Shared Intelligence for smart grids management

A Scenario for the Profitability of Electric Vehicle Frequency regulation in France

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***Abstract*—Making smart grids and microgrids an overwhelming and successful reality implies the consideration of a lot of challenges coming from different domains and collaboration is a keyword to seize the high ground. SEAS Shared Intelligence (SEAS SI) is a platform for algorithms sharing and execution developed under the scope of Smart Energy Aware Systems (SEAS) project to promote the intelligent management of smart grids and microgrids, by means of the shared usage of algorithms and tools, while ensuring code and intellectual protection. In this paper the platform goals and architecture will be described, and a case study based on SEAS-SI available algorithms, EVeSSi and FreqReg, will be presented. The case study aims at highlighting the collaborative management relevance allowing the simulation of the dynamic behavior of a huge number of electric vehicles while addressing the frequency regulation service for the smart grid.**

Keywords* — *collaborative intelligence; SEAS Shared Intelligence, smart grids management; Electric Vehicles

I. Introduction

Distributed generation was a driver for the power and energy systems complete rethinking of traditional practices. A lot of challenges remain: How to accommodate in an efficient and secure way the intensive use of renewable based and distributed generation together with demand flexibility? How to face a high penetration of electric vehicles (EVs)? How to assure and obtain knowledge from real-time monitoring? How to communicate and assure interoperability between different technologies and players? To address these challenges cross industry and cross domain cooperation is required.

Smart Energy Aware Systems (SEAS) is a project under the ITEA initiative that aims at enabling interactions for all market players in real time, for consumption and production energy systems, automation and ICT in order to optimize global energy consumption. Project most ambitious goal is to define a common language and intelligence to all types of energy aware technologies, consumers and producers [1].

In this paper we will focus on the common intelligence and how it is being achieved under the SEAS's vision, by means of different algorithms, coming from different partners, written and executed in different languages and IDEs, with complementary or competitive approaches, available through a Shared Intelligence platform (SI).

Algorithms available by now make possible the integration of partner's approaches to be tested in case studies, also available through SEAS SI, and afterwards implemented in project pilots.

The paper is organized in a total of 6 sections, with this brief introduction being the first one. In Section II particular insights about SEAS project and its goals will be given into; in Section III the SEAS – Shared Intelligence platform will be described and, in section IV the Electric Vehicle Scenario Simulator (EVeSSi) from GECAD and the Frequency regulation algorithm from ICAM are briefly described. In Section V a case study will show how complementary intelligence can be achieved, focusing on a scenario in which a significant number of EVs participate in the French regulation market. The conclusions are fully drawn in section VI.

II. Smart Energy Aware Systems

SEAS is an Eureka project, under the cluster ITEA, with nr. 12004, coordinated by ENGIE and involving 36 partners, with a total of 6 academic/research and 30 industrial ones, from 7 different countries. SEAS project addresses the problem of inefficient and unsustainable energy consumption, which is due to a lack of insufficient means to control, monitor, estimate and adapt energy usage of systems versus the dynamic usage situations and circumstances influencing the energy usage.

A. Project ambition and results

The main goal of the SEAS project is to research, develop and demonstrate a new SEAS Knowledge Model and SEAS information exchange platform for energy information representation, processing and exchange between energy systems, automation systems, ICT based digital services and all related stakeholders. Additional aim is to explore business models and solutions that will enable energy players to successfully incorporate microgrid environments and active customers [1].

In the smart grids paradigm data is a crucial enabler for advanced management. Data acquisition is the bottom layer on the top of which knowledge extraction techniques can provide a set of services, such as forecasting, optimization, context awareness, etc. However it is not enough to improve data acquisition systems but to make the data, coming in different time frames, from different systems and technologies, understandable to be used by other systems and players [2]. This is the core of SEAS: make data available and understandable, to provide "interoperable" knowledge and services to energy players.

Project objectives can be summarized through some of its most ambitious goals:

- From static to dynamic management: to enable real-time interactions for all market players, concerning monitoring and management of both consumption and production energy systems;
- A self-adaptive system: able to control on a semi-automatic or autonomous way the energy consumption and production, based on providing a semantic understanding of the system and its context;
- Active consumer participation: support consumer's role evolution into an active player. This brings a lot of new challenges concerning energetic services and cost optimization;
- Benefits for all energy players: provide a public and standardized knowledge model to support open data exchange platforms.

The most relevant project outcomes are:

- SEAS Knowledge Model, a set of ontology's are developed and publicly available;
- SEAS Information Exchange Platform: available for data sharing;
- A set of new digital services enabling proactive adaptation of consumption behavior to the changes in usage, energy costs, availability of energy sources and weather/climate/season, while making the stakeholders (e.g. utilities and consumers) aware of the changes and their impact;
- Business models and solutions that will enable energy market participants to incorporate micro-grid environments and active customers;
- SEAS Shared Intelligence Platform: algorithms and case studies available.

In the remainder sections of this paper the focus will be on the Shared Intelligence platform (SEAS SI). Its features will be described, the architecture will be presented and a case study to illustrate the sharing of intelligence will be discussed.

III. SHARED INTELLIGENCE PLATFORM

SEAS Shared Intelligence (SEAS SI) was developed under SEAS project with the goal of providing a unique platform for algorithms sharing between partners [3]. SEAS SI allows the execution of algorithms in a standalone, sequential or complementary way. Algorithms confidentiality is provided by means of a distributed system where algorithms are accessible to all the partners while keeping them running in its owner server. This methodology enables the code protection and intellectual protection while allowing the share of knowledge and intelligence between partners.

A. Shared Intelligence

The main goal of SEAS SI is the sharing of algorithms between partners without compromising the confidentiality of the algorithm. The sharing of intelligence is a very important topic in our days and enables the growth of science contributions. In big projects, like SEAS, the sharing of intelligence can be difficult to manage between partners. The creation of a unified and common platform enables and promotes these sharing while dealing with restrictions of confidentiality and protection.

Algorithms are executed in the Web Service side and use Excel files for data input and output, enabling the use of SEAS SI in the ordinary computer without the need of additional software installation, even if using different programming languages and environments.

The Web Services currently used in SEAS SI were developed in WFC framework, however SEAS SI supports communication by web services developed within other frameworks. The use of SEAS SI enables the sharing of intelligence between SEAS partners and enables the execution of algorithms sequences, when the output of an algorithm is automatically used as input for another one.

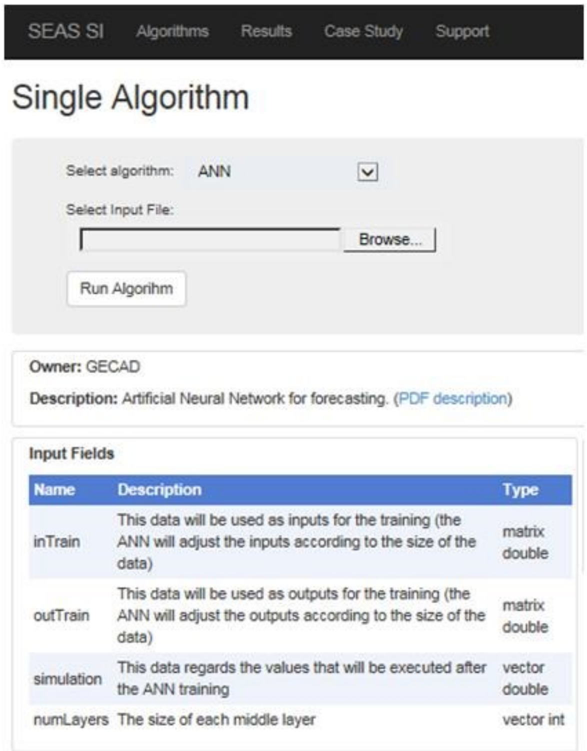

Fig. 1. Screenshot of SEAS SI: ANN algorithm

For each algorithm available in SEAS SI, input and output variables, regarding the name, description and variable type are described, a downloadable file with detailed algorithms description and parameters is also available. Figure 1 show SEAS SI when an Artificial Neural Network (ANN) is chosen. This algorithm is used for forecasting under different contexts, being useful for several of the methodologies to be applied to SEAS pilots.

At this moment, algorithms are executed in four different programming languages: C#, MATLAB, TOMLAB and R. Additional programming languages can be used while sharing new algorithms. The number of different programming languages used by the developers does not compromise the platform availability or efficiency.

B. Architecture

The architecture and functionalities of SEAS SI can be seen in Figure 2. On the top of the figure platform characteristics are presented. SEAS SI is based on a Web Service Aggregator that combines all the Web Services distributed by the partners and present them as a unique and unified platform.

SEAS SI is available as a website with an authentication service, to restrict algorithms availability only for SEAS partners [3].

Algorithms execution is available through online and offline modes. These modes are automatically chosen according to the execution time of each algorithm. For example, if an algorithm execution time is about 15 minutes it's not convenient to freeze the user browser during for such a time. So, the algorithm will run in its server and, when finished data will be available on SEAS SI.

Results tab, on the top of Figure 1, provides a list with all, both online and offline, executed algorithms results. The online mode executes the algorithm in real-time and gives the result to the user afterwards. In the offline mode algorithms run in background, without hanging the user computer, and results will be available when processing finishes.

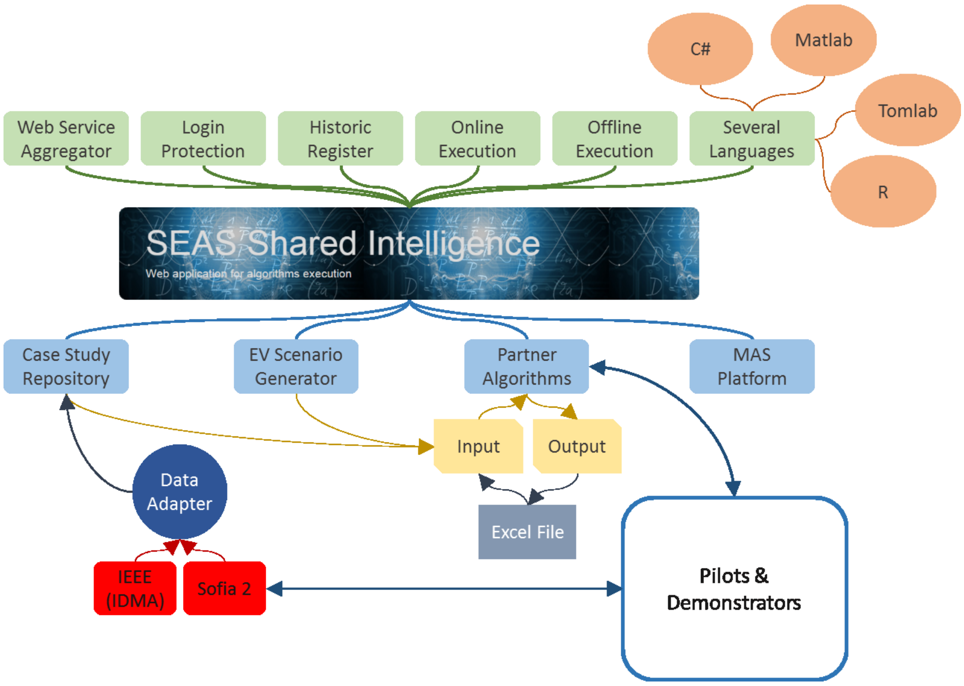

Fig. 2. SEAS SI Description

SEAS SI integrates not only the current algorithms but also a case study repository, a new EVs scenario generator and a multi-agent system platform. In the near future, the algorithms will have the ability to run using input data coming from the case study repository and the EV scenario generator, using a seamless approach.

The case study repository will receive data from an adapter that allows the conversion of data from the IEEE Intelligent Data Mining and Analysis (IDMA) [4] and Sofia 2 into the SEAS SI standard.

Built for the SEAS project, SEAS SI will also be used in SEAS pilots and demonstrators running in several European countries, such as: France, Finland, Portugal and Turkey. The pilots and demonstrators will use SEAS SI web services to execute algorithms. The data produced in the Pilots and demonstrators will be sent to Sofia 2 platform. These data can also be available in SEAS SI using data adapter to retrieve it from Sofia 2 and storage in the case study repository, where it becomes available for SEAS SI users input to execute SEAS SI algorithms or to be download.

C. Algorithms

By now 10 algorithms from 4 different partners are available in the platform. Some of them will be briefly described:

- **ANN** – Artificial Neural Network for forecasting;

- **FreqRegSingleBat** – calculates the profitability of one up/down request from the main grid for one EV battery used for frequency regulation;
- **FreqRegScenarioSimul**– simulates the dynamic behavior of an EV battery for frequency regulation. It predicts the vehicle availability, battery State of Charge (SOC) and calculates the net profit evolution per request
- **IMT-TSP's** - approximation algorithms for EV charging scheduling in SEAS microgrids: optimizing peak and revenue;
- **Metalearner** – provides a methodology that considers several different strategies' outputs as basis to build the metalearner's final output, depending on the confidence weight that the system has on each strategy. This means that the better a strategy is performing, the higher its influence on this method's results will be. This is done through the application of a weighted average of the outputs of all strategies, using their confidence values in each context as weights. The confidence values on each strategy can be the result of a learning process;
- **Net_Profit_F_R_SB** – calculates the annual profitability of frequency regulation service from the main grid for one EV battery used for frequency regulation;
- **SVM** – Support Vector Machines (SVM) for forecasting, using the regression of historic data and training by several alternative kernel functions.

The number of algorithms available will be expanded in the very near future.

IV. EVeSSi and FreqReg Algorithms Detailing

In this section SEAS SI algorithms that will be used in the case study, to be presented in section V, will be deeply described.

The algorithms belong to different partners: GECAD and ICAM, and although they run in each owner's server, they are both available at SEAS SI for authenticated partners to make use of them.

A. EVeSSi

The EVeSSi tool has been actively engineered since 2011 [5]–[7]. Its main goal is supporting the development of realistic case studies that include EVs scenarios, eliminating the need to create manually each individual vehicle profile, but other uses have been identified, e.g. to help to determining the optimal site and size of EVs charging stations in distribution networks [8].

The last developments regarding EVeSSi features was the integration with a traffic simulator, namely SUMO [9]. To achieve this some software modules and algorithms have been developed, which include: scenario and input configuration module, SUMO simulation connector, SUMO output data importer, an electric grid creator, and an intelligent grid allocator. These modules can be seen in Fig. 3.

To prepare a scenario in EVeSSi using the traffic integration, some parameterization steps need to be made in order to introduce the input data necessary for the SUMO simulation. The first step is to generate/load the road network (load a real road network or generate a fictitious one by introducing specific parameters), a second step is related to the creation of EVs and its parameters, and then it is necessary to specify the charging points or, instead, generate those charging points randomly. Finally, an algorithm can perform the daily activities and generate the necessary trips, which are then simulated by SUMO engine (the actual traffic simulation results).

The data importer module reads the files generated by SUMO application and then filters, treat and analysis the necessary data to be executed by the subsequent developed algorithms. The grid creator can generate an electric grid taking into account the dimensions of the road network. This creates a grid with intelligently distributed electrical buses and respective branches. After this step, the intelligent grid allocator finds the corresponding grid bus where EVs can connect, depending on the location, i.e. the street of the arrival or where it is parked.

The traffic model allows evaluating the chaotic behaviour of traffic, which is affected by numerous factors, including the road network topology, the number of cars and its routes, the types of vehicles, the traffic lights and the users' driving behaviour, which is hard to predict. The influence of traffic patterns in travel times can be analyzed, and the energy consumption measured. In fact, there is a huge potential in applications with EVeSSi, for instance, evaluating performance of electric public transports, analyzing optimal location of charging points and charging stations, estimating electricity network impacts, testing different control strategies like smart charging and V2G approaches, enabling adequate remuneration schemes, and predicting traffic patterns and user behavior, just to name a few.

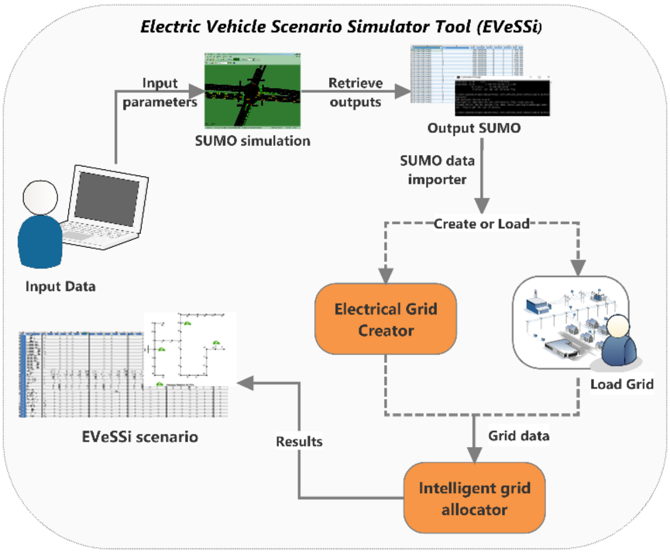

Fig. 3. Overview of EVeSSi components

EVeSSi traffic simulation integration can make the bridge between transportation department data with grid and energy operator tools, contributing to increased knowledge and improving the efficiency and sustainability of increasingly complex integrated infrastructures. More details about this topic can be founded in [6], [10]–[12].

The EVeSSi also features a version without SUMO integration, which substitutes the SUMO engine with its own algorithm that simulates the trips behavior and locations without the information of road transportation (see [5] for more details). This feature is most useful when road information is not available or a less detailed simulation is needed. This is the version available in SEAS SI.

B. Frequency Regulation

The power storage offered by EVs batteries appears to be a good solution to develop smart grid approach while supporting renewable sources of energy. In fact, a good storage potential will be available, if Vehicle to Grid (V2G) is developed in view of grid services.

The EV is particularly adapted to the primary frequency regulation service. First, it is used only 5% of the time for mobility. Moreover, the initial capital cost of the battery is not totally assigned to the V2G service because the battery was purchased for mobility. Finally, the battery response time is quick which makes it very suitable for grid support purposes.

In the literature, the potential of EVs as actors in the regulation market is confirmed for frequency regulation [13]–[17]. In fact, some markets like CAISO's one defined Non-Generator Resource (NGR) such as batteries and flywheels, to bid in the regulation market. Besides, Studies for the European parliament presented storage resources (stationary and EVs) as opportunities to improve renewable sources integration through better participation to standard balancing requirements and leading to grid balance improvement [18].

The Net_Profit_F_R_SB algorithm allows calculating the annual net profit for an EV used for frequency regulation [13], [19] depending on the EV owner behavior and the service remuneration conditions. It helps a fleet owner to apprehend the profitability at various smart grid development levels: short, medium and long term at the contract level.

The algorithm is programmed using MATLAB. The inputs are in an excel file with a detailed description of each parameter and input. The outputs are also available in an excel file.

a) Annual revenue

The revenue is calculated using the following equation:

$$R_{reg} = (p_{cap}\, P\, t_{plug}) + (p_{el}\, R_{d-c}\, P\, t_{plug}) \quad (1)$$

- p_{cap}, is the capacity price which is in €/kWh and paid for the service availability. It is fixed by the contract and benefits to the EV event if it is plugged in and not used for the service. The value is 17€/MW-h in the French market [13, 15]. In some markets it may not exist yet;
- t_{plug} is the time in hours per year when the EV is plugged in. It is an input, which depends on the EV owner behavior (supplied by EVeSSi). The study is realized for an average value of 16 hours for EV plugged in subtracting charging hours;
- p_{el} is the market selling price of electricity in €/kWh for the energy exchanged in real time. This value may vary during the day and in some markets, it does not exist;
- R_{d-c}, is the ratio of the energy dispatched over the regulation contract period assumed to be 10% of the contracted power capacity [19];
- P is the contracted capacity available for the V2G, in kW. It is limited by the line power, the driven distance before the first connection to the grid to offer the service as well as the "range buffer" in km, which is the minimum remaining range specified by the driver and/or the EV aggregator for mobility purposes. It is supplied by EVeSSI algorithm.

In regulation down, we assume that the operation is always financially positive because the battery will have to be charged anyway.

b) Annual cost

The cost from regulation up is defined as:

$$C_{reg-up} = (c_{en}\, P\, t_{plug}\, R_{d-c}) + c_c\, CRF \quad (2)$$

- c_c is the capital cost i.e. the one-time investment in € and is around 1800€ for 15kW [13]. CRF is the capital recovery factor for 10 years of amortization thus the lifetime of the V2G hardware;
- c_{en} is the cost per energy unit in €/kWh which includes: the cost of electricity, losses, plus battery degradation cost:

$$c_{en} = \frac{c_{pe}}{\eta_{conv}} + \frac{c_{bat}}{L_{ET}} \quad (3)$$

where:

- c_{pe} is the cost of purchased electricity for recharging in €/kWh. The online data for MIBEL spot market variable electricity prices per day shows a mean value of 0.0318€/kWh for the first 7 months of 2016 [20];
- η_{conv} is the Round trip electrical efficiency, grid-battery-grid around 0.73 [14];
- c_{bat} is the total battery replacement cost in € including the cost of the battery 300€/kWh [13], [19]as well as the cost of labor for the replacement 8h at 35€/h [13];
- L_{ET} is the battery Lifetime Energy Throughput for a particular cycling regime in kWh. L_{ET} includes a factor 3 due to shallow cycling having less impact on battery lifetime than the deep cycling [13].

In contrast, we assume that the cost from regulation down is null because there is no need of additional equipment.

V. Case Study

This section aims at illustrating the usefulness of SEAS SI in a case study where 2 algorithms, EVeSSi and Net_Profit_F_R_SB, are used to study a scenario with a total of 27.700 EVs, from which around 18.000 are participating in the frequency regulation in France.

This case study illustrates, beside each algorithm capabilities, how the combined usage of them brings new knowledge that is relevant for the management of smart grids with a significant EVs penetration.

The first algorithm, from SEAS SI, to be used is the EVeSSi, where some parameters need to be configured in advance. These parameters include the characteristics of the EV fleet (battery capacity, charge rate, traveling patterns, etc.) as well as the type and quantities of EVs to be considered in the simulation. EVeSSi is called remotely by the ICAM partner to perform the requested simulation. The results are then returned to its console, where it feeds the second algorithm from ICAM, namely the frequency regulation service, which calculates the net profit per vehicle in the French market.

1) EVeSSi configuration

The EVs market share in France represented 1,2% in 2015. By the end of the year around 74,000 light-duty EVs were circulating in France (less than 0,2% of the car park). According to [21] the expected EV stock is 2 million for 2020. In this case study, it is considered that around 18.000 EVs participate in the frequency regulation service.

The EVeSSI simulated fleets represent various EVs types, mobility constraints and thus availability for the regulation service. Table I shows the type of fleets considered.

TABLE I. FLEETS SIMULATED BY EVESSI

Fleet ID	Description
1	Medium passenger (e.g. Nissan Leaf)
2	Luxury passenger (e.g. Tesla S)
3	Small passenger (e.g. Renault Zoe)
4	Commercial vans (Renault Kangoo)
5	Micro electric fleet (Renault Twizzy)
6	Large commercial fleet
7	Passenger bus fleet

In order to calculate a realistic annual net profit for the frequency regulation, it is necessary to take into account a multiplication factor of 1,5 consider all the vehicles that are not with the right SOC, not connected by the EV user or out of order 1,5 [14].

Among the vehicles, there are micro EVs with a battery capacity of around 6 kWh (Renault Twizzy), medium passengers' vehicles which are also used for the commercial fleet with 22 kWh (Renault Zoe and Kangoo) to 24 kWh (Nissan Leaf). Finally, luxury cars fleet capacities are between 60 kWh and 90 kWh (Tesla S) and electric buses have various capacities depending on their size, between 90 kWh and 170 kWh (e.g. the blue bus and the Gepebus).

Regarding electric cars, it is interesting to see that the frequency regulation service will be mainly limited by the charging station capability (wires and power electronics). In fact, the fast charging/discharging must be available to allow sufficient power flow. Moreover, the V2G must be possible with power electronics allowing power flow in both ways. Regular charging rate is around 3 kW, while frequency regulation service becomes interesting above 15 kW [14].

In the case of high battery capacity like luxury cars (Tesla model S) or buses, the manufacturers develop very high charging rates (more than 100 kW). However, most of the physical installations where EVs usually charge do not allow V2G services. The additional investment costs and the manufacturers' interest have not been investigated.

Table II shows the general parameters used in EVeSSi as called by ICAM remotely. In this case EVeSSi road information is not used as for the aim of the case study it was not relevant. The 7 types of fleets represent the French EVs diversity, namely ranging from small, medium and large passenger vehicles to small and large commercial vehicles.

2) Frequency regulation net profit

In the actual Portuguese regulation market, Primary Frequency Regulation is realized through action on the turbine speed regulator and is not remunerated. Regarding secondary frequency regulation, the prices are variable during the day [22]. For instance, during a winter day (2016/01/19), the prices vary from 35 to 87 €/MWh, whereas, for a summer day (2016/07/19), the prices vary from 35 to 74 €/MWh. The study of the prices during 2016, shows that the average price is around 45€/MWh. Otherwise, the regulation markets are moving fast with the penetration of smart grid solutions and the opening to new bidders in the context of smart grid, the remuneration scheme will certainly change in the future.

TABLE II. EVESSI PARAMETERS

Parameter	Value
EV fleets	7 types (≈18,000)
Initial SOC	Random 20% to 80%
Vehicles permanently parked	2%
Total simulation time	24 hours (1 day)
Charging efficiency	90%
Probability of returning to start location	85%

In Table III, we compare various market contexts. The first scenario without capacity price benefits from an electricity price which is high enough to allow profitable service regarding the service cost (battery wear and investments) thus superior to 0,14 €/kWh.

The second scenario is with an electricity selling price equal to the average electricity price in Portugal for 2016 (c_{pe}) and a capacity price equal to the French regulation market capacity price 17 €/MWh for primary frequency regulation.

The third and fourth scenarios present the result for a remuneration only based on a capacity price corresponding to the actual French situation [15] and the actual remuneration of the secondary frequency regulation in Portugal, which is close to CAISO market situation in [19].

Table III shows also very low net profit for micro electric vehicle (ID5). It can be explained by the low available energy because of the battery capacity as well as the high mobility needs (44km per day). The annual net profit becomes interesting under very favorable remuneration conditions with the fourth scenario and reaches 887€ per year per vehicle.

TABLE III. NET PROFIT COMPARISON

Fleet Type ID	**EVs available for frequency regulation**	**Average trip per day (km)**	**Rated energy (kWh)**	**Profit per vehicle per year**			
				P_{el}=0,16 €/kWh	P_{cap} =0,017 €/kWh P_{el}=0,0318 €/kWh	P_{cap}=0,017 €/kWh	P_{cap}=0,045 €/kWh
1	6600	17.3	24 to 30	150	516	237	2690
2	660	50	60 to 90	150	516	237	2690
3	6600	18.6	22	150	516	237	2690
4	1980	80	22	59	349	128.5	2073
5	990	44	6.1	-145	3.4	-110	887
6	660	53.2	22	150	516	237	2690
7	792	108.3	85 to 170	150	516	237	2690

Besides, Table III shows the importance of the capacity price, which can become the principal source of revenue because it allows to be paid even if there is no power flow between the EV and the grid. The third scenario reaches 237€ and the fourth 2690€ per vehicle per year.

On the other hand, the first scenario, where a remuneration, to allow profitable service regarding the service cost (battery wear and investments) thus a little bit over 0,14 €/kWh, is used, may also be interesting for the frequency regulation service for a whole fleet. In fact, the annual profit for one vehicle is low (59 to 150 €), however, all the fleets (without ID5) reaches 2.413 M€.

The frequency regulation may represent an interesting revenue stream able to push EVs use in the future. Nevertheless, it is highly dependent on the market regulation evolution regarding the grid development and the smart gird solutions penetration.

Regarding the benefits sharing, the profitability must be ensured for the several actors: DSO, EV aggregator and EV owner. They are highly dependent on the regulation market context.

For the EV owner, the service may be profitable at his level if a single-vehicle is able to provide the service under real-time conditions in the regulation market through an aggregator able to offer significant level of power to the grid. The main remaining question is that if the aggregator does the necessary investments and sets contracts with the DSO, which benefits share will be applied?

VI. CONCLUSIONS

SEAS project has been promoting the intelligent management of smart grids by means of collaborative usage of algorithms and tools, while ensuring confidentiality and interoperability. In this scope, SEAS SI has been developed and presented in this paper, namely its features and architecture.

A case study involving algorithms from two different partners, GECAD and ICAM, written and executed in different programming languages, illustrate SEAS SI advantages to foster new and overwhelming scenarios that cannot be studied using the algorithms independently.

The case study makes use of EVeSSi, a GECAD algorithm, and a scenario with 18,000 EVs representing a diversified fleet of France EVs participating in the frequency regulation market. The results demonstrated that annual profit, calculated with Net_Profit_F_R_SB algorithm from ICAM, can be obtained while participating in frequency regulation, especially for larger vehicles with larger battery capacity such as the Tesla Model S (fleet ID 2). The results also indicate that the capacity price can be the most important source of revenue as EVs may offer its availability even if it is not used subsequently.

Despite the relevance of both EVeSSi and Net_Profit_F_R_SB, the case study shows the sequential use of these algorithms available in SEAS SI and the way they can together address the management and business models definition for smart grids and microgrids with different penetration of EVs.

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