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Architecture Model for a Holistic and Interoperable Digital Energy Management Platform

Pedro P. Senna[a,b,*], António H. Almeida[a], Ana C. Barros[a], Ricardo J. Bessa[a], Américo L. Azevedo[a,b]

[a]*INESC TEC - Instituto de Engenharia de Sistemas e Computadores, Tecnologia e Ciência, Rua Dr. Roberto Frias, Porto 4200-465, Portugal*
[b]*FEUP - Faculdade de Engenharia da Universidade do Porto, Rua Dr. Roberto Frias, Porto 4200-465, Portugal*

* Corresponding author. Tel.: +351-22-209-4398. *E-mail address:* pedro.senna@inesctec.pt

Abstract

The modern digital era is characterized by a plethora of emerging technologies, methodologies and techniques that are employed in the manufacturing industries with intent to improve productivity, to optimize processes and to reduce operational costs. Yet, algorithms and methodological approaches for improvement of energy consumption and environmental impact are not integrated with the current operational and planning tools used by manufacturing companies. One possible reason for this is the difficulty in bridging the gap between the most advanced energy related ICT tools, developed within the scope of the industry 4.0 era, and the legacy systems that support most manufacturing operational and planning processes. Consequently, this paper proposes a conceptual architecture model for a digital energy management platform, which is comprised of an IIoT-based platform, strongly supported by energy digital twin for interoperability and integrated with AI-based energy data-driven services. This conceptual architecture model enables companies to analyse their energy consumption behaviour, which allows for the understanding of the synergies among the variables that affect the energy demand, and to integrate this energy intelligence with their legacy systems in order to achieve a more sustainable energy demand.

Keywords: Energy efficiency; IIoT Platform; Architecture Model; Energy data driven services; Energy Digital Twin

1. Introduction

Climate change urges nations worldwide to take strong and assertive actions towards the mitigation of global warming and its impact in citizens. The current trends in energy consumption (EC) and related emissions will lead us to a bleak future, especially when considering the recent data regarding historic levels of emissions, i.e. the rise of energy-related CO2 emissions to reach the all-time high levels of 33.1Gt in 2018 [1]. On this note, the European Union (EU) is undertaking an ambitious roadmap, called "European Green Deal", to become the first climate-neutral continent by 2050, as well as to slow down global warming and mitigate its effects [2]. Within this initiative, the EU has made the commitment of achieving a 20% reduction of EC by 2020 and 32.5% reduction by 2030 compared to 2007 baseline projections [3]. To achieve such scenario, the European Commission has launched the "Energy Efficiency Plan", seeking to promote industrial energy efficiency by establishing strict energy requirements for industrial machinery and equipment [3].

The manufacturing industry is amongst the biggest consumers of primary energy, representing 31% of the primary EC, as well as amongst the largest CO2 emitters [4]. This industrial sector is capable of increasing the energy efficiency from 18% to 26%, and of reducing CO2 emissions from 19% to 32% [4], with unrealized long-term improvement capabilities of up to 60% energy-efficiency ratings in the long-

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term due to its extensive size and meaningful impact in the global energy efficiency [5].

The use of digital technologies and operations research methodologies for improving industrial efficiency has had increasing efforts since the advent of the industry 4.0 paradigm, born from the German Plattform Industrie 4.0 set out in 2013 [6]. The industry 4.0 (i4.0) paradigm presents a set of contemporary technological advances that integrate physical objects, virtual models and services, as well as coordination efforts [7], that present three major benefits to the manufacturing industry: reduction of operational costs; increase in production efficiency; and additional revenues from the servitisation of products [8]. In what concerns ICTs used for energy-efficiency purposes, the EU Strategic Energy Technology Plan (SET) aims both to propose an interoperable reference architecture, significantly improving the electricity consumption management and reduction of costs while increasing the penetration of user-friendly tools [9], as well as to promote changes in the energy mix towards increasing use of renewable and sustainable alternatives following the efforts put forward since the Paris Agreement [10].

Clearly, there is a need for stronger efforts to integrate all the developed digital solutions to achieve a smart, holistic, scalable and green manufacturing industry environment based on energy efficiency and cleaner environmental footprint. Therefore, this paper proposes a conceptual architecture model for an interoperable and holistic energy management digital platform for manufacturing plants. This conceptual architecture model will leverage energy data interoperability, capable of enriching existing legacy systems with intelligent energy perspective, thus, covering the gaps previously identified. Moreover, it will promote flexibility, interoperability and secure communication, in order to be the supporting ground for virtual and real-time simulation & optimization of industrial processes towards leapfrog improvements in energy efficiency. Its modularity perspective allows for numerous combinations of services regarding the manufacturing sector context and the individual characteristics of the industrial units.

2. Literature Review

The conceptual architecture model proposed in this research is an abstract framework for multi-case instances, based on multiple combinations of implementation configurations, and designed for empirical applications and solutions of manufacturing companies [11]. In the reference models' literature there are multiple instances targeting energy-related aspects, such as those pertaining electrical energy systems in Smart Grid environments [12], green buildings' construction [13], and cross-flow turbines [14]. Most of these reference models present sufficiently complete frameworks to address specific problematics in energy manufacturing domains. Additionally, there are multiple reference models for the digital technologies, such as the digital twin architecture reference model for cloud-based cyber-physical systems [15], Internet-of-Things (IoT) middleware [16], and hybrid reference model matching with virtual reference feedback among smart controllers [17]. Yet, it is clear that there is a lack of a conceptual reference architecture model for a combined approach of Industrial Internet-of-Things (IIoT), Digital Twin and i4.0 enabling technologies, with energy data driven services and data ubiquity, on an interoperable digital platform targeting energy management and efficiency. Each of these aspects is further described on the following subsections.

2.1. Interoperable Digital Platforms for Energy Efficiency

In technical terms, digital platforms are presented in a multi-layer setup that ranges from web portal and business interactions to the software tools and data management layers, as well as the communication layer that intertwines the entire ecosystem [18]. The foundation is usually constituted of a semantic infrastructure, with ontologies and inference rules, which is combined with a database to enable ecosystem data management capabilities and interoperability among different assets. The services are applied in a plug-and-play fashion into the ecosystem data manager, and further integrated into the web portal through a gateway orchestrator [19].

Digital platforms have notorious implications for the economy given their inherent separation between physical & virtual assets and the value created by them [20]. In order to enhance the collaborative potential and the widespread dissemination of information & data, a holistic value network perspective must be adopted, which expands from the simple matchmaking of manufacturing resources to a manufacturing ecosystem network. With such approach, the digital platform can combine tools and ecosystems, through which sustainable use of resources may be achieved [20]. The drivers to the development and implementation of digital platforms for the manufacturing industries, also known as digital platform affordances, usually pertain the bridge between technological availability & maturity, and the human-machine interaction capabilities. They have been identified as follows [20]:

- The need for enabling flexibility (from modular-driven services and sharing economy to user-IO and role changing capabilities) [21];
- Matchmaking between different attributes [22];
- Scalability capabilities and cross-sectoral reach extensions [23];
- Management of all transactions in the ecosystem [24];
- Building trust through high-security measurements and full information transparency among players [18];
- Support the engagement of the network with the aim of establishing a strong community [25].

Despite conceptual developments and the availability of solutions, a flexible, secure and interoperable digital platform has not yet been developed with the clear purpose to assess the energy-efficiency of industrial complexes through smart sensoring and simulation & optimization capabilities.

2.2. Energy Related Data Ubiquity

In order to achieve decreased EC, energy efficiency and carbon footprint reduction, companies can implement changes on manufacturing processes, which can range from renewable energy generation, energy transformation techniques and ubiquitous sensing, to smart machinery control and development of energy/comfort systems (light, air, heating and cooling, windows and doors) [26]. One way of reducing the EC is by increasing the efficiency of existing machinery, i.e. belt conveyors energy efficiency increased through variable speed control [27]. Another way is reusing the wasted energy inside the plant. Heat waste energy can be transformed into another form of energy, generally electricity. These techniques deal with the reduction of EC in individual plants separately, but a collective approach targeting multiple industrial units can be achieved through the deployment of industrial symbiotic techniques, which involve the exchange of materials, energy, water and by-products [28].

Due to the powerful embedded devices available today, the computing power is being brought closer to sensors and many tasks previously executed on desktop computers, SCADA (Supervisory Control and Data Acquisition) systems or cloud are being moved to smarter Internet-of-Things (IoT) devices. This strategy allows data pre-processing and filtering, reducing the amount of storage needed for applications, which is very important due to the huge amounts of data generated by IoT devices and the data transmission through the network [29]. In addition, this strategy reduces the response time in control applications, enabling real-time control, converting the IoT sensing devices into smarter components usually referred as edge computing devices [30]. These devices are commonly connected to the cloud for data storage and updating of the machine learning algorithms used to forecast and control. Most modern architectures allow for online update of the models while the IoT device is in operation.

Energy measurement and forecasting opens up the possibility to apply smart control to energy and production systems. Production line measurements and forecasts are combined in the literature with other data to reduce the EC and CO_2 footprint of the manufacturing process. Nevertheless, seldom research has attempted to combine all the different approaches. Energy forecasting of complete manufacturing lines or buildings have much greater potential, as it allows for a global optimization that includes not only the EC or the cost, but also other variables. Although several works in commercial areas and energy systems in buildings in general are available, there are few works that tackle energy reduction at an industrial level.

2.3. Energy Data Driven Services

Most industrial facilities are increasing their energy efficiency by implementing ISO 50001 approved methods [31], aiming to decrease energy costs and greenhouse gas emissions. This standardized practice provides monitoring and awareness of EC to human decision-makers, but does not provide prescriptive analysis and/or autonomous process control. Moreover, basic descriptive analytics (e.g., linear regression) might lead to inadequate and simplified models of energy efficiency monitoring [32], since they do not consider different factors, such as financial costs, size of the installation, consumption of different raw materials, implementation of other energy efficiency actions, etc. It is also important to underline that the level of awareness regarding EC remains low in several manufacturing processes mainly due to difficulties in obtaining shop floor calibrated measurements [33]. The state-of-the-art data-driven services are mainly limited to: product/key parts EC information monitoring and forecasting to estimate indicators (e.g., EC proportion of each key part) and integrate them in green material selection [34]; evaluate daily, week and yearly trends of EC [35]; and, cloud-based services for EC estimation in machining operations, including information from human operators and process plan [36]. In terms of process control and energy optimization, different studies explored model-driven energy optimization techniques, such as integer programming for peak load reduction in steel-plants [37] and robust optimization for real-time control of a steel powder manufacturing process under varying prices [38].

The advent of IoT technology offers technical conditions for data-driven approaches for energy optimization, where, for instance, each process can be represented by a process input/output matrix [39] or a virtual battery [40]. This approach does not require a full modelling of the process equations since its understanding is made in real-time through data and can be combined with a digital twin manufacturing system that performs simulations and decisions for different energy-saving purposes in a virtual space, e.g. event-driven energy-saving decision method that switch machines to sleep mode with minimum effect on the system throughputs [41].

Recent advances in machine and deep learning techniques, combined with the increasing monitoring and simulation capability offers by the i4.0 paradigm, enables different use cases for data-driven services, namely:

- Detection of abnormal consumption patterns and root-cause analysis to find energy efficiency actions.
- Benchmarking either between similar manufacturing industries or between “perfect” (in terms of energy consumption) digital twin and real factory.
- Data-driven modelling of industrial processes (including energy consumption) and inclusion in digital twin simulation as proxies to produce recommendations for optimal tuning scenarios.
- Estimate process flexibility for power system ancillary services provision (see [42] for taxonomy and more details about flexibility and ancillary services products), e.g. predictive consumption curtailment to offer peak load reduction to transmission system operators.
- Predictive control for energy optimization of continuous and energy-intensive processes.

For the last two services, some promising techniques from the state-of-the-art can be exploited. For flexibility modelling, the representation proposed in O’Connell et al. [43] for flexibility (i.e., power versus duration curves), and modelled with ARMAX (Auto-Regressive Moving Average with eXogeneous Input) models, can be extended to heat or coal based industrial processes. With this modelling approach, the industrial consumer can estimate the power flexibility and present offers in the electricity market (direct participation or represented by a market aggregator). For predictive energy optimization of continuous processes, a promising approach is to combine supervised learning (development of functional relations between state and control variables for different types of processes and forecast demand in energy intensive flows) and reinforcement learning (self-learning – e.g. through Proximal Policy Optimization methodology) for emulating the physical environment from data. This approach was applied to control the variable-speed pump operation in wastewater tanks (see Filipe et al. [44,45] for more details), and can be extended to other industrial processes if data from sensors that characterize the system state are available.

2.4. Digital Twin for Predictive Energy Management

Usually, IoT solutions applied to the energy domain can be structured in three logical layers [46]:

- Wireless sensor networks, which detect the signal coming from the production line;
- Registers (accumulators), where the energy consumption is measured and stored separately for process;
- External servers and software to monitor the energy consumption in the factory.

An example of such solutions are the distributed real-time energy monitoring system, build upon the wireless sensor network, aimed at supporting machine scheme selection and energy quota allocation in the shop floor [47]. On the top of the data acquisition layer, a digital twin (DT) can be applied to model the characteristics of the real networked system. This concept is further extended to the shop-floor, thus achieving the digital twin shop-floor (DTS) [48], which aims at merging the physical and virtual spaces to optimize the current production activities. In DTS, every element in Physical Shop-floor (human, the equipment, the material and the environment) has its digital representation [49]. A DTS allows the integration of data provided by both the physical and the virtual space to optimise performances of the system and manage energy consumption. These technologies allow the management of various system parameters concurrently, making them suitable for managing complex systems. Applications in this field allowed to address energy consumption monitoring, data analysis, energy efficiency improvement, environmental impact reduction, productivity increase and cost reduction [50].

3. Architecture Model for a Digital Energy Management Platform

The conceptual architecture model for Digital Energy Management Platform was designed through a combination of literature review and non-structured interviews. The literature review considered both scientific and grey literature, and aimed at understanding the current state-of-the-art of architectures for digital platforms targeting energy outcomes by combining ICT techniques and tools into legacy systems and smart machinery within manufacturing companies. The non-structured interviews were conducted with manufacturing companies from five European countries (Germany, Spain, Portugal, Italy and Sweden), and among different manufacturing sectors: testing and experimentation facilities, automotive parts, iron foundry, textile and chemical. These interviews sought to comprehend the requirements of manufacturing companies across industrial sectors regarding energetic aspects of production lines. Based on this research methodology, a conceptual architecture model for Digital Energy Management Platform was developed, grounded on six main perspectives, towards bringing energy efficiency into the manufacturing industry. These perspectives are further defined:

- Support a digital continuity paradigm towards an optimal energy management in a holistic way along the entire value chain.
- Provide a holistic and ubiquitous energetic information for full energy demand and consumption characterization amidst the different levels of granularity of complex manufacturing systems. This is achieved through an open, standardized and interoperable energy management framework, which is fully synchronized with real industrial environments.
- Enable energy data interoperability with manufacturing legacy system to include the energy and sustainable perspectives within the regular planning and optimization tools. Enriching manufacturing and enterprise legacy systems with energy intelligence will enable manufacturing companies to take decision also considering energy efficiency, maximization of energy use from RES and reduce costs with energy.
- Understand synergies between endogenous and exogenous variables and its impact on energy consumption. Using Artificial Intelligence as a tool to identify patterns on energy demand and generate intelligence on energy consumption behavior, it is expected to support manufacturing companies in understanding multi-variable cause-effect relations with impact on energy demand and consumption
- Expand Human worker cognitive capabilities to take the most sustainable option in their decision-making process. Using proper human centric technologies, it is possible to provide humans with energy intelligence that can rule the decision-making along the entire value chain.
- Optimize energy demand and promote reduction of costs and of environmental impact through smart industrial processes' configuration and parametrization. The key to fulfill this purpose is a set of innovative data-driven energy services, capable to prescribe industrial processes configuration and assets parameterization towards energy efficiency, environmental impact mitigation and energy cost reduction.

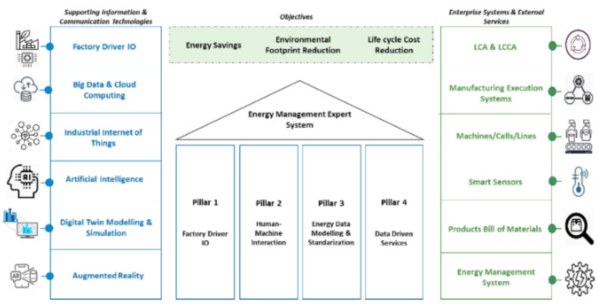

Fig. 1 Architecture Model

In order to improve their energy efficiency, companies may apply managing and monitoring activities on their factory, product and process designs in an integrated way. Typically, this incurs in optimizing the parameterization and configuration according to the specificities of the task in production, such as the product composition and the environmental characteristics (e.g. weather conditions). Furthermore, it looks to put forward the simulation tools to explore and validate potential industrial and internal processes' symbiosis, while aiming to prioritize retrofitting options, which focus on decreasing waste, leveraging the energy circular economy and maximizing the return on investment (ROI) when updating or replacing the assets and machines.

On this note, AI based data-driven services, which are fully available and accessible to employees, provide richer information on energy demand patterns and potential root causes, as well as prescribe improvement actions. In this way, it will be possible to make effective and sustainable data-driven decisions, as well as to anticipate the future impact of these decisions, especially in foreseeing potential energy savings and energy costs. The conceptual reference architecture model for a digital energy management platform will bridge two main concepts: (i) the supporting information & communication technologies (ICTs) emerging within the i4.0 context; and, (ii) the enterprise/manufacturing systems and external systems specific from the energy industry (Fig. 1). On a broad perspective, the conceptual reference architecture model aims to integrate these perspectives to propose a holistic and distributed Energy Management Expert suitable to be implemented in SMEs & mid-caps, in big companies and in multinationals.

3.1. Pillar 1 – Factory Driver IO

The main idea of the Factory Driver IO is to create an abstraction layer that makes interaction with the production system easier from high-level applications. Considering the huge quantity of energy-related data that is expected to be generated, it becomes critical to use emergent data management and data fusion techniques capable of pre-processing them and guaranteeing its accuracy and quality, which is achieved through edge computing techniques. A set of edge devices, based on Graphic Processing Unit (GPU) System-on-Chip (SoC) will be used given their seamless development, increased reliability and reduced costs & power consumption. These use industrial protocols to connect to sensors, actuators, robots and other machines, and the rest of applications, generating a unified interface. The edge devices will be installed in the production line, being capable of supporting most common industrial protocols such as Profibus, Profinet and Modbus. The architecture supports different field bus protocol in each edge device and even more than one protocol per edge device, providing flexible and hybrid communication networks. All low-level configurations are encapsulated in the edge device, which provides access to the production system always with the same data type and units, regardless of the type of sensor or communication protocol used at shop floor level. Thus, it becomes possible to distribute the data processing while keeping local control of processes and machines according to strict guidelines, mitigate the data flow with the platform, reduce data latency and guarantee stronger capacity for agile detection of bad behaviours with quick reaction. This approach will tremendously ease the development of high-level algorithms, like energy forecasting or digital twins, which do not need to deal with low-level details.

3.2. Pillar 2 – Human-Machine Interaction

An important perspective of i4.0 is the empowerment of employee's cognitive capabilities towards a more intelligent and complex decision-making process, taking advantage of enabling technologies explored and developed within the scope of the i4.0. Thus, the main objective of this pillar is to study and assess enabling technologies, such as Augmented and Virtual reality, 3D simulation environments and other technologies capable of: (i) presenting relevant energy-related information at the right moment to decision makers in a more human-centric way and (ii) enabling the power of data driven services (Pillar 4) for humans and guaranteeing that these services can be used interactively by decision makers according to their needs. These will take advantage of the green and energy efficient framework, which will be explored in Pillar 3, in order to exploit a complete and innovative way of presenting information for different decision makers along the complex manufacturing system levels (from the shop floor to the factory and supply chain perspectives). It seeks to build rich, modular and interoperable energy information models, capable of integrating and empowering existing digital twin models (e.g. production, product and building models) to support the creation of immersive environments. In these immersive environments, decision makers can enhance their awareness about real-time EC, efficiency and quality, comparisons with their digital shadow behaviour, receive alerts of potential problems and a prognosis about the root causes and points of attention. Workers can also benefit from real-time data and information exchange, which will enhance productivity, safety and complexity, while providing security and reliable decision-making strategies.

3.3. Pillar 3 – Energy Data Modelling & Standardization

Given its role in increasing energy-efficiency, the semantic interoperability based on standardized ontologies brings a significant value proposition for the complete integration of IoT energy-related information in the manufacturing domain. This evolution overcomes the limitations imposed by complex solutions of existing systems architecture, where different manufacturing systems already exist, as well as optimization and planning tools, sometimes from different providers or belonging to monolithic solutions. Yet, it requires more, and better, energy information to achieve greater green- and energy-efficient performances. The standardization of solutions and data models, and the interoperability across IoT services and datasets through reference ontologies (developed in the scope of this pillar), are key concepts towards the effective adoption of new ICT technologies and empowerment of existing ones for energy management. This pillar is executed with the main objective of enabling standardization and acceptance of new data models, both in the research and industrial domains, capable of leveraging new green- and energy-efficient certifications, labelling and regulation procedures.

3.4. Pillar 4 – Data-driven Services

The main motivation behind data-driven services is that physical modelling of different industrial processes might be complex and/or expensive to obtain and it does not fully boost the replication potential of the Energy Management Expert System. Thus, the data collected from energy- and process-related smart sensors, which is aggregated and pre-processed in the IIoT Platform, and potentially combined with data collected from digital twin simulation models, is exploited to offer data-driven energy services supported by: (i) big data solutions and (ii) state-of-the-art AI modelling framework from the AI4EU platform. The following groups of services can be developed and integrated with the Energy Management Expert System:

- Predictive analytics (or prognosis): Forecast optimized process operations, such as finding functional relations between state and control variables of industrial processes with influence in energy consumption. Modelling uncertainty (e.g., unplanned events and other perturbations) will be a key requirement to assess feasibility of process scheduling. These business-driven analytics can also provide real-time analytics and simulation (e.g., embedded in the digital twin) of KPIs related to energy consumption.
- Prescriptive analytics: Self-control of energy consumption in continuous industrial processes that can operate with minimum control and monitoring requirements and are easily traceable and adaptive to process changes. Root cause analysis of abnormal consumption partners and cause-effect analysis for identification of energy-efficiency actions are also envisioned services. These services can work both in centralized and decentralized decision-making frameworks.

The main challenge is to produce a modular framework for energy services, which can be adjusted and scaled to model systems that are continuously changing while covering different end-user requirements. Moreover, a human-centred perspective on the interface design must be considered in order to enable humans to best exploit the available data, make better decisions, focus on core tasks and be able to perform better in an increasingly networked work environment, therefore being integrated with the Factory Driver I/O of Pillar 1 and with the Human-Machine Interaction of Pillar 2.

3.5. Energy Management Expert System

Considering the complexity of today's manufacturing systems, it is clear that decision makers at all levels of the organization and value chain need expert systems for real-time decision-making on a broader, holistic overview. Therefore, for emergent topics with complex settings (i.e. high number of variables, multiple trade-off scenarios, synergetic nature and requirements, and impact on business drivers), such as the energy efficiency in manufacturing, this represent a huge advantage. Therefore, the conceptual reference architecture model explores the development of intelligence (pillar 4) capable of enriching existing planning and management enterprise tools, through a seamless interoperable mechanism based on energy digital twin models (pillar 3), with a holistic view on energy quality and demand (pillar 1), while exploring human-centric technology to enhance human decision makers' cognitive capabilities (pillar 2).

The main challenge of the Energy Management Expert System is related to the need to take advantage of intelligence related to energy demand and quality, and integrate it with the enterprise and manufacturing systems, towards a more efficient EC profile. This will be achieved through four different approaches:

- Energy Intelligence for Legacy Systems, which focuses on energy-related information interoperability through different perspectives of the production system management, aimed at achieving optimal energy saving potentials, energy- and eco-efficiency (by using energy intelligence integrated into scheduling tools – Green Scheduling), while maintaining business targets (use of ERP/MES, production planning tools, enterprise management systems, product design & management tools).
- Life Cycle Assessment and Cost Analysis (LCA/LCC) tools, which are integrated in the digital energy platform, to support the assessment of the best energy management decision considering past performances and forecasted energy behaviour, all of which are obtained through the industrial pilot cases. Having both a company-specific and a value chain-oriented approach, this integration will provide sustainability values enabling to compute the different scenarios related to energy usage and provide optimization capabilities.
- Simulation and Optimization mechanisms supported on the energy digital twin models developed. Within 3D and immersive environments, it will be possible to create and validate hypothesis not only related to the company's layout, product characteristics and industrial processes configuration, but also to their synergies and impact on different energy perspectives.
- Self-Automation and Control capabilities, achieved through an energy control station, where managers from the industrial pilot cases can define very simple business guidelines, based on IF/THEN/ELSE logic capable to be deployed in the edge computing infrastructure for cyber-physical systems (CPS) control towards a more energy-efficient performance.

4. Illustrative Use Case

To validate the proposed conceptual architecture model, a theoretical case study was designed based on the case research protocol from Yin [51]. For this purpose, a Portuguese iron foundry manufacturing company was selected, which produces rough and pre-machined parts in nodular and grey iron for the automotive industry. This theoretical case study focuses in the operational optimization of the brazing furnaces used for welding, through real-time energy consumption prediction and digital twin. The furnaces' overheating processes demand a massive EC to achieve a temperature of 1500ºC, on average, to conduct their melting tasks. This temperature set point depends on a set of variables, such as the final product characteristics and the composition of the raw material used, and their correct calculations are considered critical to achieve balance between quality and EC. It is, therefore, a complex set of processes, which is currently conducted by well-trained and experienced workforce. Nevertheless, to achieve optimized energy efficiency, it is necessary to implement intelligent systems to monitor and control the furnaces by considering the endogenous and exogenous variables of this complex system.

To overcome this limitation, a digital platform is to be deployed, where endogenous and exogenous variables can be collected and pre-processed in real-time to feed AI based data-driven services. The result is grounded knowledge generation to allow for controlled optimized decision-making, thus enabling energy efficiency. Digital twins, each exclusive to a separate furnace, are to be defined according to the machine's specifications, which will consider control mechanisms, physical-, electro-magnetic- and thermal-curve/behavior, as well as EC patterns. This digital model will be continuously updated with rich information from the algorithms, which will be pre-processing data from the furnaces, at the edge level, and publishing information to the cloud in real-time. In parallel, AI based data-driven services will be reading and correlating this information to generate knowledge that can enrich even more these digital models so that multivariable nonlinear control of the overheating process can be performed.

By combining all this information within proper simulation technologies, it is possible to provide decision-makers with the capability to optimize production planning and configuration, and the furnace parameterization, towards energy efficiency while keeping production rate within quality parameters and reducing environmental footprint. This considers all the production perspectives (e.g. final product characteristics, raw materials, furnace's status and behavior, weather/temperature conditions). A simulation engine will use this results to enable operators to monitor the current status of the furnaces and plan the overheating process considering the production scheduling.

5. Conclusions

In light of the challenges set forth by the European Commission and the current global landscape regarding EC, environmental impact reduction and the role of the manufacturing industry, this research has presented a conceptual architecture model for a digital energy management platform. Such conceptual architecture model is supported by four well-designed concepts surrounding data ubiquity, data driven services, digital interoperable platforms and digital twin modelling for energy efficiency and environmental impact reduction.

Moreover, the conceptual architecture model is comprised of four pillars that promote an energy management expert system that allows for modular applications of energy data driven services considering human-machine interactions through a factory driver i/o, and with full documentation in order to establish common framework. The proposed conceptual framework can be further extended towards full-set applications and solutions for combined ICT and enterprise systems' approach towards enhancement of energy efficiency in manufacturing industries. Thus, the proposed conceptual architecture model is a scalable, interoperable and holistic architecture model capable of collecting and pre-processing all energy-related data, taking advantage of innovative CPS connected along the shop floor, enabling access to advanced AI-based data driven services for generation of energy intelligence, which can be integrated in manufacturing companies' legacy systems.

Future works to build on this research should focus on validating the proposed conceptual architecture model through an established multi-case research design, as well as on developing solutions based on such architecture to be implemented in manufacturing companies. The multi-case studies are to be conducted within the manufacturing companies already interviewed for this research, as depicted in section 3, with a cross-sectorial approach to ensure full validation of the proposed conceptual architecture model. This instantiation within industrial companies is expected to provide energy efficiency gains, which lead to life cycle cost reductions of production lines and lower environmental impact.

From an academic perspective, the focus should be on providing interoperability capabilities among enabling technologies and legacy systems that easily integrate with this reference architecture model.

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