Process based Machine Learning for Energy Optimization in Industrial Enterprises

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***Abstract*—This paper presents the design, implementation and primary evaluation of a tool that aims to support industrial processes towards the optimization of energy consumption. The authors describe in the first part of this paper the processes followed in an industrial environment and particularly the Product Cost Accounting Information System. The second part is devoted to the technical details of the system that integrates dominant simulation tools for data generation, machine learning algorithms for energy consumption predictions, and all the appropriate mechanisms that deliver the required scalability and flexibility of the system to serve its purpose.**

Keywords—data simulation, energyplus, machine learning, energy consumption, industrial processes, prediction models

I. INTRODUCTION

Demand Response is almost exclusively supplied by energy intensive industries such as petroleum refining; chemicals, paper; metal, and cement production leaving commercial and normal energy consumption industrial enterprises, , out from the market even though demand response is technically and economically viable. Furthermore, a more efficient use of energy is the key element in cutting electricity bills, thus energy efficiency and utilization of demand-side flexibility in demand response are considered as a major priority for the realization of the European Energy Union [1]. While refurbishment of the buildings and the use of more efficient electric/electronic devices can offer significant benefits in this respect, installing simple tools such as heating/ lighting controls and thermostats can deliver significant impact on the overall energy consumption. Such controls, if accompanied by accurate metering, real-time consumption information on equipment and device levels, billing systems that reflect the real-time status of the power system (dynamic pricing schemes) and intelligence, can be effectively utilized by the relevant processes in the industry and trigger a reduction of overall energy demand by at least 20% [2]. Provided that the deployment of intelligence, i.e., an AI algorithm in production environment, requires the availability of large volume of data as an enabler for the data scientists to train, test and validate their models, the impact of contemporary data simulation tools is critical.

The scope of this paper is to present a software tool that facilitates the prediction of energy consumption of an industrial building based on simulated data. This prediction aims to support the near optimal organization of manufacturing processes and balance the energy demand for various periods of interest (daily/weekly/monthly). This balance reflects on the improved utilization of energy renewable resources that enterprises might own. The adoption of this approach is expected to have multifaceted benefits such as:

- Accurate provisioning of the actual manufacturing cost
- Reduce of the production cost due to the optimization of energy consumption
- Minimization of the energy footprint on the environment

In that context, the relevant processes in industrial enterprises are described in detail in Chapter 2 and the system requirements in Chapter 3. The system architecture of the proposed tool is presented in Chapter 4 along with the components description. In Chapter 5 the Web Interface is described while Chapter 6 describes the evaluation process followed to assess the system performance. The conclusions of this work follows in Chapter 7.

II. PROCESS MODEL

Contemporary industrial enterprises are in a constant need for greater flexibility and interoperability. The enterprise industrial environment comprises systems and applications covering the entire range of the enterprise system hierarchical model. Three main levels are established: The Production, the Plant and the Enterprise levels as depicted in Figure 1.

In the production level all the applications relevant to the distributed control code that is needed to properly execute the

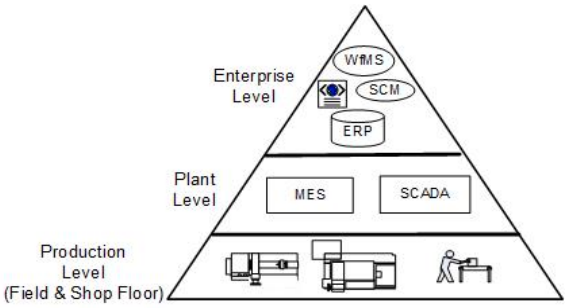

Figure 1. Industrial Enterprise Layers

manufacturing processes are residing. Sensors and actuators, and industrial controllers, such as programmable logic controllers and numeric controllers, are interconnected. In the plant and enterprise levels the deployed applications are characterized as high layer applications and their corresponding information systems are interconnected to execute processes such as the enterprise resource planning, the order handling, the warehouse management, the materials and energy control, and many others. A holistic overview of the information systems as well as indicative required information to be interchanged for the processes to be executed is depicted in Figure 3.

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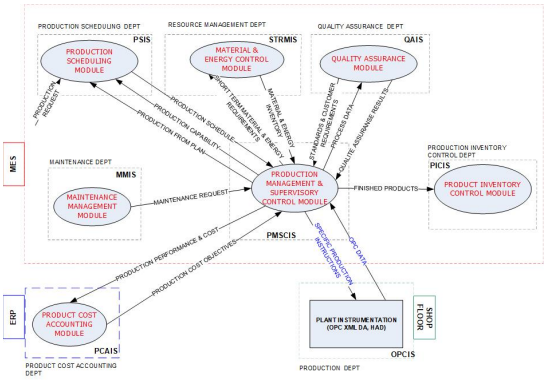

Figure 2. Industrial Enterprise Information Systems

Communication wise, the ubiquity of Internet protocols standards has made possible the integration of different systems at whatever layer they reside, thus letting critical to energy optimization processes to run unhinderedly. More specifically, the Product Cost Accounting Information System (PCAIS), as depicted below, comprises methods that deal with the management of all enterprise resources, such as labor, material and energy which formulate the cost of production and eventually outline the final product cost. As of that, this system can negotiate resources that are required for a planned or directly enforceable production request. These can be resource allocation issues, reservations for specific materials and energy, indications for current consumption of production, exemption from reservations or consumption regulations. Indicative processes of the PCAIS are described below while in Figure 3 the information exchange is depicted. All the processes are described in a standardized manner since they adhere to the ANSI/ISA-95 standard [3].

- Costs Balancing and Budget
- Raw Material and Parts Costs
- Manufacturing Material and Energy Costs
- Production Costs
- Raw Material and Energy Inventory Control
- Raw Material and Energy Movement Control

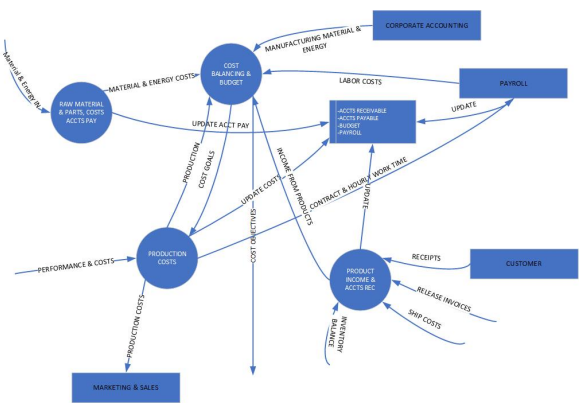

Figure 3 PCAIS information exchange

Nowadays, there is significant progress in machine learning and artificial intelligence technologies that manage to develop prediction models on energy demands with high accuracy ([4],[5]). However, these models do not fit out of the box in any infrastructure. The performance of such models is strongly connected to the peculiarities and the characteristics of each installation. On the other hand, the generation and use of the appropriate datasets cannot be feasible until a significant time of operation has been already passed and significant volume of data is collected. On that domain, there are tools that manage to simulate the behavior of a building given the specific construction details, equipment (e.g. HVAC), people, weather conditions, etc.. Civil & electrical engineers take advantage of these tools during the design phase of new infrastructures ([6],[7],[8]).

However, we have identified that there is no clear path passing from the design of an infrastructure to the operation and optimization from the energy consumption point of view. In that context, we present the design and the implementation of a tool that encapsulates the advances in building's energy behavior simulations, machine learning and cloud services. This tool aims to facilitate the power consumption predictions to support cost projections and resource planning. Particularly, is considered as part of the "Manufacturing Material and Energy Costs" module (Figure 3). The presented tool is part of a work in progress that aims to develop an environment focused on the holistic optimization of industrial processes.

III. SYSTEM REQUIREMENTS

The definition of the system requirements (functional & non – functional) are the starting point to design and implement a fully functional system that could deliver to the end user (facility manager, electrical/civil engineer, data scientist) an operational workflow able to provision energy consumption based on the building/infrastructure configuration. The defined functional requirements are listed in Table I.

TABLE I. FUNCTIONAL REQUIREMENTS

#	***Description***
FR01	The user must be able to model and describe the infrastructure under study
FR02	The system must be able to simulate and produce energy consumption data based on the infrastructure configuration
FR03	The system must be able to handle pre – generated datasets (e.g. acquired after recording data for a period)
FR04	The system must be able to receive and handle energy consumption data during the runtime of the infrastructure
FR05	The system must be able to predict energy consumption based on the current operation
FR06	The system should not have hardcoded the analytics algorithms. The user should be able to switch between existing algorithms or plug its own implementations
FR07	The actions of users should performed through a self – intuitive user interface (where possible)

Of course, non – functional requirements were also considered as they are strongly related to the architectural design of the system and highly affect the robustness and the sustainability of the system. Briefly the non – functional requirements that where defined are listed in Table II.

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TABLE II. NON - FUNCTIONAL REQUIREMENTS

#	***Description***
NFR01	The system should be scalable
NFR02	The system components should not be dependent to the implementation technology
NFR03	The system should be able to operate as an online service
NFR04	Time consuming & resource hungry tasks should not affect the overall responsiveness of the system

IV. ARCHITECTURE

Driven by the advances in software development during the last decades and the non – functional requirements, the design of the system is based on the principles of microservices [9]. The system functionality has been broken down in components, implemented as independent services that operate isolated one from the other.

Towards this direction, containers have been proven a very valuable technology that offers fine – grained execution environments, service isolation and improved initialization and execution processes for microservices. Hence, all the system services are deployed as docker containers as depicted below in Figure 4. The details for each service are given in the section that follow.

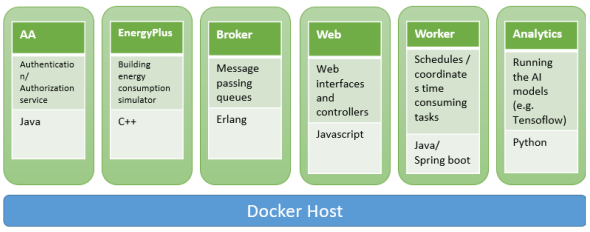

Figure 4. System Services

A. Broker

The scalability requirement dictated the message/event driven approach to be adopted as the main integration pattern between most of the services ([10]). In this approach, the broker is the heart of the system while the rest of the services run and cooperate in a loosely coupled manner. RabbitMQ ([11]) was chosen as the broker responsible to handle the queues/topics of the system. The rest of the services connect to the broker as subscribers or publishers to produce and consume messages respectively.

Apart from the integration of the system's docker services, the broker handles a respective queue (i3t.data.raw) that tackles the reception of energy consumption raw data coming from an existing infrastructure.

The integration with existing infrastructure is assigned to another service that acts as the adapter of an external component to the system. However, the fragmentation of the smart buildings domain and the lack for commonly accepted standards does not allow generic and plug n play approaches to be applied yet. The implementation of an adapter that follows the guidelines of the Open Connectivity Foundation ([12]) is a work in progress and not subject of this paper.

B. Authentication/Authorization/Identity Management

This component is responsible for the user management of the system's users along with the authentication and authorization mechanisms. All the users that access the web interface of the system are authenticated by this component. As long as the component verifies the identity of the user, it checks whether authorization is granted to access the requested resources. Authentication and authorization is performed according to the OAuth2/OpenID connect standard

C. EnergyPlus

This component is responsible to simulate the behavior of a building/infrastructure given a specific configuration. The core of this component is the EnergyPlus simulator ([13]). EnergyPlus is a popular simulator, used by architects, civil and electrical engineers that need to model the energy consumption of a building for heating, cooling, ventilation, lighting and plug and process loads. The simulation is triggered by the user through the web interface of the system and it is executed in its isolated docker container. When the simulation is completed, a message is published in the respective queue and the simulation results are extracted in the shared docker volume. Then these data are ready to be used as a training dataset for the supervised machine learning algorithm that the user will use to predict future behavior of the system. The integration of EnergyPlus data sources with machine learning tools is the major contribution of this paper that to the best of our knowledge has not been presented before.

D. Analytics

The analytics component, as already implied is responsible to process consumption data received during runtime and predict the behavior of the system in the time to follow based on the training model that was already built. In the first version of the system, the analytics component was based on Tensorflow ([15]), a popular and open source machine learning platform developed by Google. In that context we developed a multivariate multi-step LSTM network as depicted in Figure 5. LSTM networks is a subset of the Recurrent Neural Networks (RNN) and have been proven to perform well for classifying, processing and make predictions based on time – series data.

We need to highlight that the scope of this work was not to propose a new machine learning algorithm or a high accuracy energy consumption model but to present a tool that offers an end – to – end flow from data generation/preparation to energy consumption prediction, facilitating the use of various machine learning algorithms ([14],[15]) combined with the popular EnergyPlus simulation platform.

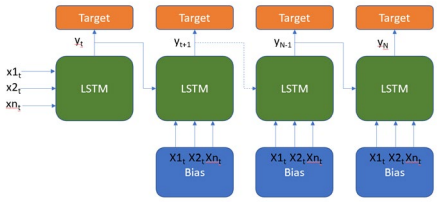

Figure 5. The LSTM Network

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E. Worker

The worker is the component that aims to schedule and execute all the heavy tasks in favor of the scalability and the responsiveness of the system. The component is subscribed to the *tasks* queue of the broker and listens for new tasks. As long as a new message is received, the worker is responsible to execute it. Such a task could be the execution of a new EnergyPlus simulation. When this event is triggered a new docker container is created to execute the simulation. When the container is up and running, the worker is released and is again available to consume the next message from the queue (if any), regardless of the EnergyPlus simulation status. Thus, the requests are served asynchronously without degrading the overall system's health (e.g. in case of long running simulations, failed tasks, etc.).

V. WEB INTERFACE

The web interface of the system as implied is responsible to offer a graphical interface to the user that facilitate his interaction with the tool. Such interactions concern:

1. Adding new data sources, whether it is data produced by EnergyPlus simulations or datasets formulated in CSV files
2. Select data sources to train existing prediction models
3. Monitor energy consumption predictions
4. Anything related to user authentication and profile management

The presentation of the web interface is beyond the scope of this paper

VI. EVALUATION

The evaluation of the system was performed in two pillars. First, we executed end – to – end flows to validate the operational status of the tool according to the functional requirements. Since an existing infrastructure with smart meters to publish their measurements was not yet available, we used publicly available datasets to simulate the training/testing phase of the algorithm and the validation phase during runtime as well.

The second pillar of our evaluation concerned the scalability of our system. To stress the system, we triggered the execution of multiple EnergyPlus simulations to emulate multiple users asking to run simulations in parallel. The system was deployed in a docker swarm with two nodes where the EnergyPlus had a scale factor of 10. With that configuration we managed to execute in parallel 10 simulations in the respective containers distributed to the two docker nodes. Each simulation had a different building configuration randomly selected by the large pool of configurations provided by EnergyPlus. In half of the simulations weather files were also used (EnergyPlus takes under consideration weather conditions if the respective file is provided as input). The simulations where successfully terminated, and the results were extracted as expected to the shared volumes.

VII. CONCLUSIONS

This paper presented the architectural and functional design of an open-source platform that aims to facilitate the prediction of energy consumption through the integration of a popular and dominant energy simulator (EnergyPlus) with cutting edge machine learning tools (Tensorflow) and algorithms (Neural Networks). This tool is expected to facilitate the provision of production cost towards an overall industrial processes' optimization.

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