for road traffic noise assessment.

Professional SLMs can accurately measure parameters related to occupational, environmental, and product noise.

Limitations

Professional SLMs can accurately measure parameters related to occupational, environmental, and product noise. However, area coverage is the main limitation because it is impossible to deploy these devices in all places at all times.

Moreover, computational model-based noise mapping also faces several limitations, which are summarized as follows:

- *Simulation results*: Model-based noise computation is the main method for generating large-scale noise maps at present. It greatly reduces the burden of manual noise collection, where appointed workers periodically go to investigated sites and collect environmental noise through the professional SLMs. However, the results generated by the model-based computation method are estimated values. In many cases, the accuracy is not good enough because the complex input parameters cannot be fully obtained [12].
- *Limited scenarios*: The sources of noise pollution are diverse: it comes from moving traffic, traffic jams, industry production, construction work, neighborhood trouble, and other activities. However, existing acoustic models can cover only a few scenarios [20], which means that many types of outdoor and indoor sound noise cannot be added for overall noise prediction in an area.
- *Static mapping*: The update period of simulated noise maps is very long. For example, the review period for strategic noise maps allowed by the Environmental Noise Directive is five years, which makes it unable to describe the time-varying sound noise. Although this problem could be mitigated by quickly updating input parameters, the predefined scenarios are unable to cover unpredictable sound events well. More importantly, static noise maps do not help the public much since the figures present only yearly global noise exposure rather than the current ambient noise situation and potential health problems.

Expectations for Next-Generation Noise Mapping

Next-generation noise mapping is expected to have the following new capabilities:

- *Accurate real-time measurement*: The levels of noise exposure can be truly reflected through accurate real-time measurement so that noise-pollution assessment in all scenarios is applicable. It does not need complex input parameters regarding traffic networks, industry, geographical information, and propagation factors.
- *Fine-grained classification*: One measured result is a mixed sound-pressure level produced by all kinds of noise sources. Therefore, it is essential to classify the sound sources and calculate their corresponding sound-pressure levels to provide precise noise maps and respond with appropriate actions.
- *Dynamic mapping*: Noise variation at different times of a day, week, and year can be well demonstrated through dynamic noise mapping. It also can present accidental and short-term sound events.

Existing acoustic models can cover only a few scenarios, which means that many types of outdoor and indoor sound noise cannot be added for overall noise prediction in an area.

- *Human-centric visualization*: Moreover, human-centric visualization of noise maps is more practical. For example, a noise map on a smartphone shows the real-time noise levels at hot spots with potential health problems, and then citizens can decide whether to go or not. Also, such noise maps are able to provide citizens with quiet and safe routes to their destinations.
- *Data-driven mitigation*: Finally, based on the precise noise-pollution information provided by noise mapping, industrial managers or officials are able to gain a deep understanding of noise in terms of sources, level, and distribution, which is extremely important for effective noise reduction.

The IIoT for Next-Generation Noise Mapping in Industrial Parks

Industrial parks (such as Jubail Industrial City, Alberta's Industrial Heartland, Tahoe Reno Industrial Center, and Suzhou Industrial Park) are the sections in a country zoned for industrial development. An example is shown in Figure 3. This type of zoning accelerates business growth and promotes modern industrial development by concentrating dedicated infrastructures, bringing companies together, providing policy incentives, and so on.

However, an industrial park is also a complex scenario, where manufacturing, production, transportation, and storage are often combined together. Thus, all three categories of noise pollution mentioned earlier might occur in an industrial park. The noise might be from industrial sources, inside an industrial facility and server room, or from the transportation of goods. The primary goal of this section is to propose a collaborative method to implement next-generation noise mapping in industrial parks. In addition, the proposed method could be seamlessly applied to noise mapping in urban areas.

The IIoT [21], [22] is a machine-oriented, service-centric ecosystem that involves identification, sensing, communication, real-time processing, data analysis, and decision making for the industrial sector. Thus, all of the industrial objects (e.g., sensors, actuators, instruments, robots, and control systems) in this paradigm are interconnected so that they can collaborate for knowledge-based factory automation and intelligent services in industrial applications.

The IIoT has been successfully applied in smart manufacturing, smart supply chain, and smart energy management, to name a few. Now, it is time to direct the IIoT toward a people-centric ecosystem. Noise mapping is one of the key applications to protect people against noise pollution, especially for industrial workers. Figure 4 presents the proposed framework of IIoT-based noise mapping, which improves current noise-mapping approaches through the following aspects.

Collaborative Sensing Capability

The real-time sound-pressure levels can be measured collaboratively using wireless acoustic sensor networks (WASNs) [23], mobile crowdsensing (MCS), robots, and unmanned aerial vehicles (UAVs). Wireless sensor networks (WSNs) have been widely used in forest fire detection, structural health monitoring, and industrial emergency alarms for many years [24]. Noise mapping is also one promising application for WSNs because they are able to capture sound noise continuously. As the deployment cost is high, the WASN

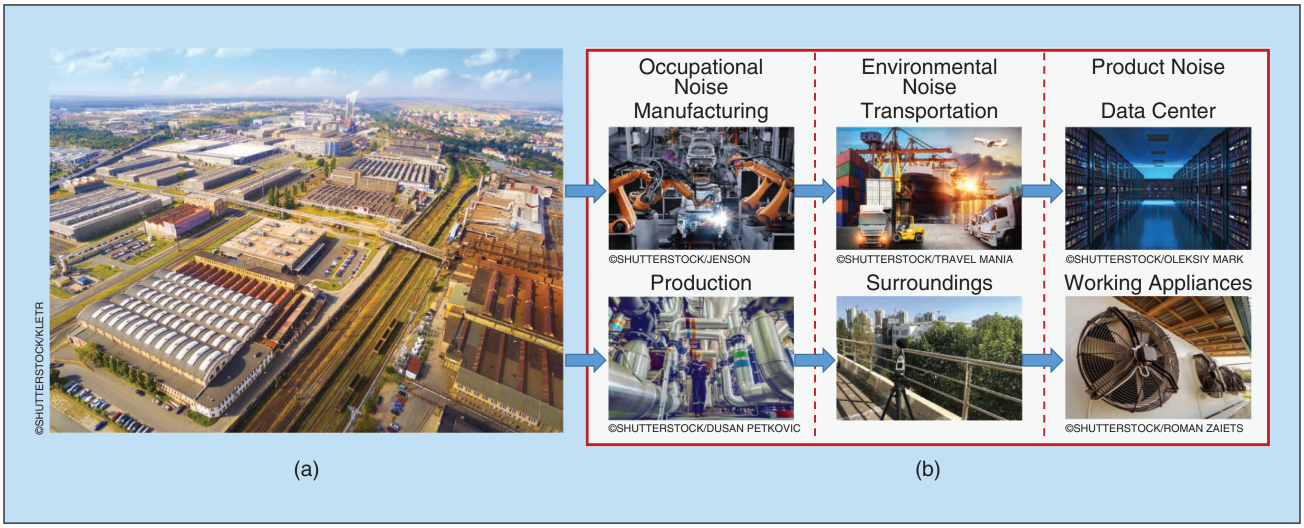

FIGURE 3 – (a) Industrial parks and (b) the related noise pollution generated during manufacturing, production, transportation, and storage.

could be placed only in key areas for fixed, long-term sound-data acquisition.

People currently spend much of their time every day on social networks to share pictures and videos as well as leave comments using mobile devices, which are also promising for large-scale sound MCS [25], [26]. The microphones in mobile devices can capture the sound-pressure level in the surroundings, and global navigation satellite systems are able to provide location information. Together with acoustic-source localization and tracking algorithms [27], the position of noise sources and their moving trajectories can be obtained. The computational model-based noise mapping can present only the sound-pressure levels on the maps. Instead, sound mobile crowdsensing can improve map information by uploading audios, videos, and comments. More importantly, the real-time health effects on humans or animals are visible with the help of smartwatches, smart bracelets, and biosensors.

An industrial park is also a complex scenario, where manufacturing, production, transportation, and storage are often combined together.

Recent advances in sound MCS and WASNs were presented in [28], where the authors gave a short review of related works and focused on the system design issues. In contrast, this article hopes to give the whole picture of next-generation noise mapping with emerging Industry 4.0 technologies in terms of collaborative sensing, computing, and intelligence.

Furthermore, robots [29] and autonomous guided vehicles can also contribute to noise measurement in factories or on roads by equipping them with loudness sensors. The 3D ambient sound-noise visualization is fascinating, and UAVs [30] are very helpful to measure sound-pressure levels vertically. In this scenario, denoising schemes and path planning are two interesting topics to be explored.

In a nutshell, the collaborative sensing capability fundamentally addresses the limitations of simulation results and limited scenarios in the computational model-based noise mapping with minimum cost. In the future, the computational model-based noise-mapping approaches and multisensor-based noise measurement can complement each other. For example, it is extremely important to estimate the noise level before construction of an industrial site or evaluate the performance of noise-control measures in advance, which can be achieved by the simulation-based approaches.

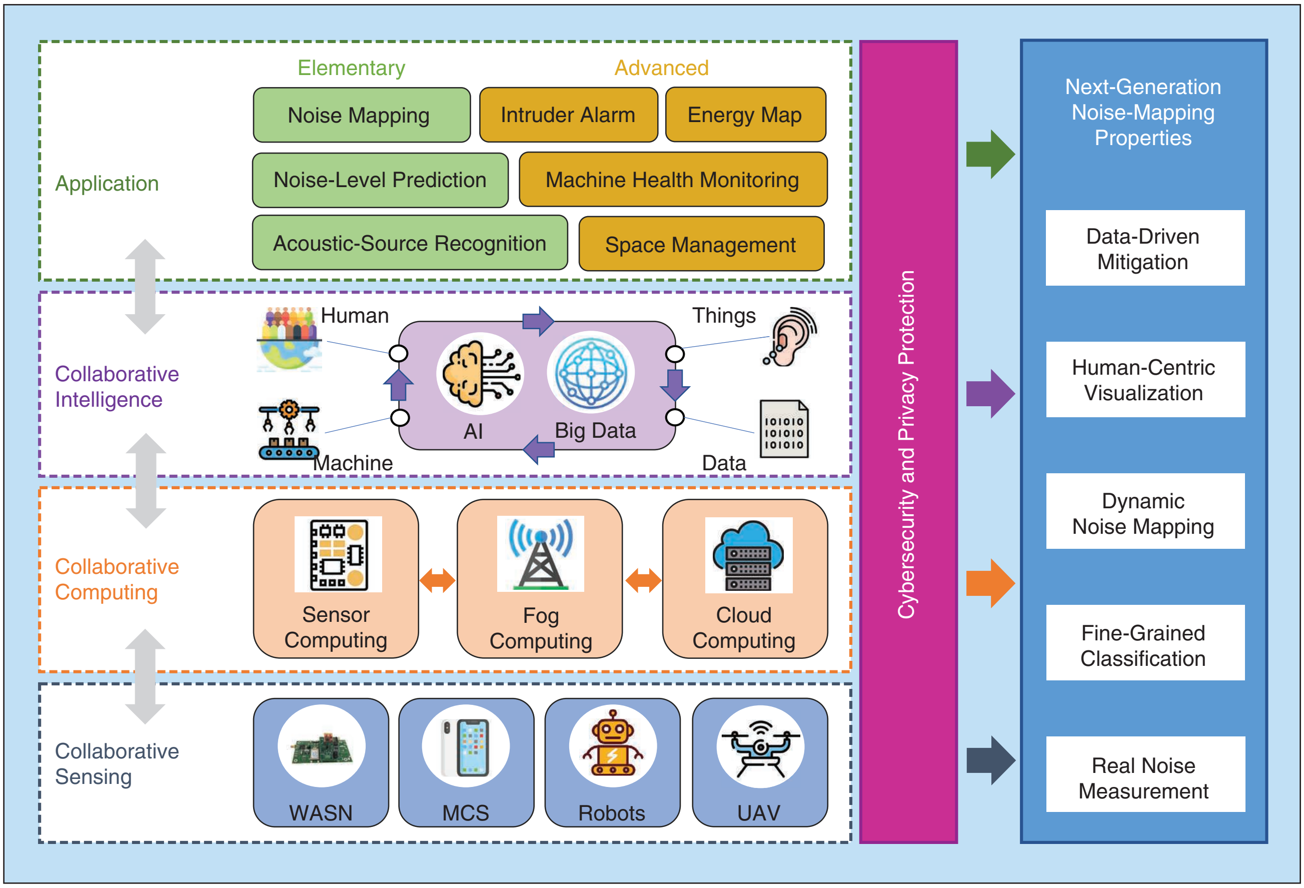

FIGURE 4 – The proposed framework of the collaborative IIoT for next-generation noise mapping in industrial parks. AI: artificial intelligence; UAV: unmanned aerial vehicle; WASN: wireless acoustic sensor network. (Source of icon images: Flaticon; used with permission.)

Noise mapping is one of the key applications to protect people against noise pollution, especially for industrial workers.

On the other hand, real-time measurement results from multisensor-based approaches can be used to calibrate computational models. However, it is worth noting that, although the multisensor-based noise-mapping approaches are capable of providing real noise measurement, they themselves cannot present noise levels in the future or noise sources. To achieve noise-level prediction and acoustic-source recognition, artificial intelligence (AI) models are necessary.

Collaborative Computing Capability

All calculations for sound emission power and propagation attenuation take place at central servers when using the computational model-based method. The requirement of dynamic noise mapping at a large scale undoubtedly aggravates the burden of central servers. The IIoT-based noise-mapping method alleviates this problem by forming a hierarchical, cross-layer, and distributed computing network [31], [32].

Collaborative computing capability could be utilized in the following manner. Sensing devices (such as sensor nodes, smartphones, smartwatches, and UAVs) initially calculate the equivalent continuous sound level at every 30 s and label every fragment as important noise events or basic background noise when capturing raw environmental sound. These data are transmitted with different compression rates to macrocell base stations or gateways through 5G, Zigbee, Narrowband IoT, long-range wide area network, and SigFox.

Then, fog computing performs fine-grained recognition to further classify the important noise events into industrial machinery, motorized transport, construction, amplified music, or human voice. Finally, this environmental noise information is delivered to the cloud service platform for noise display and reporting. Furthermore, big data analytics on sound noise can help to analyze noise trends and even social problems. In summary, the hierarchical collaborative sensor–edge/fog–cloud computing architecture in the IIoT enables real-time fine-grained noise mapping at a large scale.

Collaborative Intelligence Capability

Noise maps in the past only presented average noise-pressure levels. Next-generation noise mapping with the IIoT is able to provide much more valuable information about the context of sound noise regarding the classification of noise generators, corresponding noise levels, personal health risks, and so on.

Second, traditional noise maps are published online by officials, but they are rarely accessible for people. The interaction between people and real-time noise maps becomes possible when using IIoT-based noise mapping. The noise information recorded through smart objects could be uploaded to the Internet and then displayed on mobile applications, such as Google and Baidu Maps. Social networks, such as Facebook, Twitter, WeChat, and Weibo, could further share this information. Real-time feedback helps the public to gain a deep understanding of surrounding noise pollution and promotes public awareness to reduce noise actively.

Third, new insights about noise pollution and its adverse effects will be discovered through feeding the unprecedented amount of sound-noise data into AI systems. Thus, data-driven noise-management actions will be more efficient than ever.

Traditionally, the IoT focuses on physical objects' interconnections and is characterized by the ability to transfer data over a network without requiring human-to-human or human-to-machine interaction. Today, the concept of the Internet of Everything (IoE) [33] is proposed by Cisco and has attracted significant attention from industrial and academic communities. The IoE is considered as a superset of the passive IoT, in which machine-to-machine, human-to-human, human-to-machine, and data-to-meaning are all involved to create unprecedented opportunities and values for all communities. In noise-mapping applications, the collaborative intelligence among sensing devices, computing units, and humans allows the blueprint of people-centric visualization and data-driven noise mitigation to become realities.

Other Potential Applications for Smart Factories

In addition to presenting the distribution of sound-pressure levels in specific areas of interest, noise mapping is also helpful for smart factories. Four potential applications include:

- *Space planning and management*: Sound-pressure levels in a plant can be reflected in noise maps, which provide a guide for a line manager to control noise pollution and manage the factory area, such as workshop-layout planning.
- *Machine health monitoring*: By analyzing measured acoustic signals emitting from in situ machines, it is possible to detect early faults and diagnose machine health conditions [34], which is helpful to facilitate repair-related maintenance decision making as well as avoid unplanned downtime and safety issues.
- *Intruder alarm in industrial plants*: A burglar alarm system is of great significance for protecting factory assets from damage or theft. Noise measurement could be also used for smart/physical intrusion alert. Smart objects equipped with loudness sensors are able to detect after-work abnormal activities. By comparing predicted sound levels with the current state, they can report alarm messages to security staff immediately if unusual sounds are detected.
- *Ambient sound-energy map*: Although noise is a kind of pollution,

it is also an ambient energy [35], which can be utilized to power smart devices. Thus, noise maps can be considered as sound-energy maps. With this information, sound-powered energy-harvesting sensor nodes could be designed and deployed at certain places to perform either sound-pressure-level measurement or for other purposes.

Future Research Opportunities

The previous section explored collaborative IIoT for next-generation noise mapping and its potential applications. In this section, some fundamental issues and our suggestions for future research are discussed. For simplicity, the take-home messages are summarized in Figures 5 and 6.

Model-based noise computation is the main method for generating large-scale noise maps at present.

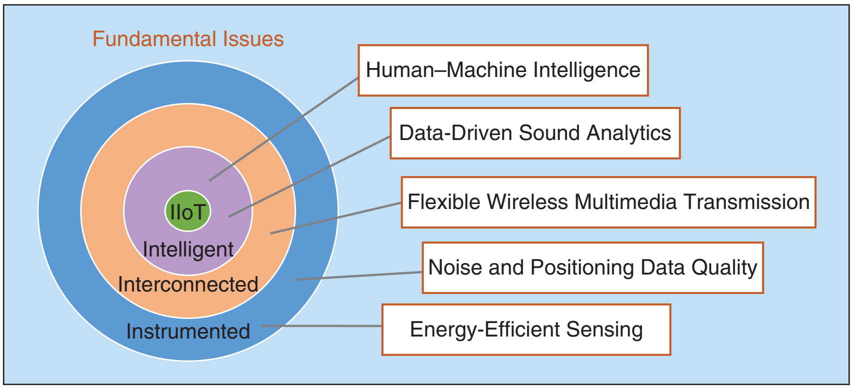

FIGURE 5 – Some fundamental issues in the collaborative IIoT for next-generation noise mapping.

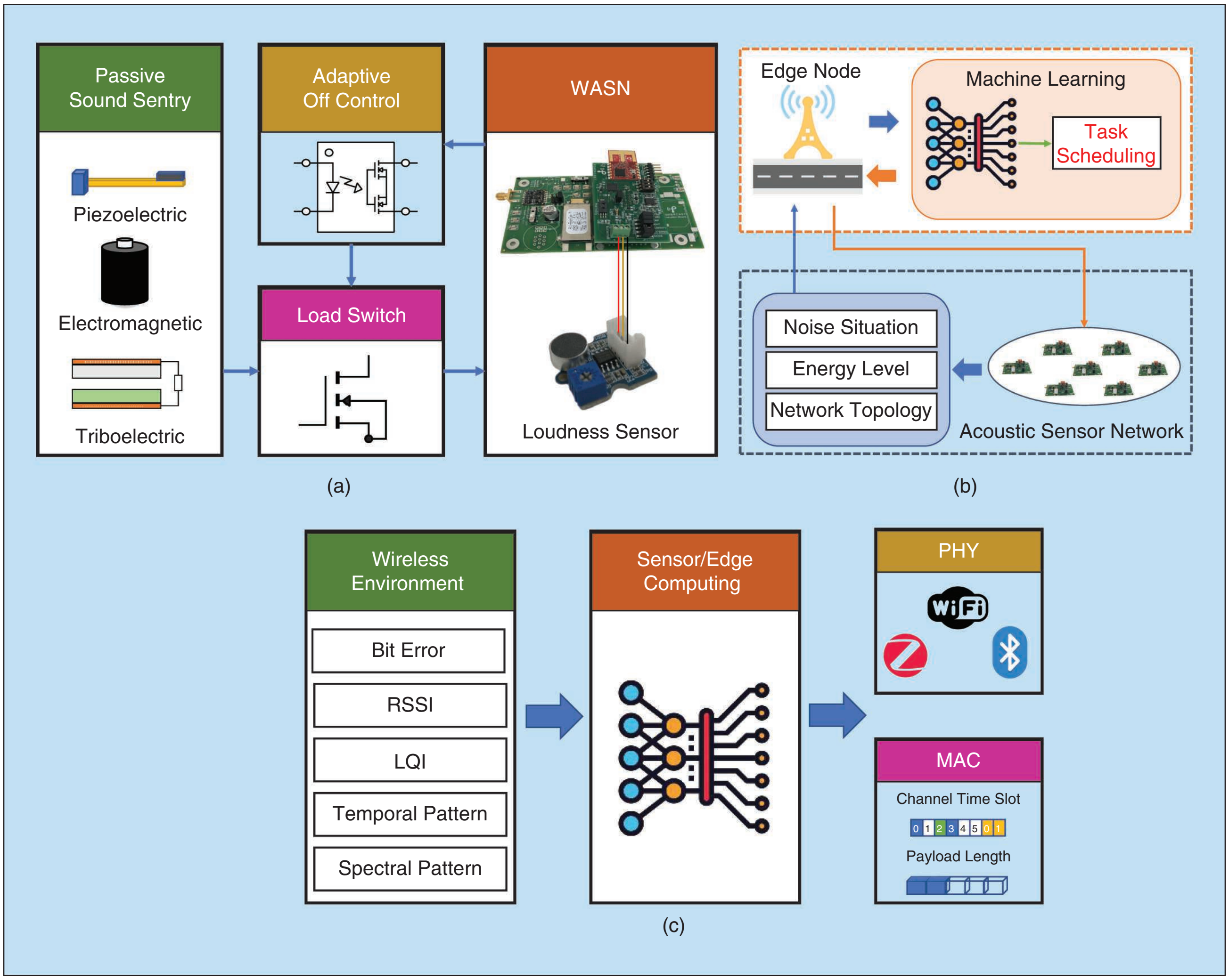

FIGURE 6 – Suggestions for future work: (a) passive event-triggered noise monitoring; (b) machine learning-based adaptive sensing; and (c) AI-assisted multi-PHY, multiprotocol transmission. LQI: link quality indicator; MAC: medium access control; PHY: physical layer; RSSI: received signal strength indicator. [Source: (b) Edge Node–signal tower icon and (c) Sensor/Edge Computing–deep learning icon: Flaticon; used with permission.]

The interaction between people and real-time noise maps becomes possible when using IIoT-based noise mapping.

Fundamental Issues

Energy-Efficient Sensing

Sound-noise monitoring has the features of both event- and time-driven applications. Noise is emitted by a series of events, which means sensor nodes should try their best to capture every noise event for fine-grained monitoring.

However, it is challenging to perform such power-hungry sensing tasks, as the battery capacity is limited. Although ambient energy harvesting from external sources (e.g., solar power, wind, and radio signals) is a promising technique to provide sustainable energy for WASNs, the ambient energy is often dynamic and insufficient. For example, in the referenced experiment setup [36], the solar-powered acoustic sensor nodes could not support continuous sensing tasks even during the summertime in the United Kingdom. Thus, it is necessary to carefully design the dimensions of photovoltaic panels [37], wind turbines, antennas, and other energy harvesters according to application-specific requirements, ambient energy in the selected area, and power consumption of the noise-sensing system.

On the other hand, background noise is relatively stable over a certain period in many scenarios [38]. For example, in working environments, it is quiet during most of the time on weekends and holidays except the short noise events related to cleaning or social activities. In a single working day, more noise is created from 10 a.m. to 4 p.m., whereas it is quieter for the rest of the time. This means that it is possible to save a lot of energy by increasing the sampling interval without sacrificing much of the performance.

Noise and Positioning Data Quality

Static sensors are always placed in a certain location as planned, and it is easy to track their geographical locations and operating statuses. However, objects in industrial environments typically are of high mobility and dynamic characteristics. As a result, it is often hard to identify and predict the trajectories of mobile sensing nodes (such as robots and workers who are equipped with wearable sensors). They may move everywhere during their work, but not all of the data they contribute is of interest for a specific application.

In addition, noise-measurement accuracy is a huge concern when humans are involved in fulfilling the noise-sensing tasks. Participants may contribute low-quality data due to inappropriate operations or malicious purposes. Any unexpected vibration or friction will lead to a fluctuation in the sound-pressure level, especially when participants collect data with smartphones or wearable devices in their pockets or bags. A possible solution to improve data quality in crowdsensing [25] is participant activity recognition. Identifying participants' activities not only helps with inferring their intentions but also facilitates user data assessment. However, data protection and privacy must be taken into consideration in the future.

Finally, there might be some blind geographic areas in complex industrial zones where accurate location information is not available due to satellite signal attenuation and multipath effects. In this case, moving-trace prediction and positioning calibration are essential.

Flexible Wireless Multimedia Transmission

Energy-efficient sensing and noise/positioning data quality are the two fundamental issues at the perception layer. When it comes to the network layer, flexible wireless transmission related to noise mapping is critical since the wireless environments in industrial plants and surroundings in industrial parks are often harsh [39]. A large number of wireless devices have been deployed for mission-critical IIoT applications. They usually operate at the 2.4-GHz unlicensed band. For example, the leading wireless industrial standards (WirelessHART and International Society of Automation 100.11a) are all based on the IEEE 802.15.4 physical and media access control layer.

As industrial process automation and control are mission-critical applications, they must be dependable [40], [41] and have a higher priority. Therefore, the wireless multimedia transmission for noise mapping should not interfere with mission-critical industrial applications. On the other hand, it has to save itself from harsh radio-frequency interference.

Data-Driven Sound Analytics

After real-time noise mapping, the application of noise-level prediction, acoustic-source recognition, fault diagnosis, and intruder alarm can be achieved by data-driven sound analytics. The basic process is demonstrated in Figure 7. First, ubiquitous noise sensing in industrial parks is accomplished through collaboration among workers, autonomous guided vehicles, robotics, and UAVs. Then, data preprocessing is needed in the second stage to fulfill data cleaning, integration, data reduction, and transformation. After that, salient feature representations are extracted at the sound-analysis module through Fourier transform, wavelet analysis, and empirical mode decomposition. Finally, decision making is performed for certain applications. Currently, cutting-edge AI technologies, such as federated learning and multiagent systems, are helpful to provide distributed machine learning training [42], data analysis [43], knowledge discovery, and decision making.

Although data-driven sound analytics is promising, many issues need to be addressed. First, sound-data sources are greatly dynamic and heterogeneous. The collaborative noise sensing causes heterogeneity in the data structure, communication, data storage, and semantic interpretation. As a result, the format and semantics of the data must be unified before analysis.

Second, the accuracy of data-driven models is highly based on the type, quality, and volume of measured data as well as mathematical models of the applied analytic tools. Therefore, it is critical to appropriately design the data-collection scheme and data-analysis methodology so that valuable knowledge can be extracted from raw data through suitable data-mining solutions.

Finally, the application of advanced machine learning techniques, such as artificial neural networks and deep learning methods, typically involves the optimization of several hyperparameters in the decision model. Considering the dynamic characteristics of industrial parks, suitable semisupervised/unsupervised learning methods and optimization techniques are needed to improve the performance of such AI systems.

Identifying participants' activities not only helps with inferring their intentions but also facilitates user data assessment.

Human–Machine Intelligence

Human–machine intelligence [44] is a new form of intelligence, which is different from AI in the traditional sense. It is based on the cooperation of human and machine intelligence, and it fully utilizes the advantages of human emotional decision making and learning capabilities, along with the advantages of machine superstorage and computing capabilities.

With fully utilized human–machine collaboration and intelligence, large-scale noise sensing and decision making are made easier. However, optimizing task allocation for human–machine collaborative intelligence [45] is an NP-hard problem. On the one hand, it is critical to determine when humans or machines should intervene in specific sensing and computing tasks. For example, allocating a large number of humans or machines to take measurements at the same time in a given region may result in energy waste and network congestion. Moreover, when the contributed data are abundant, there may exist less useful information in the data measured by humans and machines simultaneously.

On the other hand, designing how humans and machines participate and collaborate is also important. In terms of computing tasks, it is obvious that machines have advantages over humans. For context awareness, however, humans are good at giving more subjective emotion recognition and synthetic interpretation based on practical experience or expert knowledge. Therefore, the integration of human and machine intelligence requires appropriate and

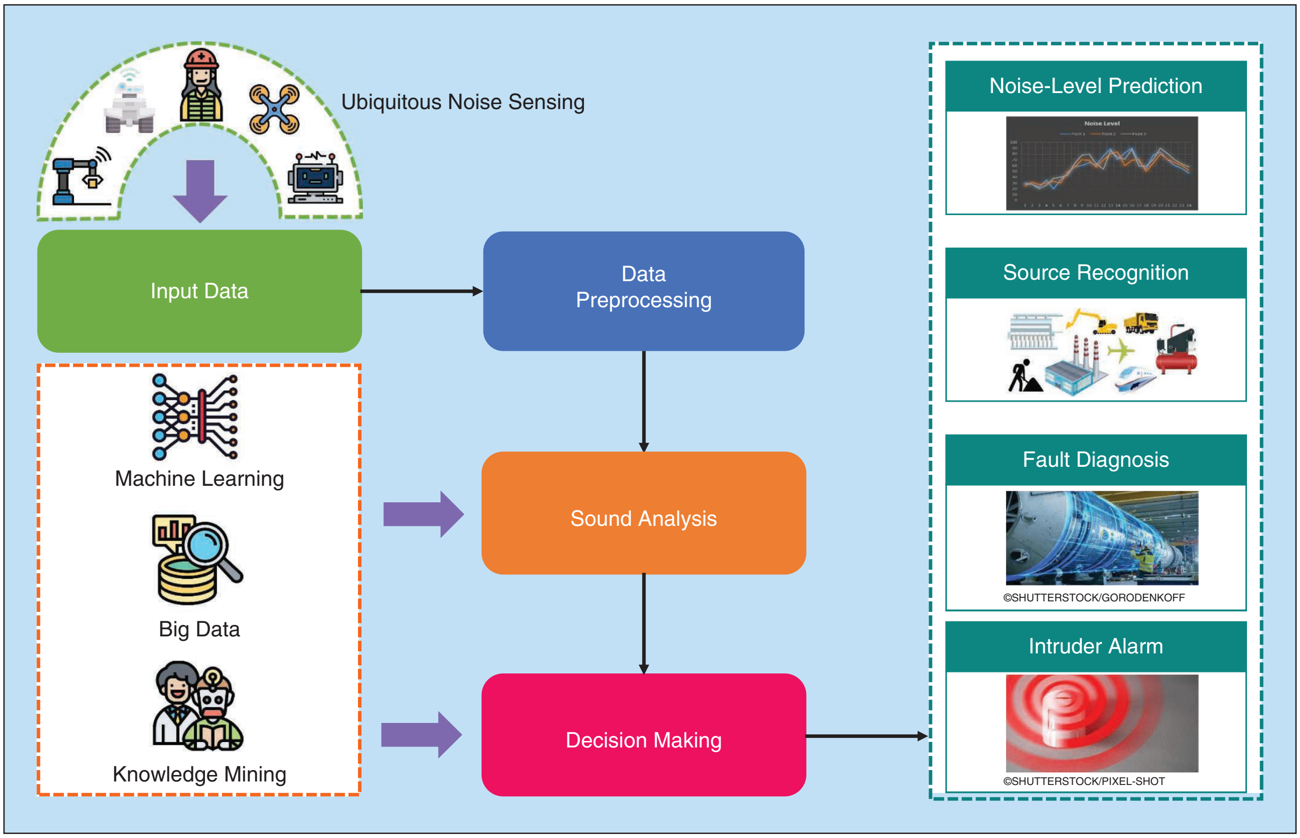

FIGURE 7 – The basic process of data-driven sound analytics. (Source of icon images: Flaticon; used with permission.)

With fully utilized human–machine collaboration and intelligence, large-scale noise sensing and decision making are made easier.

optimized design from three fundamental perspectives: data, algorithms, and decision making.

Suggestions for Future Work

Finally, three research projects that we are currently conducting are presented. We hope more investigators will be interested in these directions and promote the development of IIoT-based noise mapping together.

Passive Event-Triggered Noise Monitoring

In many cases, acoustic sensor nodes are not uniformly deployed, which results in low-density sensing regions. The event-triggered sensing system, thus, is expected to achieve rapid effective responsiveness and a long network lifetime [46]. Such systems have been used in video surveillance [47], structural health monitoring [48], and so on. The basic idea is to use a low-power sensor for coarse event detection and then trigger the main sensors for high-precision monitoring if the return value is above the predefined threshold. Surprisingly, an event-triggered sensing system for noise-mapping applications has not been proposed in the literature so far.

More importantly, we propose a new kind of event-triggered noise-sensing system that exploits the nature of sound energy, which is shown in Figure 6(a). Differing from traditional active event-triggered sensing systems that use low-power sensor as a sentry, a sound energy-harvesting circuit is designed as a passive sentry to trigger the main node when sound energy is detected. It is worth noting that the harvested sound energy might be very tiny, which is not enough to directly power the main node, but it is able to trigger a load switch (e.g., metal–oxide–semiconductor field-effect transistor) from OFF to ON [49], [50]. When the main node is activated, it can either estimate the sound using a model or perform noise measurement using high-precision loudness sensors.

Machine Learning-Based Adaptive Sensing

The A-weighted equivalent continuous sound-pressure level through a time ($L_{\mathrm{Aeq},T}$) is a common descriptor to measure environmental noise. It is defined in decibels as

$$L_{\mathrm{Aeq},T} = 10\lg\left(\frac{1}{T}\int_0^T \frac{p^2(t)}{p_0^2}dt\right)\ \mathrm{dB}, \quad (1)$$

where T is the specified time (e.g., 15 min), the reference sound pressure (p_0) is 20 μPa, and $p(t)$ denotes the instantaneous pressure level of the noise. Simply, the integral equation could be discretized by averaging the total individual event exposures. In (2), the reference time interval (T_{ref}) can be considered as the sampling interval of the sensor node. Therefore, the total samples (n) of individual sound exposure levels (L_{SEL}) are equal to T_{ref}/T over the specified time:

$$L_{\mathrm{Aeq},T} \approx 10\lg\left(\frac{T_{\mathrm{ref}}}{T}\sum_{i=1}^{n} 10^{\frac{L_{\mathrm{SEL},i}}{10}}\right)\ \mathrm{dB}. \quad (2)$$

For example, when the sampling interval is set to 2 s, the sensor node needs to perform the task 450 times in 15 min. Then, if the sensor node measures sound noise every 20 s, only 45 samples are needed at the same time.

An interesting fact presented in [38] is that root-mean-square errors of equivalent continuous sound-pressure level over 15 min with different sample intervals are all within 2.5 dB in a classroom of the university, even when the sample number is decreased to five times. The correlation of environmental noise gives us hope that the energy consumption of noise sensing can be reduced sharply using a machine learning-based adaptive sampling mechanism. As shown in Figure 6(b), a machine learning module [51] can be adapted on the edge node to train a decision agent, which outputs the optimal value of the sampling interval based on the present noise situation, energy level, and network topology reported from the WASN.

AI-Assisted Multi-Physical-Layer, Multiprotocol Transmission

This work is conducted to cope with both the wireless coexistence problem and heterogeneous sensing issue. Currently, the development trend of commodity IoT platforms is from a single-physical-layer (PHY), single-protocol supporting platform to a multi-PHY, multiprotocol supporting platform [52]. For example, both the Nordic Semiconductor nRF52840 system on chip (SoC) and Texas Instruments CC2652R microcontroller are able to support Bluetooth, IEEE 802.15.4, and proprietary 2.4-GHz stacks. The Wireless Gecko SoC from Silicon Labs can also be dynamically configured for multi-PHY and multiprotocol wireless connectivity.

This promising property could be exploited for flexible wireless multimedia transmission in noise-mapping applications. As shown in Figure 6(c), the basic idea is that the acoustic sensor nodes first autonomously get an understanding of the wireless coexistence environment that is present, and then the trained AI engine adaptively configures the PHY layer and medium access control layer based on the sensed information [53], such as the bit error, received signal strength indicator, link quality indicator, and temporal and spectral patterns.

Conclusion

This article first provides background on noise mapping by describing the three types of noise pollution; their adverse effects on humans, animals, and the environment; and the motivation for noise mapping. Then, a comprehensive overview of noise mapping is conducted, which includes the working principles of SLM-based and computational model-based noise-mapping techniques, their limitations, and expectations for next-generation noise mapping.

To achieve such a blueprint, the potential role of the IIoT for next-generation noise mapping in industrial parks is explored, which includes collaborative sensing, computing, and intelligence, followed by potential applications, such as machine health monitoring, intruder alarm systems, and an ambient sound-energy map. Moreover, five fundamental issues are discussed, including energy-efficient sensing, noise and positioning data quality, flexible wireless multimedia transmission, data-driven sound analytics, and human–machine intelligence. Finally, passive event-triggered noise monitoring; machine learning-based adaptive sensing; and AI-assisted multi-PHY, multiprotocol transmission are presented as future work suggestions. We hope this article could open up new research opportunities to investigators in the IEEE Industrial Electronics Society.

The integration of human and machine intelligence requires appropriate and optimized design from three fundamental perspectives: data, algorithms, and decision making.

Acknowledgments

We would like to thank the anonymous reviewers for their insightful comments and suggestions. We also thank the artists (Dusan Petkovic, Oleksiy Mark, Kletr, Jenson, Travel Mania, Roman Zaiets, Gerodenkoff, and PixelShot) for their images and the licenses from Shutterstock and Flaticon. This work was partially supported by the National Natural Science Foundation of China (61902188), the China Postdoctoral Science Foundation (2020T130304 and 2019M651713), and the Science and Technology Planning Project of Guangdong Province (2017A050506057). Lei Shu is the corresponding author.

Biographies

Ye Liu (yeliu@njau.edu.cn) earned his M.S. and Ph.D. degrees from Southeast University, Nanjing, China in 2013 and 2018, respectively. He is a researcher at Nanjing Agricultural University, Nanjing, 210031, China. His research interests include the Internet of Things, energy-harvesting systems, embedded machine learning, and noise mapping. He was a visiting scholar at Montana State University, Bozeman, from October 2014 to October 2015. He was a visiting Ph.D. student from February 2017 to January 2018 in the Networked Embedded Systems Group at Research Institutes of Sweden, Swedish Institute of Computer Science. He is a Member of IEEE.

Lei Shu (lei.shu@ieee.org) earned his B.S. degree in computer science from South Central University for Nationalities, China, in 2002; his M.S. degree in computer engineering from Kyung Hee University, South Korea, in 2005; and his Ph.D. degree from the Digital Enterprise Research Institute, National University of Ireland, Galway, Ireland, in 2010. He is a distinguished professor with Nanjing Agricultural University, Nanjing, 210031, China, and a Lincoln Professor with the University of Lincoln, Brayford Pool, Lincoln, LN67TS, U.K. Until 2012, he was a specially assigned researcher with the Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, Japan. He is a Senior Member of IEEE.

Zhiqiang Huo (zhuo@lincoln.ac.uk) earned his Ph.D. degree from the School of Engineering, University of Lincoln, U.K., in 2020. He is a research associate with University College London, London, WC1E 6BT, U.K., working on a project for artificial intelligence in health care. His research interests include time series complexity analysis, pattern recognition, and machine learning. He received the European Alliance for Innovation International Conference on Industrial Networks and Intelligent Systems 2017 Best Paper Award. He has served as the co-chair for international conferences/workshops, such as the 2016 International Workshop on Advances in Industrial Networks and Intelligent Systems and 2017 EAI International Conference on Collaborative Computing: Networking, Applications, and Worksharing.

Kim-Fung Tsang (ee330015@cityu.edu.hk) earned his associateship degree in electrical engineering from Hong Kong Polytechnic in 1983 and his M.Eng. and Ph.D. degrees in electrical engineering from the University of Wales College of Cardiff, U.K., in 1987 and 1995, respectively. He joined the City University of Hong Kong, Hong Kong, in 1988, where he is currently an associate professor with the Department of Electronic Engineering. He is a Fellow of the Hong Kong Institution of Engineers, a Chartered Engineer and a member of the Institution of Engineering and Technology, and associate editor of *IEEE Transactions on Industrial Informatics* and *IEEE Industrial Electronics Magazine*. He is a Senior Member of IEEE.

Gerhard P. Hancke (gp.hancke@cityu.edu.hk) earned his B.Eng. and M.Eng. degrees in computer engineering from the University of Pretoria, South Africa, in 2002 and 2003, respectively, and his Ph.D. degree in computer science from the Security Group, Computer Laboratory, University of Cambridge, U.K., in 2008. He is an associate professor in the Department of Computer Science, City University of Hong Kong, Kowloon, Hong Kong. His research interests include system security, embedded platforms, and distributed sensing applications for the Internet of Things. He is a Senior Member of IEEE.

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