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DOCTORAL THESIS

Optimal Energy Management and Performance Evaluation of an Integrated Mobility System: the "Life for Silver Coast" Case Study.

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Abstract

Nowdays, Climate Change and Global Warming are very relevant issues and Humankind relies on Renewable Energy Sources (RESs) for mitigating environmental impacts. RESs exploitation implies the adoption of a Distributed Energy Generation (DEG), implemented through local electrical grids called Microgrids (MGs). The intent of harvesting as much as energy possible, dealing with the RESs unpredictable nature, makes researchers develop suitable ICT systems (Energy Management Systems or EMSs). Smart Grids (SGs) are systems composed of many MGs, thanks to which a whole urban area can perform an efficient energy management. Energy Communities, made up of companies, research centres and Universities strive to design and realize SGs, in a sustainable development vision.

In this context, the sustainable mobility system realized in the "LIFE for Silver Coast" European Project is a very good test bench for EMSs synthesis. In fact, Electric Vehicles (EVs) and charging stations will be integrated in the Project Area and managed through proprietary EMSs. In addition, the achieved knowhow can be used by the Energy Community to develop Smart Grids, not only in the same area.

In this thesis, the Evolutionary Fuzzy System (EFS) paradigm is applied for the synthesis of an EMS. In particular, a double-step optimization Hierarchical Genetic Algorithm (HGA) procedure is implemented for reducing the computational cost. The resulting Fuzzy Inference System-Genetic Algorithm (FIS-GA) is tested for the onboard optimal energy management of the LIFE "Valentino" Class e-boat, with the purpose of implementing the same EMS in a residential MG. In addition, an application based on Life Quality indicators related to mobility systems is presented.

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CHAPTER 1 - Introduction

In this chapter, a brief introduction to Renewable Energy and Artificial Intelligence (AI) is presented, since they will be correlated later in this work.

1.1 Energy and Renewable Energy Sources (RES)

In order to contrast Climate Change, the World is trying to rely more on Renewable Energy Sources (RESs), mitigating the environmental impact of Humankind's productive activities [1].

Only the 14% of the world total primary energy supply depends on RESs, but wind electricity production increased by eight times over a period of 10 years until 2015 and solar photovoltaic production increased by over 20 times, in the same period [2].

The global electricity generation from RESs could grow by about 2.7 times between 2010 and 2035, according to predictions [3], confirming the desire to lower the large increase of CO_2 (31%) in the past 200 years.

RESs include wind, geothermal, marine and biomass energies and hydropower [4]. They can provide more than 3000 times the global energy needs (comparing it to the World energy demand in 2014) and more than 92% of that energy supply comes from Solar [3]. According to the International Energy Agency (IEA) [5], hydropower, biomass combustion and geothermal energies belong to the First Generation of technologies because their maturity. Solar and wind energy technologies can be placed in the Second Generation because in rapid growth; while ocean energy is in the Third Generation, being still under development.

1.2 Distributed Generation (DG)

The principle of Distributed Generation (DG) arises from the contrast with the more common Centralized Generation (CG), which is the energy generation by large and powerful power stations, as hydroelectric and thermoelectric.

The CG has some disadvantages. First of all, power stations have a large impact on the environment: hydroelectric is invasive for the natural environment while thermoelectric has obviously an impact in terms of pollutant and climate-altering emissions. Moreover, energy transportation is inefficient because of the long distance between the power stations and their branches, i.e. the users. In fact, the longer the distance is the more energy is wasted along the path.

The first step to solve the abovementioned problems of the CG, consists in providing small generators very close to the users, thus a DG. That is enough to reduce energy waste and partially enough to reduce the environmental impacts. Nevertheless, it is necessary to introduce RESs generators for a significant emissions abatement.

In addition, since PV and wind generators are affected by the local variability of irradiation and wind speed, the decentralization is further accentuated [6]. Supposing to have a very large free space and to be free to install wind generators. It very improbable that wind speed will be enough to generate a significant amount of power in every point of that space, over time. Thus, installing wind farm makes sense but it should be limited in size not to waste money (installing wind turbines), by exploiting only the area of that space with a sufficient wind speed. Conversely, a thermoelectric power station provides high power production, although that is reasonably independent by space, compared to the wind farm.

1.3 Computational Intelligence and Machine Learning

Complexity and lack of information, which nowadays affects many problems, lead to the use of non-rigorous techniques. In fact, an algorithm written for solving a given problem, if based on a rigorous formulation, generally has to perform many calculations and this makes the computational time increase. Moreover, the problem can't be solved with a rigorous formulation, if a lack of information occurs.

Computational Intelligence (CI) techniques are released from a rigorous formulation so that it is possible to fix the abovementioned issues [7][8].

An overview of the CI paradigms is presented in Fig. 1.1.

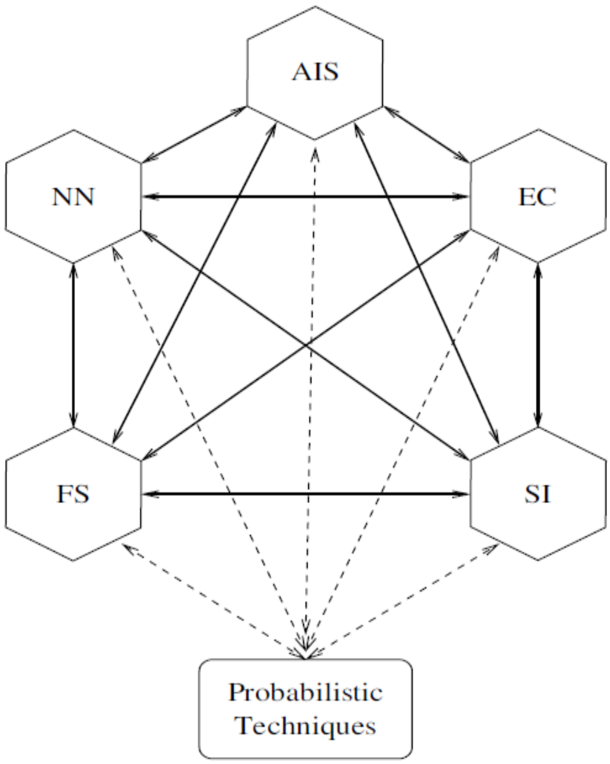

Figure 1.1 - CI paradigms overview.

Artificial Immune Models (AIs), Evolutionary Computation (EC), Swarm Intelligence (SI), Fuzzy Systems (FSs) and Neural Networks (NNs, in Fig. 1.2) are the main paradigms. It is worth mentioning that Probabilistic techniques represent a common denominator [7]. Moreover, hybrid techniques as Artificial Neural Fuzzy Systems (ANFSs) could mutually fix the issues of their fundamental components (NNs and FS, in this case) [8].

The idea behind the CI is to emulate Nature in processing information end problem solving: AIs solve problems imitating the immune system in the body; EC find the solution by comparing many solutions, which become better following the natural fit rules; SI considers all possible solutions as elements of swarms; FSs try to code some rules just like the human brain could do to interpret data and to achieve the desired outputs; NN (Fig. 1.2) emulate the human body, at the neural elementary level [7].

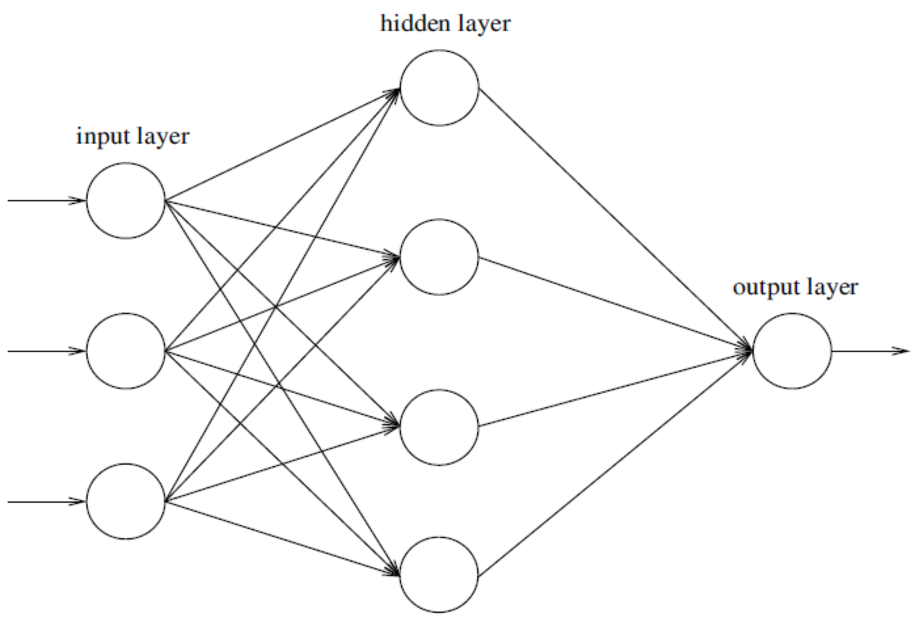

Figure 1.2 - A Neural Network structure.

Machine Learning (ML) techniques exploit the inner adaptability of CI algorithms by feeding them with data, in a way that make them learn the most relevant information from inputs.

In fact, CI algorithms are often based on a trial-and-error process, which modulates their inner parameters, enhancing the final result. If input data are provided correctly, a CI algorithm works better, like when a NN for facial recognition recognizes the face of a person (which it has been trained to recognize) even if he/she wears and hat or whatever thing reasonably different from the image it has been trained on.

Thus, CI algorithms achieve an high quality knowledge, which is focused on the core of information.

The ML process fundamentally consists in a training phase the CI algorithm inner parameters are set in, and a test phase, in which the CI algorithm functioning is verified.

1.4 Optimal Energy Management in Microgrids (MGs)

The nature of renewable energy is unpredictable. Its great variability over time, has led to the need for a smart management of energy flows through a more precise control over the energy production and distribution. Thus, there is the need for the adoption of Information and Communication Technologies (ICTs) to build ‘intelligent’ electrical grids, leading to Smart Grids [1][9].

A Smart Grid is a power grid infrastructure that is able to improve its efficiency and reliability [10] through an automated control [11], leading to an enhanced stability [12]. The main elements of a Smart Grid are [13] [14] ICT techniques and infrastructures, Energy Storage Systems (ESSs), power converters, actuators and smart meters.

A 23 million dollars Smart Grid project has been launched in France [15] and the minimization of active power losses in a real Smart Grid located in the area of Rome is studied in [16], [17] and [18]. Smart Grids one of the keywords related to the Smart City idea. The term "Smart City" has been defined by IBM as the use of ICT to sense, analyze and integrate the key information of core systems in running cities, meaning that sensors and the needed equipment could be embedded for instance into hospitals, railways, bridges and also power grids in order to achieve prosperity and effectiveness on several socio-economic levels [19] [20]. Microgrids (MGs) play a fundamental role in the economy of Smart Grids, as local electric grids (Fig. 1.3, 1.4). Energy Management Systems (EMSs) are designed to take decisions about energy flows among generators, loads, Energy Storage Systems (ESSs) [21][22][23].

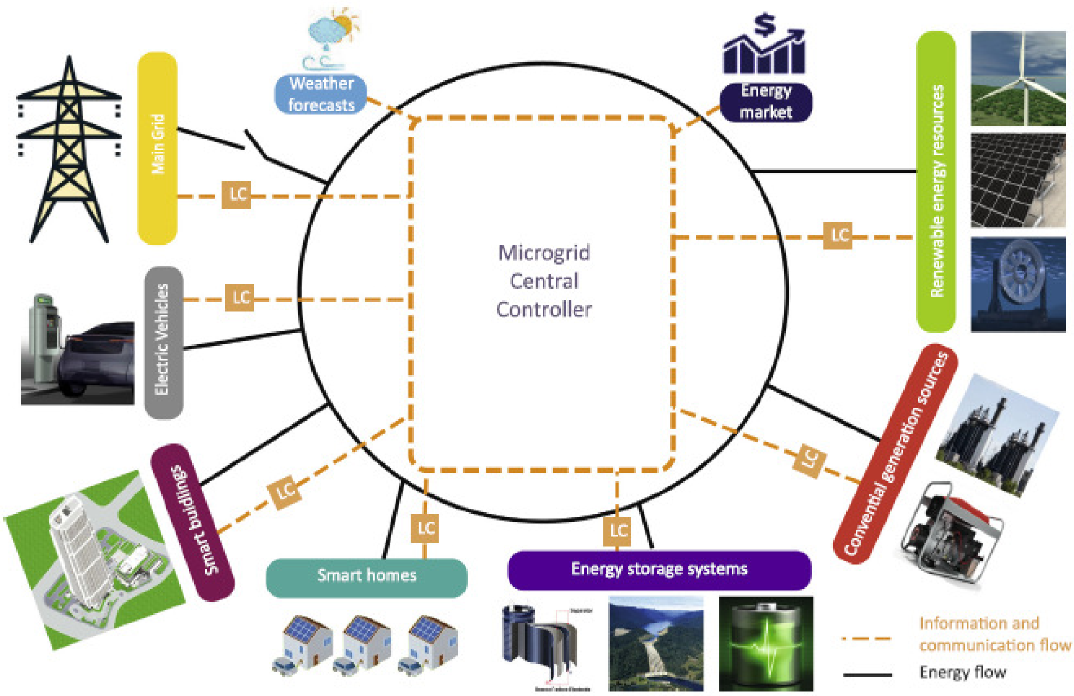

Figure 1.3. Conceptual scheme of a MG [24].

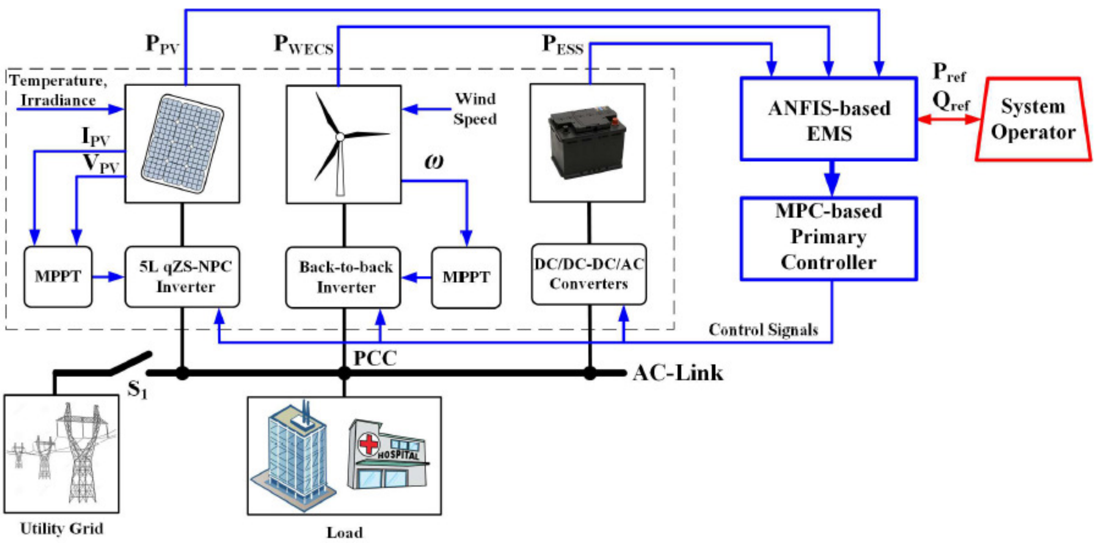

Figure 1.4. Detailed scheme of a MG [25].

Computational Intelligence (CI) is an effective tool for the EMS synthesis.

1.5 Resilience to Climate Change and Sustainable Mobility

Both rural and urban areas are subject to different kind of Climate Change impacts [26]. Among the direct effects there are storms, typhoons, heat waves, sea level rise, general temperature increase and changes in rainfall patterns. Nevertheless, also indirect impacts have to be taken into account. According to [27], indirect effects bring to significant disruptions in the socio-technical networks: coastal flooding causes issues to the transport network, on the coastline; droughts have negative effects on food and agriculture.

As a reaction, rural and urban realities are involved in progressive changes and in taking smart choices about their organization and structure. Thus, cities and their neighboring lands have to work on the improvement of their resilience to face the new challenges against the Climate Change effects. The idea of resilience is used in many different disciplines, from Engineering to Psychology and Ecology but it is also increasingly applied in Economics [28]. The origin of the term comes from Engineering: “It is the property of a material (elasticity) to retain its original form (bouncing back) after being subject to temporary stress” [29]. In the Climate Change context and according to the Intergovernmental Panel on Climate Change (IPCC) definition, resilience is the ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity of self-organization, and the capacity to adapt to stress and changes [30]. Moreover, it is worth mentioning that different time and mode in responses come from different kinds of stresses [31].

Referred to the urban sphere, resilience is the capacity of a city to absorb disturbances and shocks related to Climate Change, while retaining the same basic structure and way of functioning [32]. A better explanation of resilience is provided in [33], with a specific reference to the urban case. According to Literature, urban resilience is composed by three elements: Systems, Agents and Institutions. A System is an high level infrastructure that guarantees essential services to the city.

The city electricity distribution grid is an example of System. Agents are communities an individuals in the city. They represent a crucial node because they have the power to make decisions and to interact with the Systems or, in other words, their activity concerns the management of urban Systems. Farmers, consumers, private and public sector organizations are examples of agents. Institutions act on an higher decision level. According to Social Sciences, the meaning of Institution refers to the bunch of social rules or conventions, which structure human behaviour, together with exchanges in social an economic interactions. Institutions enable or constrain Agents in the organization and engagement about decision making. With reference to the above description of resilience, the example of a water supply system will be briefly set for better understanding the idea of resilience, through a practical application. At System level, in order to guarantee flexibility in facing emergency states, pumping stations in multiple sites have to be planned together with geographically distributed water sources exploitation. Again, protection and monitoring of the source quality, under climate stress conditions and water interlinked network distribution have to be provided, in case of System failures. At the Agent level, both suppliers and users are involved in enhancing resilience. Suppliers have to monitor highlighting the desertification risk due to land-use, for two coastal sites. Urbanization, the increase in population, forest fires, land abandonment in rural areas and rapid expansion of tourism are relevant factors of land-use. With regard to coastal areas, soil erosion, salinisation and water pollution are some of the problems to face. In the case-study, geo-referenced land use layer maps are drawn to achieve and ordered database for analyzing annual rainfalls and defining an "aridity index". With this information, the work contributes to the integrated assessment of land vulnerability and the identification of a sensitive Mediterranean areas which need an intervention. In order to deal with Climate Change effects, performing a reduction in greenhouse gas emissions is an mandatory step. Improving buildings energy efficiency [36] is a good action to mitigate Climate Change impacts. Moreover, green energy leads to appropriate distribution systems, which must be reliable for improving urban resilience. Information and Communication Technologies (ICTs) systems have to cope with service disruption and massive power failures as well as energy losses. In a whole sense, the role of Research is crucial in terms of resilience, for reaching a complex social and ecological systems adaptability to changes. Innovation for a sustainable future is the main purpose of the System and to cherish supply sources, in order to achieve abetter system responsiveness to environmental changes. Users have to develop their capacity to learn from water resource information with the aim of improving a fair water use. At the Institution level, more affordable lifeline tariffs lead to an in increment in the service usability. In addition, water allocation rules and legal procedures have to be considered to supply potable water to all citizens, even under stress conditions. Thus, achieving resilience is an hard path that goes from building concrete infrastructures to the reinforcement of communities an local governments, with reference to their power to act. Resilience to Climate Change in rural and urban areas is maintained (and when possible improved) by adopting interesting solutions. The Asian Coalition for Community Action Network is a project which concerns the grassroots level of resilience. Communities (more than 1000) visit each other city to learn how to improve resilience and the possibilities to make changes [32]. Resilience planning activities have been performed by 10 medium-size cities in the Asian Cities Cli- mate Change Resilience Network (ACCCRN), over a period of 7 years, from 2008 [32], [31]. Health, infrastructure, water, disaster, urban planning/development are the most relevant topics, in ACCCRN [33]. In [34], a Canadian Western Arctic community social-ecological resilience is taken into account. Local environmental knowledge, inter-community trade and community experience sharing improves reactive adaptation to Climate Change effects, on the Arctic environment. For example, a better knowledge and the best practical skills about living in that specific area, spread through oral tradition, can enhance the odds people properly react to critical situations besides making the link between people and the environment evolve. An interesting case-study in Italy is described in [35]. Environmental resilience in Basilicata Region is studied, the University of Rome La Sapienza. Since 10 years, POMOS carries on Research in developing electric vehicles [37], Energy Management Systems (EMS) and Battery Management Systems (BMS) [38],[39],[40]. Moreover, POMOS has contributed to the increment of socio-ecological resilience, starting from Ventotene Island (Italy), in 2010 [37]. In 2013, the use of an electric boats fleet was planned by POMOS for Pianura Pontina (Italy), in the the Bonifica 2.0 Project [41][42]. Since 2017, POMOS is the Coordinator of the LIFE for Silver Coast European Project (LIFE16 ENV/IT/000337), which aims at realizing a Sustainable Inter-modal Mobiliy System for the Silver Coast (Tuscany, Italy) [42], an area with naturalistic and touristic relevance. In this context, communities of energy providers and prosumsers belong to the use of Smart Grid technolgies and smart mobility systems for saving as much energy as possible, leading to Energy Communities.

1.6 The Life for Silver Coast European project

The “Silver Coast” is an area of touristic and naturalistic relevance, in the Southern Tuscany (Italy), near the border between Tuscany and Lazio (Fig. 1.5). The name “Silver Coast” comes from the peculiar silvery color of some stretches in its beaches, which are rich in Iron. The Coast comprehends Monte Argentario, Orbetello, Magliano and Isola del Giglio. The territory is quite heterogeneous, due to the presence of a peninsular subarea, (from Monte Argentario to the East and the North-East) and an insular subarea, which mainly consists of Isola del Giglio. A geographic peculiarity of the Silver Coast are the two pillows between Monte Argentario and the rest of the peninsula: the Giannella, on the Northern Occidental side and the Feniglia, on the Southern Oriental one.

Figure 1.5. Map of the "Silver Coast".

The “Silver Coast” is rich in naturalistic beauty and sight- seeing places, which remark the touristic importance, in the National panorama. Orbetello, although it is not a big city, has a great historical weight. In fact, it hosts ancient Etruscan ruins, dating back to the 5th century B.C.. Furthermore, Orbetello is part of a natural reserve interested by the migration of protected birds species, for example the pink flamingo. A pristine natural habitat can be observed in the WWF Oasis and the natural reserve of Duna Feniglia, which can be accessed from the two pillows of Giannella and Feniglia. In Monte Argentario, a Panoramic Road links Porto S. Stefano and Porto Ercole ports. Along the road, it is possible to enjoy the view of the Tuscan Archipelago. Isola del Giglio offers a crystal clear sea, besides the charming medieval village named Giglio Castello. Least but not last, the Silver Coast comprehends a relevant part of the Maremma Natural Park, in the North and the Giannutri Island, which is a sea protected area.

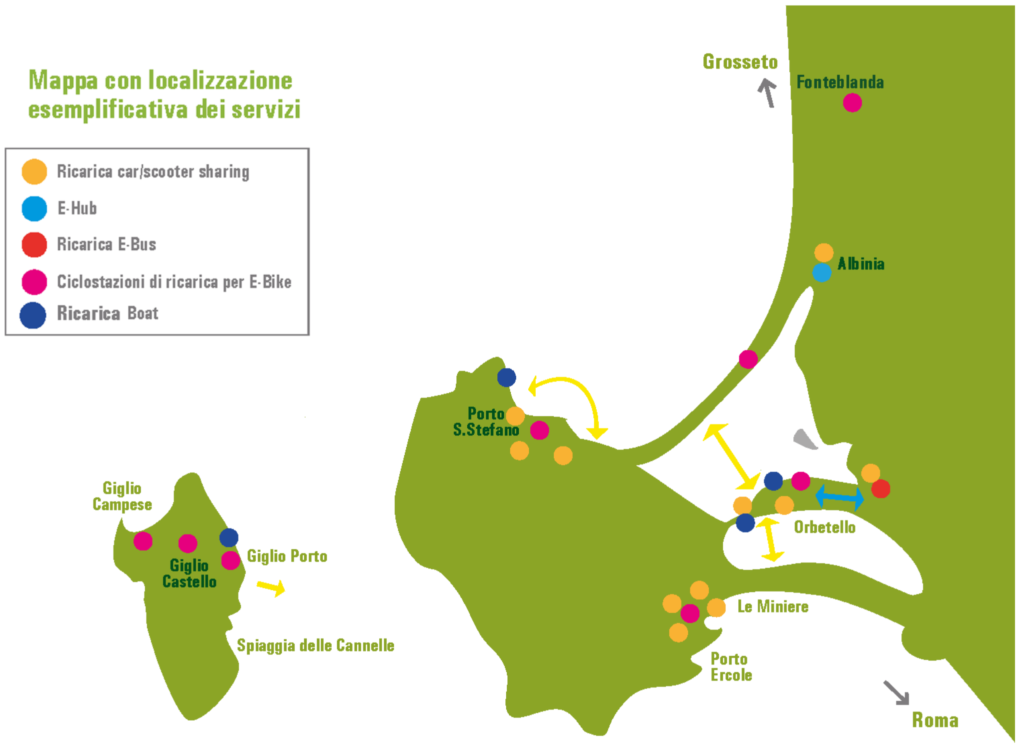

Figure 7. Mobility system overview.

The Project will cover a significant area (approximately 200 km^2) both on land and sea and also on lagoon. In fact, as it can be seen in Fig. 1.5, the peculiar conformation of Monte Argentario shapes two lagoons, bounded by the Giannella (North) and the Feniglia (South) pillows. The Mobility System will be connected to the Orbetello railway station, which is considered the main access transport node. The core of the land-side part of the System will be centered closely to the above node. Once arrived at the Orbetello railway station, users will find car sharing and bike sharing charging stations, thus they can start their trips towards Monte Argentario or inside Orbetello itself. In other words, it will be possible to cross the whole peninsula by e-bikes, e-cars and e-buses. In addition, into the lagoon-side and sea-side parts of the System, users will sail on the two lagoons or on sea (for brief routes) both in Monte Argentario and Isola del Giglio.

The Mobility System (Fig. 1.6, 1.7) consists only of Zero Emis- sions Vehicles (ZEVs): 80 e-bikes, 20 e-scooters, 14 e-cars, 2 e-buses and even 4 e-boats. The main transport access node, the Orbetello railway station, is represented by the white circle, on the map (Fig. 1.5). Users enter the transport graph with a single ticket, for all the transport modes. Thanks to the multi- modal nature of the system itself, users can move freely on the area of interest. With reference to the map in Fig. 1.6, it is possible to use one of the two “Valentino” lagoon electric boat (Fig. 1.7) to cross the lagoons between Orbetello and the two pillows of Giannella and Feniglia. If users choose to sail to North, they can take another “Valentino” e-boat to reach Porto S.Stefano, in Monte Argentario. Charging stations for e-bikes and e-cars are distributed over the area of interest, letting users travel among every part of Monte Argentario.

Figure 1.7. The mobility system.

The “LIFE for Silver Coast” Mobility System will brought to completion according to the scheme shown in Fig. 7.

Another “Valentino” e-boat connects the Southern Monte Argentario with Porto Ercole. Further sea connections are covered, in the Northern Isola del Giglio. The two main innovations of the Mobility System are the “Valentino” e- boat and the “e-Hub 360” (Fig. 1.7). The “Valentino” (Fig. 1.8), realized by POMOS, is a full-electric boat which has been designed to be inherently flexible. In fact, it can sail both lagoon and sea waters (two different models have been realized to do so). Furthermore, a Photovoltaic (PV) roof guarantees an energy supply, although the battery can be charged when the “Valentino” is docked. The “e-Hub 360” is a cylindrical e- bike charging station with a PV roof, which supplies energy for self-sufficiency. The Hub can host 14 e-bikes, with an automatic inclusion/extraction system. The Mobility System is supported by an Information Platform through which users can do so many things, like achieving information about the ticket price, for the next trip.

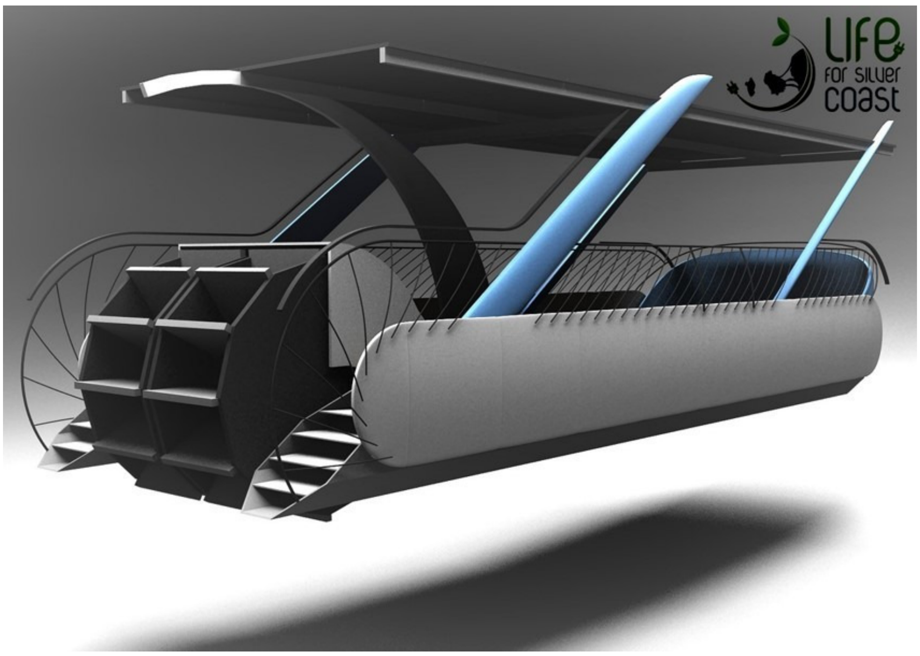

Figure 1.8. The "Valentino" e-boat.

The assessment of a project environmental impacts is a very relevant issue. Whatever project implementation, (ordinary or experimental), must take into consideration a wide range of aspects, which can lead to dangerous consequences for the environment. So many methodologies are implemented to permit the evaluation of the above impacts and each one inevitably relies on input data. The latter are sometimes called "inventory data" and they represent the fundamental informative base for the needed assessment procedures. With input data, it is possible to define the current state of the environmental implications of a project. In addition, thanks to the above information, the comparison with previous states can be performed, together with a tracking of different states, over time. Moreover, data are used to define indicators and, on an higher hierarchical level, performance indexes for a critical assessment of the impacts. The "Valentino" full electric boat. A differentiation is often done among environmental input data, depending on the type of the considered impacts. If a project was born for mitigating Global Worming (GW), the concentration of a specific set of substances, which contribute to the increment of the temperature on the global scale, has to be monitored. In this case, CO_2 is the main substance to take into consideration. In fact, with reference to the United Nations Framework Convention on Climate Change (UNFCCC), the effects on Climate Change of the greenhouse gases (CH_4, N_2O, etc...) can be expressed in CO_2 equivalent effects, through the Global Warming Potential (GWP), associated to each above gas.

The aim of a project can be also the air quality enhancement. In general, in this situation, it is not necessary to consider CO_2 but this can not be said for other greenhouse gases because they can have negative effects both on Climate and air quality (e.g.: CH_4). In order to meet the need for input data, environmental monitoring is performed, thanks to specific tools (or methodologies). The "LIFE for Silver Coast" Project is an air quality project. The air quality assessment is possible only thanks to a periodical data retrieving, for environmental performance tracking. Environmental monitoring stations will be dislocated on the area of interest.

One of the environmental monitoring stations, in the Life Project. Each station can measure the concentrations in the main air pollutants, namely SO2, PM10, O3, NO2, H2S, CO, NH3 and PM2.5. The achieved measures are then stored in a cloud platform, in charge of processing them and returning an organic representation of air quality, for each pollutant.

The LCA is a required step for the Project. It is a methodology regulated by the International Standardization Organization (ISO) through two Standards (ISO 14040 and ISO 14044). The aim of the LCA is not peculiar or well defined, in fact is can be applied to assess many aspects, related to a product or a service. To set some examples, the LCA can be adopted by an actor with the purpose of enhancing the economic revenue of a product or a provided service as well as the performance of the production processes, in terms of consumed energy. Similarly, the environmental impacts of a project, in a wide sense, can be precisely assessed with an LCA.

Some aspects of the LIFE for Silver Coast Project have to be thought as Research and experimentation while other ones, as mobility services provision to inhabitants and tourists in the Silver Coast. These aspects are strictly connected to each other with the aim of providing a sustainable and innovative mobility service to be used when the project is active and also when the project will finish. In fact, at the end of the project (2021), the mobility system will be available for investors that will continue to manage and maintain the services. In this context, it is important to create connections between the Project, local stakeholders and organizations. Local actors represent the inner functioning grid of the territory and can offer many services to a Project like the "LIFE for Silver Coast", firstly by supporting the Project spreading (they can promote the offered services). The link to the stakeholders can engcourage the Mobility System growth also after the end of the Project. In fact, in the phase of handover, investors for the system will be found and the local stakeholders could represent a potential pool, with this perspective. In other words, the Project involves local actors in the overall activities, aiming at a penetration of the Mobility System in the territory.

The collaboration with many local actors is not so easy to achieve, especially considering that the Project is in its development phase. More precisely, there is not a current product or service to exchange with a potential stakeholder in order to stimulate him to participate. More wide sense agreements are needed to involve the actors with the perspective of benefit. A suitable tool is the Memorandum of Understanding (MoU), which defines an agreement in principle, focusing on the most important aspects of a future contract or more defined agreement. Many MoUs have to be signed in the "LIFE for Silver Coast" and currently some of them have already signed.

The LIFE Project will contribute to a better territorial resilience, in different ways. Relying on Renewable Energy Sources (RESs) and thanks to the full electric vehicles of its fleet, the LIFE for Silver Coast will have a direct impact on Climate Change mitigation, because of reduction in CO_2 emissions (1200 t over 3 years, expected). That result will represent a strong preventing countermove to climate changes, with the purpose of making the area of interest less vulnerable to the deterioration of its naturalistic beauty and natural reserves. Reductions in air pollutant emissions will give to inhabitants and tourists a more healthy environment to live in. This will lead to a more livable territory, suitable for a better tourist attraction. It is also interesting to underline the importance of control over the environmental effects, in the context of the Project. The monitoring activities and the LCA studies will contribute to generate consciousness about the system responses to Climate Change stresses, which is a crucial aspect for resilience improvement. This way, effective and efficient reactions will come from the ecosystem, thanks to an accurate action planning, based on acquired knowledge. Resilience is thus enhanced by performing a more detailed control over the area of interest, tracking its evolution in the desired indicators. The LIFE for Silver Coast will increase resilience of the territory also making the social-economic system more stable. Many stakeholders will be involved, with the perspective of an improved tourist attraction capacity and possible profits will come from that. This will grant a more stable economy in the Silver Coast, with consequent effects on population. In fact, the Project predicts new jobs both in the mobility system itself and in the contingent business environment (local stakeholders). Local communities and Institutions will work together, in a synergistic network. It will be possible to reach a common consciousness about the territorial ecosystem by exchanging information and solutions, to continuously increase performance and advantages. This distributed knowledge and know-how will act as an elastic tissue for external excitation adsorption, in case of sporadic punctual failures. In other words, the territory will progressively become like an organic system with an accurate sensitivity towards the external stimulation and a proper reaction architecture for stability maintenance.

1.7 Thesis scope

The scope of this work is to assess the effectiveness and the efficiency of a Fuzzy Inference System - Genetic Algorithm (FIS-GA) algorithm for and EMS, which could be used in the LIFE for Silver Coast sustainable mobility system and in a residential building. In addition, results of a custom GA developed at POMOS laboratories are presented and the GA is tested on a mobility system design problem, with the aim of providing further improvements to the FIS-GA.

CHAPTER 2 - Energy Management Systems (EMSs) in Microgrids

The main features about energy optimization in Mirogrids are described below.

2.1 Nature and Purposes of an Energy Management System (EMS)

An EMS is a system consisting in hardware and software, with the aim of performing and energy optimization [43][44][45]. In the contest of MGs, a workstation, installed *in loco*, represents the fundamental hardware component [46][47]. A software is installed in the workstation, with the purpose of returning the optimal decisions about the energy flows throughout a MG. The software can pertain both Mathematics and AI, according to the specific needs for the problem at hand. Part of the input for the software comes from recorded data. Thus, smart meters achieve information from the MG, feeding the algorithm which runs inside the workstation [48][46][49][50]. Smart meters (Fig. 2.1) measure the amount of energy which flows through the MG. They can both measure and communicate information, time-step by time-step, to the workstation.

Figure 2.1 - A smart meter (Wikipedia).

Actuators, connected to the MG power converters, are in charge of concretizing the abovementioned decisions, performing the MG energy optimization [1][51][52][53].

More precisely, the software runs until it calculates the desired output. In other words, the optimal actions the actuators will concretize in the MG are decided at this step. Once the decisions have been formulated, the appropriate signals are sent from the workstation to the actuators. Here, actuators are triggered by signals and MG power converters are modulated. As a consequence, energy flows are modified to fulfil to the prosumer predefined optimal policy. A GUI systems is usually part of an EMS for the process supervision [54][55][56][57] (Fig. 2.2, 2.3)

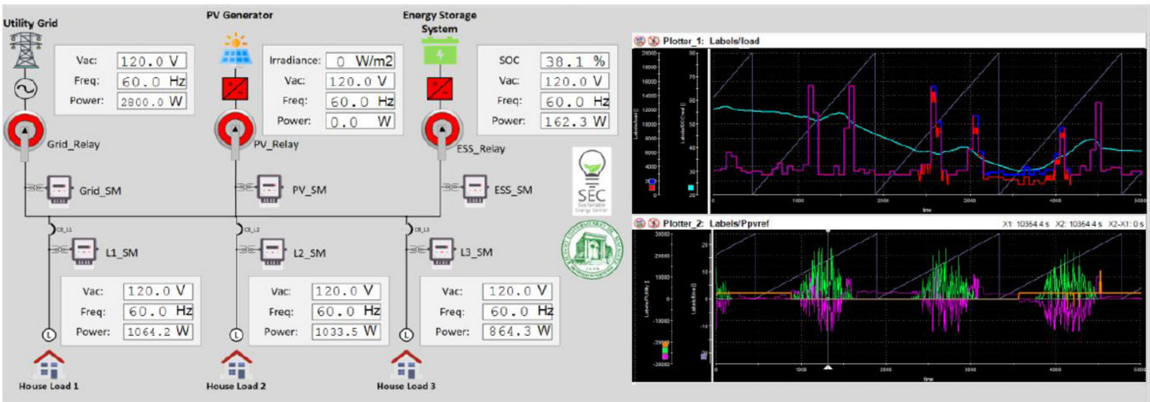

Figure 2.2. An EMS GUI main display [alzate-drada2019].

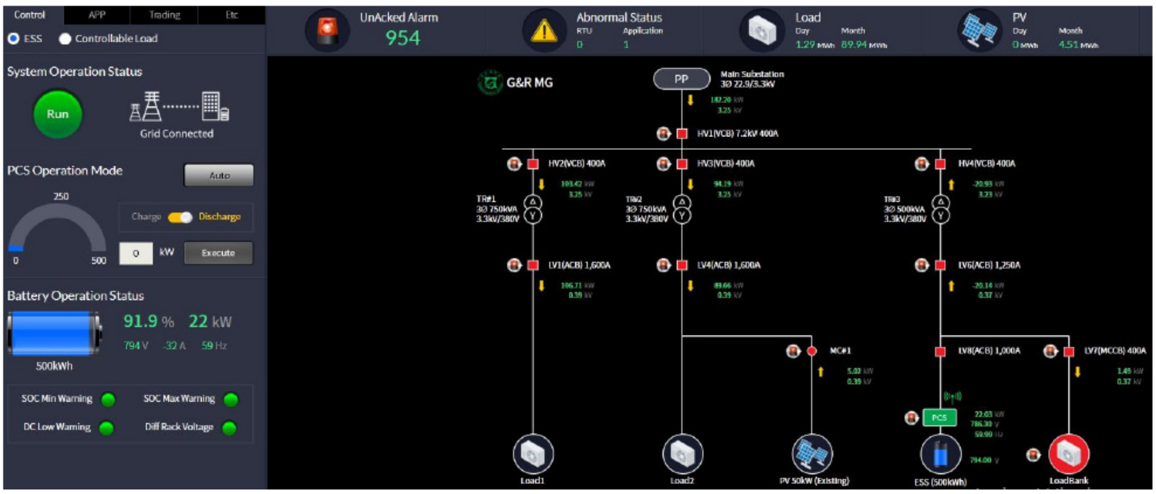

Figure 2.3. Am EMS GUI main display [58].

Energy optimization is a very important procedure, in the context of MGs. According to the principle of the Distributed Generation (DG), wind and PV generators are crucial elements of a MG, but at the same time, very difficult to manage due to the variability and unpredictable nature of green energy.

Precisely, within a given time interval, wind and PV energy production could change largely. For example, the wind speed could drop from one minute to the next or the Sun could be temporary covered by clouds, maybe during a potential peak of production, at noon. In such circumstances, it is important to save or to require energy from the Main Grid, with the aim of pursuing a purpose, such as the MG auto-consumption [46]: the MG becomes less dependent from the Main Grid as possible, meaning that the minimum energy is imported from the Main Grid, during the given time lapse.

Energy optimization means that, in a MG, energy flows avoiding energy waste as much as possible. The prosumer usually want to save the energy produced by a PV or a wind generator, when demand is lower than production and he will use that energy every time the demand is higher that production. Otherwise, the green energy would flow to the Main Grid and the prosumer would be forced to buy it when necessary. In that way, considering the MG\prosumer point of view, not giving the locally produced energy to the Main Grid is a saving while otherwise is a waste. It is worth mentioning that an energy waste is correlated to an economic cost: the Main Grid energy purchasing cost.

Sometimes, other purposes could be taking into account. For example, the prosumer could want to spend less money for the ESS [59]. This purpose is in contrast with the abovementioned energy saving purpose because, the more the energy has to be saved the more the ESS has to be used, leading to higher wear costs until the need for an ESS substitution. According to the example, saving money and saving energy sometimes require a trade-off.

In the context of the whole electrical Grid (MG and Main Grid), regardless of the use of PV and wind generators, energy optimization means that energy flows in a way that both the MG and the Main Grid take advantage. Through the practice of the Demand Response, the Maing Grid sets higher energy purchase prices [60] when peaks in the energy demand occur and the prosumer schedules the MG loads (e.g. households) or modulates their absorbed power, accordingly. The Main Grid reduces maintenance costs coming from peaks in power demand while the prosumer saves money, reducing energy purchasing costs.

Energy optimization is achieved through decisions about the amounts of energy to convey among the MG elements but also setting which households to switch on over time [61]. In the last case, the focus is on the MG energy consumption, which is modulated for being congruent to PV, to set an example. Moreover, the problem the EMS software is in charge to solve is bound by the fact that some households are not controllable, due to the priority it has for the prosumer (i.e. a TV). However, many households are flexible enough to be controlled in order to achieve the best result.

Besides the abovementioned EMS objectives, many other ones can be listed. It is worth mentioning that constraints are very important, since they add a realistic component to the calculation [62].

In Fig. 2.4 comprehensive framework of EMS objectives and constraint is presented.

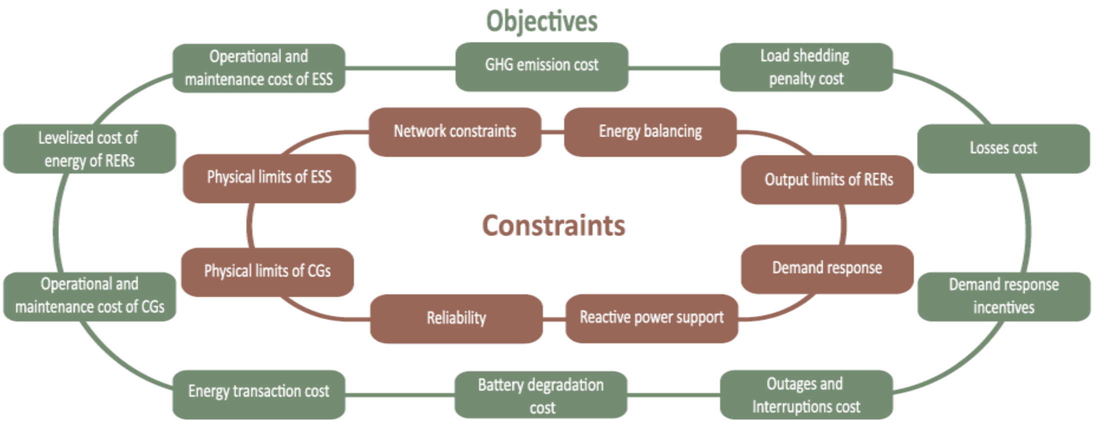

Figure 2.4. Objective and constraints in EMSs [62].

Even though forecasts about produced and/or consumed energy are not properly part of energy optimization, they are relevant in the overall economy of calculation; thus, they are worth mentioning.

First of all, it has to be said that there are two types of EMS (referring only to the software): the online EMS and the day-ahead EMS. They both have pros and cons and they are used in different circumstances. An online EMS returns outputs in real time, meaning that every time the software receives a new input, it rectifies the optimal energy policy for the MG. To set an example, when the software reads the PV energy production input from the smart meter, at the given time-step, it determines which households it is convenient to switch on over the next time-steps. It is not the same for the day-ahead EMS. Instead of reading inputs in real time, the software relies on the energy forecasts (e.g. PV production) made by another software, or a predictor. Thus, if the prediction is reasonably reliable, the EMS software will make optimal decisions which will be valuable for the near future. That said, forecasts (Fig. 2.5) can't be perfect but there is a reason why this approach could be preferred: results accuracy. In fact, the EMS software performs calculations a day before their concretization and it could run longer than in the online approach. On the other hand, an online EMS software needs less computation time and it is a good solution, is a reasonable trade-off between time and accuracy is achieved.

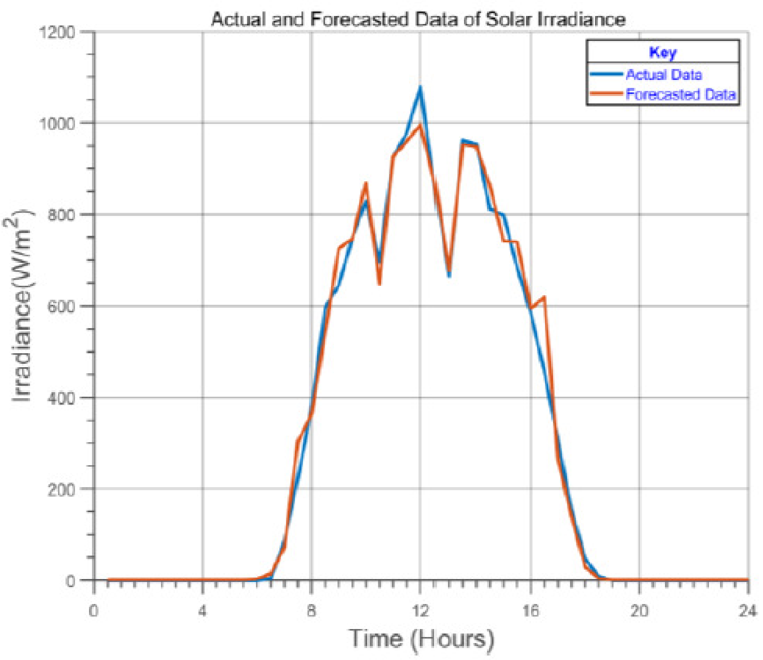

Figure 2.5. PV generation and energy consumption forecast [63].

2.2. Overview of Optimization Techniques and Algorithms

The EMS software component can rely on both mathematical and AI techniques [62].

The more classic mathematical approach leads to an exact solution of the optimization problem at hand. That can be done when enough information about the problem is known. In addition, mathematical optimization requires a large computation time, when many variables are accounted. Thus, this approach is useful but not applicable in circumstances of partial knowledge and not so efficient with complicated solutions to be found. Moreover, mathematical techniques require the physical equations of the problems at hand, which are not necessary in the field of ML, at the cost of an approximation. Neverthless, the abovementioned approximation is the key of the ML techniques generalization property, which leads to treat problems affected by uncertainties .

On the contrary, Computational Intelligence (CI) techniques are advantageous when information about the problem at hand is not completely known and they generally require less computation time than mathematical techniques. In fact, CI algorithms are based on the trial and error principle, being released from a rigorous formulation. In other words, a CI algorithm doesn't compute the first member of an equation which rules the relations between inputs and energy flows, in the MG but it performs trials measuring the goodness of the found solution.

Mixed Integer Linear Programming (MILP) [64] and Non Linear Programming [65] methods, together with Dynamic Programming (DP) [valencia2016][venayagamoorthy2016], Approximate Linear Programming and also Rule-based approaches [peixotodesouza2018] are among the mathematical approaches adopted for the EMS software.

On the other hand, Genetic Algorithms (GAs) [1][46], Particle swarm optimization (PSO), Artificial bee colony, Tabu search, Fuzzy Logic, Neural Network, Recurrent Neural Network, Reinforcement learning based-NN, Multi-agent system and Game Theory are among the main AI techniques used in this context.

CHAPTER 3 - Two-steps EAFS Optimization by a Hierarchical Genetic Algorithm (HGA)

Detailed information about Fuzzy Inference Systems and Evolutionary Algorithms are shown by highlighting their synergic relation.

3.1 Fuzzy Logic and Fuzzy Inference Systems (FISs)

Fuzzy Logic makes it possible to introduce partial truth when including an element into a set. As a consequence, Fuzzy Systems are not based on a rigorous mathematical approach, being suitable for dealing with complex problems whose exact formulation could be very hard to achieve. All of this, at the cost of a reasonable lack of precision [8]. Through the Fuzzy Logic paradigm, a System involves errors which come from partial truths and which can lead to a good generalization, in the analysis of the reality (input space), performing a learning process.   For a better understanding of partial truth, in Fig. 3.1 a real-world situation is presented.

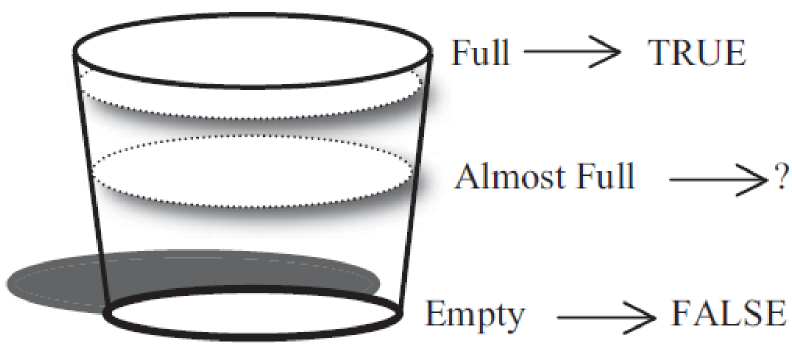

Figure 3.1 - Partial truth, in the real world [8].

It can be said that the glass is almost full, which could correspond to a different quantity from person to person. This is an implicit error in the presented reasoning. Nevertheless, if it was possible to tune the abovementioned quantity according to the problem at hand, the faculty of assessing the partial truth "almost full" would be an advantage because it would let evaluate that quantity in more than only two ways ("full" and "empty").

The principle above can be explained more abstractly and rigorously, through the introduction of the Fuzzy Set (Eq. 3.1).

$$A = \{x, \mu_A(x) | x \in X\} \tag{3.1}$$

The Fuzzy Set A (Fig. 3.2) is composed by couples of numbers and each couple includes the original crisp value x, which belongs to the given Domain (or Universe of Discourse) and the assigned Membership Function (MF) value (which sans from 0 to 1). The latter introduces the partial truth by linking a crisp value to a numeric evaluation of membership to a given set. For example, if the crisp value is the height of a person, i.e. 1,70 m, its MF value, with reference to the "middle height" set could be 0,9, meaning that the person is quite a perfect middle height one.

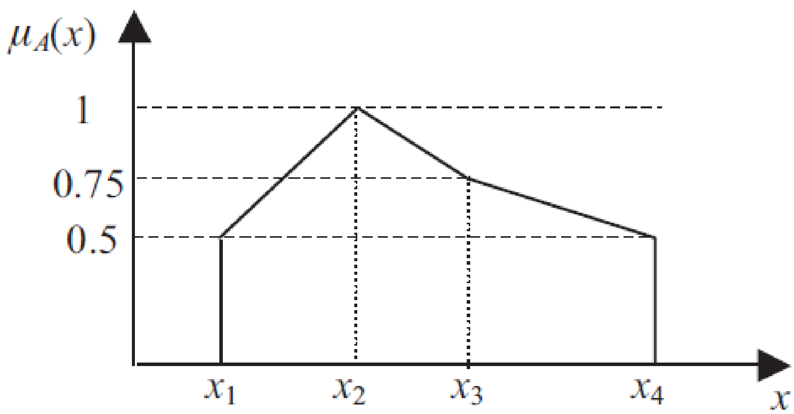

Figure 3.2 - A Fuzzy Set [8].

The Fuzzy Set is the essence of Fuzzy Logic. The process of achieving an output, given the inputs of a problem is done through Fuzzy Inference Systems (FISs). A FIS exploits the properties of Fuzzy Sets to compute a output, with the advantage of providing an intuitive explanation of the reasoning behind that computation. In fact, as it is shown below, the core of a FIS is composed by a set of Rules which explain the logic connection between data and result.

Different kinds of FIS exist but the following explanation is referred to the Mamdani type. In Fig. 3.3, the Mamdani FIS model is shown.

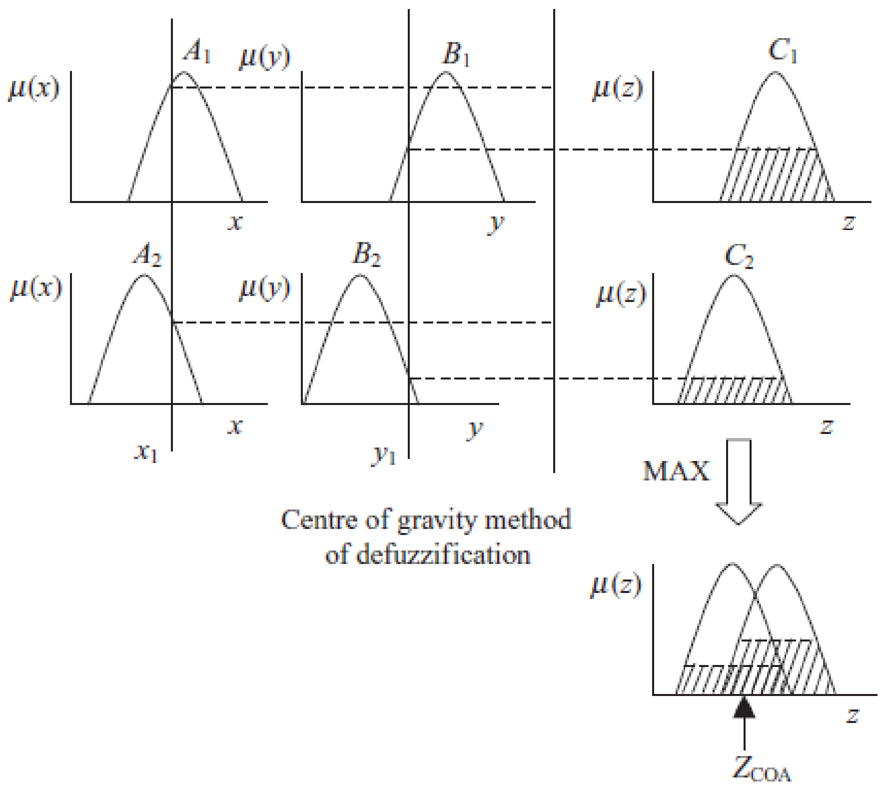

Figure 3.3 - Mamdani FIS model [8].

The FIS performs a Fuzzification by assigning MF values to the crisp inputs x. Then, input Fuzzy Sets are related to each others and to the output Fuzzy Set (Implication). The latter procedure is made by applying logical operators to the MFs values (for example, the operator AND, which generally implies taking the minimum MFs input value) and that information is encoded in the FIS Rules. A FIS Rule is a logical expression, as shown below:

if x is A_1 AND y is B_1 then z is C_1

In the example above, two Rules are considered, thus it is necessary to add the following:

if x is A_2 AND y is B_2 then z is C_2

The Rule Set for this example is the set of the two abovementioned Rules. The results of Implication for each Rule are put together in the Aggregation process (which generally implies taking the maximum MFs input value, as shown in Fig. 3). Finally, the Aggregation process occurs (generally based on center of gravity calculation for the area below the MFs value coming from Aggregation), in charge of achieving the desired crisp output number. To sum up, a FIS receives crisp input values and returns crisp output values but also returning a trace about the reasoning process, which consists in the Rule Set.

3.2 Evolutionary Algorithms (EAs)

Evolutionary Algorithms aim at solving optimization problems in a way similar to Natural Evolution [8].

An EA considers an initial Population of Individuals and each Individual represents a potential solution to the optimization problem. The Population is updated over iterations called Generations, in order to select Individuals, increasing the probability to have the optimal one among them. It can be said that Individuals have to survive over Generations and only the best ones can do that. More precisely, the problem at hand consists in an Objective Function (OF), which has to be minimized or maximized. An initial Population of random individuals is created. Each Individual is made of Genes, namely numbers which encode the phenotype of the respective Individuals. Over Generation, some Operators perform transformations on the Individuals, updating the Population. The Crossover Operator combines Individuals Genes simulating a biological mating and achieving new Individuals. This operator is applied on the best Individuals, in order to let only the best ones mating for a better evolution of the Population. This way the probability to preserve good features from "parents" is increased. The Mutation Operator introduces random Genes modifications to the worst Individuals in the Population. This way, even if Individuals are not so good, they could be enhanced by randomness, as it happens in nature. Finally, the Selection Operator selects Individuals to be passed to Crossover for generating the new Population. In general, Crossover makes already good Individuals better, thus it is a good way for the exploitation of the final solution. Instead, Mutation is suitable for the exploration of the domain, for avoiding local minima (or maxima). Stopping conditions for an EA could be reaching a pre-set maximum number of Generation or a pre-set number of Generations with roughly the OF value for the best Individual or a pre-set timespan without significant improvement of the OF. The Genetic Algorithm (GA) is part of the EAs family.

3.3 The EAFS Hybrid Paradigm

Evolutionary Adaptive Fuzzy Systems (EA Fuzzy Systems) involve tuning the FIS structure (Rule Base) and\or parameters or Membership Functions (MFs) abscissas [8]. Different implementations according to the approach at hand, can be found in Literature [46][66][67][68].

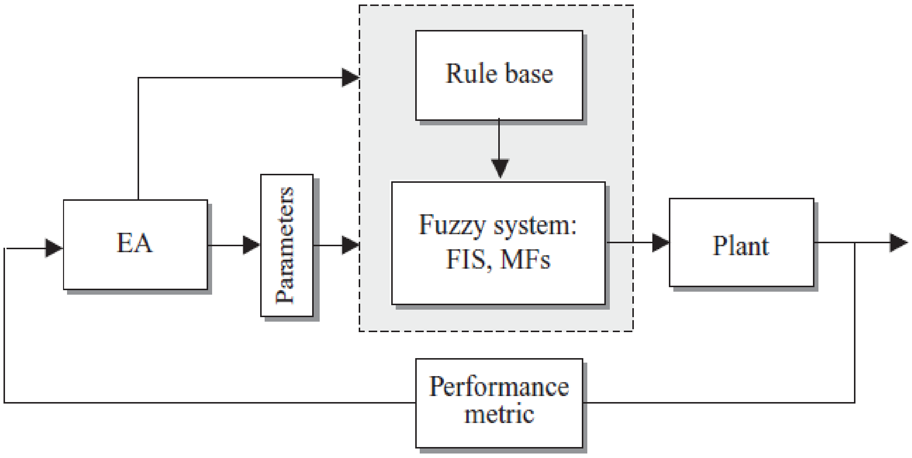

Figure 3.4 - EAFS architecture.

An EA is in charge of minimizing\maximizing an encoded form of the above quantities, with a given OF. In particular, each Individual of an EA encodes a FIS, i.e. the potential best FIS through which the optimal OF value is achieved by elaborating the given inputs (Fig. 3.4). The Genes of each Individual represent Antecedents, Consequents, Rule Weights and MFs parameters. A two-steps optimization could be a reliable solution for saving execution time, because of a reduction in the number of Rules, performed in the first step. The HGA fosters the core Rules selection, thanks to its peculiar architecture.

3.4 FIS structure and parameters

A Mamdani type FIS has been chosen to be optimized by the Genetic Algorithm, together with the Centroid defuzzification method. According to Literature [46][66][67][68], the Term Set (both for Inputs and Outputs) counts

5 trapezoidal and triangular Membership Functions (MFs), as shown in Fig. 3.5.

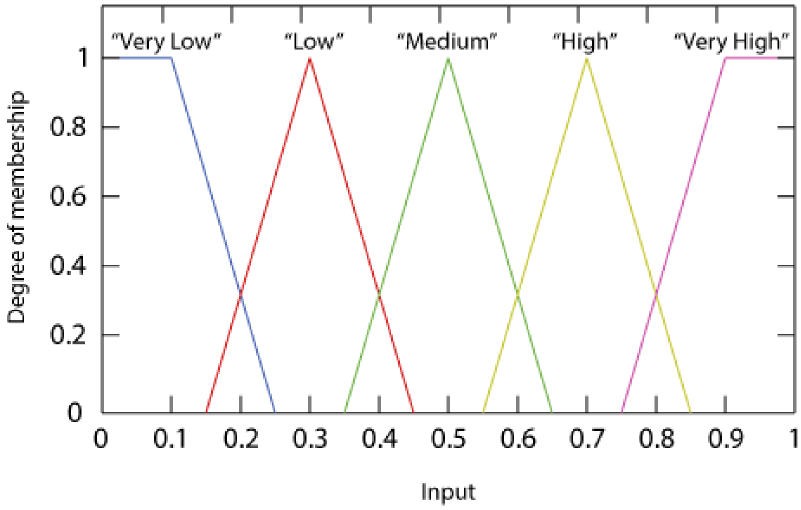

Figure 3.5. The Term Set.

The MFs vertexes abscissas are initialized in a way that a partial overlapping is done. The distance between overlapped vertexes abscissas is set arbitrary. The generic Rule r is encoded as follows (assuming to have 4 Inputs and 2 Outputs, for the problem at hand, by way of example): $a_{1,k}a_{2,k}a_{3,k}, a_{4,k}, \ c_{1,k}c_{2,k} : p_k$, with $a_{i,r}$, integer Antecedent which represents the active MF in the i-*th* Input Term Set, for the *k-th* Rule; $c_{j,k}$, integer Consequent which represents the active MF in the j-th Output Term Set, for the *k-th* Rule; p_k, real valued number which represents the *k-th* Rule Weight.

3.5 FIS encoding

The FIS is encoded as an Individual of the HGA. The HGA is quite similar to a GA, in terms of optimization workflow and operators. Nevertheless, the Individual structure is different because the HGA needs for a set of Genes which are related to the selection of the core Rules.

The generic Individual is encoded as follows:

$$Ind = [\overline{g^{hier}}, \overline{g^{parMF}}, \overline{g^{cons}}, \overline{g^{w}}] \tag{3.2}$$

with $\overline{g^{hier}}$, vector of binary Genes. Each Gene represents the activation/deactivation of the corresponding Antecedent MF. The Antecedent MFs are encoded from the first one of the first Input Term Set, to the last one of the last Input Term Set; $\overline{g^{parMF}}$, vector of real valued Genes. Each Gene represents a MF vertex abscissa; $\overline{g^{cons}}$, vector of integer Genes. Each Gene represents the active Consequent MF. The Consequent MFs are encoded from the first one of the first Output Term Set, to the last one of the last Output Term Set; $\overline{g^{w}}$, vector of real valued Genes. Each Gene represents a Rule Weight.

3.6. Two-steps EFS Optimization

A two steps optimization of the FIS-HGA optimization is performed by:

1. Finding the optimal Rule base;
2. Optimizing together MFs parameters, Consequents and Weights.

The first optimization step consists in running the HGA against a given Objective Function (OF) with the restriction of optimizing the vector $\overline{g^{hier}}$only, for each Individual. That way, each Individual encodes a FIS with fixed MFs parameters (shapes), Consequents and Weights, as they have been initialized. The Rule base only changes between Individuals because the Rules in which at least one Antecedent MF is deactivated according to the corresponding $\overline{g^{hier}}$ value, is deleted from the Rule set. Usually, setting a limited number of HGA generations in this phase is a good practice for preventing overfitting. At the end of the first optimization step, a Rule base is fixed and the HGA is ready to optimize the remaining Genes.

In the second optimization step, the HGA runs against the same OF used in the first step. By optimizing the Genes which encode MFs parameters, Consequents and Weight, the HGA finds the Individual which encodes the best FIS for the problem at end.

3.7 The HGA Operators and Hyper-parameters

The following choices are the best one for the problems solved until now. It could be possible that another configuration is more suitable for future problems at hand.

For the first optimization, a *one-point crossover* and a *bit string mutation* are chosen while for second optimization step, that design choice is related to type of Genes, for the Crossover Operator. In fact, for the real valued Genes of the vertices abscissas, a *Convex Crossover* [46] is performed and for the Weights and Consequent Genes, a *Uniform Crossover*. A *Uniform Mutation* is performed during the second optimization. A *Tournament Selection* with tournament size 2 is adopted for both the first and the second optimization phases. The Population consists of 100 Individuals for both the optimization processes, as well as for the C*rossover Fraction*, set to 0.8. The stopping condition is always the reaching of the *maximum stall generations* while the maximum number of generations is set to 50 for the first optimization and to 300 for the second optimization.

In this Chapter, the main results of the presented research are discussed.

4.1 Implementation of a GA for the Optimal Energy Transduction of a Wave Energy Converter (WEC)

In the context of RESs harvesting, sea waves are a reliable energy source. In fact, a sea waves energy converter could exploit both locally generated waves and waves generated elsewhere, which moves towards the installation area. Thus, unlike solar an eolic, sea waves energy transduction benefits of more continuity.

In [1], the energy transduction optimization of a Wave Energy Converter (WEC) is performed. In particular, the best internal parameters configuration for achieving the maximum energy from waves is defined, by the use of three Computational Intelligence (CI) algorithms. A comparison between the latter is aimed at assessing the best algorithm in terms of effectiveness and efficiency, for future applications.

The WEC under study is the Inertial Sea Wave Energy Converter (ISWEC). It is a punctual WEC because it can not translate, like a buoy.

As it can be seen in Fig. 4.1, the ISWEC consists of an external hull with a shaft inside. The shaft supports a gyroscope and a Power Take Off (PTO) and two rotational bearings guarantee rotation around its axis. The flywheel motor is placed on the top of the gyroscope frame, which comprehends a vacuum box with the flywheel inside.

Waves make the hull pitch by an angle δ. At the same time, the flywheel motor makes the gyroscope rotate by an angle ϕ. Thus, thanks to the gyroscopic effect, the two rotations generate a rotation around the shaft, by an angle ε. The generated power (Eq. 4.1) is directly proportional to the reaction torque of the PTO T_ε, made explicit in Eq. 4.2.

$$P_\varepsilon = T_\varepsilon \omega_\varepsilon \tag{4.1}$$

$$T_\varepsilon = I_\varepsilon \dot{\omega}_\varepsilon + \left(I_\varepsilon - I_\phi\right)(\omega_\delta)^2 sin\varepsilon\ cos\varepsilon - I_\phi\ \omega_\phi \omega_\delta cos\varepsilon \tag{4.2}$$

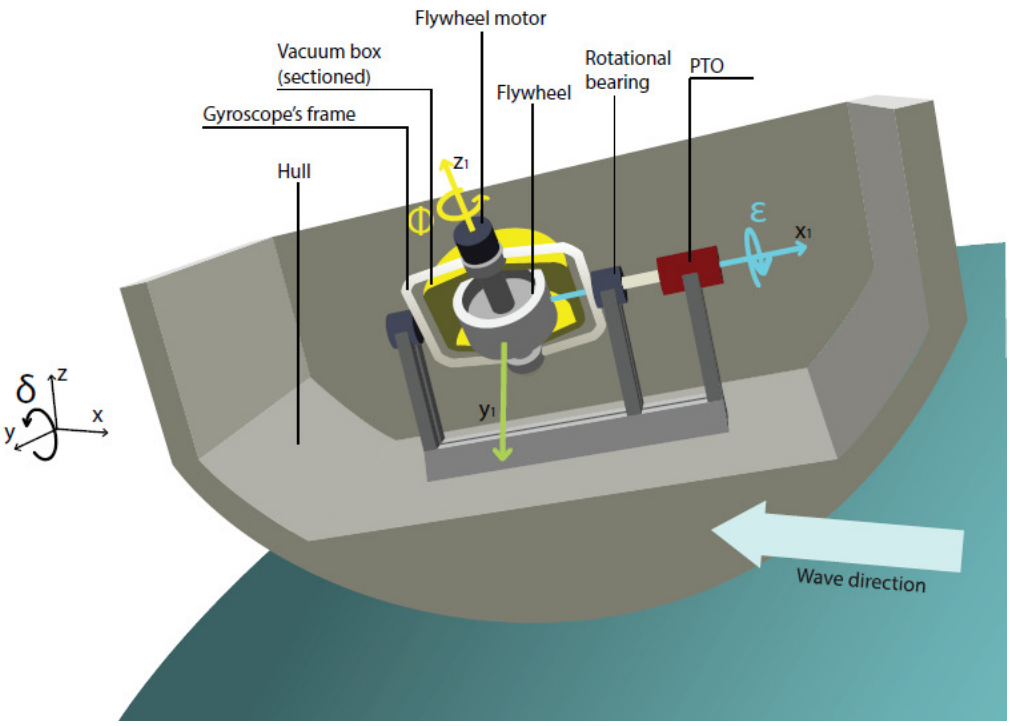

Figure 4.1 - Rendering of the ISWEC.

P_ε [W] is the generated power, T_ε [Nm] is the reaction torque of the hull, I_ε [kg m^2] is the moment of inertia of the gyroscope around the x_1 axis, ω_ε [rad/s] is the angular velocity of the gyroscope around the x_1 axis, I_ϕ [kg m^2] is the moment of inertia of the gyroscope's flywheel around the z_1 axis, ω_ϕ

[rad/s] is the angular velocity of the gyroscope's flywheel around the z_1 axis, ω_δ [rad/s] is the pitching angular velocity and ε [rad] is the rotation angle of the gyroscope around the x_1 axis. The PTO acts like a linear damper (Fig. 22), according to Eq. 4.3.

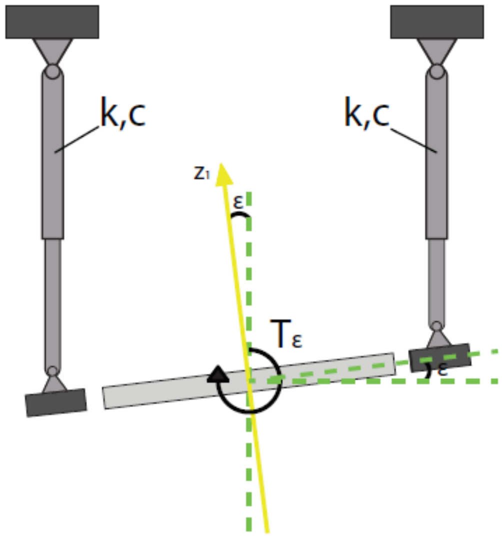

Figure 4.2 - ISWEC linear damper model.

$$T_\varepsilon = -k\varepsilon - c\omega_\varepsilon \tag{4.3}$$

where k [Nm/rad] and c [Nms/rad] are the PTO stiffness and damping coefficients, respectively. The ISWEC is modelled as a nonlinear dynamic system. The system is described by the following equations:

$$\begin{cases} \dot{\boldsymbol{X}} = \boldsymbol{F}(\boldsymbol{X}, \boldsymbol{U}) \\ \boldsymbol{Y} = \boldsymbol{G}(\boldsymbol{X}, \boldsymbol{U}) \end{cases} \tag{4.4}$$

with:

$$\boldsymbol{X} = [\varepsilon, \omega_\varepsilon] \tag{4.5}$$

$$\boldsymbol{Y} = T_\varepsilon = -k\varepsilon - c\omega_\varepsilon \tag{4.6}$$

$$\boldsymbol{U} = \omega_\delta \tag{4.7}$$

$$\begin{cases} \dot{\varepsilon} = \omega_\varepsilon \\ \dot{\omega}_\varepsilon = -\dfrac{k}{I_\varepsilon}\varepsilon - \dfrac{c}{C}\omega_\varepsilon + \dfrac{I_\phi}{I_\varepsilon}\omega_\phi \cos(\varepsilon)\omega_\delta - \dfrac{\left(I_\varepsilon - I_\phi\right)}{I_\varepsilon}\sin(\varepsilon)\cos(\varepsilon)(\omega_\delta)^2 \\ T_\varepsilon = -k\varepsilon - c\omega_\varepsilon \end{cases} \tag{4.8}$$

where **X**, **Y** and **U** are the state the output and the input of the system. The system is solved using the finite differences method. The work at hand aims at maximizing the transducted energy in function of *c*, *k* and ω_ϕ, as shown in Eq. 4.9:

$$\max_{c,k,\omega_\phi} E = P_\varepsilon t = f(c, k, \omega_\phi) \tag{4.9}$$

subject to

$$30 \text{ [Nms/rad]} < c < 120 \text{ [Nms/rad]} \tag{4.10}$$

$$225 \text{ [Nm/rad]} < k < 450 \text{ [Nm/rad]} \tag{4.11}$$

$$104\ [rad/s] < \omega_{\phi} < 157\ [rad/s] \tag{4.12}$$

where t is the time span, which has been set to 25 s and the ISWEC parameters boundaries have been taken from Literature [69].

The optimization (energy maximization task) has been performed by an Evolutionaey Algorithm (EA), i.e. a Genetic Algorithm (GA). According to the optimization flowchart (Fig. 4.3), there are 20 iterations of EA optimization. In fact, EAs are stochastic algorithms and their results have to be averaged. Moreover, energy is maximized for each value of wave frequency, from a set deduced from Literature.

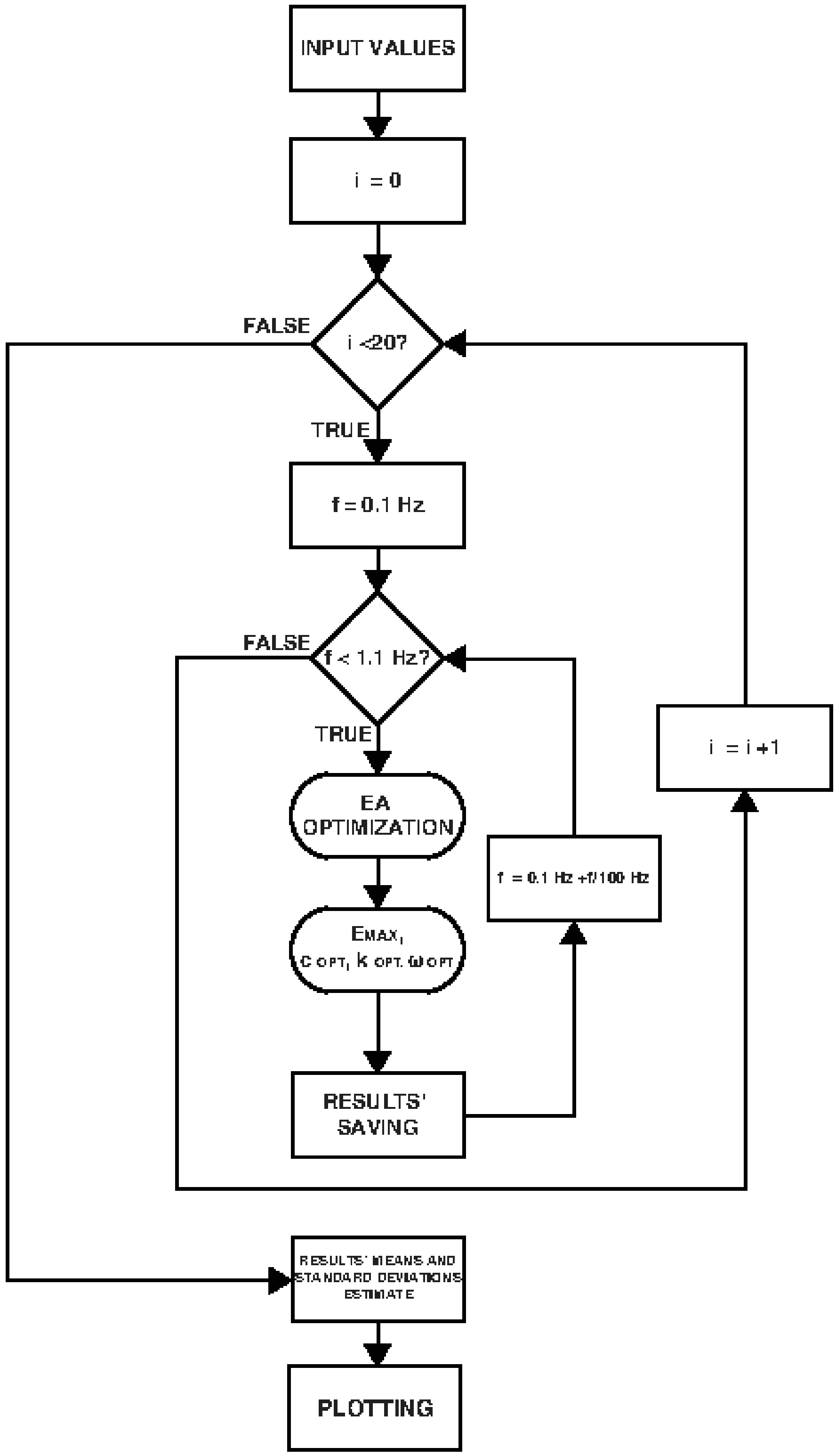

Figure 4.3 - Energy optimization flowchart.

The pseudo-code is given below

Algorithm 1 Optimization script

```
for each run do
    for each frequency do
        run the EA
        save the results (E_max, c_opt, k_opt, ω_φ_opt) for the given frequency
    end for
    save the results for the current iteration, for all the considered frequencies
end for
calculate means and standard deviations of the results among all the runs
```

The GA hyper-parameter are chosen according to Literature, experience and tests on the problem at hand. They are reported in Tab. 4.1:

Parameter	**Value**
MaxGen	300.00
PopSize	50.00
CrossFract	0.80
MutFract	f(MaxGen)
EliteCount	3.00

Table 4.1. GA hyper-parameters.

MaxGen is the maximum number of generations, *PopSize* is the population size, *CrossFract* and *MutFract* are the percentage of the population which is subject to Crossover and the percentage of the population which is subject to Mutation, respectively; *EliteCount* is the number of elite individuals in the population.

The GA has been run 20 times for averaging results, due to the stochastic nature of the optimization algorithm. The optimal figures of the transducted energy E_{max} and the ISWEC parameters c_{opt}, k_{opt} and $w_{\phi opt}$ are shown in Tab. 4.2.

Parameter	**Average value**
MaxGen	0.92
PopSize	1.30
CrossFract	0.80
MutFract	f(MaxGen)
EliteCount	3.00

Table 4.2. Average and maximum percentage standard deviations over 20 iterations of the optimization script.

4.2 Synthesis of an EMS for a Full-Electric Boat by a FIS-HGA Algorithm

In this work, the optimal energy management for a full-electric boat with a PV roof and an energy storage has been performed. It is an application of the FIS-HGA algorithm, which has been tested on this occasion.

The full-electric boat is "Valentino" class e-boat, designed by POMOS Research center (Pole for Sustainable Mobility - Cisterna di Latina, Italy). Since it is equipped with a PV roof and a battery and also it could be charged when docked, it can be represented a small-scale electric grid, i.e. a nanogrid (Fig. 4.4).

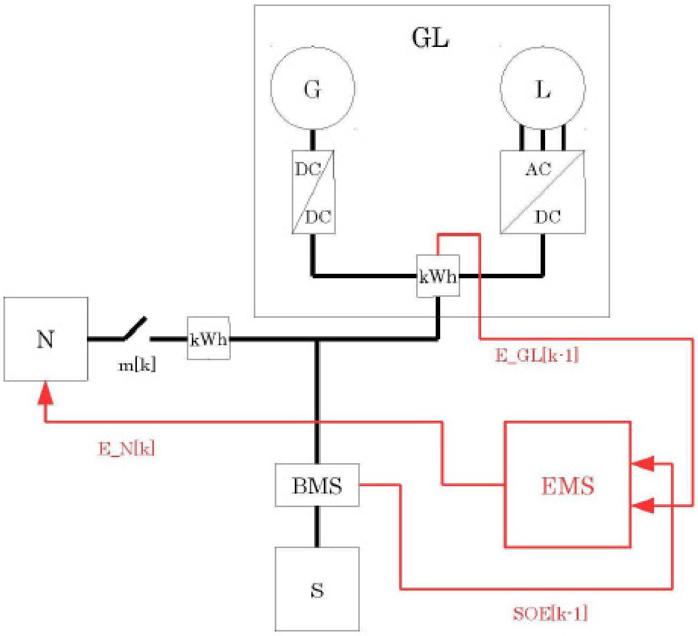

Figure 4.4 - The e-boat MG architecture.

With reference to the figure above, the square nodes represent the Main Grid (on the dock) N and the battery S, which can exchange energy in both directions. In other words, N and S can absorb but also provide energy to the other nodes of the nanogrid, although not at the same time. These quantities are E_k^N and E_k^S , respectively. The circular nodes represent the PV roof generator G and the load (i.e. the e-boat motor) L, which can only provide and absorb energy, respectively. Appropriate DC/DC and AC/DC converters are accounted, together with energy meters. The Energy Management System (EMS) is in charge of computing the system inputs offline, which are the energy balance between G and L nodes in the current timeslot $E_{GL\ k-1}$ and the State of Energy of the battery in the same timeslot SOE_{k-1}, provided by a Battery Management System (BMS). The EMS output is the amount of energy to exchange with the node N, in the next timeslot k. The value of binary variable m_k represents the presence/absence of connection to the Main Grid, when the e-boat is docked.

The EMS optimized energy flows in the Microgrid with the aim of minimizing the battery stress, in operation. The problem formulation is the following:

$$\min_{P_k^S} \frac{1}{n} \sum_{k=1}^{n} P_k^S \tag{4.13}$$

with

$$E_k^S + E_k^N m_k + E^{GL} = 0 \tag{4.14}$$

$$E_k^S \leq E_k^{S,MaxDischarge} = 0 \tag{4.15}$$

$$E_k^S \geq -E_k^{S,MaxDischarge} = 0 \tag{4.16}$$

$$E_k^{S,MaxDischarge} = SOE_k E_{max}^S \tag{4.17}$$

$$E_k^{S,MaxCharge} = (1 - SOE_k) E_{max}^S \tag{4.18}$$

$$E_{max}^S = V_{nom}^S I_{max}^S dt \tag{4.19}$$

$$P_k^S = f(SOE_k) = \left(\frac{SOE_k - SOE_{opt}}{SOE_{opt}} \right)^{12} \tag{4.20}$$

where P_k^S is the battery stress penalty function; $E_k^{S,\mathrm{Max}\,Discharge}$ is the maximum amount of energy that can be provided by the battery to the other nodes, in the timeslot k; $E_k^{S,\mathrm{Max}\,Charge}$ is the maximum amount of energy that can be absorbed by the battery, in the timeslot *k*; E_{max}^S is the maximum amount of energy that can be exchanged by the battery, in the timeslot *k*, according to its nominal voltage V_{nom}^S, its maximum current I_{max}^S and the BMS sampling period δt; n is the total number of timeslots considered in the simulation.

The battery penalty function is designed to be high as much as the SOE is far from 0.5 (half charge), as shown in Fig. 4.5:

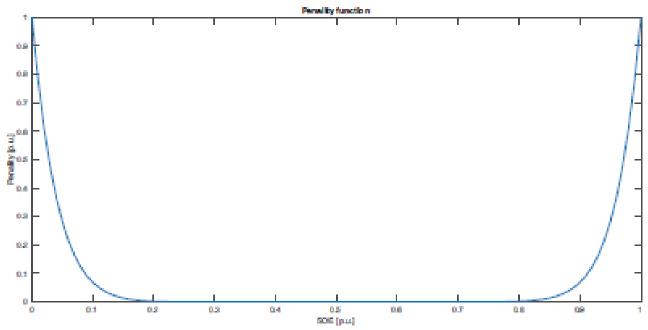

Figure 4.5 - The battery penalty function.

The optimization process is the EMS computational core and it is make thanks the HGA. To be precise, a FIS in encoded in each HGA individual so that the latter in charge of finding the best FIS which fullfills the OF minimzation.

The FIS is encoded as follows:

- The first 10 binary genes represent the presence or the absence of a Membership Function (MF) in the two input Term Sets. The number of these genes is the product between the number of MFs in a Term Set and the number of inputs;
- The next 39 real genes encode the vertices abscissas of all the input and output MFs. All the abscissas can be tuned, except the ones outside the Universe of Discourse (Fig. 26). The number of these genes is the product between the tunable abscissas of each input and output Term Sets and the total number of inputs and outputs of the FIS;
- The next 25 real genes encode the rule weights;
- The last 25 integer genes represent the MFs from the output Term Sets (each rule must have only one MF, in as a consequent).

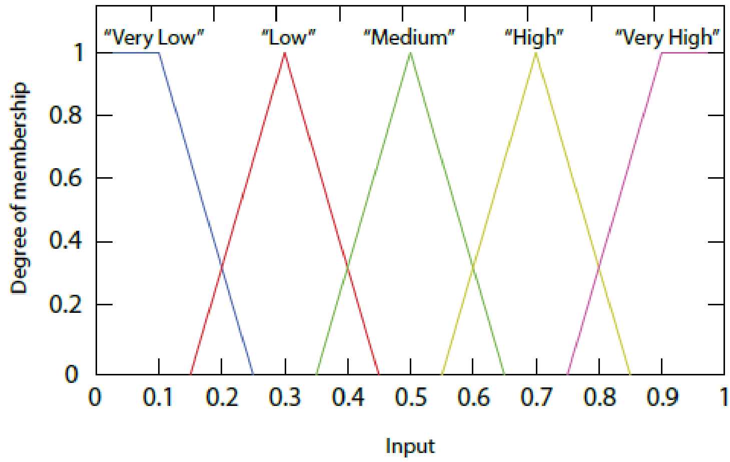

Figure 26. The Term Set for EMS inputs and outputs.

The optimization process consists in two subsequent steps. During the first optimization, the HGA tunes the FIS rule base. In this phase, only the first 10 binary genes of the generic individual evolve through generations, while the OF is minimized. If the *i-th* gene is set to 0, this means that the *i-th* MF in the set of the whole inputs MFs (from the first to the last input) is deleted. As a consequence, each rule enclosing the i-th MF as antecedent is deleted from the rule set. Thus, the first optimization aims at reducing the number of rules by selecting the most relevant ones for the problem at hand. It is worth mentioning that, when a MF is deleted, the vertices abscissas of the remaining adjacent MFs are modified in order to cover the entire Universe of Discourse (Fig. 4.6).

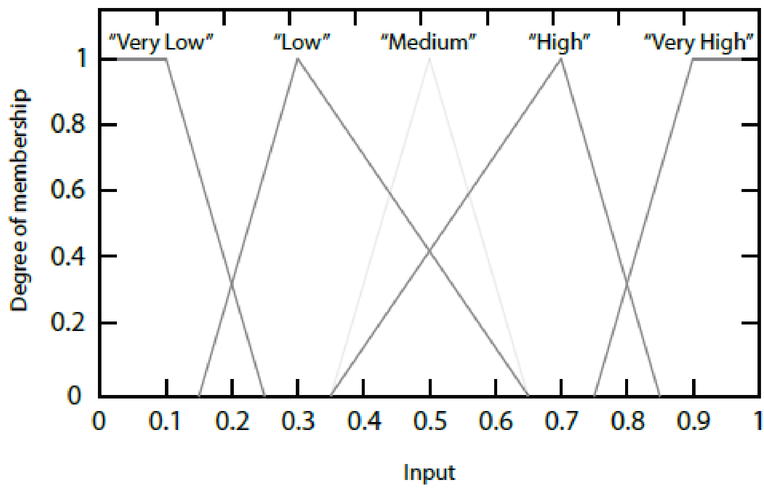

Figure 4.6. Universe of Discourse coverage
after deleting a MF (in this case, the central one).

During the second optimization, the rest of genes of the generic individual evolve over generations, meaning that the FIS parameters (MFs vertices abscissas and rule weights) and the consequent are tuned, while the OF is minimized. Only the genes related to the rule base coming from the first optimization are tuned. In this sense, the first binary genes are at an higher hierarchical level than the others, making the GA hierarchical.

The FIS-HGA results are compared with the output of a Convex Optimization tool(CVX), as a benchmark test for the Computational Intelligence algorithm.

As a reference value for assessing the FIS-HGA effectiveness, the RMSEP is adopted both for E^N and SOE figures, in the simulation time lapse (one day). In Tab. 4.3, the abovementioned figures together with the optimum (minimum) value of the OF, returned from the FIS-HGA and the CVX algorithm are reported:

Opt. OF p.u.	**Sub Opt. OF p.u.**	**EN err. [%]**	**SOE err. [%]**
3.7E-08	5.8E-08	4.56	4.79

Table 4.3. FIS-GA results.

Results show that the FIS-GA has good performance, being the percentage error reasonably low and the OF optimum value very close the true (CVX) optimum.

4.3 Performance comparison with a single-step optimization

Results for both single and double optimization FIS-GA, over 5 executions, are shown in Tab. 4.4.

Figure	Single optimization (var)	Double optimization (var)
OF	6.445E-08 (1.355E-16)	7.328E-08 (9.979E-18)
Computation time	7.442E+03 (9.131E+06)	8.013E+03 (1.673E+06)

Table 4.4 - FIS-GA results, for single and double optimization.

With a double optimization, the FIS-GA returns an average output that is about 13% worst, compared to a single optimization. However, a double optimization leads to a more robust solution, with a lower variance than in a single optimization. The computation time with a double optimization is about 7.5% higher than the single optimization case.

4.4 Custom GA

A new custom GA has been written with the aim of achieving more efficient and effective results. The characteristics of the custom GA are the following:

- value encoding (real valued genes);
- population of 100 individuals;
- *Tournament* selection operator, with tournament size 2;
- *Convex* crossover operator;
- Crossover fraction 0.8;
- *Uniform* mutation operator;
- Mutation probability of 0.5;
- Both maximum stall generation limit (50) and maximum generations stopping conditions.

Preliminary tests in benchmark objective functions have returned good results. In particular, both effectiveness tests (with fixed maximum number of generations) and efficiency tests (with unlimited maximum number of generations - set to 10.000, in the code - and a suboptimal OF threshold to reach) have been performed. The GA run for 10 times per test (10 executions).

4.4.1 Effectiveness tests

Rastrigin benchmark function <u>Genes interval is [-5.12; 5.12]; optimum is 0 at (0,0)</u>	
Average solution	[-7.7E-09; 1.1E-09]
Variance of solutions	[6.7E-15; 8.4E-17]
Average optimal output	1.3E-12
Variange optimal output	2.7E-23
Average generations needed	150
Average time per execution	7.329
Average time per generation	0.048

Table 4.5 - Test results (a).

Rosenbrock benchmark function <u>Genes interval is [-2.048; 2.040]; optimum is 0 at (1,1)</u>	
Average solution	[0.994; 0.989]
Variance of solutions	[1E-04; 4.3E-04]
Average optimal output	1.4E-04
Variange optimal output	2.6E-07
Average generations needed	150
Average time per execution	7.385
Average time per generation	0.049

Table 4.6 - Test results (b).

Swefel benchmark function Genes interval is [-500; 500]; optimum is 0 at (420.9687, 420.9687)	
Average solution	[420.9687; 420.9687]
Variance of solutions	[2.1E-11; 1E-11]
Average optimal output	2.5E-05
Variange optimal output	2.5E-22
Average generations needed	150
Average time per execution	7.300
Average time per generation	0.048

Table 4.7 - Test results (c).

Griewank benchmark function Genes interval is [-600; 600]; optimum is 0 at (0, 0)	
Average solution	[0.228; 0.223]
Variance of solutions	[7.204; 7.205]
Average optimal output	0.0041
Variange optimal output	2.3E-05
Average generations needed	150
Average time per execution	7.378
Average time per generation	0.046

Table 4.8 - Test results (d).

4.4.2 Efficiency tests

Rastrigin benchmark function Genes interval is [-5.12; 5.12]; threshold is 2.8E-09	
Average generations needed	56.550
Average computation time	62.478

Table 4.9 - Test results (e).

Rosenbrock benchmark function Genes interval is [-2.048; 2.040]; threshold is 0.031	
Average generations needed	17.4
Average computation time	23.77

Table 4.10 - Test results (f).

Swefel benchmark function Genes interval is [-500; 500]; threshold is 2.75E-05	
Average generations needed	63.85
Average computation time	64.506

Table 4.11 - Test results (g).

Griewank benchmark function Genes interval is [-600; 600]; threshold is 4.1E-04	
Average generations needed	n.a.
Average computation time	n.a.

Table 4.12 - Test results (h).

CHAPTER 5 - Other Research activities: Design of a Sustainable Mobility System by a GA

In the context of sustainable development, a measure of life quality is needed. In fact, since sustainability implies a fair exploitation of resources, the latter comes from the need for a better and lasting life quality. Sustainable mobility is among of the sustainable development factors and in this work its impact on life quality is assessed. More precisely, the sustainable mobility system design solutions which make a city (Rieti) reach a life quality threshold are investigated, with an estimation of the related monetary costs.

5.1 Assumptions

For the sake of simplicity, a sustainable mobility system is seen as the overall number of means of transport per type and its running time. The "*Indice della Qualità della Vita 2019* (IQV 2019)" by "*Il Sole 24 Ore*", is the chosen city life quality index. The values of some parameters have been fixed according to the "*LIFE for Silver Coast*" European Project (LIFE project). The custom GA is used for exploring the domain of the potential solutions.

5.2 Mobility system encoding

The generic mobility system *s* is a vector of numbers, defined by Eq. 5.1.

$$s = [n_{e-bus}, n_{e-car}, n_{e-scooter}, n_{e-bike}, t] \quad (5.1)$$

where $n_{e\text{-}bus}$, $n_{e\text{-}car}$, $n_{e\text{-}scooter}$ and $n_{e\text{-}bike}$ are the number of e-buses, e-cars, e-scooters and e-bikes, respectively; *t* is the running time.

5.3 Indicators selection and estimation

Among the indicators used for the calculation of the IQV 2019 index [1], only one of them has been selected to be estimated. In fact, considering the indicators etherogeneity, not all the necessary input data are available. Insted, the selected indicator is estimated thanks to an appropriate formula and the abovementioned data. The indicator *Offerta del Trasporto Pubblico*, in the *Ambiente e Servizi* category, is the chosen indicator. It measures the traveled distance trough public transport. The introduction ofa sustainable mobility system leads to a delta in the value of *Offerta del Trasporto Pubblico*:

$$\Delta I_{ot} = \frac{(v_{e-bus}n_{e-bus} + v_{e-car}n_{e-car} + v_{e-scooter}n_{e-scooter} + v_{e-bike}n_{e-bike})\,t}{n_{cit}\,n_m} \quad (5.2)$$

where ΔI_{ot} the *Offerta del Trasporto Pubblico* delta, in km/(means · inhabitant); $v_{e\text{-}bus}$, $v_{e\text{-}car,}$ $v_{e\text{-}scooter}$ e $v_{e\text{-}bike}$ are the average operating speeds of e-buses, e-cars, e-scooters and e-bikes respectively, in km/h; $n_{e\text{-}bus}$, $n_{e\text{-}car}$, $n_{e\text{-}scooter}$ and $n_{e\text{-}bike}$ are the number of e-buses, e-cars, e-scooters and e-bikes, respectively; *t* is the mobility system running time, in; n_{cit} is the total number of inhabitants; n_m is the sum of all the means of transport in the mobility system, given by Eq. 5. 3:

$$n_m = n_{e-bus} + n_{e-car} + n_{e-scooter} + n_{e-bike} \quad (5.3)$$

The average speeds are taken from the *Report sulla Mobilità in Italia 2018* by *Osservatorio Audimob* about Italians mobility - Istituto Superiore di Formazione e Ricerca per i Trasporti (ISFORT) [2], and more precisely, they are average speeds of urban travel, for 2017. The above figures are calculated *"[...] on the base of time and distances indicated by respondents, for each "* - *Audimob*.

The above figures are reported in Tab 5.1.

AVERAGE SPEED	**VALUE [km/h]**
$v_{e\text{-}bus}$	14,3
$v_{e\text{-}car}$	23,4
$v_{e\text{-}scooter}$	25,2
$v_{e\text{-}bike}$	11,4

Table 5.1. Average speeds of the means of transport in the mobility system.

Thus, the *Offerta del trasporto pubblico* indicator is calculated as follows:

$$I_{ot} = \Delta I_{ot} + I_{ot_0} \quad (5.4)$$

where I_{ot0} is the initial value of *Offerta del trasporto pubblico* for the chosen city, i.e. before the introduction of the mobility system.

5.3 Calculating the IQV 2019

The regression line between IQV 2019 and *Offerta del Trasporto Pubblico* (Fig. 28) is determined, thanks to the 107 Provincial capitals data, published by "Il Sole 24 Ore" [1]. It is assumed that, beyond the indicator *Offerta del Trasporto*, the other indicators the IQV 2019 is based on will be modified once the transport system in introduced.

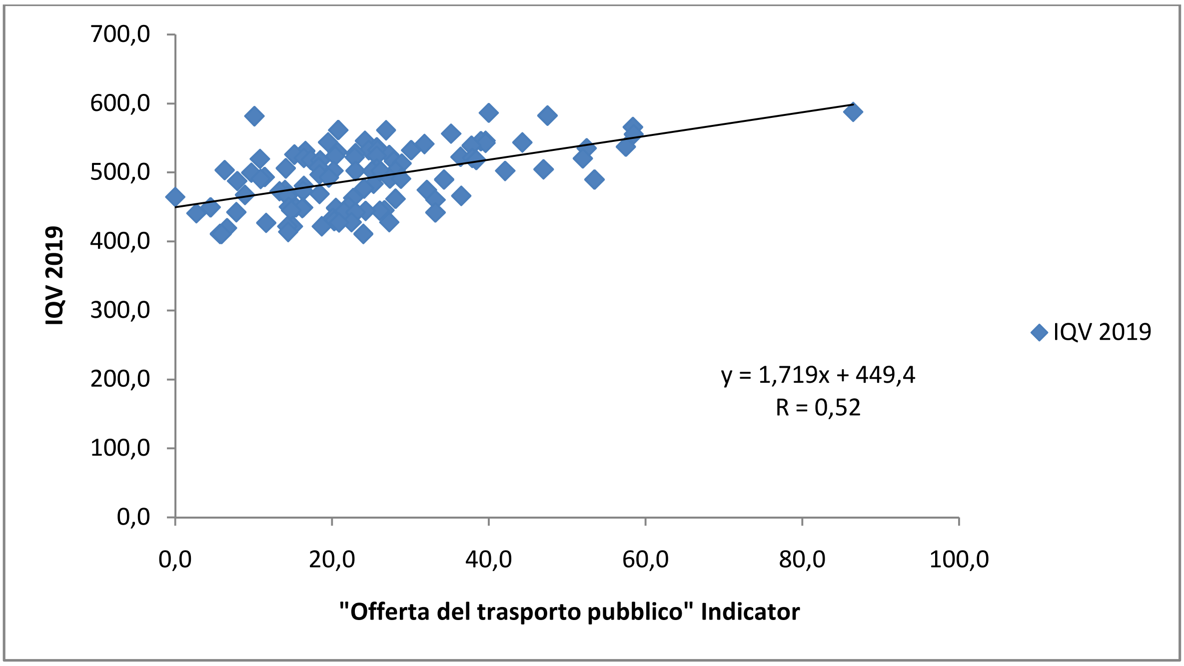

Figura 28. Retta di regressione per il calcolo dell'IQV 2019.

The Correlation Coefficent R is about 0,52. The equation of the regression line is the following:

$$IQV\ 2019 = 1{,}179 \cdot I_{ot} + 449{,}4 \tag{5.5}$$

5.4 Cost of the mobility system

Fixed costs come from the manufacturer (Tab. 5.2). Based on the experience of LIFE, it is assumed that the charge station for cars is the same of the charge station for ebikes. [4].

Unit	Cost [€]	Model	Manufacturer
e-bus	39.521	E-NV 200 Evalia [5]	Nissan
e-car	25.900	Zoe LIFE [6]	Nissan
e-scooter	3.950	VX-2 [7]	Moto.it
e-bike	439	Tender 20 21V [8]	Atala
Charge station	3.350	EVlink Parkplatz 2 (2x22 kW) [9]	Shneider Electric

Table 5.2. Mobility system's costs.

The cost of the mobility system is calculated as follows:

$$C = n_{e-bus} \cdot c_{e-bus} + n_{e-car} \cdot c_{e-car} + n_{e-scooter} \cdot c_{e-scooter} + n_{e-bike} \cdot c_{e-bike} + n_{ch} \cdot c_{ch} \tag{5.6}$$

where C (€) is the overall cost, $c_{e\text{-}bus}$, $c_{e\text{-}car}$, $c_{e\text{-}scooter}$, $c_{e\text{-}bike}$ e c_{ch} are the costs of one e-bus , on e-car, one e-scooter, one e-bike and one charging station, respectively; n_{ch} is the number of charging station, calculated as follows:

$$n_{ch} = \frac{n_m \cdot n_{ch(LIFE)}}{n_{m(LIFE)}} \tag{5.7}$$

with $n_{ch(LIFE)}$ and $n_{m(LIFE)}$ the number of charging stations and of means of transport in the LIFE (13 and 116, respectively). It is assumed that the relation between the number of vehicles and the number of charging stations is linear.

5.5 Objective function

The objective function is the following:

$$OF = \frac{1}{2}(IQV\ 2019 - M)^2 \tag{5.8}$$

with the average IQV 2019 of Lazio Region M of about 473.7.

5.6 Results

The GA runs for 10 times returning the results in Tab. 5.3. To sum up, the solution is a Mobility System which consists of 47 e-buses, 56 e-cars, 45 e-scooters and 55 e-bikes, connected with 23 charging stations, which will cost about 2,2 M €.

E-buses p.u.	**E-cars p.u.**	**E-scooters p.u.**	**E-bikes p.u.**	**Ch. stations p.u.**	**Running time [years]**	**Cost [€]**
47	56	45	55	23	3	2.281.832

Table 5.3 - GA results.

CONCLUSION

A FIS-GA algorithm for Microgrids energy optimization has been synthesized. In addition, a custom GA has been designed and tested against the most widespread benchmark objective functions, showing reasonably good results, if compared to a Matlab GA in a standard configuration. The custom GA has been applied to a mobility system design problem, coherently with the application field, represented by the LIFE for Silver Coast Project Both a single and a double optimization approaches have been explored. Although the latter guarantees a robust solution, the former offers more effectiveness (about 13% more than double optimization) and a lower computational cost.

It could be interesting to improve the optimization process by further developing the presented custom GA, since it returns promising results. More precisely, new tests with the double optimization approach could be carried on for achieving the effectiveness of the single optimization approach but maintaining the solution roboustness.

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