Emerging Ecosystems Empowered by AI and IoT Technologies

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ABSTRACT
As latest advancements signify the 4th industrial revolution, Artificial Intelligence (AI) and Internet of Things (IoT) become the focal point for innovators. IoT-enabled technology can be used to gather and explore huge amounts of data from both virtual and physical environments, and AI provides the means for effectively processing and manipulating resulting information to optimize or automate processes. In this chapter, the related state of the art is presented, along with the characteristics that enable the creation of hybrid innovation ecosystems. An overview of IoT and AI platforms is included, which can be utilized even by non-experts to compose advanced cost-effective services. Also, related notions such as interoperability and engagement are also discussed. Although such components can be applied in a multitude of domains, to provide a concrete example of innovation enablement, the Smart Grid ecosystem is employed. Here, participants, either from the supply or the demand side, take advantage of IoT and AI technology to address new business requirements that arise.

Keywords: Hybrid Innovation Ecosystems, Mechanism Design, Smart Grid, Interoperability, X-as-a-Service, X-on-Demand, Demand Side Management, Vehicle-to-Grid/Grid-to-Vehicle, AI4EU, BigIoT, SYNAISTHISI

INTRODUCTION
During the recent years, quite a few technological achievements that were once deemed as fiction now exist, either as laboratory prototypes, or as products with high technology readiness levels. Examples include autonomous vehicles and mobile robots of advanced capability, home and personal assistants that simplify a number of every-day processes, machines that are by far faster than humans in solving specific problems, and so on. Although such ideas have already been introduced during the past few decades (Kurzweil, 1992), their manifestation into real-world products and solutions was made possible only recently, mainly due to advancements in two broad domains of electronics and computer science, the Internet of Things (IoT), and Artificial Intelligence (AI).

Internet of Things is a result of breakthroughs in a multitude of fields, e.g. electronics and telecommunications, embedded systems, software engineering, web and cloud services, as well as finance and marketing (Ibarra-Esquer et al., 2012). Nevertheless, the main market requirement that provides a boost for IoT adoption is the fact that it enables enterprises to gather and make effective use of huge amounts of data originating from the real, physical world. This collected data is then turned into usable information and actionable knowledge regarding improvements in products and services, market analysis and various predictions, and can be employed for the optimization of a number of business and production processes within the enterprise or organization (Erevelles et al., 2016).

However, very large amounts of collected measurements and calculated indices cannot be easily processed and analyzed by the human brain. Thus, in parallel to the outspread of IoT technology adoption, the requirement for efficient manipulation and processing of the available data has also
appeared. For this purpose, scientists, engineers, and decision makers turn their attention mainly to AI. AI is far from a new term and notion, as it has been conceptualized from the middle of the last century as computational methods that simulate the human brain’s operations with respect to learning and decision making (Russel & Norvig, 2019). Occasionally being in and out of researchers’ spotlights, AI is currently an “umbrella” term covering multiple sub-fields, such as natural language processing, machine learning, symbolic computation, intelligent agents, and multi-agent systems, among others.

Generally, such technologies can be considered as innovation enablers, e.g. concepts of the fourth industrial revolution can be made possible with the advent of 5G communications (Gundall et al., 2018), and adaptive/personalizable mechanisms can be improved by using machine learning techniques (Vermesan, 2017). Furthermore, these approaches are also characterized as disrupting, introducing this way the need for novelties in business model design and assessment as well (Amshoff et al., 2015), (Renda, 2019). However, this disruption is regarded by business and industries differently in each case, according to the application domain and the strategy that each party decides to adopt, and vary from partial, to full integration of such novel technologies (Laudien & Daxböck, 2016).

Now, IoT and AI, like other technologies, follow the hype cycle, and after a “Media exposure” period, when increased public attention is given, comes the “Peak of inflated Expectations” (Hahanov, 2018). Currently, most SMEs or even larger organizations do not have a complete and realistic perspective of what such technologies and related products and services are actually capable of, and how they can be integrated into their processes to their benefit one hand, and that of society in general on the other.

Moreover, since AI and IoT are mainly dealt with in the scope of research and academic activities, there are certain constraints that make their transformation into industrial and commercial products difficult. Experts ask for actual incentives towards their commercialization and the formation of funding bodies that will set the grounds for startup creation and innovation more fertile. Now, in order to deliver innovation, different technologies must be exploited and be subjects of exhaustive testing. This can be achieved by large hybrid ecosystems consisting of numerous types of actors, either contributing as providers, end-users, or both at the same time. Such ecosystems mainly refer to activities around certain application areas or business objectives that aim to capture value (Ritala et al., 2013). The impact on innovation by such ecosystems can be substantial, since adoption rate is increased by the large number of participants, and emerging technologies such as AI and IoT induce major shifts in the techno-economic paradigm. To allow more broad applicability though, the incentives of different types of participants must be aligned, to render their active and long-term engagement. This can be made possible by employing solutions from the field of Mechanism Design (MD), where notions such as truthfulness in participation, fair reward distribution, and incentive compatibility are mathematically guaranteed.

The aim of this chapter is to briefly review advancements in ‘viral’ fields of information and telecommunication technology, i.e. Artificial Intelligence and Internet of Things, and to highlight how their incorporation in hybrid innovation ecosystems can allow the realization of large-scale cyber-physical systems and human-agent collectives. Enabling concepts such as X-on-Demand and X-as-a-Service paradigms are examined, and focus is given on existing examples of related platforms that can be combined to deliver solutions to complex problems. To better illustrate the means of application of such technologies, two use-cases related to energy management in Smart Grid scenarios are analyzed, in particular an application for large scale Demand-Side Management (DSM), and for Vehicle-to-Grid/Grid-to-Vehicle (V2G/G2V) charging and energy exchange. Both these cases include (a) actors of various types and categories---often with contradicting interests, (b) the incorporation of interoperable IoT and AI tools, methods, and platforms that significantly reduce the difficulties of realization, and (c) requirements for carefully designed incentivization mechanisms to maximize stakeholder participation, social welfare, and fairness.
The chapter is structured as follows: First, a brief overview of the state of the art in IoT, AI, Hybrid Ecosystems, and applied MD is provided, highlighting the current opportunities for innovation related to each sub-field. Next, existing ecosystem-enabling platforms are presented, i.e. the AI4EU the European AI-on Demand platform, the architectural and interoperability guidelines of the BigIoT API and marketplace, and SYNAISTHISI, an application enabling IoT platform based on open-source frameworks. Their capabilities are analyzed from an innovation enablement aspect, and to better illustrate their applicability, focus is put on the complex case of the Smart Electricity Grid. Here, multiple stakeholders of various types need to interact and reschedule processes in a collective manner to reduce monetary costs and environmental impacts. Although a complex domain, by taking advantage of the discussed emerging technologies, effective marketable solutions can be realised to the benefit of every participant type.

BACKGROUND

In this part we provide some basic background regarding IoT and AI, two horizontal technologies that can be applied among different sectors. Also, we refer to the concept of Mechanism Design, which can be used to align the incentives of various types of stakeholders, and and analyze how these can be combined altogether to form crowdsourced Hybrid Innovation Ecosystems. We begin with AI, since it is an “older” notion with significantly longer history.

Artificial Intelligence

Many attempts have been made towards defining what the term AI actually includes. The book that is used by many universities around the world to introduce undergraduates to AI (Russel & Norvig, 2009), presents four different definition categories, which characterize a system’s behaviour according to, i.e. if it is thinking like humans, if it acts like them, if it thinks in a strictly rational way, and if it acts like so. According to the more recent definition of EC (2018), “AI refers to systems that display intelligent behaviour by analyzing their environment and taking actions --- with some degree of autonomy --- to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones, or Internet of Things applications).”

The subfields that roughly constitute AI are: Computational Logic, Decision Support Systems, Search and Planning, Knowledge Representation and Reasoning, Multiagent Systems, Machine Learning, Computer Vision, and Natural Language Processing. Methods originating from these subfields, often in combination, are used in a plethora of application areas, such as health, education, telecommunications, security, manufacturing, and so on (Ramos, 20007). Now, although it may appear that AI methods can readily be adopted in a generic way to any aspect of business or process, there are still limitations when transiting in real world applications. Take as an example a trained neural network black box that can provide 99 correct answers out of 100 times, though it fails to sufficiently explain why a particular answer is given, or another case, where the 1% error rate might not be acceptable, e.g. when human lives depend on an erroneous decision. Thus, recently, there is an urge in the research community to explore respective features and properties towards AI methods applicability in the real world, that should be considered in any approach incorporating AI, despite the application vertical, such as, explainability, verifiability, trustworthiness, and human centricity (Renda, 2019).

Kaplan & Haenlein (2019) classify AI approaches from a business-wise aspect, based on the capabilities that successful humans also possess, those that make them perform above average in corporate environments, i.e. Analytical AI, Human-inspired AI, and Humanized AI. Authors discuss existing systems of the first two categories and their application in academic, corporate, and governmental environments. Focus is also given on the implications of wide adoption of AI-related tools. The
implications are further categorized into the three Cs, confidence, change, and control. Authors argue that in the following years, innovative approaches will be required for managers to decide which positions suits an employee better, in hybrid cyber-physical business mechanisms. Also, employees themselves will have to be able to face new challenges, and keep improving on their skills in order to complement the advances in AI. Apart from professionals, consumers as well will have to put trust and confidence on AI, competing companies and corporations will have to change their processes and adoption strategies, and, finally, states should be able to control how much of citizen and customer privacy will be constricted, in order to leave space for further economic growth. Note that this trade-off is quite important and will be a key decision for the control of future developments.

Kruse et al. (2019) focus on the financial sector, and investigate how modern AI can be applied to this complex and highly data driven business field. Reports show that AI techniques have been successfully applied to reduce costs, increase customer orientation and satisfaction, and have driven major innovations in payments and wealth management. Chatbots in particular, although being capable to answer only simple questions, currently engage in conversations with customers and achieve faster response times with reduced cost for real-world banks and insurance companies.

Hager et al. (2019) discuss the notion AI for social good, and the further implications that accrue. Ongoing work in the fields of urban computing, sustainability, health, public welfare is also discussed. Transportation in particular, is a sector that has been significantly impacted by technological advancements, and many pilot demonstrations have been set up that optimize traffic flow, and provide on-demand transportation systems with fleets of small vehicles. Also, large-scale data collection and the training of models can lead to policy optimization approaches. Interestingly, the role of data science platforms is highlighted, i.e. cloud based infrastructure that can be used to collect and share data, define common data models, and conduct experiments in shared experimental test-beds. It is argued that such approaches will help lowering the barrier of entry for researchers and enterprises.

Potentials for Innovation

Cockburn et al. (2018) highlight the impact that AI has on innovation and further advancements in research on different application areas. Taking into account the breakthroughs in key sectors, e.g. Robotics and Deep Learning, there are limitless cases where general purpose AI methods can be integrated into and improve production processes, for example highly accurate predictors trained over very large pools of unstructured data, industrial automations etc. Importantly, AI can be considered as an “invention of a method for inventing”, and as such it is not limited to just reducing costs of innovation activities, but it introduces new approaches to innovation itself.

Of course, AI has found its place in multiple verticals in the form of special purpose approaches as well, and will definitely continue to do so in the future. Examples of verticals that have been impacted so far are the following (Vocke et al., 2019):

- In smart energy grids, for monitoring, management, and maintenance (Santofimia-Romero et al., 2011)(Akasiadis & Chalkiadakis, 2017).
- In autonomous vehicle design, for planning, autonomous coordination, and intelligent driver assistance (Driankov & Saffiotti, 2013)(Schwarting et al., 2018).
- In healthcare, for diagnosis, drug design, and genome interpretation (Nichols et al., 2019)(Hessler & Baringhaus, 2018)(Yu et al., 2018).
- In financial services, for fraud detection, and decision support for planning (Bahrammirzaee, 2010)(Ryman-Tubb et al., 2018).
- In manufacturing, for operations monitoring, predictive maintenance, and supply chain optimization (Lee et al., 2018)(Li et al., 2017).
- In advanced cyber-physical systems, and transportation/logistics (Klumpp, 2018).
Moreover, Quan et al. (2018) characterize the various business applications that AI enables, as an ecosystem by itself. Various categories include open source software platforms, core technology algorithms, AI-specific open platforms, and applications incorporating AI. Such components are used by the industry to identify fruitful domains and particular novel application scenarios that can be built upon existing infrastructure, e.g. AI applications provided via the use of smart phones.

**Internet of Things**

According to a European commission staff working document (CSWD, 2016), IoT is defined as “a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual things have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network”. Similarly to AI, IoT research directions focus too on human centricity and trustworthiness. Moreover, it has also overlapping areas of application, i.e. smart energy, smart manufacturing, automated driving, etc. In other words, IoT can be considered as the layer that links physically isolated and virtual processes (e.g. AI modules) with the real world by employing heterogeneous sensory, processing, and actuation equipment, and effectively interconnecting it.

By definition, IoT is strongly related to actual objects that are placed in the physical environment (Mazhelis et al., 2012). In contrast to the virtual domain, where a software process can very easily be duplicated or destroyed, the same does not hold for the physical devices and objects related to the IoT ecosystem. Devices and hardware are created and destroyed (or recycled) following complex processes that require significant effort and infrastructure to be completed. Thus, when designing IoT systems one should keep in mind that the components utilized should be reused for additional purposes, possibly different than those that we originally planned to use them for (Jarwar et al., 2018).

Apart from being reusable, IoT-enabled systems should also be interoperable. This means that (a) the interconnection of heterogeneous platforms, systems, and services, should be seamless, and (b) it is possible to orchestrate the functionality of these components, in every aspect of their operation, e.g. turning on / off, reconfiguration, exchange of sensor information, etc. (Fortino et al., 2018). The vision is to also provide an infrastructure for the automatic discoverability, configuration, and execution of complex IoT services and platforms. However, still, recent works highlight the interoperability requirement, and convergence to specific technologies, e.g. a single standard, is deemed unlikely (Soursos et al., 2016).

To facilitate IoT and to overcome the vertical barriers of the use-case specific solutions that mainly emerge, attention is given to the so-called IoT platforms. This kind of solutions are used to discover, manage, and interconnect vast numbers of IoT-enabled devices and data sources via single (web)portals, and aggregate the available information as well as the monitoring and control capabilities for every IoT resource available. The key features of IoT platforms are scalability, high availability, interoperability, and support for a multitude of open protocols for communication, monitoring, and device control. IoT platforms mainly aim to create IoT services marketplaces and give the opportunity to developers and end-users to participate with devices, data, and algorithms, where such resources can be discovered and used by others as well.

The FP7-ICT project “Internet of Things Architecture” (IoT-A), managed to set a reference architecture for IoT platforms in 2013, with the main goal to promote the interoperability of IoT systems and outline the principles and guidelines for the creation of appropriate protocols, interfaces, and algorithms (Bauer et al., 2013). In this approach, abstract functional components are divided into seven functional groups,
management, security, communication, IoT service, virtual entity, service organization and IoT process management.

Apart from IoT-A, which defines the modules from a computer-engineering point of view, additional reference architectures have been defined in the later years, which highlight industrial and business process aspects as well. Particularly, in 2015, the Industrial Internet Consortium introduced the Industrial Internet Reference Architecture (IIRA), which in 2017 became part of the Industrial Internet of Things (IIC-IoT) collection of specifications (Lin et al., 2017). IIRA aims to provide an open and standards-based architecture for industrial IoT systems, which has broad industry applicability regarding interoperability, mapping of applicable technologies, and general guidance in systems development. Descriptions of components come in a generic and highly abstract way in order for it to be more comprehensive by various industry-related parties. A characteristic of IIRA is that it constitutes a distillation of common characteristics, patterns, and features that exist in the industrial sector in general. Similarly to the “divide and conquer” approach, IIRA decomposes the main solution into various models, as seen from different viewpoints, i.e., according to its implementation, functional, usage, and business aspects. Taking these categories into account, respective concerns are analyzed, and guidance is provided towards their resolution.

In a similar approach to the IIRA, the Industry 4.0 technical committee introduced the Reference Architecture Model for Industry 4.0 (RAMI 4.0), which highlights the development layers of a product, system, or service, under the scope of smart industries and factories (Hankel et al., 2015). The difference in RAMI 4.0 however, is that it defines a three-dimensional schema, where each axis represents different dimensions of the design requirements of smart industry solutions: smart factory hierarchy, product life-cycle, and the IT architecture of the solution.

In 2015, the Alliance for Internet of Things Innovation (AIOTI - https://aioti.eu) was launched, with the aim to strengthen the dialogue and interaction among stakeholders in the European Internet of Things (IoT) domain, and to speed up the uptake of IoT by contributing to the creation of a dynamic European IoT ecosystem including industry, academia, and regulators. Members are structured into horizontal and vertical working groups intersecting this way every area of interest. AIOTI issues studies and recommendations, and organizes events and large scale pilots in order to build trustworthy IoT solutions for worldwide usage.

Ray (2018) presents a survey on the most recent advancements in the IoT reference architectures in various domains of application, such as, app development, devices, systems, heterogeneity, and data management, analytics, deployment management, monitoring management, visualization, and research. The important aspect of IoT is that it can enable interoperable ecosystems that include hardware devices, software components, as well as humans.

**Potentials for Innovation**

Even from the beginning of this decade, Bucherer & Uckelmann (2011) have highlighted the value of IoT technologies as an innovation enabler in a number of example cases such as information service providers, right-time business analysis and decision making, etc. The most important enabler feature though is the fact that a product is still interconnected and can provide information to manufacturers and enterprises, even after it is sold and ownership is transferred to the end-user. This property allows higher visibility and advanced control mechanisms. Moreover, the generated data and information can be shared with third parties without loss in value, which actually increases when combined with other information, and, additionally, it is not a depletable resource. Thus, the potentials of added value creation are indeed very high and, importantly, can be combined with the possibilities that AI enables, as discussed in the previous subsection, and provide the means for incorporation of crowd-driven factors, such as sharing
individually owned data and devices. Additionally, IoT can be employed to support Product-as-a-Service (PaaS) approaches. Sensors can track a product’s position, precisely monitor usage time, the environmental conditions, as well as the health of specific parts or submodules, leading also to predictive maintenance solutions.

Also, application enabler platforms give the possibility to generate crowdsourced service ecosystems in a marketplace-like form. In such cases, various types of stakeholders, either individual developers, or entire R&D departments, can share data, devices, and algorithms with the appropriate pricing, which can be combined with other available and compatible modules to deliver solutions to even more complex problems involving actors in large numbers, such as designing smart environments, web enhanced automation systems, emergency response, and so on (Bessis & Dobre, 2014).

A good example area that can be significantly impacted is that of the industry. Industrial IoT (IIoT) in particular, refers to interconnected and interoperable factories, production lines, and reconfigurable appliances, which gather and exchange information and commands to deliver advanced application scenarios. Improvements include intelligent automation, high resolution and predictable production planning and execution, sustainability, and multi-level feedback to designers, engineers, and operators. IIoT can also enable the implementation of new business models that make effective use of the transparent pipeline from the customer requirements and feedback, to product manufacturing, and delivery (Jeschke et al., 2016).

In another study, Andersson & Mattsson (2015) focus on cases of service innovation, and present a conceptual framework using reference cases enabled by IoT technologies. Authors argue that to deliver innovation, the community must focus on the innovative services themselves, instead of the underlying technologies that enable them, and that new cooperation schemes between the stakeholders and the different contexts must be established.

**The Concept of Applied Mechanism Design**

The resulting ecosystem of intelligent and physically-capable services should most probably operate under specific regulations and rules. However, even since the emergence of the internet, it has become impossible to expect that every part or module of a complex application will precisely act as instructed, e.g. due to malfunctions or malicious behavior (Nisan & Ronen, 2001). In the current circumstances, this issue is exaggerated when taking into account the nature of AI models, which are trained using different data sources—thus might provide different output for the same input, and, even worse, for some black-box approaches, there is lack of explainability of results, i.e. humans are not able to understand why a particular decision or result has been obtained (Holzinger, 2018).

A possible answer to the above concerns regarding the uncontrollability of intelligent rational agents behavior, is the concept of Mechanism Design (MD). MD is a subdomain of game theory that explores how to design rules and regulations so that individual actors that act rationally adopt desired behaviours from the designer’s perspective (Nisan, 2007). For example, in a crowdsensing scenario where multiple individuals are called in to provide measurements via mobile sensors, the objective is to offer the appropriate incentives to the individuals to keep participating constantly (Nava Auza et al., 2019). In other settings, the mechanism should select only the most appropriate candidates, and exclude those that systemically misbehave, e.g. prefer accurate measurements to inaccurate ones, or penalize “bad” players and in parallel reward the “good”, so that gradually, “bad” players tend to lose more, than what they would gain.

Apart from application specific settings, MD can be employed in more generic forms, e.g. by governments and regulators. In their work, Mukherjee et al. (2017) illustrate the effect of corporate taxes on future innovations of corporates in the US, showing that increasing taxation results to reduced output.
of corporate patents; and decreasing taxes on the other hand, does not have proportionally the same positive impact. Thus, the provision of state incentives must be very carefully designed and provide guarantees that would allow innovators to overcome uncertainty and risks, reduce the variability of rewards, and to constantly conduct quality R&D operations. Except for tax regulation, other incentives that could foster innovation include additional subsidies for AI- and IoT-enabled equipment acquisition, or for subscriptions in respective platforms. Sophisticated “win-win” mechanisms that aim to maximize the social welfare on the long-run can be the answer to how governments and NGOs are involved in innovation ecosystems (Oh et al., 2016), and how the concept of value co-creation can be promoted (Smorodinskaya et al., 2017). MD can be seen as an engineered higher level aspect of the ecosystem from a market perspective, so that the involved parties can self-organize in fruitful ways.

**Hybrid Innovation Ecosystems**

In existing business literature, the term ecosystem mainly refers to groups of interlinked organizations operating on a specific subject, that also include the consumer side in the process of designing and delivering novel products, processes, or services (Autio & Thomas, 2014) (Smorodinskaya et al., 2017) (Venkatraman et al., 2014) (Zahra & Nambisan, 2011). Typically, the impact that such activities result to is pooling of complementary skills, the refinement of production processes, and the solutions’ extended application to a horizontal scope, which includes multiple industries and domains. Now, considering the extended capabilities that AI and IoT resources ‘unlock’, innovation ecosystems that incorporate these are composed of businesses, regulators, end-users, as well as intelligent cyber components and physical devices that interact and can learn to behave collectively. To ensure that the desired equilibrium in the innovation ecosystems---which is one of their basic components (Jackson, 2011)---is reached, MD techniques can be included. This way, hybrid innovation ecosystems emerge that include heterogeneous sets of participants, i.e. humans, devices, and processes (both business and software), all aiming to cooperate, optimize processes, deliver innovative products and services, and doing so in an relatively quick, worthwhile, and scalable manner.

Furthermore, parts of the resources of an ecosystem can be crowdsourced. Respectively to what the ‘crowd’ is asked to provide for, different subcategories of crowdsourcing exist, such as crowdsensing for gathering measurements and crowdfunding for collecting funds (Komninos, 2013). Crowdsourced approaches are expected to be able to match dynamically varying user needs, and to achieve shorter production cycles (Kohler, 2015). Here, the IoT and AI layers can be used to gather information from the crowd, and communicate back results after analysis and decision-making. The value of each contribution and the price that each requester would pay for each result can be balanced and considered objectively fairly, after performing game theoretic analysis from the scope of MD. Taking this into account, the ‘hybrid’ term in an innovation ecosystem can also refer to the combination of human and artificial actors working together towards a specific goal in the so-called cyber-physical systems.

A good example of such types of systems operating in large scale is the case of the Smart Electricity Grid. As is further explained in a later section, the operation of region-wide electricity systems require the coordination of many different stakeholder types, including the large numbers of individual customers. To sustain a more environmental-friendly behavior, complex pricing mechanisms are established by regulators and companies to induce changes in end-users energy consumption profiles so that it matches the production levels of renewable sources. To make this process possible, a series of AI- and IoT-oriented components need to be utilized, such as smart meters and other sensors, and autonomous agents that take into account user preferences and ambient conditions.

In the following, we explain how open digital innovation platforms can contribute to the formation of crowdsourced hybrid ecosystems by taking advantage of the dynamic ICT-enabled “on-demand” and “as-a-service” features that are currently thriving in the global market (Duan et al., 2015) (Lindner et al., 2010).
X-ON-DEMAND AND X-AS-A-SERVICE: PLATFORMS AND ECOSYSTEMS

Originating from the Cloud domain, the terms “as-a-Service” and “on-Demand” indicate respectively, the ability to deliver offerings over the network in the form of off-the-shelf services, and the ability to dynamically assign resources based on the real-time needs of the end-user (Duan et al., 2015) (Počuča et al., 2012). In our case, the technologies that we are describing have all the required characteristics to be offered as services, and if the relevant stakeholders choose, can make them available on-demand, based on the time-varying user needs. Attention is first drawn by platform offering capabilities, since platforms have become the main building block of contemporary solutions, and, as also stressed by Kenney & Zysman (2015), constitute a new type of emerging economy.

The importance of platforms as an instrument for industrial research and management has also been highlighted by Gawer & Cusumano (2014). Industrial platforms are categorized as (a) internal, which refers to company assets, such as new products that are continuously developed and reused to deliver a family of incrementally innovative products or services, and (b) external, i.e. products, services, or technologies that serve as foundations upon which several firms develop complementary innovations, and which come in different levels of openness, e.g. varying access levels to information or platform components, usage policy, etc. Either way, increasing interests ask for X-on-Demand and X-as-a-Service approaches, where X represents any type of technology, e.g. AI, IoT, Platforms, etc.

In the following, an overview of existing platforms is provided, and specific desirable characteristics that enable innovation are highlighted, such as high availability, polymorphism with respect to application areas, remote access and management, as well as interoperability. In particular, such platforms are able to utilize crowdsourced ecosystems that co-create value outside the boundaries of company-specific production processes (Hein et. al, 2019).

Digital platform ecosystems consist of three main components, (a) the platform ownership processes, (b) the value-creating mechanisms, and (c) complementor autonomy. This means that, first, a platform is supposed to have responsible bodies for its management, such as hosting, maintenance, and administration, and the policies via which added value is created or co-created should be clear; and, second, the ecosystem should be open so that end-users and contributors have the freedom to innovate according to respective needs, which most probably cannot be foreseen a priori when the platform is designed in the first place.

Next, specific examples of modern digital platforms that enable innovation ecosystems are described, which focus mainly on the exploitation of AI and IoT technologies. Specifically, we refer to AI4EU, a European on-demand platform for AI resources, BigIoT, a marketplace approach that aims to establish common protocols for interoperability, and a case of an IoT application enabler platform, named SYNAISTHISI, that can be used to interconnect data and processing components to form complex services whose availability to third parties can be directly controlled by the end-users that design them. Such approaches can satisfy both main needs of innovation ecosystems creation as described by Ritala et al. (2013) that is, the ability to gather all relevant actors for building the ecosystem and promoting the application of key technologies in other sectors, and the ability to integrate open collaborative structures into the industry to enable their creation and maintenance. Also, their combination can address all the dimensions of the factors that drive digital business innovation, i.e. intelligent data, interoperable technologies, and input from co-creators. as highlighted by Venkatraman et al. (2014). Note that a number of platform implementations that are similar to those we include in this analysis are currently being researched and are in the stage of development, e.g. Bonseyes, European Language Grid, etc. However,
the cases that are presented here adopt a more generic model and are not specialized towards specific business application areas, enabling this way more innovation potential.

**AI4EU**

In an advent to create an integrated European Artificial Intelligence on-demand platform, the AI4EU project (http://www.ai4eu.eu/) was initiated in the beginning of 2019, with funding from the H2020 European Commission programme. By bringing together more than 80 partners from all around Europe, AI4EU aims to create an "one-stop-shop" that enables knowledge transfer, both among the research community, and to non-expert innovators from any business area as well. The main goals of AI4EU are:

- To create and support a large ecosystem of European AI for promoting collaboration between various actor categories, such as scientists, entrepreneurs, SMEs, industrial, funding organizations, and so on.
- To design and implement a platform that supports such an ecosystem, and via which effective and applicable AI resources of high technology readiness level are shared and made available. Examples of AI resources include trained models, expertise in AI, executable components, datasets, high performance computation resources, and seed funding for innovative projects.
- To implement industrial pilots that make effective use of the platform, and demonstrate the potentials of innovation enablement.
- To bridge technological gaps in five key AI-related scientific areas that have come up from real-world applications requirements: Explainable AI, Verifiable AI, Collaborative AI, Integrative AI, and Physical AI.
- To fund SMEs and start-ups that effectively employ the available AI resources to their business processes.
- To create a European Ethical Observatory that will monitor European AI developments and make sure that they adhere to high ethical, legal, and socio-economic standards.
- To work towards a comprehensive Strategic Research Innovation Agenda for Europe.
- To establish AI4EU Foundation, which will ensure the sustainable platform structure and operability in the long run.

Additionally, AI4EU employs the instrument of open calls and will distribute 3 million Euro, equity-free, among individuals, start-ups, and SMEs. There will be two different types of calls, (a) AI Prototypes, where 25 individuals will be granted up to 30.000 and 4-month support programs to develop AI-based prototypes, and (b) Technology Transfer Programs, where 20 scale-ups will be selected, to be funded up to 180.000 Euro and online premium acceleration programs, i.e. mentoring from top entrepreneurs, training, and access to technology and investment.

With the successful delivery of the AI4EU project, end users of multiple categories will be able to compose pipelines of various executable AI resources, for research and innovation purposes. By browsing a catalogue of AI resources that include both datasets and executable tools, and by discovering related information such as past cases of application, publications, tutorials, and experts’ opinions, non-specialized individuals can very quickly educate themselves and gain intuition on how available tools and resources may contribute in the improvement of their own business processes and lead to products of increased quality. Additionally, by combining funding instruments such as open calls and venture capitals, AI4EU can significantly boost innovators to design and deliver new products that are of higher quality and value. Thus, end-users will have the possibility to test and compare their solutions to other benchmarks, and define workflows of composite AI solutions, which can be easily deployed in high performance computers or other experimentation infrastructure.
AI4EU offers interoperability on functional and semantic levels between various other platforms, e.g. Acumos, Bonseyes, European Language Grid, and Mundi. Functional interoperability, i.e. the ability of modules of different implementations and origin to work together and interconnect seamlessly, is achieved by utilizing open standards and interfaces. Syntactic interoperability, on the other hand, refers to the incorporation of open semantic models and ontologies, which allows the meaningful and accurate interpretation of data and results from processes by any platform or framework. In AI4EU, this is achieved by the definition of a common AI Resource Semantic Model that extends well known ontologies and also introduces new concepts related to AI resources. A respective knowledge graph has been developed using the open and well established RDF and RDFS W3C specifications.

Apart from the networking and communication capabilities, AI4EU offers an AI-as-a-Service infrastructure, where any user can create an account, be granted access to the AI resources catalogue, and educate themselves around the functionality of each, the usage, and application scenario recommendations. Then, they can choose the most suitable ones for their case and download a ‘production’ copy to be readily deployed and integrated into their business processes. Also, AI4EU offers AI-on-Demand services, since selected AI resources can be deployed in the form of composite workflows in the available high performance computing infrastructure that is available, the so called AI Playground.

**BigIoT**

A few years earlier than AI4EU, in the scope of another European research project, the BigIoT (http://bigiot.eu/), an approach based on three key enablers to deliver a unified IoT ecosystem has been proposed. These enablers are (a) a common application programming interface (API) that supports identity management, the discovery of available IoT offerings, and the communication and information exchange between them and other resources, external to the BigIoT platform, (b) well defined semantic descriptions and information models so that offerings are clearly describe and can be easily reused, and (c) a marketplace to help with the monetization and promotion of such offerings’ usage (Bröring et. al, 2017).

Focus is put on BigIoT here since the interoperability feature is of utmost importance for allowing collective functionality between platforms, AI and IoT resources, as well as end-users. In particular, BigIoT defined five different patterns for achieving interoperability between heterogeneous services and platforms, that allow different schemes of communication between the modules, as well as various deployment configurations. By distinguishing among basic and advanced interoperability modes of IoT ecosystems, third-party developers and integrators may choose the one that fits most to their needs, among ‘cross platform access’, ‘cross application domain access’, ‘platform independence’, ‘platform scale independence’, and ‘higher level service facades’. The results of adopting any of these patterns are the easy integration of services and data from heterogeneous devices and providers, dynamic discovery and orchestration of modules offered by different vendors, and increased compliance of solutions.

Apart from the interoperability patterns, an important factor is also the semantic framework by which data and services are described. Apart from matching context and prevention of incompatible interconnections, semantic descriptions can be also utilized for automatic reasoning and manipulation of unforeseen combinations of data and services (Tzortzis et. al, 2017). For example, consider the case of a future domestic energy usage predictor. Such an application would utilize sensors that collect real-time measurements and create historical profiles, a learning module that manipulates these measurements and generates predictions, and perhaps a graphical interface component that is used to interact with the end-users. Now, the performance of the predictor is very important and significantly impacts the overall accuracy of the forecasts. Meanwhile, there can be different types of predictors with respect to their internal functionality, and it is hard to manually evaluate and compare them all, one by one. In case the various available modules are adequately described semantically, the platform could automatically determine compatible candidates and perform an ‘ex officio’ evaluation to recommend for incorporation the most well performing ones for each case.
The third aspect of BigIoT that integrates the two others is the marketplace architecture. In such a setting, third party platforms and developers can be content providers and share resources with others and receive monetary gains in return. To achieve wide market adoption, participation opportunities should be as open as possible, e.g. for providers or consumers from different application domain verticals and for resources hosted on different IoT platforms, both in terms of the underlying technology and platform geographical placement.

Overall, the potentials for innovation in these cases are multiple, and include various stakeholder types. In the discussed scenarios there are data owners, providers of sensors and devices, providers of platforms, marketplaces, of services and applications, as well as of standardizations. The availability of commonly used and open marketplaces enable inter- and intra-segment interactions for value creation and revenue generation across multiple vertical application areas (Schladofsky et al., 2017). For example, a predictor that has been proven valuable in the energy domain in one pilot case, can easily be integrated to other geographical regions’ energy systems, or be utilized in solutions for other business areas, e.g. for the financial sector.

**SYNAISTHISI IoT platform**

SYNAISTHISI (http://iot.synaisthisi.iit.demokritos.gr/) is an application enabler IoT platform developed by the Institute of Informatics and Telecommunications of NCSR “Demokritos”. The platform is equipped with open and commonly used APIs for communication between objects, such as sensors exposed via gateways, processing systems running on the cloud, user interfaces executing on end-users’ devices, or decision making mechanisms, etc. These objects are virtualized as vendor/technology-agnostic services, and can be published on cloud, local, or edge infrastructures for further use. Developers can create services on-the-fly by integrating humans, sensors, devices, data and processing systems (Akasiadis et al., 2019).

The communication among services is realized by a middleware mechanism composed by distributed message brokers that can support multiple protocols which are widely used in the IoT domain. The platform also provides storage capabilities using database agnostic interfaces for storing, managing and recovering the distributed data generated. Having this, it is possible to create analytics and reports that monitor various key performance indicators for every use-case. Also, platform operations and data exchange are processes governed by appropriate authentication and authorization policies.

SYNAISTHISI platform has so far been used as the basis for five different pilot use-cases categories. In particular, it was employed to deliver smart meeting room applications, which combine a multitude of sensors placed in a room (depth PTZ cameras, microphone arrays, power consumption meters, temperature and humidity sensors, motion detectors, etc.), a number of processing cloud services (person counting, data storage and fusion, decision making, energy usage optimizers, text-to-speech modules, resource management and monitoring dashboards, complex event recognition modules, etc.), as well as multiple actuators (lights and plugs switches, infrared remote controls, and speakers). Also, prototype applications have been developed for the automatic lighting and HVAC control in common building areas, for visitor management scenarios, for safety and surveillance, and energy management applications (Pierris et al., 2015). By combining available IoT resources, integrated solutions can be quickly composed and instantly redeployed for any similar use case that includes respective physical equipment, or just parts of it.

Currently, SYNAISTHISI is available in containerized versions for end-users, so that they can deploy the platform on a local level. This way, apart from being able to directly control, customize, and enrich platform components, developers can test and evaluate newly developed IoT services and solution candidates before releasing them to the marketplace and making them available for use by third parties.
under preferred sharing policies. Additionally, the marketplace-oriented architecture that the platform adopts allows advanced capabilities for the participants to discover, use, and rate IoT services and resources that have been provided by others, so that their reusability is promoted in the presence of well defined financial and social incentives.

Another feature of the platform that further simplifies usage and IoT resource discoverability is the utilization of semantic annotations for services and datastreams. SYNAISTHISI incorporates RDF triplestores that hold descriptions of IoT resources, based on ontologies of specific standardizations. Additional specialized modules and enriched relevant ontologies can also be equipped according to the priorities of the platform administrator. As discussed earlier, semantic annotations may be used in the future for the delivery of automatic service composition techniques, where existing services are automatically combined, deployed, and evaluated to be offered for further use.

Moreover, SYNAISTHISI can be used to define complex application blueprints, that is abstract descriptions of complex IoT services constituting of simpler microservices, which are interconnected and demonstrate desired behaviors. The blueprints are precise descriptions of the input and output datastreams for each of the composing microservices, and of the nature that each of them has, e.g. lighting optimization, face recognition, etc., and also incorporate semantics. Also, they can be equipped by other end-users of the platform, apart from their creators themselves, and this way make the deployment of complex applications much easier and faster.

Innovation is enabled by SYNAISTHISI as it constitutes an IoT Platform as a Service (IoT-PaaS) solution based on open-source frameworks that allows businesses and developers with limited technical expertise or lacking the necessary resources, to convert custom or third party internet-ready devices to web-services in their internal infrastructure. These services can then be directly incorporated in B2B or B2C schemes any time and from anywhere without limitations. User authentication and authorization processes guarantee privacy and direct control of third-party access by resource owners, as an answer to disputes on practices followed by large corporations regarding private data usage and sharing (Parra-Arnau et al., 2018). Additionally, the resources available on the platform can be offered via flexible deployments to clients and collaborators of the integrating businesses or organizations for various use-cases. Excluding the lower level of things and devices that in most cases must have been physically installed to begin functioning, the other layers, i.e. management platform, processing type services, and computational resources, can be available on a ‘IoT-on-Demand’ basis.

**Potential Barriers and Issues**

Naturally, apart from all the opportunities that this chapter so far presented, there also exist specific barriers that decelerate wide AI and IoT adoption, mainly generated by the lack of willingness of people to put their trust on such systems.

Regarding AI, to characterize an approach as trustworthy, systems must be clear with respect to their functionality and goals. Yampolskiy (2016) provides a taxonomy of AI related risks, and distinguishes eight different pathways towards a potentially dangerous AI system, either by external or internal causes, prior to deployment, or after. The author argues that unless legal limitations against malevolent AI systems development are applied, the risk of dangerous AI deployments is high.

Apart from security issues, the property of explainability is also very important to gain trust in AI-based computer systems. Decisions, especially when impacting human lives, should not be taken thoughtlessly even if the suggestion was based on the most accurate predictor. Currently, there are legal implications behind decisions, which should be taken by humans. Before taking a decision, the decision maker should clearly monitor and examine all factors that can and should influence the outcome. With respect to
trustworthiness in general, it is on the hands of societies and states to decide on the trade-off between fast and wide market adoption, or ethicality and human-centricity.

In the IoT domain, the trustworthiness risks are mostly related to privacy and security, since if unauthorized access to sensitive data and equipment is granted, then many types of life- and prosperity-threatening issues might come up (Macaulay, 2016). Examples include cases that could have large negative impacts to public health and society, such as malicious access to critical infrastructure, or more narrow and personalized cases, such as unauthorized control of house door locks. It is very important to always keep in mind security, since it is often sidelined by the urge for fast and cheap market entrance.

Additionally to security and ethical barriers, there also exist technical ones for both AI- and IoT-related applications. In particular, there are increased accessibility costs for SMEs to new technologies, and this problem gets exaggerated when focusing on non technology related entities. Let alone the electronics equipment required to take a first leap, human force should also receive special training and get prepared, introducing this way huge difficulties in the adoption. With the emergence of X-on-Demand and X-as-a-Service solutions however, this situation will be improved, since less specialized personnel will also be able to get their hands on and experiment on a higher level, and also receive guidance via the platforms, towards delivering new technology enabled services. Furthermore, the remote access to such ecosystems will boost innovation in areas outside the large technological centres, as this is where innovation currently thrives the most, creating this way additional barriers to smaller SMEs that are not located in such large and technology friendly cities (Mulas et al., 2016).

Having the issues and barriers in mind, the next section illustrates how the examined platforms could be used to deliver solutions in complex real-world settings, where different types of stakeholders with possibly contradicting interests participate. In particular, the domain of the Smart Electricity Grid is examined, and two related innovation use-cases are illustrated.

INNOVATION ENABLEMENT IN THE SMART GRID DOMAIN
A good example of how AI and IoT technology can be combined into hybrid innovation ecosystems to solve emerging real-world issues and in parallel generate innovation opportunities, is the domain of the Smart Electricity Grid (Fang et al., 2012). This term refers to the technological evolution in energy systems that end-up creating more secure, reliable and efficient networks infrastructure, with energy produced mostly by distributed and renewable sources, production costs minimized, and energy savings maximized. Smart Grid (SG) approaches assume bidirectional flow of energy and information between the various actors. Such a transition has significantly disrupted the energy market, as well as the related management processes, since in legacy energy systems the generation of energy was performed in large centralized facilities. Now, with the turn to renewable energy and energy harvesting sources, any consumer of energy can be also a producer, e.g. by installing arrays of photovoltaic panels in their premises, or by storing energy when availability is in excess to offer it later during periods of shortage, e.g. via employing domestic energy storage equipment or car parks of electric vehicles (Ramchurn et. al, 2017).

Specifically, two particular use-cases are introduced. First, a large-scale demand-side management setting is examined, where end-users are called in to take action for altering their individual energy demand profiles, in order to make aggregate demand match the available renewable production levels; and a second case, that of vehicle-to-grid and grid-to-vehicle energy exchange, which is used to optimize the process of charging large fleets of electric vehicles. Parties interested to be involved such cases can benefit by utilizing XaaS and X-on-Demand solutions and deliver innovation in the SG ecosystem in a fast and cost-effective manner.

The SG ecosystem, involves a multitude of stakeholders:
• **Producers:** Utility companies and large energy production sites using fossil fuel, such as oil, nuclear and coal, or renewable sources, e.g. wind, or solar.
• **Consumers:** Residences, commercial, retail, or industrial corporates, any facility that uses energy.
• **Prosumers:** Buildings and facilities that have energy needs that can be fulfilled by the main grid, but also possess equipment for the production of energy, which is either consumed locally, or sold back to the main grid.
• **Aggregators:** Companies, organizations, or cooperatives that act as mediators between large numbers of smaller entities and represent them as a whole to regulators and other, larger entities.
• **Transmission System Operators:** Entities undertaking to transport energy on a national or regional level.
• **Distribution System Operators:** Owners or operating managers of distribution networks.
• **Regulators:** Entities that monitor the markets and the network to ensure that governmental laws are not violated and that policies are properly applied.

In the SG concept, communication infrastructure is utilized in all levels, from generators, to transmission systems, and, finally, to the end-users, with the IoT technology making this possible. The data and information gathered from large numbers of sensors and smart meters is exchanged at real-time and, apart from providing insights to managers and regulators via prediction models, it can also be used by individuals for other kinds of innovative crowdsourced operations. For example, with the increased penetration of renewable sources that often have intermittent output, generation is not controllable, thus one should focus on how to change demand to meet production. This is termed as Demand-Side Management (DSM), where instead of the producer side controlling the production levels, the end-users are asked to alter their demand profiles. DSM generally aims to induce changes to the consumers’ individual demand curves via providing lower prices or other kinds of rebates and incentives, so that total demand levels match those of the available production (Gottwalt et. al, 2011).

However, even if a single consumer decides to alter their consumption profile and finally does so, this is only one drop in the ocean of the total demand of a region. Acting alone is not enough, and coordinated behaviour in the large-scale is required. As a first step, this can be achieved by the formation of cooperatives, or by subscribing to aggregator entities, which can issue demand-response requests or design appropriate incentivization mechanisms. Though, it is not easy for end-users to constantly take into account the respective constraints, and take last minute action, or reschedule pre planned tasks, even with advanced monitoring and remote control capabilities at hand enabled by IoT. This is a task for personalized AI applications that undertake to elicit end-user preferences and guarantee to pursue their best interests by acting in an autonomous manner. Akasiadis & Chalkiadakis (2017) put forward a multiagent systems and mechanism design approach to drive coordination of individual consumers organized in cooperatives in highly constrained large-scale DSM cases to maximize renewable energy usage, increase grid stability, and reduce energy consumption costs. Here, although pricing mechanisms and regulations might be universal means of incentivization at a regional level, different types of optimizer agents can be developed and deployed as seen fit for each case. This creates opportunities for innovative services that may take into account many different objectives, e.g. easy-to-use solutions, agents that pursue high comfort for the end-user, others that provide intuitive recommendations and seek to engage users in “greener” behaviours, etc.
Moreover, aggregators may choose to select subsets of subscribers that have shown to be more reliable with less uncertainty with respect to their performance. In an attempt to engage individuals into participating truthfully, the aggregator or cooperative manager can also apply penalization mechanisms, which generate small but tangible profits for the aggregator, while still the majority of participants enjoy reduced rates for consumption (Akasiadis & Chalkiadakis, 2017b).

Cooperatives can also be formed by energy prosumers, necessitating fair reward sharing, transparency, and trustworthiness guarantees. The scientific literature is rich with methods that offer such guarantees and even more, however, the capability to integrate them in products and services is limited to the few large companies that are able to financially support R&D and pilot use-cases applications. This is expected to change with the wider availability of XaaS and X-on-Demand solutions that are used to boost knowledge transfer to SMEs and startups as well.

Figure 1 presents an example of a Home Energy Usage Assistant composition that can be used to enable ease-of-use in DSM and energy usage optimization scenarios. In this case, the corresponding complex application blueprint is discovered and deployed on a local-level IoT PaaS instance. This particular blueprint is composed of a Decision Maker, that monitors user preferences and optimization results, a Natural Language Processing component, that is used to engage in dialogs with the residents, a User Preferences Extractor, that can help to elicit user preferences in a non intrusive way, and various sensors, such as energy data, e.g. variable prices, levels of renewable production, etc., temperature meters, presence detectors, etc. and, finally, the device controller virtualizations that are used to enable, disable, or reconfigure electrical appliances, e.g. heating and lighting equipment. Note that for the Decision Making and the Natural Language Processing modules, existing AI resources from the AI on Demand platform catalogue can be selected for incorporation. In this case, the SG stakeholders combined with the smart equipment constitute a hybrid ecosystem, which co-operates to crowdsource energy usage promises of customers whose realization will result to reduced costs and ‘greener’ production.

Furthermore, another area that has not yet reached its peak and requires novel services energy network-wise, is the emerging market of electric vehicles. This kind of products will further alter electricity
consumption baselines, and will require the development of a new family of services, termed as Grid-to-Vehicle/Vehicle-to-Grid (G2V/V2G) mechanisms. In such settings, simultaneous initiation of charging for large numbers of vehicles might induce serious problems in the network (Jain & Jain, 2014). Thus, the charging schedules must be shaped in an appropriate “smart charging” manner (G2V). Moreover, fleets of already charged electric vehicles that are not expected to be used for determined time intervals, e.g. not yet rented cars from a rental company, may collectively offer the energy stored in their batteries back to the grid in order to contribute to the network’s stability (V2G). If the interaction protocols between the grid, the charging stations, and the vehicles are open, then customized applications following diverse business models can be composed, by manipulating available IoT and AI resources from the respective ecosystems appropriately (Spanoudakis et al., 2019).

As an illustration example, Figure 2 presents a case of a car rental and parking SME, that aims to innovate in the field of green transportation, i.e. owns a fleet of electric vehicles and charges them using own renewable energy sources. The development of applications that solve the G2V/V2G problem becomes easier if a G2V/V2G optimizer application blueprint is utilized by the IoT Platform-as-a-Service marketplace. This complex application blueprint interconnects smart meters, smart chargers, and other data, e.g. end-user preferences, weather conditions etc., and predicts the output of the renewable energy sources, optimizes the charging schedules based on the predictions, and, if it is required, initiates negotiations with the customers. To realise this innovative service, an IoT PaaS instance is deployed on a local level within the SME’s premises, and the equipment (i.e. smart chargers, smart meters, etc.) is virtualized and interconnected. To fill the various processing type components of the complex application, i.e. the predictor and the charging schedule optimizer, the catalogue of the AI on Demand platform is used, where the most preferable between the various available solutions are chosen for deployment.

As can be observed by the previous use-cases, the generally applicable nature of IoT Platform-as-a-Service and AI-on-Demand allows the fast deployment of innovations with advanced capabilities. Less informed users can browse available solutions and educate themselves regarding existing approaches and choose and deploy the most appropriate ones for their case. Respective platforms, such as AI4EU and
SYNAISTHISI, by following the necessary interoperability standards---e.g. those set by BigIoT, and incentivization mechanisms resulting from MD---make the deployment of composite applications a relatively easy task. In the first case, the interested party is composed of individuals in their residencies with the aim to minimize energy costs, as a crowdsourced solution that is used by themselves. The second one, includes business entities that aim to deliver innovative G2V/V2G services in an emerging field, and in a new set of customers, since such solutions are not deployed in the large-scale yet. Still, technology professionals are required for the deployment of the solutions and to tackle potential technical issues, but significantly less effort is needed regarding development and validation, than creating such applications from scratch. Although utilizing different components, both use-cases are enabled by XaaS and X-on-Demand hybrid approaches. Of course, these could also be utilized in a multitude of application areas, other than SG, e.g. in additive manufacturing, traffic management, supply-chain optimization, and so on.

The business components present in these two scenarios can be categorized according to the dimensions presented in Morris et al. (2005). First of all, value is created by leveraging on the price variances as a result of the balancing between supply and demand. Most countries have established variable pricing either on wholesale, or retail levels. By coordinating their consumption, end-users can collectively seek ‘bargains’ and thus reduce energy costs. Coordination can be performed by equipping AI-on-Demand services that analyze forecasts, prices, and consumption patterns. Automatic control of equipment is enabled by IoT platforms. Next, created value is enjoyed by energy end-users and the respective mediators (e.g. energy cooperatives, smart parking lots, etc) that take part in such efforts. The source of competence of such business entities is mainly the innovative services that are based on cutting-edge technologies, such as AI and IoT. The same can be used for the competence positioning.

CONCLUSION

This chapter provided a brief overview of the latest advancements of innovation ecosystems combined with the fields of Artificial Intelligence and Internet of Things. The related background from a business aspect has been discussed and the potentials for innovation have been highlighted, together with the concept of Mechanism Design, a subfield of economics and game theory that provides tools for trustworthy and large scale participation in various types of ecosystems. Next, focus was put on AI4EU, an AI-on Demand platform that aims to lower the barriers for widespread AI adoption even by individuals and SMEs that mainly do not possess strong scientific background and the technical expertise required to transform current processes to “smarter” versions. Also, the SYNAISTHISI IoT Platform-as-a-Service approach was presented that enables IoT applications and is based on open source frameworks. Finally, to showcase the applicability of X-on-Demand and X-as-a-Service platforms in delivering innovative services and applications, two use cases from the domain of Smart Grid were analyzed. It is expected that innovation ecosystems of various application areas will be invigorated by such platforms, enabling professionals and entrepreneurs to deliver smart products and services of advanced capabilities without having to go through long training and education programmes that require significant amount of time, effort, and money.

Still, appropriate policies and incentives must be put in place to engage individuals into large-scale participation, and to promote fair and trustworthy use of the newly emerging technologies. This is also a direction for future work, that is how to create fertile grounds from a regulation and economic perspective, to allow the fostering of such hybrid approaches. Also, more efforts should be put in place towards the establishment of new types of standards, which, although being restrictive by the definition of the term, should promote the diversibility of solutions, be as inclusive as possible, and aim to lower barriers for systems interoperability. In addition, further research is required in the field of semi- and fully automatic deployment and orchestration of complex services, as well as in the analysis and prediction regarding return on investments.
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**ADDITIONAL READING**


