THE I-NERGY REFERENCE ARCHITECTURE FOR THE PROVISION OF NEXT GENERATION ENERGY SERVICES THROUGH ARTIFICIAL INTELLIGENCE

Evangelos Karakolis, Sotiris Pelekis, Spiros Mouzakitis, Georgios Kormpakis,
Vasilis Michalakopoulos and John Psarras
Decision Support Systems Laboratory, National Technical University of Athens, Iroon Polytechneiou 9, 15772, Zografou, Greece

ABSTRACT

Recently the energy sector undergoes a rapid transformation that revolves around digitalization, decentralization and democratization. This is because global energy crisis contributes to rising poverty, raising prices and slowing economies. At the same time disrupting ICT technologies such as Artificial Intelligence (AI), Big Data Analytics, and Internet of Things (IoT) pose great potential towards improving several processes followed in the energy sector such as better forecasts for energy demand and consumption, that can contribute to significant energy savings. To this end, I-NERGY project aims at promoting and supporting AI in the energy sector through services and applications that support the entire energy value chain. In this publication, the I-NERGY big data reference architecture (RA) is presented, along with the most important technologies that have been used to cover the main requirements of I-NERGY platform. Moreover, I-NERGY is compared to other well-known big data RAs both general-purpose and energy sector specific, and the most important conclusions are presented in brief.

KEYWORDS

Artificial Intelligence, Big Data, Energy, AI on Demand, Data Governance, Energy Analytics

1. INTRODUCTION

People's well-being, industrial competitiveness and the overall functioning of society depend on safe, secure, sustainable and affordable energy. Hence, the energy sector and the underlying value chain are central in people's everyday life. Especially, in the last few years, with the advancements on technologies such as AI and Big Data Analytics, and due to the energy crisis, the energy sector undergoes a rapid transformation. In fact, AI and Big Data Analytics are expected to reshape drastically the entire energy value chain focusing mostly on digitalization, decentralization and democratization. Indicatively, General Electric estimates that the production of a wind farm can be increased by 20% through the use of AI (GeneralElectric, 2019). Moreover, McKinsey estimates that by 2030 Big Data, IoT and AI technologies can unlock 5.5 trillion to 12.6 trillion dollars in value globally (McKinsey, 2021). Also, there are already several examples that showcase the value that AI and Big Data technologies can unlock in the energy sector. For instance, Google Data Center operation achieved 40% energy savings through DeepMind AI (Yao, 2018).

Of course, there are several companies that already use such technologies and derive significant value from them, however in most cases they act as consolidated data siloes, unwilling to share neither their data nor the techniques, methodologies and technologies they are using. In this context, collaborative platforms and projects that combine data from different data sources and provide transparency about the techniques and technologies they are using are of utmost importance. In this direction, AI on Demand (AIoD) platform aims at bringing together the AI community and facilitate knowledge transfer from research to multiple business sectors (AI4EU, 2020). In addition GAIA-X project provides a federated and secure data infrastructure, in order to enable companies and citizens to share data, while they maintain control over them, while special attention is paid to data sovereignty (GAIA-X, 2022). The same objective of secure and sovereign data sharing poses also the International Data Space Association (IDSA) (IDSA, 2021).

All the above-mentioned projects focus on data and knowledge sharing for multiple business domains, however there is a variety of projects that focus on the value of AI and Big Data in the energy domain and their applications. For instance, the MATRYCS project focuses on big data analytics applications for smart buildings (MATRYCS, 2021). BD4NRG aims to exploit the full potential of Big Data to the entire energy value chain (BD4NRG, 2021). ENERSHARE aims at enabling secure and sovereign data sharing in the energy sector to facilitate the energy transition that was mentioned earlier (ENERSHARE, 2022).

The research presented in this publication, has been conducted under the context of the EU funded research project I-NERGY. The main objective of I-NERGY is the promotion and support of AI in the energy sector through novel AI services and applications that facilitate the entire energy value chain, as well as the reinforcement of AIoD platform with new knowledge and assets for energy (I-NERGY, 2021).

Specifically, in this paper, the I-NERGY high level architecture is presented along with its main components and building blocks based on which each component has been built, together with the main requirements that I-NERGY platform should cover. Moreover, a comparison with other similar big data architectures for the energy sector and other related works, is presented.

2. RELATED WORK

Recently Big Data Analytics, IoT and AI technologies are becoming popular in literature, leading to numerous publications and research work for relevant applications in the energy domain. Those include services about electrical load forecasting through AI (Pelekis et al., 2022), anomaly detection in smart buildings and smart grids (Karakolis, Alexakis, et al., 2022) predictive maintenance services, flexibility forecasting and demand response services (Ahmadiahangar et al., 2019) among others. Moreover, there are several publications on general purpose big data services, such as query engine applications (Alexakis et al., 2022) and visual analytics services (Kormpakis et al., 2022). However, most of them are focusing on specific problems rather than the entire architecture of a big data system.

On the other hand, there is a variety of publications and well-known big data architectures that have been proposed as general-purpose big data architectures that support a number of different and heterogeneous big data analytics and AI services. Such well-known architectures include BRIDGE (Lambert et al., 2021), IDS-Reference Architecture Model (IDS-RAM) (Otto et al., 2019) and GAIA-X (GAIA-X, 2022). Moreover, system architectures from similar projects in the energy domain are BD4NRG and MATRYCS architectures. All these architectures will be presented in a nutshell and compared to the one proposed in the following sections.

Specifically, BRIDGE initiative (BRIDGE, 2021) aims to address cross-cutting issues regarding smart grid, energy storage, islands and digitalization, by involving multiple stakeholders from a large number of related projects. The results of this initiative include BRIDGE Reference Architecture (RA), a multi-layered, cross-sectoral architecture model based on Smart Grid Architecture Model (SGAM). BRIDGE RA consists of five layers, namely the Component Layer, that includes all connected devices and data sources; the Communication layer that has to do with standardization of protocols and formats; the Information Layer that is responsible for forming the data according to the selected data models to facilitate interoperability; the Function Layer, which is responsible for decision making processes based on available data; and the Business Layer, which is responsible for business associations, roles and processes (Lambert et al., 2021).

BD4NRG architecture (Wehrmeister et al., 2022) has been designed on top of the BRIDGE architecture. Specifically, it consists of four layers illustrating the different layers of the data value chain and one vertical pillar that includes different dataspace enablers that are relevant with all the aforementioned layers. The layers include the Data Sources layer, which is similar to the component layer of BRIDGE RA, the Data Interoperability layer that accommodates the responsibilities of Communication and Information layers of BRIDGE RA, the Data Analytics Services layer, which is similar to the Function layer of BRIDGE RA, and the Business Actors layer that includes all the different stakeholders interacting with the platform. Regarding the vertical pillar (Data Space Enablers), it consists of all components and functions required for a distributed dataspace that is aligned with the design principles of IDSA and GAIA-X.

Furthermore, IDSA proposed their own architecture model, named IDS Reference Architecture Model (IDS-RAM) (Otto et al., 2019) that focuses on secure and trusted data exchange between organizations paying special attention to data sovereignty. The main building block for IDS-RAM is the IDS connector which acts as a gateway and enables peer to peer sovereign data exchange between users. The main participants of a data space are data owners, data providers, data consumers and data users. Similar to BRIDGE and BD4NRG RAs, IDS-RAM consists of several layers, namely the System Layer, the Information Layer, the Process Layer, the Functional Layer and the Business Layer. These layers provide similar functionalities to the layers of the previously presented architectures.

With respect to GAIA-X RA (GAIA-X, 2020), it focuses on decentralization and transparency and consists of a data ecosystem that provides data sharing services, as well as an infrastructure ecosystem that is responsible for portability, interoperability and interconnectivity. GAIA-X RA focuses more on cloud services and infrastructure compared to IDSA. Of course, these architectures can be integrated in a common approach (Otto, 2022), as IDS connectors can be used as secure gateways to GAIA-X RA nodes.

In addition, MATRYCS big data architecture is a high-level architecture focusing on big data management in the building domain, that facilitates data sharing, interoperability and seamless operation of big data-enabled services. It consists of four layers of functionalities, namely the Infrastructure Layer, the Data Governance Layer, the Processing Layer and the Analytics layer. All these layers are built, using well-known open-source technologies. MATRYCS high-level architecture, follows a similar approach to the one proposed in the publication at hand and the I-NERGY architecture. A brief comparison of all the presented reference architectures will be presented in section 5.

3. I-NERGY REQUIREMENTS

I-NERGY project provides AI-enabled analytical energy services to several pilot sites, covering the entire energy value chain, from TSOs, DSOs and ESCOs, to investors and policy makers, all of them posing different objectives and requirements. Specifically, the pilots include 9 pilot hubs and 15 different use cases, that have been described in detail in (Karakolis, Pelekis, et al., 2022). These use cases are distributed across three domains, namely, i) **AI for energy networks, aiming at the optimized operation of electricity and district heating networks**; ii) **AI for Renewable Energy Sources (RES) generation in buildings, districts and communities** and iii) **AI for enabling synergies and implications on other energy and non-energy domains**. Indicatively, the use cases under the first domain, include a use case for **AI enabled network assets predictive maintenance** and one for **AI enabled efficient operational planning through network load forecasting**. The use cases under the second domain include an **AI-based consumption and flexibility prediction for a local community** and an **AI for EV charging stations** use case. The third domain includes use cases such as **De-risking of energy efficiency investments through AI** and **AI-enabled prediction of climate change impact at a regional level.** Note here that the abovementioned use cases are indicative and the full list alongside their descriptions can be sought in (Karakolis, Pelekis, et al., 2022).

Given that there is a large number of different and heterogeneous pilots and use cases, that serve different stakeholder groups through the I-NERGY platform, a number of requirements should be satisfied in order for the platform to be able to serve all the aforementioned use cases. In particular, I-NERGY platform should be capable of:

Connecting with different and heterogeneous data sources. I-NERGY services are built on top of a variety of available data both static and streaming from multiple sources. Such data include weather data for different regions, sensor data from smart grids and smart buildings and data from network assets among others. To this end, the platform should be able to connect to different databases, use APIs and receive messages in real time through message broking technologies to facilitate near real-time services.

Preprocessing and harmonizing incoming data according to a common data model. As there are different data sources for different organizations and use cases, there is a requirement for storing information in a unified way, meaning that datasets that represent similar concepts and measurements should be represented in the same fashion, to establish interoperability and reusability, even though different organizations may use different models. Hence, a predefined commonly accepted data model should be established, in conjunction with a preprocessing and harmonization phase that brings the incoming data to a compliant form to the aforementioned common data model.

Providing efficient big data storage and querying capabilities. A variety of different data providers are envisaged to continuously send data to I-NERGY platform. These data should be stored efficiently and at a low latency to a database that is available for querying. Moreover, as several analytical and AI services are using these data, a mechanism for efficient querying is required, both in terms of low latency and high availability.

Accessing real-time data streams and facilitating access to the latter to related analytics services. Some of I-NERGY platform's services are near real-time services, such as real-time anomaly detection in smart buildings as well as fault detection in smart grid's network assets. To enable such services, incoming real-time data streams should be available to the services in near real-time.

Efficiently training, evaluating and serving AI models. Most of I-NERGY services heavily rely on AI, machine learning (ML) and deep learning (DL) models. As several of these models are very complex and require significant amounts of time and computational resources for training and inference, the platform should be able to provide efficient training, evaluation and serving capabilities (e.g. memory, GPUs etc.) to facilitate the development of these models.

Providing transfer learning capabilities. A common problem in energy related AI services is the insufficient amount or quality of available data, when it comes to training complex AI models. In such cases, the usage of transfer learning is often proposed by researchers (Sarmas et al., 2022), as it enables knowledge transfer from different domains to solve related problems.

Providing utilities for incremental (online) learning. It is commonly accepted that AI models that are trained offline tend to underperform, after a time period, due to the dynamic nature of the incoming data. To this end, I-NERGY platform should provide utilities for incremental learning, in order to dynamically adapt the developed models, once AI models stop performing as expected.

Serving multiple stakeholders, providing access to authorized users. I-NERGY assets (services, applications, data, etc.) should be available only to registered users, that have the appropriate permissions to access them.

Addressing cybersecurity. A complex big data platform with multiple stakeholders, and data from different organizations should be accompanied by high levels of security, including identification and prevention of malicious actions. Security measures should include service usage monitoring, vulnerability detection, access control and identity management and system monitoring among others**.**

Reinforcing the AIoD platform by sharing I-NERGY assets. One of the main objectives of I-NERGY project is to reinforce AIoD platform with a variety of energy analytics services. To this end, services, must be compliant with AIoD Experiments platform requirements, to be onboarded to the latter.

4. I-NERGY REFERENCE ARCHITECTURE

In Figure 1 the conceptual architecture of I-NERGY is illustrated alongside the interconnection with AIoD platform. It consists of several components responsible for different functionalities, namely the Data Management component, the AI models Training Component, the Energy Analytics component, and the Security and Access Control component. Moreover, the interconnection with the AIoD platform (formerly AI4EU) is presented, as I-NERGY project is tightly coupled with the AIoD platform. Hence, the main assets that are provided by I-NERGY platform (e.g., AI models, APIs, datasets, documentation) will also be available to AIoD platform, through the AI Catalog, and the AI Experiments platform.

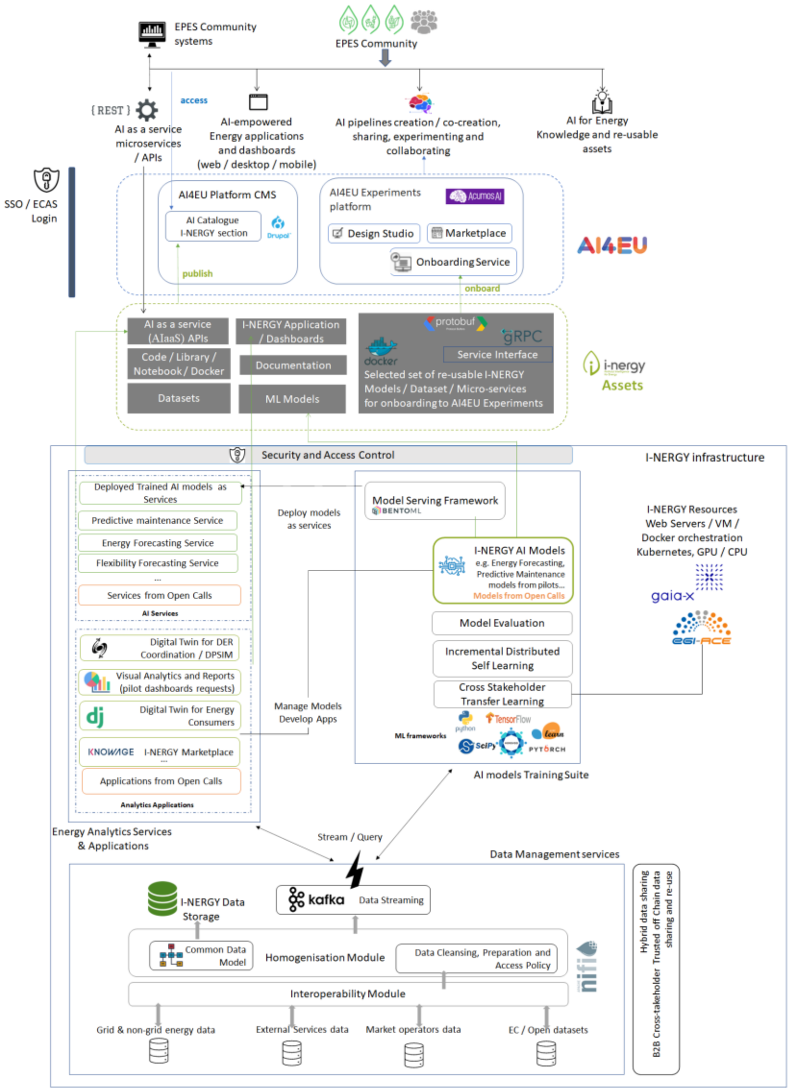

Figure 1. I-NERGY reference architecture

More specifically, the **Data Management component** is responsible for receiving incoming data from different data sources such as energy related data streams from smart grids and smart buildings and weather-related data and perform preprocessing, curation and harmonization procedures, in order to store these data in a commonly accepted form, according to a common data model. Additionally, this component is responsible for providing stored data, as well as real-time streaming data to the energy analytics services. The ingested data are also available to third parties and external stakeholders through a service based on blockchain and smart contracts that secures trusted data sharing and controlled access to data. The main technologies that are used in the Data Management component are Apache NiFi (Pandya et al., 2019), Apache Kafka (Kafka, n.d.) and MongoDB (MongoDB, 2018). Apache NiFi supports powerful directed graphs for data routing, transformation and system mediation logic, and within I-NERGY it facilitates the data ingestion and preprocessing phase. Apache Kafka is responsible for real-time data processing and, on the one hand, facilitates the reception of real-time data while, on the other hand, acts as a stream data provider for services that are based on streaming data. Finally, MongoDB, a highly scalable NoSQL database, is used for storing all the data, while analytics services are querying the latter.

The **AI models Training Suite** provides all the necessary tools for training evaluating and serving AI and ML models. Moreover, it provides capabilities for transfer learning and incremental learning, as well as storage of the aforementioned models. The main technology that is used for serving AI models is BentoML, while JupyterLab and MLFlow are used for model training and evaluation (Pelekis et al., 2022). Also, several technologies like TensorFlow, and Pytorch are used for transfer learning and incremental learning.

The **Energy Analytics services component** includes all analytics services that are available to the end-user. These services cover the entire energy value chain and include an electrical load forecasting service, an energy flexibility forecasting and demand response service, a service for real time anomaly detection in smart buildings, a predictive maintenance service, a service for evaluation and prioritization of energy efficiency investments in buildings, as well as a digital twin (DT) application for distributed energy resources (DER) coordination, and a DT application for electrical communities and energy consumers. On top of these services, a visual analytics service provides interactive data visualisations. All these services are available to external users through the I-NERGY Marketplace, which, on the one hand, enables the view of the project's available ML models and resources to promote their quick adaptation and reuse within different contexts, and on the other hand provides users with a graphical UI to develop in scale new services, algorithms, applications, and micro-services taking advantage of the available project assets such as datasets and ML models. For the development of AI models several python libraries are used such as TensorFlow, PyTorch, Darts, and Scikit-Learn. Moreover, for the DT for DER application DPSim simulator (Mirz et al., 2019) has been used, while DT for electrical communities as well as the Visual Analytics service were developed as web applications using the Django Python framework. Lastly, for the development of the marketplace the Knowage suite (Knowage, 2022) has been configured and deployed in accordance with user requirements.

The **Security and Access Control component** is responsible for ensuring that only authenticated users can access the platform services and data, on condition that they have the permission to access the requested resources. Moreover, this component is responsible for the overall security of I-NERGY platform, in order to protect platform data and services from cyber attacks. Identity and Access Control Management are achieved using Keycloak open-source identity and access management platform, while security is provided through Wazuh open-source security platform, which is installed on virtual machines of the project to provide endpoint security, threat and vulnerability detection, and continuous monitoring among others.

Of course, all these services require significant computational resources to operate smoothly. To this end, several cloud providers have been examined to be used for I-NERGY platform. Finally, EGI-ACE project's (EGI-ACE, 2021) cloud has been selected among the different cloud service providers. EGI-ACE is a project coordinated by EGI foundation (EGI, 2010) and is funded under EU Horizon 2020 research and innovation program. It provides free-at-point-of-use computing, storage resources, training and support for researchers and scientific projects. EGI is a federation of computation and storage resource providers that are united to provide computing and storage for analytics services and facilitate research and innovation across Europe.

The assets that I-NERGY provides are AI services available through APIs (AIaaS) and web interfaces, applications and dashboards, datasets, code and libraries, AI models and documentation. These assets can be utilised by different EPES stakeholders. All of them are planned to be published to AIoD catalogue, while several services amongst them will be onboarded as docker container-based pipelines to AIoD Experiments platform accompanied by the proper protobuf (Google, 2022) configuration as required by the platform for interoperability purposes. By publishing assets to AIoD catalogue and onboarding services to AIoD Experiments platform, more interested stakeholders can access them through the Single Sign On (SSO) mechanism of AIoD, which controls the identity of the users as well as their rights to the assets.

5. DISCUSSION

I-NERGY RA is the architecture of I-NERGY Big Data platform that provides energy analytics services and applications (static and near real-time) to the entire energy value chain, serving a variety of energy stakeholders. To this end, it gathers data from a number of different and heterogeneous data sources and then these data are preprocessed, harmonized according to a common data model, and stored to I-NERGY data storage. On top of that, different AI models and services are being developed utilizing an AI models' training suite, for training, evaluation, serving and storage of the models. Developed services, applications and other assets are available through both the I-NERGY and AIoD platforms. The usage of assets is protected by an Identity and Access Control Management component. All components of the presented architecture are deployed on EGI-ACE cloud, that offers storage and computational resources, such as CPUs and GPUs. The proposed architecture fulfills all the requirements presented in section 3, as illustrated also in section 4 that presents the architecture and provides a brief description of the most important components and services of I-NERGY platform.

Compared to other well-known big data architectures, both energy domain related and general-purpose ones, I-NERGY RA addresses the entire big data value chain, from data ingestion and governance to AI models and end-users' energy analytics services. It also proposes specific open-source technologies for each functionality instead of generic description of functionalities without related technologies and implementation details. On the other hand, IDS-RAM and GAIA-X RAs focus mostly on data exchange, sovereignty and transparency, neglecting other crucial functionalities of the big data value chain. Similarly, BRIDGE and BD4NRG RAs focus on smart grid applications of Big Data, without proposing specific technologies for addressing each layer of functionalities. Last but not least, contrary to the other RAs I-NERGY RA takes advantage of AIoD platform for knowledge transfer and sharing.

Regarding MATRYCS RA, it is the most similar RA to I-NERGY, as it provides components that cover the entire big data value chain, alongside the underlying technologies for each component. However, it does not cover all the requirements of I-NERGY project. For instance, MATRYCS, does not take into consideration AIoD platform, while neither transfer learning nor online learning issues are addressed.

6. CONCLUSION AND FUTURE OUTLOOK

In this paper, I-NERGY Big Data RA for the energy domain is presented, alongside the most important use cases and requirements that have been elicited and addressed by the architecture in question. Additionally, I-NERGY-RA is compared with other well-known big data RAs (both general purpose and energy specific) demonstrating the excellence of I-NERGY RA with respect to i) consideration of the entire energy value-chain compared to general purpose big data architectures that focus on data sharing, ii) proposition of specific open source technologies instead of generic high-level components and iii) consideration and addressing of novel AI concepts such as transfer learning and online learning.

Regarding, future extensions of the proposed RA, they include the validation of the entire platform by different energy stakeholders and the elicitation of new requirements for improvements. Finally, compliance with GAIA-X and IDSA will be further examined to facilitate efficient and effective data sharing among different organizations.

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