DESIGN AND DEVELOPMENT OF INDUSTRIAL IoT-BASED SYSTEM FOR BEHAVIOR PROFILING OF NON-LINEAR DYNAMIC PRODUCTION SYSTEMS BASED ON ENERGY FLOW THEORY

by

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In this paper, a solution effective energy consumption monitoring of fast-response energy systems in industrial environments was proposed, designed, and developed. Moreover, in this research, production systems are characterized as non-linear dynamic systems, with the hypothesis that the identification and introduction of non-linear members (variables) can have a significant impact on improving system performance by providing clear insight and realistic representation of system behavior due to a series of non-linear activities that stimulate the system state changes, which can be spotted through the manner and intensity of energy use in the observed system. The research is oriented towards achieving favorable conditions to deploy dynamic energy management systems by means of the IoT and big data, as highly prominent concepts of Industry 4.0 technologies into scientifically-driven industrial practice. The motivation behind this is driven by the transition that this highly digital modern age brought upon us, in which energy management systems could be treated as a continual, dynamic process instead of remaining characterized as static with periodical system audits. In addition, a segmented system architecture of the proposed solution was described in detail, while initial experimental results justified the given hypothesis. The generated results indicated that the process of energy consumption quantification, not only ensures reliable, accurate, and real-time information but opens the door towards system behavior profiling, predictive maintenance, event forensics, data-driven prognostics, etc. Lastly, the points of future investigations were indicated as well.

Key words*: energy management, monitoring, electricity, production systems, non-linear dynamics, Iot, Industry 4.0, behavior profiling, data-driven prognostics*

Introduction

Notwithstanding that the industry plays an indispensable role within the global economy since it provides goods to a variety of users around the world, it also accounts for a significant share of employment and economic strength. On the other hand, the industry is directly associated with a large environmental burden because it consumes both renewable and non-renewable materials (*e.g.* metals, fossil oil-derived materials, water, *etc.*) as well as significant amounts of energy as inputs to generate products, which as a result has substantial stress on

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the environment [1]. Bearing in mind that all the consumed resources and wastes generated by industrial activities affect the environment to a greater or lesser extent, this research is focused on one particular resource, without which there are no fundamental system functionalities. This resource is energy. Energy is a key factor in the development of modern society, both in the 21st century as well as in the future, which will be determined by the current actions and deeds of that society. The issue of energy availability and use is becoming increasingly important given the high level of concern primarily about climate change, the availability of energy resources, but also the security of supply of an exponentially growing population around the world [2]. Among the five key sectors (industry, buildings, services, transport, and agriculture), the industry is ranked third at the level of the European Union (EU28), while in the Republic of Serbia it ranks second in terms of intensity of finally available energy use [3]. The EU28 industry sector uses 24.62% of total final energy [3], where this ratio is expected to remain at the same rate at the best scenario, while from a pessimistic point of view, exponential growth can be expected in the near future [4]. In the Republic of Serbia, the situation is similar, ie the industry sector uses 27.8% of the total final energy, which is 12.92% more than the EU28 average [3]. Changes in industrial activity, accompanied by a series of improvements [5] in energy use through energy efficiency measures, have reduced, but not eliminated, the impact of increased economic activity on the energy demand of this sector. Therefore, the ability to understand and predict changes in energy use in industrial systems with reasonable accuracy is a very important task. Also, industry, ie production systems represent very complex energy users due to the non-linear dynamics of numerous processes and sub-processes that exist in it, which significantly complicates the analysis, modelling, and prediction of their behavior [6]. In addition, effectively dealing with and resolving energy issues is further complicated by the fact that the majority of the energy forms are mostly intangible or insensitive, invisible by their nature. With this in mind, determining the energy efficiency of a system or process, as an important step towards the controlled management of energy use and the associated costs incurred as a result of that use, is quite complex [7]. On the other hand, the highly developed modern age triggered a new technological revolution, known as Industry 4.0 which stemmed from a German strategic initiative to transform conventional production systems into smart systems in such a way that has not been possible so far [8, 9]. This transformation stipulates innovative upgrades towards environments in which smart production systems are able to monitor physical processes, create a so-called *digital twi*n (or *cyber twin*) of the physical world [10], and make smart decisions through real-time communication and cooperation with humans, machines, sensors, and so forth [11]. Eventually, this transition is enabled due to rapid development concepts such as rapid prototyping, blockchain, augmented reality, cloud computing, and so on. However, there are two concepts especially interesting when it comes to energy efficiency in Industry 4.0 environments [12]. These are the IoT and big data. It should be noted that the previously mentioned concepts are considered as dominant ones, which does not mean that those who are not mentioned have a minor significance. Subsequently, these two will be devoted to the greatest attention hereinafter.

The IoT: A missing link for superior energy efficiency in Industry 4.0 environment

The modern society reached another development stage where over time, as the energy sector became increasingly digital given with sensors, while also becoming more decentralized with energy coming from local renewable energy or microgrid systems, users can have exceptional ability to monitor and manage their energy usage [12]. Energy availability and reliability are not just important for critical energy utility buildings, manufacturing processes, and all the other mission-critical operations in the scope of Industry 4.0. They are an essential part of it. Or in other words, without energy management overall at the center of Industry 4.0 there is no Industry 4.0. While traditional industrial energy management focuses on the efficient provision and use of process energy needs, such as heating, cooling, compressed air, and electricity, the IoT has a wealth of new data streams to support energy efficiency and management activities. More precisely, IoT-based technologies enable a completely new perspective whether it is about to gain operating benefits, such as reduced maintenance and improved safety, as well as to increase reliability and efficiency, where condition monitoring of pumps, acoustic monitoring of steam traps, heat exchanger performance*, etc.*, all wirelessly connected to supervisory control, data acquisition, and analytics systems, provide cost-effective installation and pay-backs of less than a year in most cases [13]. Having this in mind, the implementation of energy management in Industry 4.0 environment starts from understanding energy flows, while the integration of IoT solutions, carefully designed and implemented can quantify missing stochastic variables, which when became the part of the equation provide powerful insight, and more importantly, a completely new dimension the decision-making process [12].

The problem formulation

Bearing in mind the fact that the digital era delivers more actionable data than ever before by providing exact and comprehensive data in real-time, enables and stimulates the development of an environment in which is possible to make relevant decisions instantaneously. Accordingly, the former practice, in which energy management systems (EnMS) are characterized as static with periodical system audits which occur about every six months, where the data generated through these audits are subjected to human-based analysis, is simply no longer effective. It is a fact that human minds simply cannot compete with micro-controllers for example as not being designed to be that fast in solving infinitely large sets of calculations in real-time. This means that this requires a lot of time which is a significant constraint, especially if observed from the energy aspect, in which systems can change their state in a matter of nanoseconds, even less. This indicates that the results generated through traditional energy audits are practically ineffectual. Given the aforementioned, energy management is a continual, dynamic process whereby by applying periodic data collection and static methods for those incomplete data processing, it is not possible to fully comprehend and sometimes even understand the states and behavior of the observed system as they remain hidden. Therefore, the results generated in this way can be misleading, highly risky in terms of reliability, while it is necessary to invest significant efforts and time in order to possibly obtain useful information.

The methodological concept and research hypothesis

The methodology approach is based on the identification of energy flows and provides a fundamental basis for research, ie determining the state and behavior of production systems characterized by non-linear dynamic activity. Here, although it may seem obvious, it is important to stress that practical engineering systems are inherently non-linear, where in most cases linear assumptions and analysis do not show important phenomena, thus as a consequence a continuous doubt in the accuracy of the generated results remains ubiquitous. The method used in the research of dynamic systems is based on the universal law of conservation and transformation of energy, therefore, it provides a common approach to the analysis of different types of systems including mechanical, thermal and electrical/magnetic, control systems, and some complex systems involving their mergers or interactions. In doing so, the variable determined by this approach combines the effects of both, forces and velocities, and their product, power, or intensity of energy change, is characterized by dynamic behavior, which includes and reflects complete information about its balance and movement, and therefore, exceeds the study of changes in force and motion separately [14]. Approaches adopted in the analysis of energy flows focus on global statistical energy estimates of distribution, transmission, design, and control of dynamic systems or subsystems, and not on a detailed spatial pattern of structural responses (system response is the output function of the system and occurs in response to the input function of the system – excitation). With this in mind, this method overcomes the difficulties that are inevitable when using finite element methods or experimental modal analysis of vibrating responses in medium and high frequency regions, which requires extremely small element sizes to achieve the required computational accuracy. This statement clearly indicates the necessity of applying non-linear system analysis where a holistic approach based on the principles of energy flow theory in real-time can be used to monitor the behavior of production systems characterized by a non-linear dynamic property.

Therefore, this research is based on the hypothesis that the identification and introduction of non-linear members (variables) can have a significant impact on improving system performance by providing clear insight and realistic representation of system behavior due to a series of non-linear activities that stimulate the system state changes, which can be spotted through the manner and intensity of energy use in the observed system.

Related work

The application of IoT in different sectors and industries has been widely discussed and reviewed in *e.g.* [15-17], while sensors [18] and 5G network [19] received a high level of technical assessment regarding the challenges and opportunities associated to deployment. However, when it comes to the potential of a certain IoT technology in energy analysis, most studies have focused on one specific subsector [20]. For example, there are reviews regarding smart home applications of IoT [21], the methods, recent advances, and implementation of 5G with a focus on the energy demand side [22], the role of IoT in improving energy efficiency in buildings and public transport [23-27], the key challenges in the suitability of IoT data transfer and communication protocols for smart grids [28], and so on. In some studies [29], IoT enables solutions based on thermal imaging to detect insulation problems in a building eggshell [30]. Also, the durability of the material used in a building's walls, such as concrete can be monitored through IoT real-time sensors [31]. There are researches related to Indoor Air Quality based on low cost and energy-efficient sensors [32], as well as investigations regarding impacts of occupancy and occupant behavior on energy efficiency, as a consequence of the use of HVAC, lighting, and other electric devices by occupants [33-35]. Subsequently, applied research of intelligent monitoring system of a hot spring water temperature was based on IoT [36], while the IoT platform based on genetic algorithm was designed and proposed for heat energy collection system [37].

The aforementioned logical concepts can be implemented in industrial environments with certain modifications, thus these processes vary from case to case. However, comprehensive reviews of using cutting-edge information and communication technologies for improving energy efficiency in the manufacturing industry regarding wasted heat and thus energy. Improvement of management process regarding energy, materials, and process productivity or restructure processes by adopting new production concepts are also available [38-41]. Until recently, most of the production systems had monitor their energy consumption through monthly energy bills [42], while the idea of having the data on energy consumption regarding overall system/processes/subprocesses and even machines for each of multi departments was a far-fetched story [43]. The times had changed and what was unthinkable yesterday has become possible today, since this issue can be successfully addressed by having access to real-time data on energy consumption in a flexible and customized way. This has triggered a new development era in which integration of supervisory controllers and EnMS was proposed to optimize the operation of the systems [44]. Subsequently, a general method to manage the application of IoT in supply chains that enables production systems to improve operational performance by having better insights into their processes and the relationships between actors was proposed [45, 46]. Similarly, some research work considered using sensor portfolios and information fusion create a value-centric business-technology framework [47]. In addition, an IoT-based support system on food recommendation-based health management was developed, which turned out to help reducing energy consumption [48].

The IoT has swiftly spread its wings across various operations within production systems, while the energy issue is one of the most prominent domains where it can have a significant impact and influence. Therefore, IoT can be seen as an enabler that provides real-time solutions for monitoring energy consumption decision-makers with crucial information regardless of the level of observation (system/processes/subprocesses/machine level). Lastly, to advocate the use of IoT, especially from the energy efficiency point of view, some studies summarized major challenges in the IoT applications and proposed different solutions in order to overcome them [49].

Design and development of IIoT-based system

In this section, relevant information regarding the design and development of industrial IoT systems for behavior profiling of non-linear dynamic production systems based on energy flow theory is provided. Before continuing further, it is necessary to note that for this research, energy systems are categorized into two basic groups. The first group considers thermal energy processes whose state and behavior are characterized by changes in enthalpy and entropy of the system, influenced by stochastic variables such as temperature, relative humidity, atmospheric pressure*, etc.* From the aspect of this research, thermal systems are characterized as inert systems in which changes in energy use occur relatively slow. The second group refers to fast-response energy systems, which is a characteristic of systems that use electricity for their operation. Although both groups are equally important and figure in parallel in all production systems to a greater or lesser extent, in this research the focus is on the fast-response energy systems, or more precisely electrical machining processes and systems.

System architecture

Due to the rapid development of computing and networking technologies, the ability to sense, store, analyze and process data into information has significantly improved. During this evolution, the IoT has taken the center stage as a bridge between the real (physical) and virtual (informational) world [50]. In general, the IoT system is composed of five crucial layers (perceptual, network, intermediate service, application, and business layer) located in two different levels [51]. Therefore, perceptual and network layers are integrated into the information sense level (ISL), tasked to collect and optionally convert the data, aggregate, and transmit useful information or processed data. The second level, the application operation level (AOL) consolidates intermediate service, application, and business layers intending to grade and process information realize classification management necessary for decision making and practical actions.

In this concrete case, the perceptual layer is actually a sensing node named CURRENT PROFILER. The CURRENT PROFILER is a hardware device for non-invasive, continuous monitoring, and acquisition of data on the intensity of electric current and profiling the behavior of the system/process/machine/device. Moreover, except for functioning as a classical sensing node, this device can operate independently since it consists of a motherboard with supporting components and connectors, microcontroller, SD module, real-time clock module, OLED display 128×64, DC-DC converter (Step Down), Battery charge controller, DC-DC converter (Step Up), Wi-Fi module, Housing (base + cover) and supporting elements in terms of 12 V Power Adapter, Battery and accompanied sensors.

In this study, the main objective is to gather reliable data regarding the intensity of electrical current because if the voltage is stable, without significant variations (which is one of the basic conditions for the operation of electrical machines in industrial environments), changes in the intensity of electric current reflect the behavior of the observed system through a series of recorded states, while simultaneously providing exact data on energy use. For that purpose a YHDC SCT-013-000, a non-invasive current transformer (CT) was used for sensing, measuring, and logging the data regarding alternating current. In addition, the network layer is based on ESP8266 ESP-07 Wi-Fi Serial Transceiver Module. Figure 1, illustrates all of the components necessary to provide stated functionalities at the ISL.

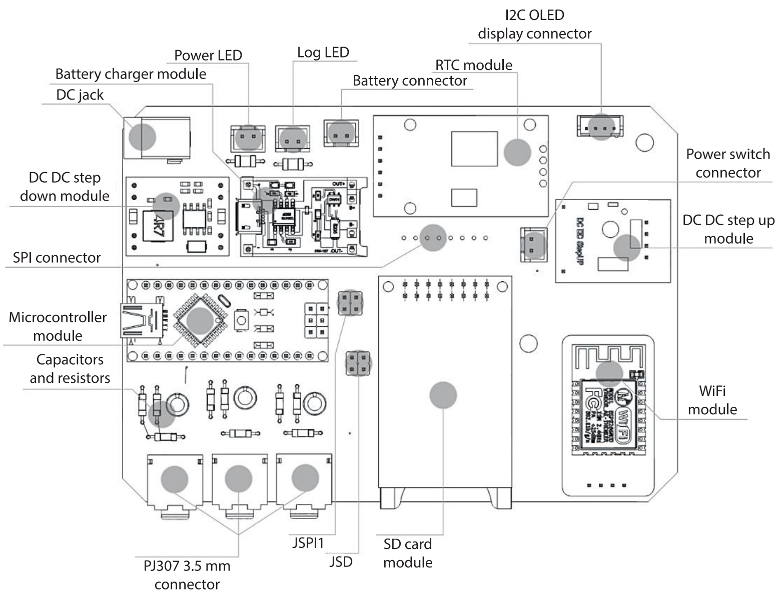

Figure 1. The CURRENT PROFILER PCB with supporting modules and components

From the perspective of AOL, the CURRENT PROFILER nodes communicate via a hidden Wi-Fi network with a network Router/Switch which is connected to the client-server via Ethernet. The communication was established using the MQTT publish/subscribe protocol, aimed at simple and lightweight messaging, designed for constrained devices, low bandwidth, and unreliable networks. A data pump service, necessary to be established for automated data import to the database, was ensured by the ECLIPSE MOSQUITTO software. Subsequently, all messages as time-series data are stored in the InfluxDB database, optimized for fast queries regarding the stored sensor data in the time domain. Most importantly, the main reason behind the selection of InfluxDB is that it allows the use of Grafana for advanced data analysis, visualization, and representation.

Finally, at the business layer, to eliminate boundaries between production and management, by providing that ERP, MES, and other critical systems are well linked to share and structure the information according to their needs, application programming interface or in other words, a software intermediary that allows two applications to talk to each other, was developed to provide extension mechanisms to extend existing functionalities to varying degrees in various ways.

Given the aforementioned, the main functionalities of the CURRENT PROFILER are listed hereinafter:

– The device measures, stores, and displays data on thrre channels in real-time (0-100A).
– The device connects the measured value to timestamp.
– The device measures and displays the operating temperature (–40-85 °C).
– The device records data to the SD card.
– The device can be powered via USB and DC connectors.
– The current data collection speed is 1 second.
– Real-time visualization
– Software-defined variable sampling rate.
– Online data display.
– Data display on the device.
– Time detection of interruption and re-establishment of the system power supply.
– Possibility of expansion in the form of SPI and I2C protocols.
– Possibility to select the supply voltage of the SPI connector (3.3 V or 5 V).

Lastly, more details regarding overall system architecture, accompanied by technical specifications, illustrations, and references could be found in section *Appendix*.

Current Profiler initial testing, obtained results, and discussion

The initial testing of the previously described IIoT system was conducted on a Shizuoka SV-4020 CNC Horizontal Machining Center. The CURRENT PROFILER was placed on each phase after the main power switch of the observed machine. The tasked operation was quite basic and considered the creation of six perforated holes in the workpiece by drilling (8.5 mm drill bit), where the thickness of the workpiece amounts to 20 mm. However, the two types of workpiece material were considered, namely aluminum and steel. Operation parameters for steel cutting were 1000 rpm (spindle rotational speed), with material removal rate (MRR) of 80 mm per minute, while the same parameters for aluminum cutting were 2000 rpm with MRR of 180 mm per minute. The obtained results are illustratively given in fig. 2.

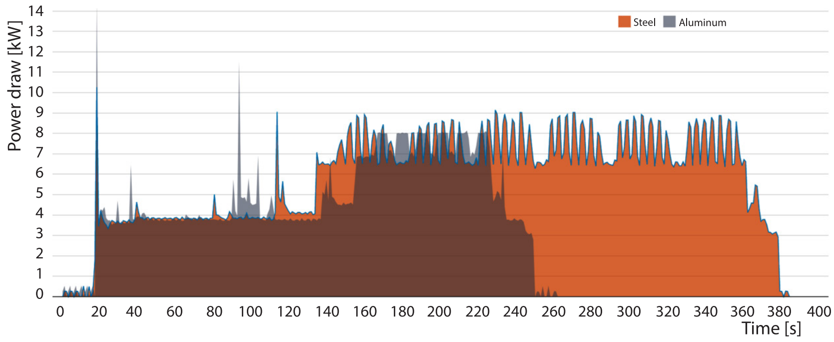

Figure 2. Operation behavior profile based on series of states in terms of power draw over time

Based on fig. 2., one cannot only determine the exact energy consumption, the intensity of changes in power draw, relevant peeks, and so on, but also generate operation behavior (as a continual series of logged states) profile which provides useful process insights based on energy flow, event forensics, change patterns*, etc.*

Subsequently, the basic key process indicators (KPI's) are given in tab. 1, while the data sets and interactive charts are available in section *Appendix*.

Table 1. Identified KPI's of observed operation process

KPI (values)			
Material	Energy consumption [kWhe]	Time consumption [s]	CO_2 emission [kg]
Al	0.34	262	0.24
Steel	0.62	385	0.438
KPI (Ratios)			
Ratio	Energy consumption [%]	Time consumption [%]	
(Al/Steel)	54.68	68.05	
(Steel/Al)	183	146.95	

In addition, from this perspective energy stands for the inherent ability of the observed system to generate external impact [52], or in other words to execute any kind of given task. Therefore, energy represents the state variable, which is obtained by correlation with changes in work as a process variable, over time. Here fig. 2, unequivocally indicates that energy consumption by production-associated equipment is typically not constant over time, but dynamic as being conditioned and impacted by the non-linearity of the production process and the actual machine state. Machines consist of several energy-consuming components that generate a specific energy load profile during operation [53]. A modern milling machine, for example, can include a wide range of functions, including workpiece handling, lubrication, chip removal, tool change, and tool crack detection, all with the basic function of a machine tool which is material removal by cutting. Although this typically applies to electricity, the same goes for other forms of energy or media like compressed air, process heat, gas, coolants*, etc.*

On the other hand, different patterns of machine states can be distinguished, where a variety of classifications can be found [54, 55]. Here, the most common ones are: *Off state* (main switch off, no energy consumption as a consequence of no connectivity to the power grid), *start-up/Powered on state* (energy demand peaks caused by switching on certain components, heating-up*, etc.*), *Idle state* (relatively constant energy consumption as main supporting components finished ramp-up and machine is ready for operation.), and *Operation state* (the actual value-creating process takes place, *e.g.* material removal). In the testing experiment related to this study, identification of the relevant states was performed on the operation in which the steel-based workpiece was processed. This has illustratively been given in fig. 3. From the given figure, the non-linearity in performing repetitive operations of the machine tool when making perforated holes by drilling could be clearly noticed. The ability to identify non-linearity ensures more accurate and reliable data for the decision-making process, while on the other hand, the possibility of quantification of the intensity of change of non-linear members indicates the occurrence of anomalies within the observed process where analysis, as well as instant actions, can be implemented in real-time.

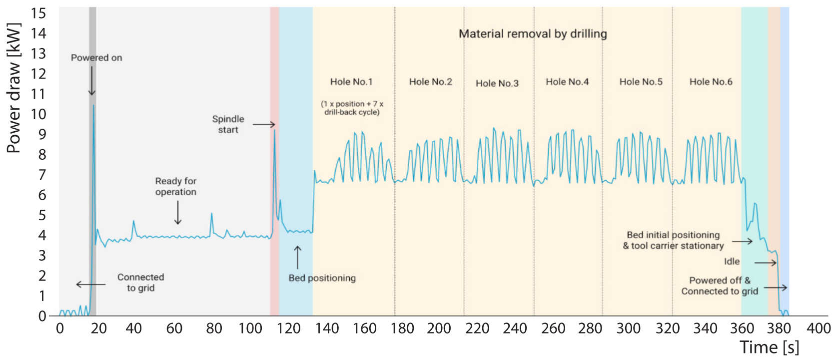

Figure 3. Identified states in the operation of the steel-based workpiece processing

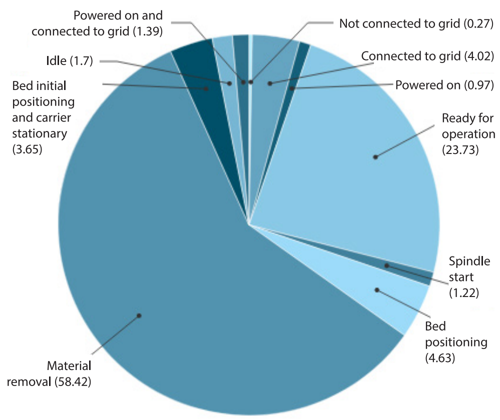

Figure 4. The first order states distribution in the observed operation [%]

Most importantly, these changes leave a trace that can be discerned by continuous monitoring of energy flows. By further analysis, the first-order state's distribution in the observed operation was determined and given in fig. 4.

The data provided in fig. 4, are particularly interesting observing from the value stream mapping (VSM) methodology point of view. Here, VSM is a methodological tool for the simplified study of the production process from its beginning to the end, by dividing it into individual segments of activities in which value is added and those in which no value is added. The general goal of VSM is to improve process performance by optimizing activities in which there is no value addition, and thus to increase the efficiency of value flow [56]. In this case, the value-adding process accounts roughly for 58.42% of overall cycle time (it accounts less actually, due to the fact that material removal by drilling integrates tool positioning time in which no value is being added, fig. 3. This could be determined by applying second-order states distribution focused on one or all repetitions within material removal state). Having in mind that in only one shift, on only one machine 70 cycles occurs (cycle time = 385 seconds = 6.4167 minutes; $\wedge$ 1 shift = 7.5 hours = 450 mininutes $\rightarrow$ cycles per shift = 70.13), reducing non-value-adding activities time consumption simultaneously improves both, energy and process efficiency while leading to reduced costs and emissions, productivity gain as well as more sustainable environments. Lastly and most importantly, all of the inputted efforts are possible to be segmented and quantified with sufficient precision, at an enviable level from the aspect of the time domain.

Potential of proposed system application and future research orientations

Although this may seem obvious, many organizations have an insufficient understanding of the relationship between energy use and process settings. Those who have deployed the IoT and transit to Industry 4.0 realized that the digitization of the manufacturing processes allowed them to better understand the actual energy demand of their systems, processes, or even machines. For example, considering PV-based prosumer profiles based on monthly energy consumption data, a certain error occurs primarily since the monthly consumption profiles do not include the relevant data regarding energy-related machine behavior during their operation, where to obtain the most accurate estimation, it is necessary to establish a system of continuous measurement and data logging of the electrical current and voltage during machine operation [57, 58]. This implies that basically, both Industry 4.0 and energy management are fundamentally about collecting, using, and combining data in their quest for optimization. A typical factory sits on a treasure trove of data, which unfortunately are not being used in the majority of cases. By integrating relevant data generated through IoT devices, specially tailored models of factory energy consumption could be established, upon which specific process simulations could be developed and implemented to validate the system performance before the actual production process begins. Historically, for production managers, it was almost impossible to include actual energy or water consumption into the equation determine which machine is the best to run certain products. With an Intelligent EnMS, those actual numbers become part of the equation, and this provides a completely new dimension in the decision-making process.

Optimized, data-driven decision-making provides an accurate allocation of energy costs to the products and the work centers they are produced in. These considerations are important and minimize costs while providing fundamental knowledge and experience in understanding process behavior, while simultaneously boosts efficiency. Although the model-based prognostics approaches, which are mainly based on analytical/mathematical models to describe behaviors of systems and mechanisms of degradation phenomenon [59, 60] proved advantageous due to their high accuracy and flexibility in configuring input data, the prediction accuracy of these approaches highly depends on the precision of the given models. Here, non-linear and stochastic characteristics of industrial systems often significantly increase the difficulty in factory analytical modelling, as the flexible configuration of systems impacts the model parameters, which implies that these situations have to be taken into account in the real-time modifications of these models. On the other hand, the data-driven prognostics approach allows to identify trends/patterns of a developing fault and to predict the amount of time before it reaches a predetermined threshold [61-63] using information from historical treated data (trained data). These prognostic approaches can identify the real-time health condition of a system by various techniques such as regression analyses, Bayesian algorithms, neural networks, fuzzy logic, support vector machine, and so forth. These prognostic approaches are precise in their ability to link with recognized system behaviors by experience methods. Despite no specific physical model is needed, the data-driven approaches require a monitoring system and learning time which can be insured by applying a variety of existing IoT solutions.

Given the aforementioned, especially focusing on the availability of real-time data thanks to IoT solutions, energy consumption could be observed and treated as a stochastic process with the Markov property, where the term *Markov chain* scrutinize the sequence of random variables as the process moves through, with the Markov property elucidating serial dependence only between adjacent periods (as in a *chain*). It can thus be used for describing systems that follow a series of linked events, where what happens next depends only on the present system state. Here, Markov prediction uses the stochastic process change law to perform prediction, while an adequate decision could be made based on the present state of the system. This enables so-called event forensics and the possibility not only to effectively locate the failure but also to link all suspicious changes in system states to find the cause or causes why and when the failure occurred [12].

Lastly, in order to reach the next level in real-time and data-driven EnMS, in our future research we will strive to develop a similar solution related to the previously mentioned inert energy systems to provide real-time data regarding the changes in the temperature field of objects of a certain volume, as well as to ensure enthalpy and entropy-based system behavior profiling by processing stochastic changes in actual pressure, relative humidity, and dry bulb temperature. This will be accompanied by additional sensing units for tracking UV index, IR, and visible light, as well as for air quality profiling in terms of concentration of hazardous gases (such as CH_4, C_4H_{10}, C_3H_8, H_2, CO, CO_2, *etc.*). In such an industrial environment set-up, holistic, and above all dynamic EnMS could be deployed which will eventually be able to provide a complete, reliable, and accurate overview of how the energy is being used in it, while the possibility of integrating those dynamic data and KPI's can boost productivity and overall resource efficiency. In addition the aforementioned, significant effort will be made to identify numerous models for studying the energy efficiency of the system in general, where the vast majority of them is considered as being static by nature, which implies that the quest towards how to modify and implement them in this dynamic context could be quite challenging.

Conclusions

As being indicated several times, energy consumption in production systems represents one of the most discussed and relevant subjects, in which scarcity of resources and environmental impact have imposed greater sensitivity on the topic, while overall sustainability arises as one of the main objectives in this 4th technological revolution. However, more and more production-oriented companies embarking on systematic energy management are realizing that they lack one key resource, the data, upon which reliable, accurate, and highly insightful information regarding energy consumption and correlation with production as well as costs, is a gold-worth raw material for effective and efficient decision making. Guided by the aforementioned, in this paper, many studies related to different energy consumption-related sectors were reviewed to validate and bring to the front the need and benefits that cutting-edge technologies could provide in order to address operating EnMS in the industry at an advanced level.

Subsequently, a solution in terms of the industrial IoT system was proposed to enable exact quantification regarding the energy consumption of fast-response energy systems. The initial test conducted on a Horizontal Machining Center aimed to determine process behavior in the case where the two types of workpiece material were considered (namely aluminum and steel), revealed not only the exact energy consumption, the intensity of changes in power draw, relevant peeks, and so on, but also generated operation behavior (as a continual series of logged states) profile which provides useful process insights based on energy flow, in terms of event forensics, change patterns*, etc.* Also, the initial test justified the given hypothesis that energy consumption by production-associated equipment is typically not constant over time, but dynamic as being conditioned and impacted by the non-linearity of the production process and the actual machine state, where the non-linearity in performing repetitive operations of the machine tool when making perforated holes by drilling could be noticed through energy flows monitoring of the observed process. This ability to identify non-linearity ensures more accurate and reliable data for the decision-making process, while on the other hand, the possibility of quantification of the intensity of change of non-linear members indicates the occurrence of anomalies within the observed process where analysis, as well as instant actions, can be implemented in real-time. Most importantly, these changes leave a trace that can be discerned by continuous monitoring of energy flows. Moreover, upon generated data and by further analysis, the first-order state's distribution in the observed operation was defined and subjected to the VSM methodology analysis upon which was possible to determine that the value-adding process accounts roughly for 58.42% of overall cycle time. Therefore, reducing non-value-adding activities time consumption simultaneously improves both, energy and process efficiency while leading to reduced costs and emissions, productivity gain as well as more sustainable environments.

Here, the process of energy consumption quantification, not only ensures reliable, accurate, and real-time information but opens the door towards system behavior profiling, predictive maintenance, event forensics, data-driven prognostics*, etc.*, which gives a completely new dimension the decision-making process, by making it practically instantaneous because, in essence, the problem of decision-making would not exist if there were no alternatives to choose from. By such an approach, the possibility of alternative occurrence can be effectively reduced to a greater scale, while in some cases it could be completely eliminated, which enables timely response and significant reduction of time devoted to the decision-making process. Lastly, managing energy and energy data has become a discipline in itself in which the ability to access the data and information as desired, when desired and in a customizable manner, with the absence of technology conditioning, combines two absolutely contradictory concepts into one, known as flexible automation, upon which the majority of future systems will be eventually postulated. Although the topic itself is quite complex, the take-out message from all of the previously given is quite simple. The infrastructure needed to implement Industry 4.0 environments could be the same infrastructure that enables intelligent energy management, which if carefully implemented enables production systems to seize the enormous potential of this technological transition, and thus easily overcome rising challenges associated with energy such as price and security of supply, while simultaneously being able to utilize broader benefits in terms of competitiveness and productivity.

Appendix

All previously mentioned appendices are available here[*].

Acknowledgment

The solution provided in this research reached finals in Competition for the best technological innovation in Serbia in the category of realized innovation 2020 and was awarded 6th place among 142 teams (536 innovators). Moreover, this research was supported through Climate KIC Programme, by the EIT a body of the European Union.

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