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Low Power Stochastic Sensor in IoT, IIoT and Industry 4.0 Environments

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***Abstract*: The low-power stochastic sensor is proposed, and its suitability for operation in Internet of Things and Industrial Internet of Things for Industry 4.0 environments is emphasized. Unlike typical digital sensors, instead of a digitizing module, this sensor has a digital stochastic measurement module that enables low-power yet fast and accurate measurements. Assessment model includes test signal generator, the standard calibrator and the sensor prototype. Multi-channel and large sensor network applications in Industry 4.0 are considered, as well as cost-effective upgrades of the existing sensor networks and adaptability to changing requirements.**

Keywords*−*Low-Power, Internet-of-Things, Sensor, Measurement, Stochastic, Industry 4.0, Industrial Internet of Things

I. INTRODUCTION

The low power devices and modules are needed in many applications like portable, computing, processing, and video and audio controller designs. Most of the system-on-a-chip designs require low power design support. [1-4].

In the commercial Internet of Things (IoT) ecosystem, the number of sensors placed around the world is increasing at an accelerated pace. Market research has shown meaningful growth in sensor placement over the past decade and has predicted a meaningful increase in the growth rate in the future[5]. These sensors mostly need power autonomy, which underscores the need for low power designed sensors. [5-7]

Digital sensors typically consist of a transducing component and a digitizing module. The transducing element transduces a measured data into an electrical signal suitable for digitalization, while the digitizing module makes analog-to-digital (A/D) conversion. [8].

Digital Stochastic Measurement (DSM) is an essential path to measure signal values and parameters. DSM approach and its methods produce advantages for accurate measurements – high accuracies can be accomplished even with modest hardware. The modest hardware also enables effortless paralleling of the elementary instrument compositions and this grants possibilities for simultaneous measurements of many variables. [9]

In [10] a new utilization of DSM method, for measurement of noise power and true RMS, is presented. This use is very simple and combined with the utilization of the very fast 2-bit flash A/D converters, allows a very high sampling frequency. It has an anticipated measurement uncertainty, which can be further decreased by increasing the sampling rate and/or lengthening the measurement time interval. These results seemed to be exceptionally important for applications that demand detection and precise measurement of noise-like scattered signals. An example is the technology of graphene-based chemical and biological sensors where the interaction between the substance molecules and the graphene sensor surface molecules creates a low-frequency noise.

Further developing the concept, DSM can be implemented in Industrial Internet of Things (IIoT) environment [15]. This technology is the basis of Industry 4.0 (I4.0) concept of industrial modernization, [16], [17]. An example of DSM used in a smart grid energy meter is given in [12], and an improved biomedical device in [13]. Coupling DSM with IIoT enables several new industrial applications with strategic goals:

1. Upgrading of existing sensors with digital DSM, enabling higher precision, low power, IIoT communication and control.
2. Expansion of the existing network of sensors. As the DSM uses off-the-shelf standard components, it provides economical solution for adding new sensors into the network, interconnected via IIoT.
3. Adaptability. DSM's unique inherent characteristic is ability to have controllable measurement error. As the measurement is performed over the given time period, by changing period length and sampling frequency, almost any set measurement uncertainty can be achieved, [12], [14]. This enables cost benefits over long work-life period of the measurement equipment, as changes in specifications or technology improvements often render equipment obsolete. Ability to improve measurement error when needed enables this solution to be very cost-effective.
4. One of the main I4.0 tasks is to enable cost-effective and practical precision multi-channel measurements,

at the level of thousands or more channels in parallel. Technologies then enable high precision measurements are expensive, and high-level multi-channel measurements incorporate lower-performance technologies in order to maintain costs at affordable margin. Stochastic solution incorporates both demands in a single solution. Low-power ability is another benefit, enabling remote controlled IIoT modules to perform in the field without permanent hardwire connection to the network, meaning long life-span and movability, according to changing requirements and conditions.

II. STOCHASTIC SENSOR MODEL AND ASSESSMENT SYSTEM

An example of a stochastic sensor (Fig. 1), which includes a transducing element at its input, is offered in this paper. Rather than a digitizing module, stochastic sensors have a Digital Stochastic Measurement Module (DSMM) as the one presented in [10].

This DSMM module (Fig. 1) is based on digital stochastic measurement approach, and it contains 2-bit flash A/D converters. The module doesn't require sample and hold circuits at the input but involves operational amplifiers, which act as high-speed comparators. Quantization error of 2-bit A/D conversion is practically eliminated by analogue superposition of random uncorrelated dither (a controlled noise with uniform probability density function) signals onto the input noise signal, as well as by averaging [10], [12], [13]. Detailed description of DSMM structure and functioning is given in [9-10, 12-14].

Measurement uncertainty U of the DSMM is determined as [14]:

$$|U|_{\%} \leq \frac{A_{in}}{\sqrt{f_s \cdot t_m}} \cdot 100\,\% \tag{1}$$

where:

A_{in} – input value range,

f_s – sampling frequency,

t_m – measurement time period.

It is clear that measurement error could be lowered by increasing period or sampling frequency.

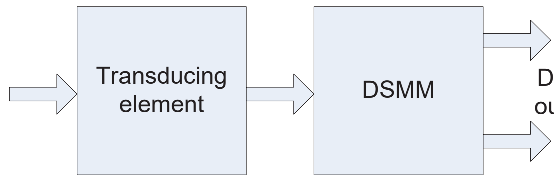

Fig. 1. *Stochastic sensor model.*

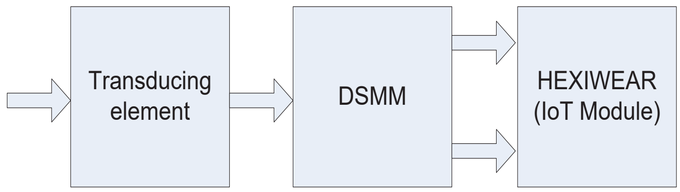

Fig. 2. *Model of stochastic sensor extended with IoT module.*

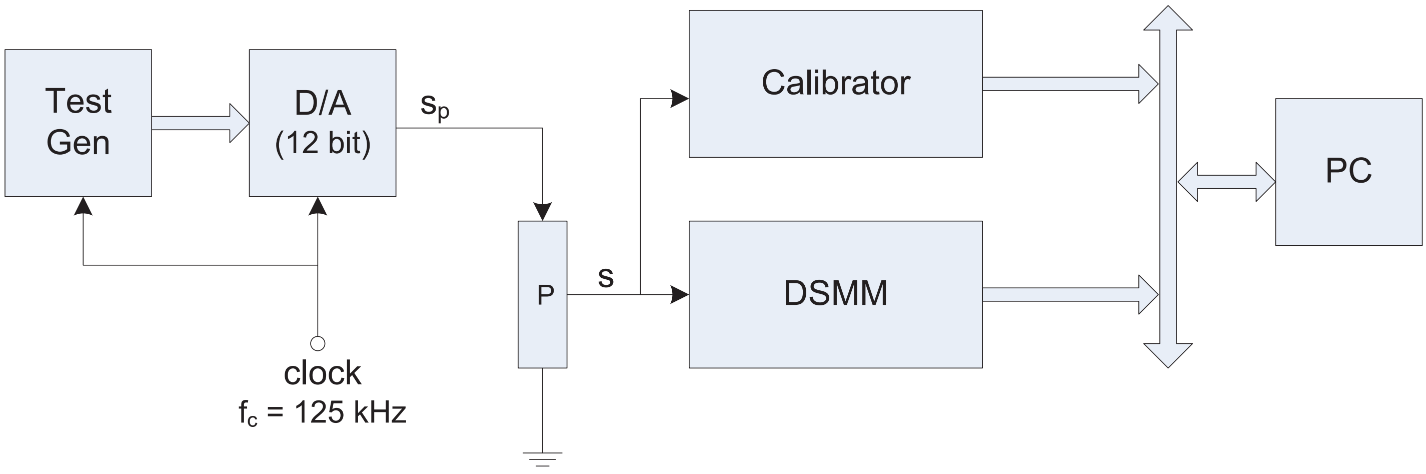

Fig. 3. *Block diagram of the assessment system.*

The sensor can be extended with the Internet of Things module, which enables wireless connectivity to the Internet of Things module (Fig 2). In this configuration Hexiwear, an IoT module for wireless connectivity [11] is chosen. Assessment system is presented in Fig.3, and purpose of this assessment system is to obtain experimental results of relative measurement error. Test generator (Test Gen) is realized as a stable generator of digitally synthesized random voltage. 12-bit D/A converter forms a test signal. The test signal is then regulated with a voltage divider (potentiometer P) to produce the final test signal, which is simultaneously measured by DSMM (Fig 4 presents DSMM architecture, based on detailed description from [9-10, 12-14]) and the standard calibrator.

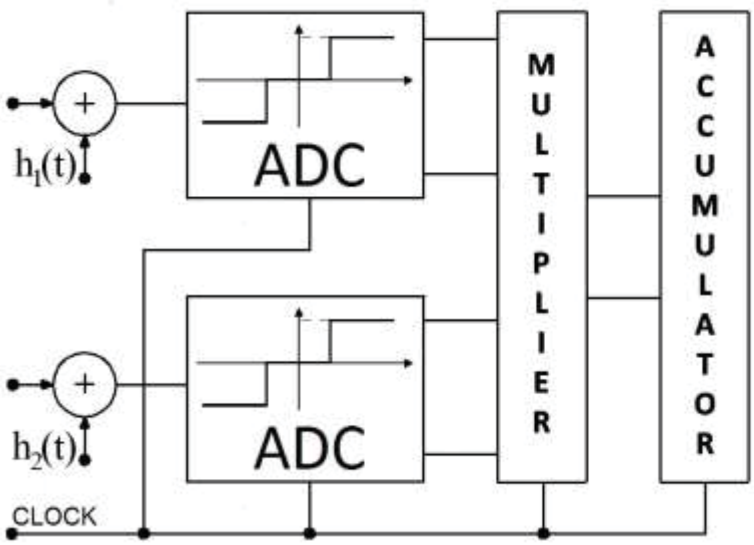

Fig. 4. *Architecture of DSMM.*

The regulation with potentiometer P is performed for keeping the test signal within the range of the highest achievable accuracy of the standard calibrator. The instrument and module are attached to the supporting PC via the serial interface. Tests were performed with the following properties: the duration of measurement interval is 1 second, A/D converter input range is ±1 V and sampling frequencies are set to 0.5 MHz, 2 MHz, or 8 MHz. For various types of the test signal (test signals were random signals – uniform and Gaussian – adjusted to ±1 V A/D converter input range), the relative error ranged from 8% for 0.5 MHz sampling frequency to 1% for 8 MHz sampling frequency.

What can we conclude about power consumption of DSMM by having these results of relative errors, which by far overcomes relative errors expected by 2-bit flash A/D converter? Knowing the standard structure of flash A/D converters, it is obvious that energy consumption of a flash A/D converter is lower with lower precision. Consequently, DSMM with 2-bit flash A/D converter has lower power consumption than typical digital measurement module with flash A/D converter of higher precision. Main direction of further research is to investigate theoretical calculations, simulation and experimental setups in order to obtain numerical representation of this obvious gain in lower power consumption.

This prototype is the basis for further development in I4.0 environment. IoT module could be substituted with IIoT standard module (automotive, biomedical, aerospace, etc.), as in Fig. 5, forming a compact Stochastic Sensor Unit for Industrial Applications (SSUIA). This approach of implementing DSM into a sensor, and further into IoT module is a novel approach, which advantages are most obvious in the situations when opposite requirements of IoT module precision and power consumption should be fulfilled. Also, this approach is not related only to particular wireless protocol, used application protocol or structure of sensor data. In order to obtain previously mentioned numerical representation of gain in lower power consumption, the further research will include implementation of ZigBee [18] protocol as a protocol intended for low power IoT modules.

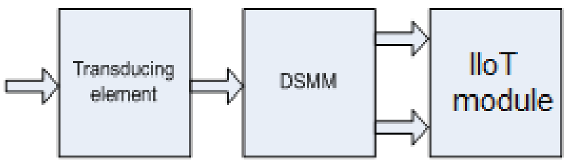

Fig. 5 Model of a single stochastic sensor with IIoT module for industrial applications (SSUIA).

Large number of SSUIA nodes can be controlled and coupled in a single IIoT network, Fig 6. Given that the DSMM module is a low-power load, the main power limiting factor is the communication module used.

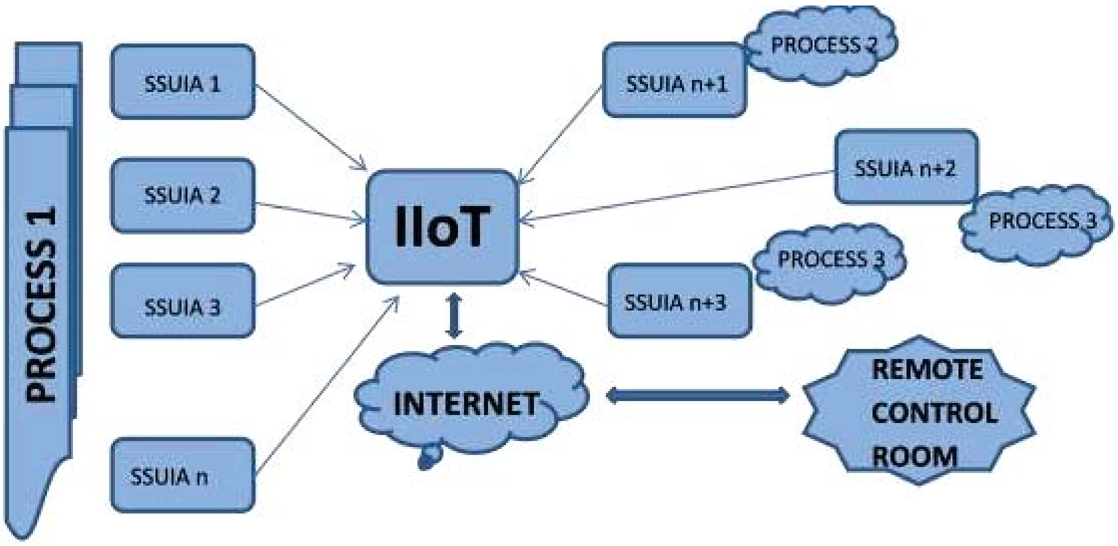

Fig. 6 IIoT network example with independent SSUIA nodes.

III. SSUIA AND WORKPLACE SAFETY

There is one another benefit of having a large number of low-cost SSUIA units spread over the wide area in the production facility – and that is increase in safety.

Workplace safety is one of the most important topics in modern industrial environment, and there are significant resources invested every year in prevention, lowering the health risks, but also large funds are also spent for mitigation of those risks, health and accident insurance claims, medical bills, etc.

Lowering the level of hazard at the plants, especially at the manufacturing facilities of the "classical" industries, is one of the goals of the Industry 4.0. IoT and IIoT are already considered ideal for this task, as presented in [19-23]. While advantages of new technologies are discussed in detail in these and other similar articles and are very clear, SSUIA adds another level of safety improvement.

As SSUIA enables a large number of low-cost, autonomous, reliable, low power and highly economical modules with high precision to be implemented in much more places and in greater numbers, monitoring becomes more detailed and intrinsic in every part of the industrial process. More data is provided and with greater accuracy and precision, more reliable models can be formed, relying less on human intervention and inclusion. Less workers are needed to remain in hazardous areas, lowering the risks. If the artificial intelligence (AI) is trained and included in the process of the safety monitoring and critical decision-making, those large quantities of real-time data from all the stochastic sensors could be processed in much shorter time than a human operator. With these short processing and decision times, potential safety issues are prevented even before they happen, or at the very beginning of their emanation. Response time in such situations is the crucial element in saving lives and health of the workers, but also for damage control and prevention of environment pollution. Also, AI could also prevent response teams (firefighters, repair crews) entering dangerous areas before all parts are safe enough (e.g. local source of toxic fumes in a large plant).
Cost-effective and high-precision sensors, coupled with IoT/IIoT and AI, provide for significant increase in workplace safety.

IV. CONCLUSION

The low power stochastic sensor, extendible for operation in the Internet of Things (IoT) and Industrial Internet of Things (IIoT) environments for Industry 4.0, is demonstrated. Unlike ordinary digital sensors, in place of a digitizing module, this sensor has a digital stochastic measurement module (DSMM). DSMM empowers low-power though fast, precise and accurate operation of the sensor. The assessment model incorporates a test signal generator, the standard calibrator, DSMM of the sensor. The relative error can be controlled by changing sampling frequency (the error decreases with the increase of sampling frequency) as well as by increasing the measurement period (if applications support it). This solution also supports cost-effective large sensor networks and multi-channels measurements, as needed in Industry 4.0 applications. Another great benefit of the cost-effective DSMM modules is the improvement in workplace safety with a large number of high-precision sensors spread over a wide area and in every part of an industrial process.

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