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ARTICLE TYPE

New Technologies for Smart Cities – High Resolution Air Pollution Maps Based on Intelligent Sensors

Marzena Banach*[1] | Tomasz Talaśka*[2] | Jakub Dalecki[2] | Rafał Długosz[2,3]

[1]Institute of Architecture and Spatial Planning, Poznań University of Technology, Poznań, Poland
[2]Faculty of Telecommunication, Computer Science and Electrical Engineering, UTP University of Science and Technology, Bydgoszcz, Poland
[3]Algorithm Development, Aptiv Services Poland S.A., Kraków, Poland

Correspondence
*Marzena Banach, Email: marzena.banach@erba.com.pl
*Tomasz Talaśka, Email: talaska@utp.edu.pl

Present Address
1 – ul. Nieszawska 13C, 61-021, Poznań, Poland
2 – ul. Kaliskiego 7, 85-796, Bydgoszcz, Poland

Summary

The paper presents a contribution in the development of a wireless sensor network, that can be used for building, in real time, dense air pollution maps, for compact urban areas. Such system may be useful for cyclists and pedestrians moving through the city. Based on such data they can select the route in such a way, as to avoid the most polluted areas. An important step here may be development of miniaturized and cheap intelligent sensors, capable not only of data recording and transmitting, but also of some on-site data processing and prediction. Such sensors require a development of small and power efficient circuit, including data processing unit integrated with an artificial neural network (ANN) in a single chip. We present a prototype chip, that contains main components of such sensors, which include: a programmable 10-bit analog-to-digital converter, a programmable clock generator, and selected blocks of the ANN. The chip is a reconfigurable device, with many testing abilities. For this reason, one of the main challenges was a fast and efficient programming and testing tool. Such tool has been developed by us and is described in this work in detail along with selected measurement results. The presented work is an extended version of our conference paper[1].

KEYWORDS:
Air pollution maps, Smart cities, Wireless Sensor Network, Artificial Neural Network, Intelligent Sensor, ASIC Implementation

1 | INTRODUCTION

Modern cities are increasingly developing towards the, so-called, smart cities. The role of technologies as well as administrative regulations behind this idea is not only to increase the comfort of living in the city. First of all, this means creating solutions that make cities more robust against various unforeseen situations, and positively affect e.g. the health of residents. The issues connected with creation of such cities and changes in their structure are being discussed by many researchers[2,3,4]. Those authors show further, much more balanced evolution of cities. They emphasize the necessity of equilibrium between intensively built up and biological active terrains, which may be provided within the sustainable development rule. It is very important, especially in the context of the negative, phenomenons such as the globalization or natural environment degradation, along with deterioration of living environment. In 2018 the World Health Organization has public the outcomes of estimations, which show, that each year, around seven million people die from exposure to fine particles in polluted air. This kind exposure leads to diseases such as chronic obstructive pulmonary, stroke, lung cancer, heart disease etc.[5].

It is also connected with the degradation of quality of city-life. Reduction of green areas and increase of cars amount in parallel, substantially contributes to the noise and pollution. That is why, at present, cities need a brand new transport solutions, accompanying with intelligent technological improvements in other areas[6].

Cities are not homogeneous systems. Depending on the area, different may be the terrain, as well as the urban occupation. The type of buildings includes such parameters as its density and height, width and location of streets in relation to wind directions, distribution of green areas, etc. Particular areas play a different function, which often translates into the intensity of traffic, which is one of the main factors causing pollutions. The described factors affect the natural possibilities of the ventilation and the absorption of the pollutants. For this reason, the susceptibility of particular areas of the city to changes in pollution levels may be different[7]. An important factor here is the time of persistence of specific levels of pollutions, even after the expiry of stimulus affecting them.

Air pollution is also affected by the seasons. This is due not only to the fact of a larger emission, due to heating, but also to natural changes in green areas. The biologically active surface (lawns, parks, green walls, green roofs, trees) has a significant impact on the absorption of pollutants[8]. The role of the environmental city system is very important for its influence on energy and matter flow in the ecosystem. So called "green infrastructure" (GI), meaning the net of environmental areas related to each other, including the greenery areas, wetlands etc. and among others affect the quality of air[9].

An important parameter having an impact on the strategy of solving the problems of pollutions, is the terrain that affects the process of natural ventilation of cities. For example, in Kraków in Poland, the terrain does not support the natural ventilation, so the pollution level is frequently very high. On the other hand, when designing new cities, this factor may be taken into account. An example here is Zenata Eco-city, developed in Morocco near the city of Casablanca. One of the examples of the smart approach at the city's design stage is taking into account natural conditions. For example, the wind directions in the surrounding area were examined in order to build the city in the way, that allows for natural ventilation and lowering the temperature by several degrees in the summer[10].

Various technologies are used in solving the problem of pollutions. The basis of their operation is always an appropriate net of pollution sensors that collect, on a regular basis, information about contaminations. These data can then be processed in various ways. Increasingly, solutions based on artificial intelligence are used for this purpose, mainly various types of neural networks. The accuracy and efficiency of the pollution monitoring system depends largely on the distribution of sensors in a given area, taking into account the urban structure, the rate of change in pollution levels in a given area, etc.

With a diversity of conditions in cities described above, relying only on a few or a dozen stations measuring levels of pollutions in a given area is not sufficient. At present, in main cities in Poland, on average, there are only a few to a dozen or so automatic stations measuring the pollution levels[11,12]. Recently the Airly company in Poland proposed a much denser network of measuring stations. In this way, they drew attention to insufficiency in this regard. However, the optimal solution would be to increase the resolution of the offered maps of pollutions even to the level of particular streets. The problem in this case, however, may be the cost of the used devices themselves. For example, a single sensor offered by Airly costs about 400 Euro. Important factors also include the costs of assembly of such devices and their operation, e.g. the access to power line. In case of the Airly solutions, the collected data are transferred to a base station, where a neural network is used for a detailed data analysis. This requires securing appropriate transmission links for data transmission.

To enable building a very dense network of pollution sensors, the price of a single device of this type has to be further substantially reduced. Additionally, it is necessary to reduce the amount of data sent over the network. For this reason, we propose a solution based on the development and the use of integrated sensors equipped with an on-board miniaturized artificial neural network (ANN). As shown in next Section, examples of the realization of integrated pollution sensors can be already found in the literature. This is an important step towards the solutions proposed in this work.

Another issue is the function performed by the measuring device (sensor). The simplest, one can say a classic, approach is the use relatively simple sensors, whose role is to measure the levels of impurities, which after a basic preprocessing are transfered to a central station of the overall system for a further processing and analysis. In case of a very dense wireless sensor network (large number of independent data sources), the computing power of the central station, as well as the throughput of the communication links may become a bottleneck here. The solution of this problem may be a development of more sophisticated measurement devices able to perform an analysis and prediction tasks on site, independently from the main station.

Yet another need is to increase the prediction abilities offered by the overall monitoring system, especially for a short time horizon. Such information may be of fundamental importance, for example for cyclists and pedestrians moving around the city. Based on such data, they may consciously choose particular sections of their route through the city. The prediction of changes in levels and distributions of pollutant is frequently performed by advanced algorithms belonging to the artificial intelligence (AI) area. Various types of artificial neural networks (ANN) are used for this purpose. They make the prediction on the basis of input data, that include pollution levels and parameters related to weather (pressure, direction and wind force, etc.). More details are provided in the next state-of-the art section.

A basic question here is the way of the implementation of the AI algorithms. In contrast to typical software solutions, we propose the realization of the ANN as a low power, low chip area and parallel device that can be integrated along with other sensor components in a single specialized chip (ASIC – application specific integrated circuit). This approach is an substantial step towards the construction of miniature intelligent sensors with the prediction function, and crucial for a system built of a large number of such measuring devices. The assumption here is to limit the communication via the wireless sensor network (WSN) only to the situations when the measured data may have an impact on the changes of the pollution map, e.g. with clear changes in pollution levels. In such situations, the collected data may be sent to the central station for a more detailed analysis, as well as in order to update the created pollution maps.

The described approach is of great importance from the technical point of view. Typically, in the WSN sensors the modules responsible for data transmission consume a significant portion of the power consumed by the overall device [13]. Therefore, a substantial limitation of data transmitted over the network will enable the development of low power devices, operating on the basis on energy scavenged from the environment. This approach greatly simplifies the assembly and operation of such devices over a longer period of time. Our investigations show, that even large neural networks, implemented in the CMOS technology, operating at low data rates (for example, 1 kSample/s) do not dissipate power exceeding a few μW [14]. Systems of this type are part of the scope of smart city solutions, in which sustainable development is emphasized.

The paper has the following structure. Next Section presents state-of-the art study in areas related to the subject of this work. Discussed are existing solutions of pollutant monitoring systems, wireless sensor networks as potential systems used in such systems, then solutions for the pollution sensors themselves, and finally examples of the application of artificial neural networks (ANN) in such systems. In the following Section, provided are details on our contribution to the development of integrated intelligent sensors, that may be used in novel, high resolution, air monitoring system. In last Section, the conclusions are drawn.

2 | STATE-OF-THE ART STUDY

2.1 | Air pollution monitoring systems

The quality of air is a very important factor, affecting the functioning of the city users. For this reason, it requires from the urban planners, computer specialists, ecologists, to work together toward solving the problems in this regard.

The problem of the pollutions is commonly observed and therefore various solutions are created to monitor them and predict their levels. One of them are large monitoring stations. They are expensive and usually their density in a given area is relatively low. In Poland, for example, Voivodship Environmental Protection Inspectorates provide data from environmental monitoring for particular voivodships [15]. The offered system is based mainly on networks of measurement stations located in sensitive points of voivodships – mainly in large cities. Such stations measure concentrations, among others, of such gases and substances as sulfur dioxide, nitrogen oxides, benzene, carbon monoxide, ozone, suspended dust PM_{10} and $PM_{2.5}$. In 2017, in Poland, air quality measurements were carried out by 1,924 measuring stations, including 1,098 automated stations (57 %).

In recent years, the Airly company mentioned above works on its own system, which is supposed to offer much denser network of the measuring stations. Currently, the highest density of such devices is available in Kraków, and therefore this city is treated in this work as a point of reference. The measurement results offered to the public throughout the company's web page show, that it is justified, as concentrations of pollutants can change significantly in short periods of time. Additionally, large differences between pollution levels may be visible even between areas located close to each other. Selected results from the Airly website, are shown in Figure 1. Diagrams (a) and (b), show the results for two following hours for the overall city. Diagram (c) illustrates the way the data for particular measurement stations are presented in 24-hours windows. The system offered by Airly includes essential stages of data acquisition and sharing such as: sensing, data processing, prediction, building of the map.

At this point, it is also worth to mention available wearable pollution sensors already offered on the market [16]. Their usage is limited, as they require a person equipped with the sensor to be present in a given area of the city. It does not protect this person from the effects of the pollutions. A better possible solution would be stationary sensors participating in building on-line pollution maps, available for everybody. In this way, city users could plan their route or the mean of transport more consciously in advance. One of the useful options related to the described wearable sensors would be sharing collected data with a central system, so

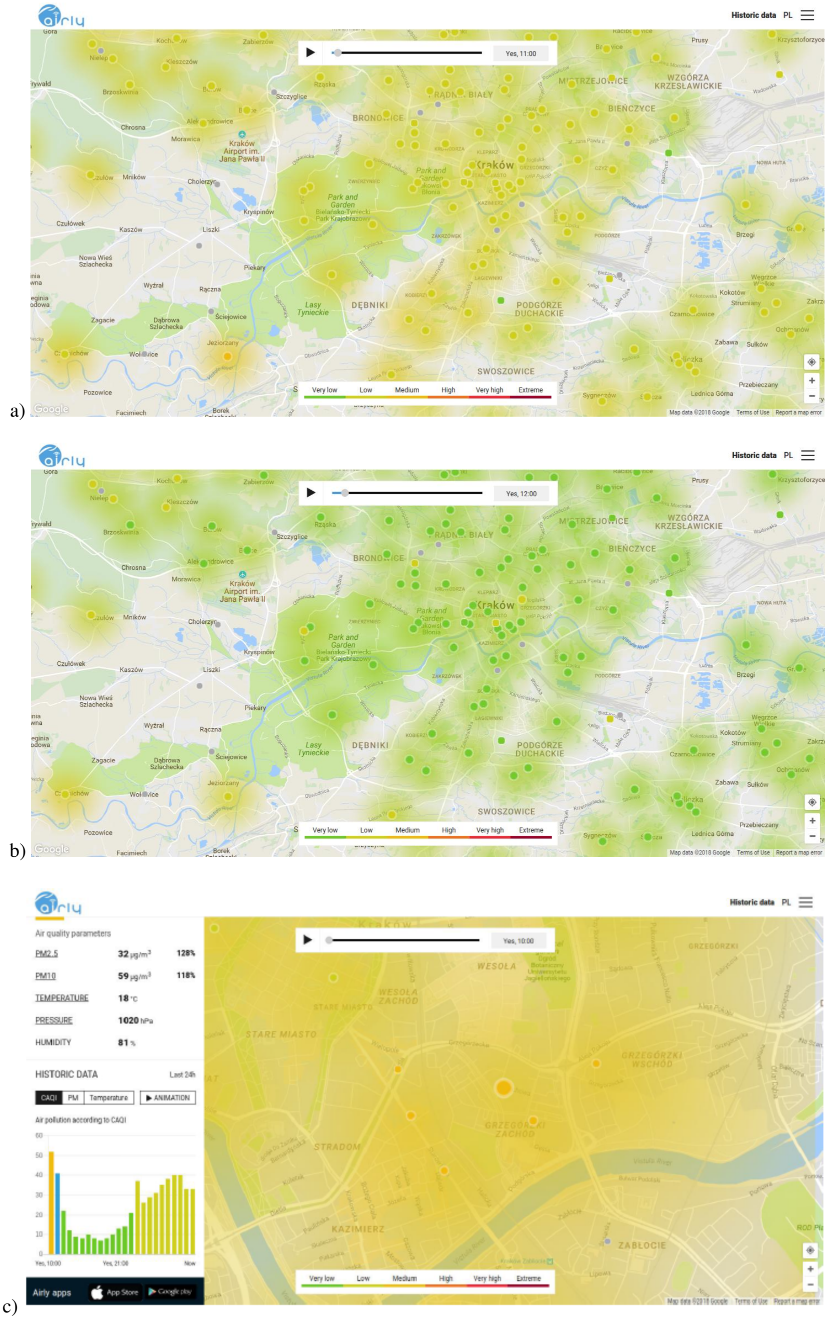

FIGURE 1 Selected maps obtained from the Airly company's web page (source: Airly sp. z o.o., Aleja Pokoju 1a, 31-548, Kraków, Poland, https://map.airly.eu/pl/) for the overall city for two following hours, (c) illustration of a 24h record for a selected measurement point.

that other people could use them. Such an approach could support the existing or planned stationary systems, increasing their prediction abilities and increasing the resolutions of created maps.

2.2 | Wireless Sensor Networks in smart cities

New technologies in the area of the information and communication technologies (ICT) are crucial for the development of the future pollution monitoring systems. The ability to collect data from a large number of locations, transferring them to a central station in real time is the key feature here [17].

Development of energy-efficient WSNs calls for novel solutions from such areas as microelectronics (hardware layer of the overall network), IT (control and data processing) and telecommunications (data exchange). Networks of this type are currently intensively developed around the world [18]. The key issue here is the reduction of the sized of the sensors and the consumed energy. One of the possible development directions is to introduce intelligent sensors, mentioned above, capable of preprocessing of collected data and making decisions independently regardless of the central station (to some extent). This is important from the point of view of the possibility of limiting the amount of data sent over the network. This in turn, is crucial due to rapidly growing number of wireless sensors in the environment [18].

Conditions in which sensors must work stably in urban systems are very demanding, which includes, for example, fluctuations in ambient temperatures in the range from -40 °C to +100 °C (during exposition to sun), large changes in humidity, pressure and light intensity. These conditions are much more demanding than those occurring, for example, in buildings or in sensor networks used for medical diagnosis purposes.

Another important aspect related to the development of the WSN hardware layer is its energy efficiency. One of the objectives of the WSN network is the pursuit of energy self-sufficiency of particular sensors / nodes [19]. For this purpose, various solutions are developed that can work using energy scavenged from the environment (heat, solar energy, kinetic energy, etc.). To make this possible, a lot of efforts are made to minimize the power consumed by electronic circuits included in the sensors [20,21,18].

An additional way to miniaturize the devices and to reduce their energy consumption is to adapt their structure to a specific range of tasks. Example sensors designed for the application in the 'Internet of Things' (IoT) area is a series of devices released commercially by Cypress Semiconductor from USA [18] in 2015. An example device of this type, self-sufficient in energy, features the sizes not exceeding 1 cm^3.

2.3 | Microelectronic sensors of pollution particles

In the literature, one can find several examples of the implementation of particle sensors of various air contaminations. Texas Instruments company proposed an optoelectronic system for the detection and measurement of the $PM_{2.5}$ and the PM_{10} particles. The system is based on the detection of scattered light by particles suspended in the air [22]. In [23] presented are methods of implementing the $PM_{2.5}$ and PM_{10} particle micrometer using the zinc oxide based on the Solidly Mounted Resonator (SMD). The authors of [23] present a complete system mounted on a printed board (PCB). On the board, apart from the particle PM_{10} and $PM_{2.5}$ sensor, there is also available an ASIC that is used to process data provided by the sensor. The reported efficiency of the system, shows that such an approach is a right development direction. However, since it consists of two separate blocks (the sensor and the system managing it), it has an impact on the sizes of the overall device. Another issue, important in such applications, is the lack of the encapsulation of the electronic circuits.

Another example is an integrated capacitive sensor designed in the CMOS 0.35 μm technology [24,25]. A very important advantage here is the realization of the sensor inside the integrated circuit, which enables, apart from the detection of the pollution molecules, also parallel data processing typical for ASICs. The system is capable of detecting microscopic particle sizes of pollutants. This work is an important novelty in this area in the world, as the sensor solutions inside the integrated circuit are presented for the first time here.

The availability of the described works is very important from the point of view of the results presented in this paper. They show that the proposed concept of intelligent sensors for pollution monitoring is reliable. It is not necessary to create all elements of such sensors from scratch. Since some of the building blocks may be based on available standard solutions, that's why in our work we focus on those components that are not currently available. They include an artificial neural network adapted for the use in very low power devices. We were guided by these premises during the works on the prototype integrated circuit.

2.4 | Application of ANNs in monitoring and prediction of air pollutants

Development of smart cities would not be possible without the use of artificial intelligence (AI) methods, that include artificial neural networks (ANN), genetic algorithms (AG), fuzzy systems (FS), as well as expert systems (SE). The AI will play a significant role in the development and functioning of such cities. On one hand, this is due to a large complexity of the system which such a city is. On the other hand, there is a large difficulty of an accurate mathematical description of the interdependencies between various parameters of the city system. Complexity here also means a huge amount of data, which is often difficult to express unequivocally with the help of unified indicators.

ANNs are universal tools frequently used in different areas of daily life. They are frequently employed for data classification, prediction, recognition, detection, etc. Neural networks operate more effectively if they receive properly prepared data (initially preprocessed and normalized) and when they are offered with a sufficiently large computing power to process them within an acceptable time interval. It is also necessary to match a given type of the ANN to a specific problem. One of the areas, in which these tools are more and more frequently used, is the problem of the air pollution, which is the topic of this work. In this case, they are are used in contamination forecasting[26,27,28,29,30,31,32,33].

One of the examples here is the application of the MultiLayer Perceptron (MLP) and the Radial Basic Function (RBF) neural networks for a long-term prediction of pollutants dust (PM_{10}, $PM_{2.5}$) (especially in cities)[26,27]. The authors of these works have conducted comparative studies of both types of the networks. The examined networks are well suited to air quality prediction based on basic meteorological data and mean values of dust (particle) concentration of PM_{10}, $PM_{2.5}$ from the day before.

In another work[28] a multilayer perceptron (MLP) has been applied in forecasting the impact of pollutions, caused by road traffic (exhaust fumes) on residents health. The inputs of the NN are in this case only traffic and the meteorological data. A relatively small NN build of 50 neurons in the hidden layer, acting as a classifier, was able to minimize the prediction error to only 11 %. The authors of[28] emphasize the advantages of the proposed method, which eliminates the need of using expensive maintenance stations that would monitor the air quality.

Cellular neural networks (CNNs) may be also used in such applications. In[29], for example, the CNN was used for an efficient forecasting of the contamination in the event of the sensor failure. Comparison of the prediction results and available measurement data has confirmed the effectiveness of such methods.

In[30] three different machine learning algorithms are presented, including, among others, an ANN used for the monitoring and forecasting the pollutant levels, such as ground level ozone O_3, nitrogen dioxide NO_2 and dioxide sulfur SO_2. The ANN was trained using the backward error propagation algorithm (BPN). The authors of[30] presents the forecasting results for time horizons of 1, 8, 12 and 24 hours before the expected occurrence of pollution concentration. They have shown that the NNs used in this case exhibit worse properties, when compared with two other machine learning algorithms, i.e. the Support Vector Machines (SVM) and the M5P model trees. Nevertheless, it is worth to note that the ANN coped well with the realized prediction tasks. A further increase of its efficiency depends on the modification of several parameters of the ANN and input dataset, for example, by increasing the number of the learning patterns and the addition of some new data, e.g. a typical seasonal changes in the pollution levels.

Another work in this area[31] presents the concept of using self-organizing networks[32] for the classification of sulfur dioxide hazards SO_2. Meteorological parameters such as temperature, humidity, wind or pressure that are needed to assess and forecast the hazard have been accepted as known and widely available. The paper evaluates the influence of some of the tested parameters (e.g. the air pressure and temperature) on the air pollution levels.

Self-organizing networks allow for the integration and processing of data, provided by various sensors and to ensure an easy interpretation of the obtained results. We can even assume, that the meteorological parameters such as temperature, humidity, pressure, wind strength and its direction, are in most cities known and freely available. Self-organizing networks are interesting tools, as they allow for a visualization of correlations between parameters of different types.

In our work since many years we focus on the development of such ANNs at the transistor level in the CMOS technology[14,34,35]. We proposed and implemented in the CMOS technology particular building blocks of the ANNs in the form of energy-efficient and miniaturized circuits. We have realized NNs both as analog and digital systems. Most of the realized components are universal solutions, suitable for thee application in different learning algorithms, including the MLP and the BPN ones. Self-organizing networks realized by us include Winner Takes All (WTA), Winner Takes Most (WTM) and the Neural Gas (NG) learning algorithms.

3 | PROPOSED CONTRIBUTION TO THE DEVELOPMENT OF THE INTELLIGENT POLLUTION SENSORS

In this Section, we present a model of an integrated system for the detection and prediction of air pollution particles in the form of a specialized chip implemented in the CMOS technology. State-of-the art works in this area, described above, focus

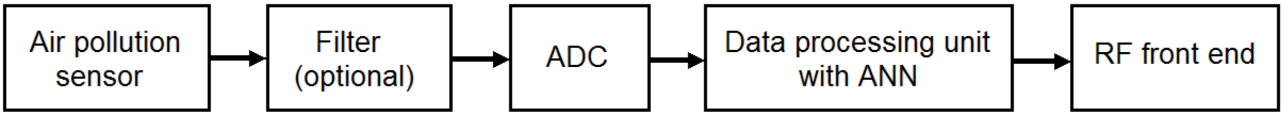

FIGURE 2 A general structure of the proposed wireless intelligent pollution measurement device.

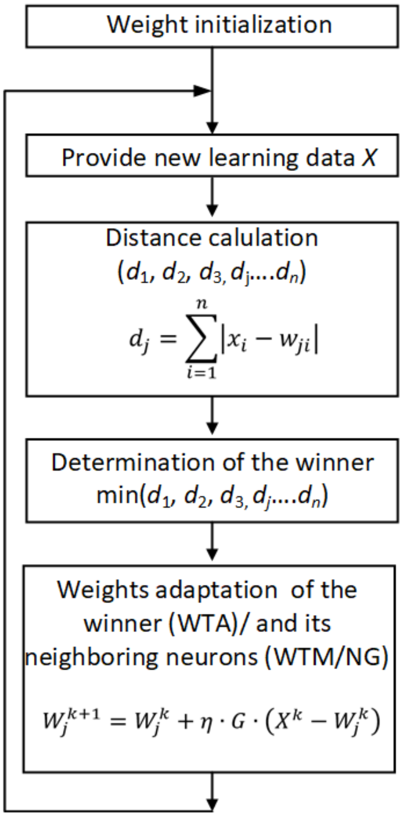

FIGURE 3 Diagram illustrating following steps of the learning algorithm of typical self-organizing neural networks[1].

on the implementation of either the pollution particles sensors alone in the form of an integrated circuit or the use of software implemented NNs in tasks that aim at detecting the impurities. In this work, we present the solutions that will allow joining those two areas into a single integrated device, capable of working as a node of the WSN.

The proposed intelligent sensor may consist of several main components (see Figure 2), such as:

- air pollution sensor (a standard solution) used to collect data from the city (one of described solutions may be used),
- optionally an anti aliasing filter and filters used to remove noises from the signal,
- an ADC used to convert measured analog data into a digital signal further processed in:
- a data processing unit with a hardware realized ANN, which is our proposition here,
- a radio-frequency (RF) communication block responsible for transferring the processed data to a base station (a standard solution is to be used).

The first element in the computation chain is the pollution sensor. Information on the level of pollutants is provided by the sensor in the form of an analog voltage or current signal (after appropriate conversion). Possible sensor solutions were discussed in previous Section[24,25]. Due to the availability of such solutions, in our work we do not focus on such circuits. We pay a more attention to the blocks directly involved in the signal processing tasks carried out within the wireless sensors. The filters as well as the ADC were already designed by us, as described in[36,37,38].

The main area of our interests is one of the key elements of the proposed intelligent sensors, the ANN that is going to be integrated with other sensor components in a single chip. Theoretically, in the WSN node either the analog or digital ANNs may be used. In the second case, a preliminary analog-to-digital conversion with the appropriate resolution is required. Nevertheless, the preferred approach here is the use of digital ANN, as such circuits offer a large immunity to fluctuations of external conditions and to an impact of the imperfections of the technological process.

In the presented approach, we propose the use of self-organizing networks. As shown in the literature study above, such networks were already used for the analysis and prediction of the air pollutions. Moreover, such networks offer a relatively simple structure, which is crucial from the point of view of the implementation as an ASIC. Low mathematical complexity allows for a large miniaturization, as shown in several of our previous works[14,34,35]. As mentioned earlier, self-organizing algorithms include, for example, the WTA, WTM and the NG ones. At several stages these algorithms perform similar operations, as shown in general in Figure 3. The main steps performed for each input learning pattern X are described below:

- initialization of the neuron weights so that to distribute them over the input data space,
- providing a new learning pattern to the inputs of the NN (after initial preprocessing),
- calculation of distances (d_1, d_2, d_3, d_j, …, d_n) between this learning pattern and weight vectors W of all neurons in the NN. The distance is calculated according to one of typical distance measures, for example, such as the Manhattan or Euclidean ones[34],
- determination of the winning neuron. Mathematically the $\min(d_1, d_2, d_3, d_j, \ldots, d_n)$ operation is used here,
- indication of neurons that belong to the, so called, neighborhood of the winning neuron. The distances between particular neurons from the neighborhood and the winner have an impact on the values of the learning rates η for these neurons,
- adaptation of the wights of the winning neuron (in the WTA algorithm only this neuron is adapted) and of its neighbors (in the WTM and the NG algorithms). The adaptation process is performed according to a formula:

$$W_j(k+1) = W_k(l) + \eta(k) \cdot G() \cdot [X(k) - W_j(k)] \tag{1}$$

  where W_k is the weights vector of a j^{th} neuron. The neurons that belong to the winner's neighborhood, are trained with the intensities determined by the applied neighborhood function $G()$[34,35].

The main differences between described three self-organizing networks are visible in the structure of the block responsible for the neighborhood mechanism. In the WTA NN, the neighborhood is not used. In this case, however the so-called conscience mechanism may be applied to enable stimulation of all neurons in the NN[14]. In the WTM NN, particular neurons are permanently linked to their neighbors. In contrast, in the NG NNs, the neighborhood is created 'ad hoc' based on the current positions of particular neurons in the input data space. This requires sorting of neurons according to their distance to a given learning pattern X (sort $(d_1, d_2, d_3, d_j, \ldots, d_n)$).

In the WTM and the NG approaches, a neighborhood function is required to differentiate the strength with which the weights of particular neurons are adapted. Our previous theoretical and simulation studies have shown that it is effective to use the triangular neighborhood function instead of the Gaussian one, due to hardware implementation issues[39]. This function has been also implemented in the presented prototype chip, shown in Figure 4. The chip contains also other components of the SOM, such as distance calculation circuit (DCC), winning neuron selection circuit (WSC). It also contains other components of the WSN node, such as 10-bits, programmable ADC equipped with its own 10-phases clock generator.

The realized chip is a reconfigurable / programmable device. This means, that the parameters of particular components as well as the connection scheme in the overall chip may be easily reconfigured. The problem we faced with was a limited number of external pins, so that particular digital inputs and outputs have to be multiplexed in a proper way. This required a development of three important components of the the overall system. One of them is an appropriate programmable I/O block that includes a set of switches, an address decoder and memory blocks. A general diagram of the realized Input / Output block is shown in Fig. 5. The circuit is described in more detail below.

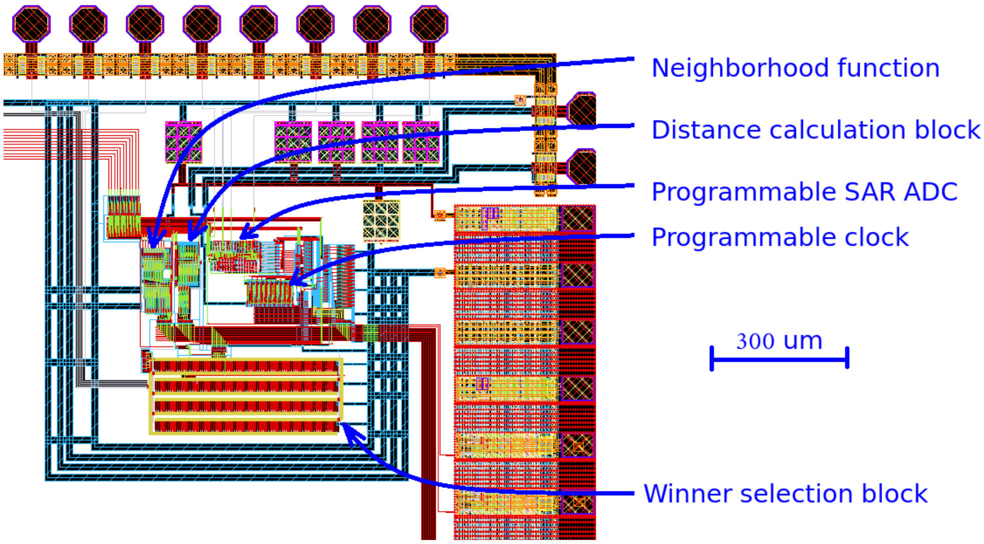

FIGURE 4 A prototype chip fabricated in the CMOS 130 nm technology. The chip contains selected components of the intelligent sensor, including main blocks of the ANN[1].

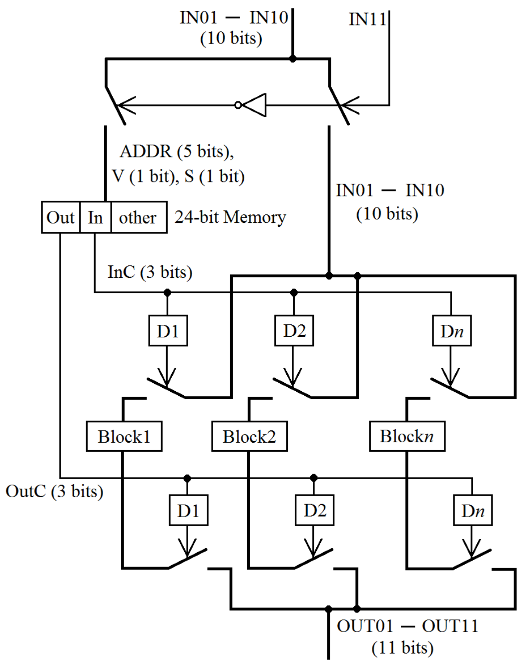

FIGURE 5 An Input/Output programming block of the prototype chip.

The second component is a dedicated scripting like-language to efficiently define all signals necessary to program the chip and then to test it. The problem, that had to be solved was how to describe in an efficient way signals with different delays, fills, etc. The third component is a software tool responsible for the conversion of the created scripts into appropriate sequences of programming and testing signals for particular inputs, to enable automatic tests. In the following part of the article we present these components in more detail.

The chip was designed in the CMOS 130 nm technology. The overall area including the external pads equals 1.4 mm^2, with the areas of particular developed components not exceeding 0.06 mm^2.

4 | PROPOSED TOOL USED TO PROGRAM AND VERIFY THE PROTOTYPE CHIP

With the current technological miniaturization, the final area of the chip is often determined by the ring of pads (sizes of the pads and the pitch) used to exchange data between the chip and its environment. While designing this circuit, several restrictions were important, such as the area limited to 1.5 mm^2, the minimum pitch of 100 μ and the maximum number of pads equal to 40, which resulted from the availability of the package. Considering these constraints and requirements, it was necessary to design an appropriate input-output block, responsible for changing internal configuration of the chip. Among the 40 available pads, the system provides 11 digital inputs, 11 digital outputs, 7 different purpose power lines, and 11 analog inputs and outputs. Such a division of the pool of pads resulted from the requirements for the main implemented blocks, including the 10-bit ADC.

The chip operates in one of two modes: (i) programming, and (ii) standard data processing, additionally determined by the needs of a tested block. In the first mode, i.e. for the logical '1' at the most significant bit (MSB) (IN11 in Fig. 5), the inputs are used to appropriately setup internal connections of the chip and the parameters of particular blocks. In the second mode, the inputs provide signals to particular blocks, according to the configuration stored in the internal memory cells, shown in Fig. 5. In the programming phase the IN01 – IN10 signals provide address of a given memory cell (ADDR), a value (V) to be stored and store (S) signal, that latches the V signal in the memory. The Out and the In sections are composed of 3 bit cells (InC and OutC signals), which throughout the decoding blocks (D1 – D*n*) determine which block will receive input signal, and will provide computed data to the output of the chip.

In order to effectively and quickly test particular blocks of the chip, we proposed a tool composed of two modules. One of them is a scripting language that enables an efficient and simple description of the input signals. The second module is a C++ program (a signal generator) used to process the prepared configuration scripts and to quickly generate appropriate test sequences. The tool was first used at the stage of the verification of the chip in the Cadence / Spectre environment, before the fabrication. At this stage, it generates separate text files for each input. The files are then coupled with the pwl voltage sources representing the input signals. After the chip fabrication, the same tool was used to generate test sequences uploaded to a Field Programmable Gate Array (FPGA) or a microcontroller, directly used to drive the chip.

4.1 | Proposed description of programming and test signals

Figure 6 illustrates the way how the signals are defined in the proposed method. All tests of the designed integrated circuit are prepared and carried out usually in two phases as shown in the figure, designated as Programming and Testing phases, respectively. The number of phases may be larger than two. Programming and testing phases may occur alternately, or there may be multiple test phases for different signals after a single programming phase.

Particular lines in the script have a specific meaning, determined by the first character in the line, as described below:

Sign '-' – Comments

This sign means a starting point of a comment. The reminder of the line in which it appears is ignored by the program. This sign may appear at the beginning of the line but also in any other place.

Sign '#' – Definition of the signal prototype

In lines marked in this way, prototypes (or classes) of signals required in a given test are defined. The sequence '#*n*#' is the identification number (ID) of a given prototype. In the proposed tool, up to 10 different prototypes may be defined, differing from each other in the parameters described below. The ID numbers do not have to be used in the ascending order. A given prototype may then be used or not, depending on needs. In the carried out tests of the chip, the maximum number of prototypes did not exceed three. The prototypes of the signals may be modified at any time, by a new definition. The remaining parameters of the prototypes, separated by the ';' character, specify:

- the signal high level (voltage – VDD),
- delay of the overall signal relative to the beginning of the simulation or measurement (SHIFT),
- period of the signal (PER),
- pulse width (PW)

```
 1: --------------------------------------------------------------------------------
 2: ------------------------------ PROGRAMMING PHASE -----------------------------------
 3: --------------------------------------------------------------------------------
 4: #0#3.3;100;500;450;4;4;  1;  - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 1st signal prototype
 5: #1#3.3;100;500;200;4;4;250;  - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 2nd signal prototype
 6: T00000 0 1 000 0             - Assigning signal prototypes to particular inputs
 7: --------------------------------------------------------------------------------
 8: -ADDR. V S NUS M             - ADDR.-address; V-value; S-store; NUS-not used; M-mode
 9: ----------------------------- OUT MODE     : 4 (clock generator) ------------------
10: .10000 1 1 000 1             - address of 1st bit      (A =  1, V = 1)
11: .01000 0 1 000 1             - address of 2nd bit      (A =  2, V = 0)
12: .11000 0 1 000 1             - address of 3rd bit      (A =  3, V = 0)
13: ----------------------------- IN MODE      : 4 (clock generator) ------------------
14: .00100 1 1 000 1             - address of 1st bit      (A =  4, V = 1)
15: .10100 0 1 000 1             - address of 2nd bit      (A =  5, V = 0)
16: .01100 0 1 000 1             - address of 3rd bit      (A =  6, V = 0)
17: ----------------------------- Settings of ADC & WSC blocks ------------------------
18: .11100 1 1 000 1             - ADC / DAC               (A =  7, V = 1)
19: .00010 0 1 000 1             - WSC MODE                (A =  8, V = 0)
20: ----------------------------- Programming the clock generator ---------------------
21: .00001 1 1 000 1             - clock 10-phase inactive (A = 16, V = 1)
22: .10001 1 1 000 1             - clock  9-phase inactive (A = 17, V = 1)
23: .01001 0 1 000 1             - clock  8-phase   active (A = 18, V = 0)
24: .11001 1 1 000 1             - clock  7-phase   active (A = 19, V = 1)
25: .00101 1 1 000 1             - clock  6-phase   active (A = 20, V = 1)
26: .10101 1 1 000 1             - clock  5-phase   active (A = 21, V = 1)
27: .01101 1 1 000 1             - clock  4-phase   active (A = 22, V = 1)
28: .11101 0 1 000 1             - clock  3-phase inactive (A = 23, V = 0)
29: .00011 1 1 000 1             - clock  2-phase inactive (A = 24, V = 1)
30: .10011 1 1 000 1             - clock  1-phase inactive (A = 25, V = 1)
31: --------------------------------------------------------------------------------
32: ------------------------------- CONTROL & TEST PHASE ------------------------------
33: --------------------------------------------------------------------------------
34: #0#3.3;100;1000;990;4;4;  1; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 1st signal prototype
35: #1#3.3;100;1000;400;4;4;500; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 2nd signal prototype
36: #2#3.3;100;1000;590;4;4;400; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 3rd signal prototype
37: T21111 1 0 000 0             - New assignment of signal prototypes to chip inputs
38: -12345 ---------------------- F-fill; 2-ck1; 3-ck2; 4-Reset; 5-ext. control clock;
39: .00111 0 1 000 0             - Reset clock
40: .01001 0 1 000 0
41: .50101 0 1 000 0
42: .01001 0 1 000 0
.......................
47: .40101 0 1 000 0
48: .01001 0 1 000 0
49: .40101 0 1 000 0
50: .01001 0 1 000 0
51: .40101 0 1 000 0
52: .01001 0 1 000 0
53: ---------------------------
54: #2#3.3;100;1000;900;4;4;90; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - modify 3rd prototype
55: ---------------------------
56: .40101 0 1 000 0
57: .01001 0 1 000 0
58: ---------------------------
59: #4#3.3;100;1000;200;4;4;500; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 4th signal prototype
60: #5#3.3;100;1000;200;4;4;500; - VDD;SHIFT;PER;PW;TR;TF;PDEL; - 5th signal prototype
61: T21111 1 0 454 5             - New assignment of signal prototypes to chip inputs
62: ---------------------------
63: .40101 0 1 252 5
64: .01001 0 1 000 0
65: .40101 0 1 360 0
66: .01001 0 1 003 6
67: .40101 0 1 250 0
68: .01001 0 1 000 0
69: .40101 0 1 362 5
70: .01001 0 1 000 0
71: .40101 0 1 250 0
......................
```

FIGURE 6 An example script created according to proposed signal generation tool for testing the clock generator implemented inside the prototype chip. The programming phase is visible in-between the line No. 4 and 30, while the test phase in-between the line No. 34 and 71.

- pulse rise time (TR)
- pulse fall time (TF)
- pulse delay relative to the beginning of the period (PDEL)

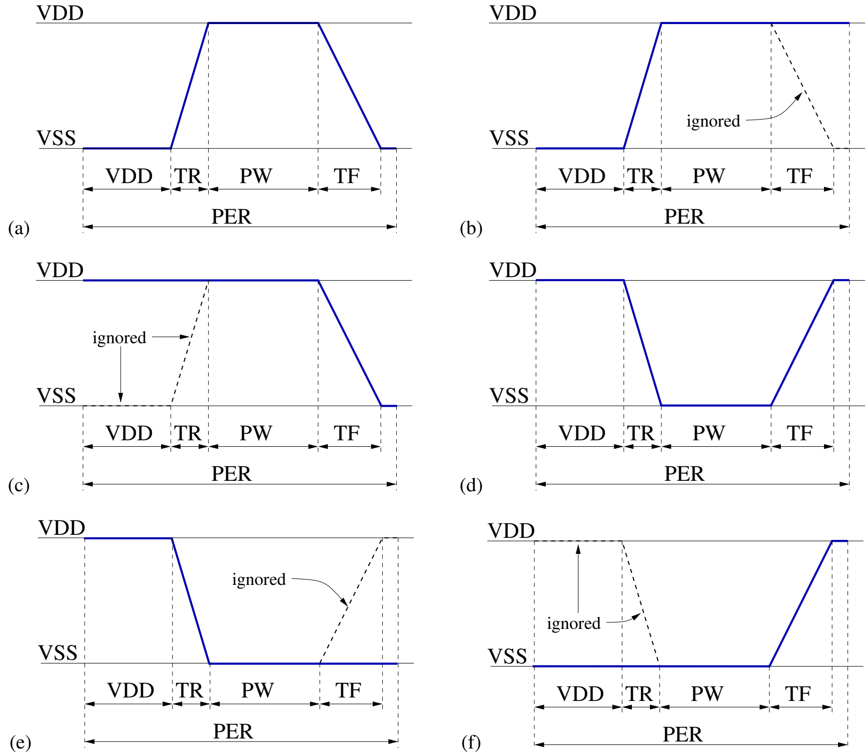

FIGURE 7 Illustration of particular pulse modes used to define waveforms of the input programming and control signals: (a) mode 1, (b) mode 2, (c) mode 3, (d) mode 4, (e) mode 5, (f) mode 6.

Sign 'T' – Assigning signal prototypes to particular signal lines

In this type of line particular signal prototypes are assigned to particular input lines. In the presented example (line No. 37), the prototype #2 is assigned to the first line. The following five lines are assigned with the #1 prototype. The remaining lines are assigned with the #0 prototype. This means that the basis of the signal shapes in these lines will be trapezoidal pulses with given pre-set parameters. The presented example shows, that at any time both the prototypes and the assignment may be modified according to needs (lines No. 54, 59 – 61).

Sign '.' – Definition of particular signals provided to the chip

Each line marked with this sign determines the next period of all input signals. This is a symbolic time stamp equal for all input lines. In the following positions behind '.' it is defined what is happening in a given period on a given line. The accepted values are from 0 to 6. This convention allows for an additionally control of the shapes of the signals. The meaning of particular values is discussed below and shown in Figure 7.

0 – in a given period the pulse on a given line does not appear. To be more precise, there is no change of state from the previous impulse, so if the state was VDD it remains VDD. A given line in this period is ignored by the program.

1 – in a given period a full pulse appears, defined by means of one of the signal prototypes. The impulse starts raising from 0 to VDD after a relative delay (in respect to the beginning of this period) equal to PDEL. The raise time equals TR. After the following PW time it falls to 0 again (TF is the fall time).

2 – in a given period there is only the opening phase of the pulse, i.e. the phase marked as TF is ignored. The pulse starts from 0, increases to VDD and remains at this level.

3 – only the closing phase of the pulse occurs in this period, i.e. the phases indicated as PDEL and TR are ignored. The pulse starts from VDD and then falls to zero after a time equal to the sum of PDEL, TR and the PW times.

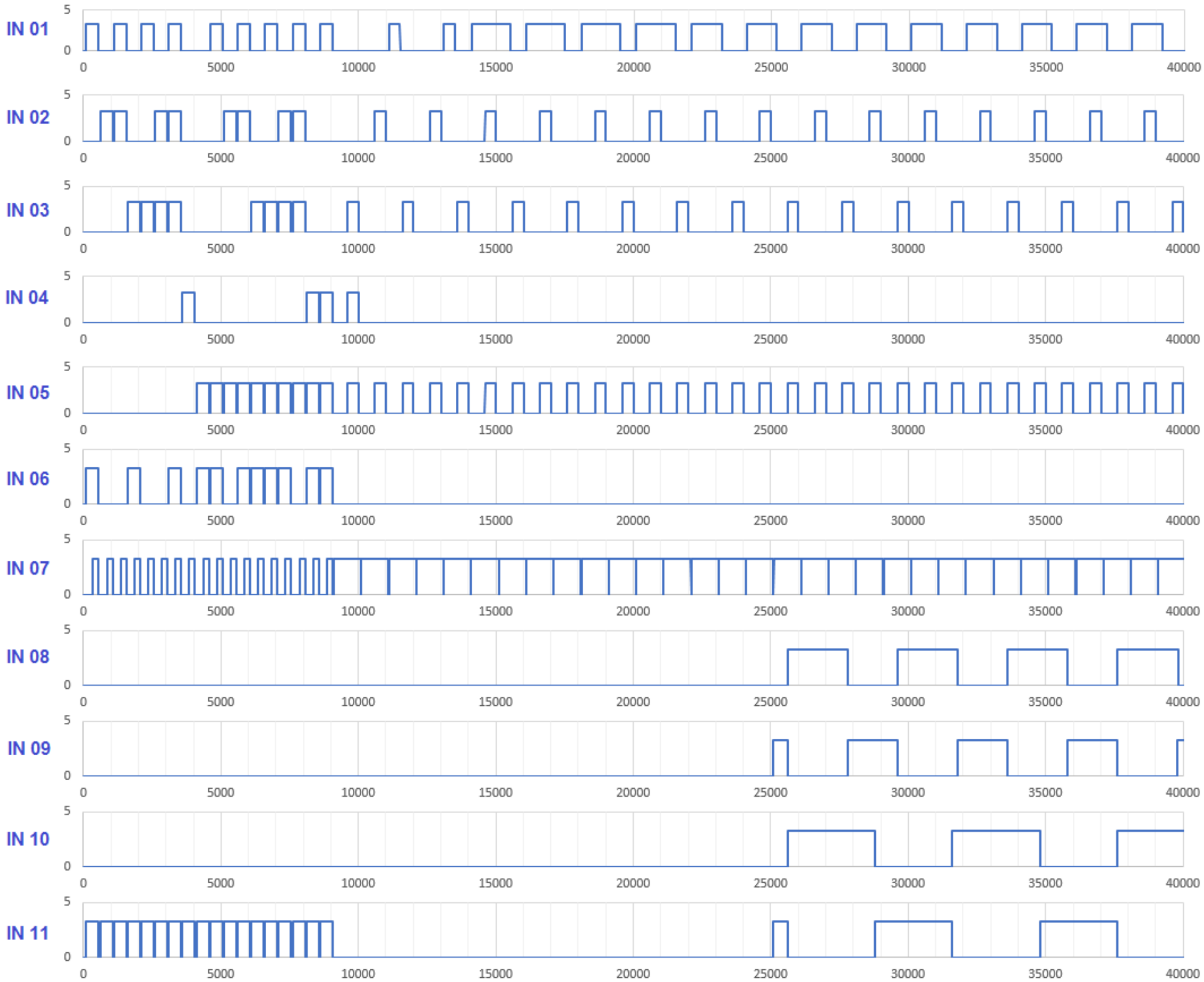

FIGURE 8 Digital input signals generated on the basis of an example script illustrated in Figure 6

4 – in a given period there is a full impulse defined by means of a given prototype, but in a negated version. The period in this case starts with the VDD value, then after the PDEL time there appears a negative pulse falling to 0, which lasts the TR time, and then it rises again to VDD after the PW time.

5 – the meaning of this state is similar to that in case 2, but for the negated impulse. The period starts with the VDD value, then there is a negative impulse that reduces the signal level to 0 and this state is kept on the line.

6 – the meaning of this state is similar to that in case 3, but for the negated impulse. The period starts with 0. The opening phase of the negative impulse is ignored. After the time equal to the sum of PDEL, TR, and PW the pulse raises to the VDD value.

The described modes significantly extend the capabilities of the signal generator. They allow to obtain positive and negative pulses lasting for a larger number of periods than one. This was important from the point of view of some of the tests carried out.

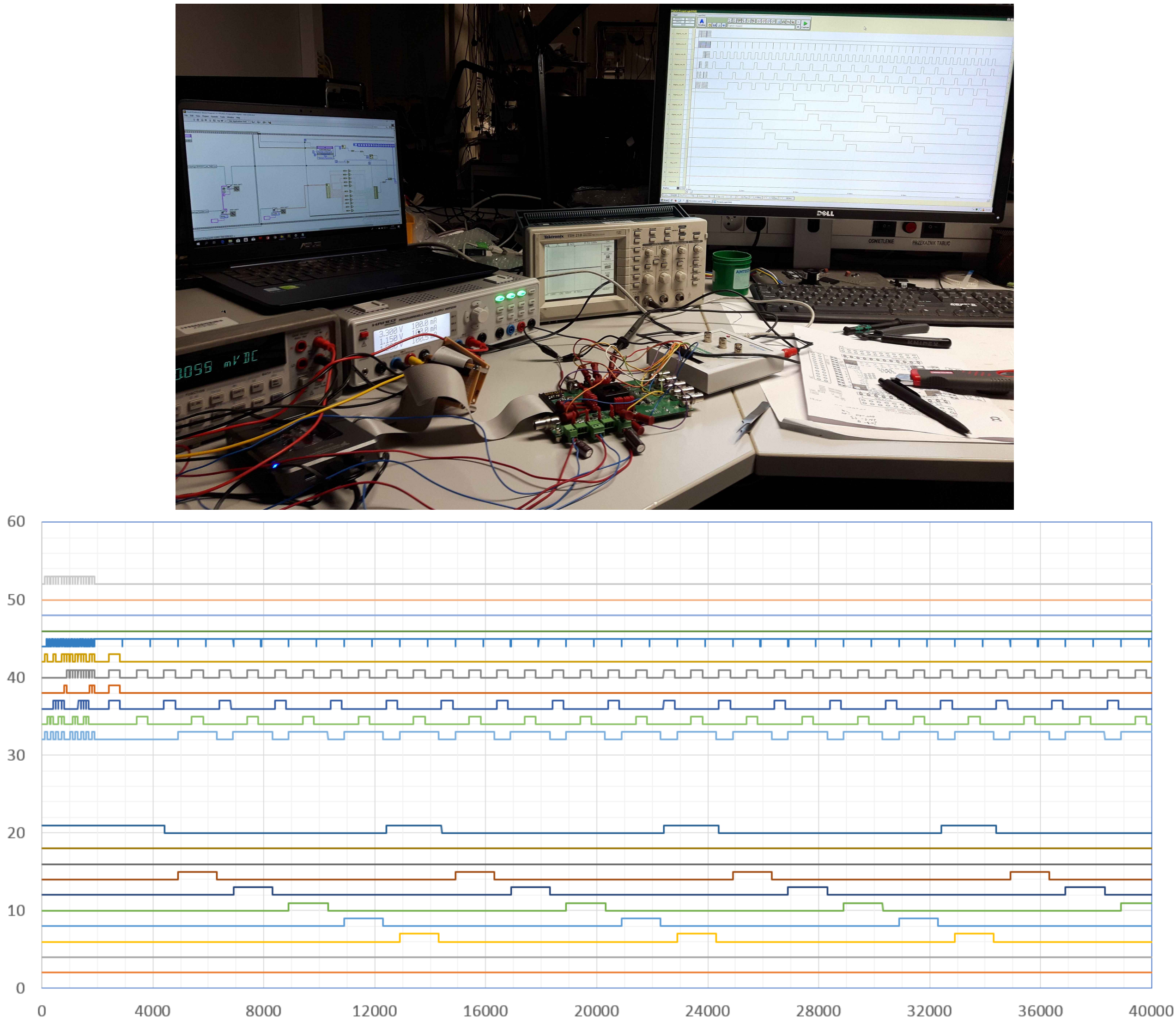

FIGURE 9 Selected measurement results. An example case of the multi-phase clock generator, programmed to provide 5 phases at lines 8, 7, 6, 5, 4. Upper bunch of signals illustrates inputs with LSB at line marked as 32 and MSB at line marked as 52. The bottom signals are the output signals of the chip, with OUT01 at line 0 and OUT11 at line 20.

4.2 | Generation of signals on the basis of prepared scripts

As an important part of the project, it has been developed a software tool (in C++) used to process the described scripts. The tool allows to generate signals that are directly used in the simulations (during the chip design in Cadence environment), as well as in the measurements of the fabricated prototype. The input script is processed in several stages, described below:

Stage 1 – depending on the used modes (values 0 – 6 described above), in particular periods determined by the PER parameter, the signals are converted to the form of lists build of time-value pairs. During the conversion, the parameters of the defined signal prototypes are taken into account. The pairs are generated and saved in the output files only when there is a change in the signal value. At this stage a separate file is created for each signal line. The lengths of the files depend on the number of the changes of the values. In an extreme case, when the signal does not change at all, the file contains only a single line (time=0, value=0 or VDD). The files in this form can be directly used for transistor level simulations performed in such tools as HSpice and Spectre. Spectre simulator is one of basic components of Cadence environment. Particular files are associated with PWL voltage sources assigned to chip inputs.

Stage 2 – the files created in the first stage there is no uniform time stamp, which means that these files can not be directly used in measurements. The measurements are performed by the use of the FPGA that directly controls the chip. At this stage, the output the files are further converted into a form, in which time-value pairs are determined for each time unit (for example, nanosecond). These files are then merged into one file with a single time axis.

Stage 3 – in this phase, the signal may be decimated by a specific value. This allows to reduce the amount of data in case if the signal changes are not very fast.

In Figure 8 we present example signal waveforms for an example case of the script shown in Figure 6.

4.3 | Measurements of the prototype chip with the use of generated signals

The proposed test system, described above, allowed us to perform comprehensive measurement verification of all designed components of the artificial neural network, as well as of the overall wireless sensor. The system strongly facilitates automate tests. It is provided with a list of prepared scripts for particular components and different values of their parameters. The measures are then carried out automatically with automatic saving of test results. Selected measurements results are shown in Figure 9 for one of example components of the chip.

As an illustration, a multi-phase programmable clock generator was selected for this purpose. It was selected for several reasons. It is one of the basic blocks of the overall wireless intelligent sensor. It is used to control the designed programmable ADC. It is also widely used at several important stages of the learning process of the proposed neural network. In this case, the clock is used in the phase of determining the distances, in the input data space, between the weight vectors of particular neurons and the learning patterns, X. It is also used in the adaptation phase of the winning neuron and its neighbors.

The clock is is also one of the most complex realized blocks. It is based on dynamic memories realized on parasitic capacitances of logical NOT gates. The clock is programmable circuit, which means that it allows to obtain different numbers of clock phases and different fillings of particular clock impulses.

A simplified diagram of this circuit, without the blocks responsible for its programming, is shown in Figure 10. Its basic component is a delay line, consisting of alternating connection of switches and NOT gates. The witches are implemented as transmission gates consisting of NMOS and PMOS transistors connected in parallel. The switches are controlled by a complementary 2-phases external (ext1 and ext2 signals). It in general operates as follows. If the outputs of all UnitClk blocks are logical '0', the NOR gate generates the logical '1' signal, that is provided at the beginning of the delay line. In subsequent ext1 / ext2 clock cycles, this signal moves along the line, generating subsequent clock phases. Depending on the configuration, the '1' signal generated by the NOR gate may be provided to other UnitClk blocks, instead of the first one. The advantage of this approach, in the comparison to typical implementations based on D-flip flops (DFF) is that, in this case, the power is dissipated only by those NOT gates that are switched over (two for each clock phase). As a result, the proposed clock is very energy efficient.

5 | CONCLUSIONS

The presented work deals with several important aspects. The first of them is the concept of a wireless system for the monitoring of air pollution in dense urban areas. It is very important from the city users point of view – the pedestrians and cyclists in particular. The knowledge about the level of the air pollution in a certain area, may affect their choice of time of exit/departure or their choice of route. In longer perspective, it may also influence on the price of real estates. For this reason we propose the application of a dense wireless network of miniature, low power, intelligent pollution sensors as a support of larger monitoring stations. In case if all components of such sensors, including artificial neural networks, would be realized as a single system-on-chip or system-in-package the sensors may be realized as cheap devices, additionally self-sufficient in energy. In this way, they can be easily deployed on city streets without an access to power line.

Realization of such sensors requires a development of its particular components, with a particular attention paid to their sizes and the energy consumption. One of basic challenges here is how to reduce the computation complexity of these blocks, without reduction of their functionality.

It has been developed a prototype chip, composed of several main components of the wireless sensor. We, in particular, focused on the components responsible for data processing and analysis, hence the proposed solutions for a hardware parallel ANN. We assume, that remaining blocks, such as for example pollution sensor and the RF communication blocks will be standard circuits, which may be found in the literature.

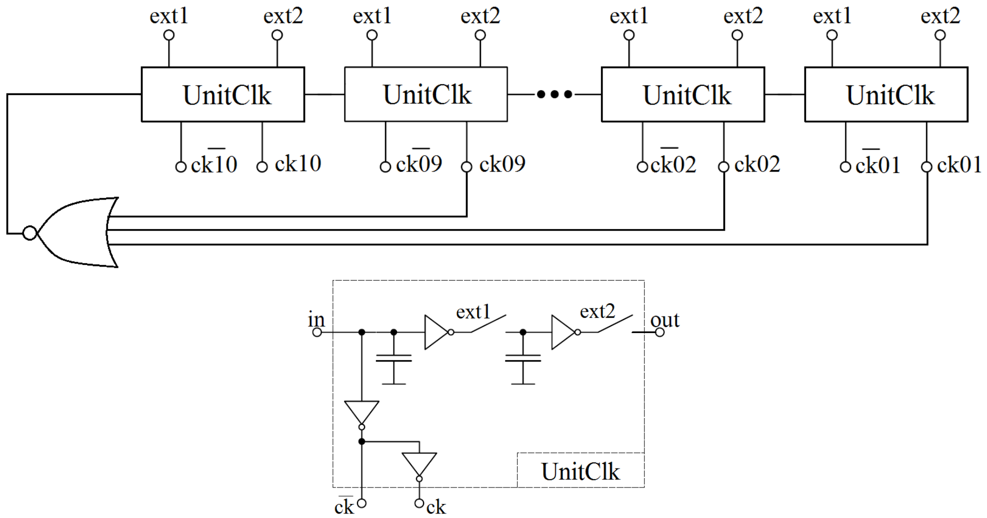

FIGURE 10 A general, simplified, diagram of the implemented multiphase clock generator: (top) a chain of unit blocks (UnitClk), (bottom) structure of the unit block.

One of the most important stages of the project is the verification of the chip by means of laboratory tests. The chip has been realized as a programmable device. The goal was to test as many of the sensor component as possible, with minimal available number of pins. To enable fast and automatic tests, it has been proposed and implemented an appropriate software tool that facilitates generation of test signals. We present an example how this tool may be used in practice, with selected simulation and measurement results of one of the blocks.

The presented results are one of the stages of a larger project. The next stage will be the implementation and testing of the overall neural network, then the overall wireless intelligent sensor. It is worth to add, that the proposed solutions are universal and may be used in many other applications.

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