Universidad de Alcalá
COMISIÓN DE ESTUDIOS OFICIALES DE POSGRADO Y DOCTORADO

ACTA DE EVALUACIÓN DE LA TESIS DOCTORAL

Año académico 2017/18

DOCTORANDO: **PINO GONZÁLEZ, JUAN MIGUEL DEL**
D.N.I./PASAPORTE: ******7150Z**

PROGRAMA DE DOCTORADO: **D445-TECNOLOGÍAS DE LA INFORMACIÓN Y LAS COMUNICACIONES**
DPTO. COORDINADOR DEL PROGRAMA: **TEORÍA DE LA SEÑAL Y LAS COMUNICACIONES**
TITULACIÓN DE DOCTOR EN: **DOCTOR/A POR LA UNIVERSIDAD DE ALCALÁ**

En el día de hoy 22/05/18, reunido el tribunal de evaluación nombrado por la Comisión de Estudios Oficiales de Posgrado y Doctorado de la Universidad y constituido por los miembros que suscriben la presente Acta, el aspirante defendió su Tesis Doctoral, elaborada bajo la dirección de **LUCAS CUADRA RODRÍGUEZ.**

Sobre el siguiente tema: *SOFT COMPUTING APPROACHES IN OCEAN WAVE HEIGHT PREDICCTION FOR MARINE ENERGY APPLICATIONS*

Finalizada la defensa y discusión de la tesis, el tribunal acordó otorgar la CALIFICACIÓN GLOBAL[1] de (**no apto, aprobado, notable y sobresaliente**): SOBRESALIENTE

Alcalá de Henares, 22 de Mayo de 2018

EL PRESIDENTE
Fdo.: ....

EL SECRETARIO
Fdo.: Sancho Salcedo

EL VOCAL
Fdo.: Carlos Casanova

Con fecha 11 de junio de 2018 la Comisión Delegada de la Comisión de Estudios Oficiales de Posgrado, a la vista de los votos emitidos de manera anónima por el tribunal que ha juzgado la tesis, resuelve:

- ☐ Conceder la Mención de "Cum Laude"
- ☒ No conceder la Mención de "Cum Laude"

La Secretaria de la Comisión Delegada

FIRMA DEL ALUMNO,

Fdo.: ....

UNIVERSIDAD DE ALCALÁ, PATRIMONIO DE LA HUMANIDAD

[1] La calificación podrá ser "**no apto**" "**aprobado**" "**notable**" y "**sobresaliente**". El tribunal podrá otorgar la mención de "cum laude" si la calificación global es de sobresaliente y se emite en tal sentido el voto secreto positivo por unanimidad.

INCIDENCIAS / OBSERVACIONES:

NO HAY

Universidad de Alcalá

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En aplicación del art. 14.7 del RD. 99/2011 y el art. 14 del Reglamento de Elaboración, Autorización y Defensa de la Tesis Doctoral, la Comisión Delegada de la Comisión de Estudios Oficiales de Posgrado y Doctorado, en sesión pública de fecha 11 de junio, procedió al escrutinio de los votos emitidos por los miembros del tribunal de la tesis defendida por *PINO GONZÁLEZ, JUAN MIGUEL DEL*, el día 22 de mayo de 2018, titulada *SOFT COMPUTING APPROACHES IN OCEAN WAVE HEIGHT PREDICCTION FOR MARINE ENERGY APPLICATIONS*, para determinar si a la misma se le concede la mención "cum laude", arrojando como resultado, 3 votos en contra.

Por lo tanto, la Comisión de Estudios Oficiales de Posgrado **resuelve no otorgar la Mención de "cum laude"** a dicha Tesis.

Alcalá de Henares, 12 de junio de 2018

EL VICERRECTOR DE INVESTIGACIÓN Y TRANSFERENCIA

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Copia por e-mail a:

Doctorando: PINO GONZÁLEZ, JUAN MIGUEL DEL

Secretario del Tribunal: SANCHO SALCEDO SANZ

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Servicio de Estudios Oficiales de Posgrado

DILIGENCIA DE DEPÓSITO DE TESIS.

Comprobado que el expediente académico de D./Dª JUAN MIGUEL PINO GONZÁLEZ reúne los requisitos exigidos para la presentación de la Tesis, de acuerdo a la normativa vigente, y habiendo presentado la misma en formato: ☒ soporte electrónico ☐ impreso en papel, para el depósito de la misma, en el Servicio de Estudios Oficiales de Posgrado, con el nº de páginas: 170 se procede, con fecha de hoy a registrar el depósito de la tesis.

Alcalá de Henares a 19 de diciembre de 2017

PURIFICACIÓN REVIEJO

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Dr. D. LUCAS CUADRA RODRÍGUEZ, Profesor Titular de Universidad del Área de Conocimiento de Teoría de la Señal y Comunicaciones de la Universidad de Alcalá,

CERTIFICA

Que la tesis "**Soft Computing approaches in ocean wave height prediction for marine energy applications**", presentada por D. Juan Miguel del Pino González, realizada en el Departamento de Teoría de la Señal y Comunicaciones bajo mi dirección, reúne méritos suficientes para optar al grado de Doctor, por lo que puede procederse a su depósito y lectura.

Alcalá de Henares, 14 de diciembre de 2017.

UNIVERSIDAD DE ALCALÁ * DPTO. DE TEORÍA DE LA SEÑAL Y COMUNICACIONES

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D. Juan Miguel del Pino González ha realizado, en el Departamento de Teoría de la Señal y Comunicaciones, y bajo la dirección del doctor D. Lucas Cuadra Rodríguez, la tesis doctoral titulada "**Soft Computing approaches in ocean wave height prediction for marine energy applications**", cumpliéndose todos los requisitos para la tramitación que conduce a su posterior lectura.

Alcalá de Henares, 14 de diciembre de 2017.

EL COORDINADOR DEL PROGRAMA DE DOCTORADO EN TECNOLOGÍAS DE LA INFORMACIÓN Y LAS COMUNICACIONES (D445)

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Universidad de Alcalá

Escuela Politécnica Superior

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Doctorate Thesis

Soft Computing approaches in ocean wave height prediction for marine energy applications

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A mi madre, Marichari, por su continuo apoyo en todo lo que suponga un aprendizaje.

A mis hijos, Ramiro, Carlota y Jimena, por el continuo desafío que supone tratar de enseñar y descubrir que eres tú quién tiene que aprender.

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A Lucas Cuadra, por su constante ayuda y motivación para la culminación de esta tesis.

Resumen

Entre todas las energías marinas disponibles, la energía de las olas (undimotriz) es la que exhibe el mayor potencial futuro porque, además de ser eficiente desde el punto de vista técnico, no causa problemas ambientales significativos. Su conversión eficiente se basa en una considerable variedad de convertidores "WECs" (*wave energy converters*), que transforman la energía cinética de las olas en energía eléctrica mediante la oscilación vertical de las olas o el movimiento lineal de éstas. Su importancia práctica radica en dos hechos: 1) es aproximadamente 1000 veces más densa que la energía eólica, y 2) hay muchas regiones oceánicas con fuertes recursos de olaje que están cerca de zonas muy pobladas que demandan energía eléctrica.

La contrapartida negativa se encuentra en que las olas son más difíciles de caracterizar que las mareas debido a su naturaleza estocástica. Tal caracterización puede llevarse a cabo esencialmente a través de dos familias de técnicas: modelos físicos y enfoques basados en datos. Los modelos físicos se basan en la ecuación del balance de energía de las olas, una ecuación diferencial que se resuelve numéricamente. Son más precisos en la predicción de grandes dominios espaciales y temporales (dentro de una ventana de unos pocos días) pero a costa de requerir una gran cantidad de datos y esfuerzo computacional. Este no es el caso del segundo grupo de técnicas. Estas se basan en series de datos medidas por boyas, radares o satélites, y abarcan desde métodos estadísticos convencionales (como ARMA) hasta enfoques de *Soft Computing* (SC) (métodos neuronales, difusos y evolutivos). Las técnicas SC exhiben resultados similares e incluso superiores a los de los métodos estadísticos en las estimaciones a corto plazo (hasta 24 h), y tienen la ventaja adicional de requerir un esfuerzo computacional mucho menor que los métodos numérico-físicos. Esta es una de las razones por la que hemos decidido explorar el uso de técnicas de SC en energía undimotriz. La otra se encuentra en el hecho de que su intermitencia puede afectar a la forma en la que se integra con la red eléctrica.

Estas dos son las razones que nos han impulsado a explorar la viabilidad de nuevos enfoques de SC en dos líneas concretas de investigación en energía undimotriz.

En la primera línea de investigación, hemos abordado el problema de reconstruir un parámetro importante utilizado en la energía de las olas llamado "altura de ola significativa", H_s. Específicamente, nos hemos centrado en un tipo de problema que consiste en reconstruir H_s en la ubicación de una boya de medición (fuera de operación y cuyas medidas se han perdido) mediante el uso de parámetros del oleaje

medidos en otras boyas cercanas. Esta situación es bastante común en ciertas ocasiones en las que, debido a una tormenta u otro tipo de accidente, se destruye o desactiva una boya, de modo que se pierden los datos de las olas que se tenían que medir con dicha boya y en esa ubicación particular. Los datos en las boyas cercanas se pueden usar para reconstruir los datos "perdidos" de la boya dañada. Esta reconstrucción es importante porque, como se ha mencionado, H_s, juega un papel clave en el diseño y operación de los WEC. Nos hemos enfrentado al problema de rellenar los huecos o valores perdidos de H_s en el marco del aprendizaje automático (*Machine Learning*, ML), en un proceso de dos pasos, que ha dado lugar a dos contribuciones. El primero consiste en diseñar un algoritmo evolutivo híbrido que selecciona, entre los parámetros de oleaje disponibles (de las boyas cercanas), un subconjunto más pequeño $\mathcal{F}_{n_{SP}}$ con n_{SP} parámetros que minimiza el error de reconstrucción. Para hacer esto, hemos propuesto un enfoque novedoso en aplicaciones de energía marina que consiste en un Algoritmo Genético (GA: *Genetic Algorithm*) que calcula la aptitud de los individuos candidatos (soluciones de prueba) en cada generación mediante el uso de una Máquina de Aprendizaje Extremo (ELM: *Extreme Learning Machine*). En este contexto, la ventaja clave de las ELMs cuando se comparan con otros enfoques (redes neuronales o máquinas de vectores de soporte, por ejemplo) es que las ELM aprenden muy rápido, lo cual es esencial en algoritmos evolutivos basados en poblaciones, como los GAs. Esa es precisamente la razón por la que hemos hibridado la ELM con el GA en detrimento de otros regresores alternativos. El método GA-ELM híbrido propuesto genera un subconjunto $\mathcal{F}_{n_{SP}}$ de n_{SP} parámetros que minimiza el error cuadrático medio (RMSE) de la reconstrucción H_s, RMSE($\hat{H}_s$) (m). Para valorar la viabilidad del algoritmo en condiciones de oleaje distintas hemos explorado dos casos de estudio: uno en el Mar Caribe, y el otro, en la costa atlántica oeste cerca de Florida. Los resultados sugieren que, en ambos casos, el método funciona muy bien, seleccionando 5 parámetros (entre los 60 disponibles) y consiguiendo errores pequeños: RMSE($\hat{H}_s$) < 0.5 m en el mar Caribe, y RMSE($\hat{H}_s$) < 0.75 m en el Atlantico Oeste.

La segunda línea de investigación explorada en esta Tesis ha sido motivada debido a la existencia de dos problemas mutuamente vinculados. El primero está relacionado con la forma en que los WECs deben estar conectados eléctricamente entre sí (formando un parque de WECs) para suministrar suficiente energía eléctrica. El segundo aspecto está relacionado con la forma de conectar eficientemente el parque de WECs con la red eléctrica en la costa. Esto se debe a que la variabilidad e intermitencia de la energía de las olas puede afectar la estabilidad de la red eléctrica. Este segundo problema se puede englobar dentro de un marco conceptual más amplio, que es común a todas las energías renovables masivas (RE). En este marco más amplio, el paradigma Smart Grid (SG) permite integrar el creciente número actual de generadores distribuidos basados en energía renovables, sin afectar significativamente la estabilidad de la red eléctrica. La novedad de nuestro enfoque es doble, en el sentido de optimizar la robustez de la SG (nodos de conexión que generan, consumen o almacenan electricidad) contra "condiciones de funcionamiento anormales" –por ejemplo, el fallo o la rotura de un WEC (o un conjunto de ellos) causado por una tormenta– por (1) usar un Algoritmo Evolutivo (EA) que optimiza la estructura de la SG modelada mediante (2) la aplicación de conceptos de la Ciencia de Redes Complejas (CN).

Nuestro enfoque aprovecha algunas propiedades importantes del paradigma SG: una red inteligente permite el intercambio bidireccional de energía eléctrica a escala local, mediante la integración eficiente de generadores RE distribuidos utilizando tecnologías de comunicación y detección inteligente. Gracias a la integración eficiente de RE distribuidas en la red, los consumidores de electricidad también pueden convertirse en productores ("*prosumers*"), ayudando a los usuarios finales a obtener beneficios económicos vendiendo la energía generada en exceso. En una abstracción similar, un *Smart Wave Farm* (SWF), formado por WECs y dispositivos de almacenamiento de energía, se puede ver como un conjunto de nodos que intercambian energía eléctrica a escala local. En este contexto, hemos modelado la SG como un grafo no dirigido de modo que cada enlace (cable eléctrico) permite el intercambio bidireccional de energía eléctrica entre los nodos.

Con el objetivo de optimizar la estructura de dicho SG contra condiciones anormales, hemos propuesto una nueva función objetivo (que debe minimizarse) que combina elementos de coste, relacionados con la cantidad de cables eléctricos y varias medidas que cuantifican las propiedades que son beneficiosas para el SG (intercambio de energía a escala local y alta robustez y resiliencia). La estructura optimizada de la SG se obtiene aplicando un EA en el que el cromosoma que codifica cada grafo potencial (o individuo) es la matriz triangular superior de su matriz de adyacencia. Esto permite adaptar completamente los operadores de cruce y mutación a dicha codificación. Dado que se ha descubierto que las redes *small world* son beneficiosas para las SGs, hemos propuesto una población inicial específica que incluye redes aleatorias y redes *small world*. Esto ayuda al EA propuesto a converger rápidamente. El trabajo experimental señala que el método propuesto funciona bien y genera una estructura óptima, sintética, no dispersa, de tipo *small world*, que conduce a propiedades beneficiosas tales como la mejora tanto del intercambio de energía a escala local como de la robustez y resiliencia. Específicamente, la topología óptima cumple un equilibrio entre coste moderado y suficiente robustez frente a condiciones anormales.

Extended Abstract

Among all the available marine energies, wave energy is the most used because, in addition to being efficient from a technical viewpoint, it does not cause significant environmental problems. Its efficient conversion is based on a variety of wave energy converters (WECs), which transform the kinetic energy of waves into electric energy by means of either the vertical oscillation of waves or the linear motion of waves. Its practical importance lies in two facts: 1) it is about 1000 times denser than wind energy, and 2) there are many ocean regions with strong wave resources that are near populated zones demanding electric energy.

The counterpart is that waves are more difficult to characterize than tides because of the stochastic nature of waves (although they are less variable on an hourly basis than wind). Such characterization can be carried out essentially through two families of techniques: physical models and data-driven approaches. Physical models are based on the wave energy balance equation, a differential equation which is solve numerically. They are more accurate in forecasting over large spatial and temporal domains (within a window of a few days) but at the expense of requiring a huge amount of data and computational effort. This is not the case of data-driven models. These are based on data series measured by buoys, radars, or satellites. Data-driven models involve statistical regressive methods (such as auto regressive moving average) and Soft Computing (SC) approaches (neural, fuzzy, and evolutionary methods). SC techniques exhibit similar and even superior results than statistical methods in short term estimations (up to 24 h), and have the additional bonus of requiring much smaller computational cost than numerical-physical methods.

Furthermore, the intermittency suffered by massive renewable energies (mainly solar, wind and wave energies), in general, and wave energy, in particular, is another problem that must be tackled in the effort of efficiently integrating wave energies in the electricity network (or power grid).

These are the reasons that have compelled us to explore the feasibility of novel SC approaches in wave energy applications. Specifically, in this thesis we have focused on two research lines with applications in wave energy and its integration in the power grid.

In the first research line we have centered on characterizing the wave energy resource. In particular, we have tackled a problem of reconstructing an important parameter used in wave energy called "significant wave height", H_s. Specifically, we have focused on a kind of problem which consists in reconstructing the significant wave height H_s at the location of an out-of-operation measuring buoy by using wave parameters from other nearby buoys. This situation is quite common in certain occasions in which, due to a storm or other type of accident, a buoy is destroyed or deactivated, so that those wave data that had to be measured by such buoy at that particular location are lost. Data at near buoys can be used to reconstruct the missing data that had to be measured in the damaged buoy. This reconstruction is important because, as mentioned, H_s, plays a key role in the design and operation of WECs. We have faced the problem of filling up missing values of H_s within the framework of Machine Learning (ML), in a two-step process, which has led to two contributions. The first one consists in designing a hybrid evolutionary algorithm that selects, among the available wave parameters (from the nearby buoys), a smaller subset $\mathcal{F}_{n_{SP}}$ with n_{SP} parameters that minimizes the H_s reconstruction error. For doing this, we have proposed a novel approach in marine energy applications consisting of a Genetic Algorithm (GA) that computes the fitness of the candidate individuals (trial solutions) in each generation by using an Extreme Learning Machine (ELM). In this context, the key advantage of the ELM when compared to other ML approaches (Neural Networks, or Support Vector Machines, for instance) is that ELMs learn very fast, this being essential in population-based evolutionary algorithms such as GAs. This is why we have hybridized the ELM with the GA in the detriment of other alternative ML regressors. The proposed hybrid GA-ELM method generates a subset $\mathcal{F}_{n_{SP}}$ of n_{SP} parameters that minimizes the root mean square error of H_s reconstruction, RMSE($\hat{H}_s$)(m). In the effort of testing its performance in two different coastal regions, we have explored two case studies: one in the Caribbean Sea, and the other, in the West Atlantic coast nearby Florida. The results suggest that:

- The proposed GA-ELM algorithm works very well in the sense that it selects a very reduced subset of parameters ($n_{SP} = 10$ parameters) among the available 60 parameters. Using $5 \leqslant n_{SP} \leqslant 10$ parameters lead to small reconstruction errors: RMSE$(\hat{H}_s)_{\text{Caribbean}} \lesssim 0.50$ m, and RMSE$(\hat{H}_s)_{\text{Atlantic}} \lesssim 0.75$ m.
- The selected wave parameters in subset $\mathcal{F}_{n_{SP}}$ assist other ML regressors −Extreme Learning Machines, Support Vector Regression (SVR), and Gaussian Process Regression (GPR)− in reconstructing H_s. All the ML method explored have H_s reconstruction errors below 1m in the two different locations studied: RMSE($\hat{H}_s$) < 0.5 m in the Caribbean Sea, and RMSE($\hat{H}_s$) < 0.75 m in the West Atlantic scenario.

As a general conclusion, the twofold approach explored in our first publication seems to be a feasible tool to fill missing wave parameter values by using data from neighbor buoys.

The second research line explored in this Thesis has been motivated because of the existence of two mutually linked issues. The first one is related to the way in which the WECs must be electrically connected to each other (forming a WEC farm) to supply enough electrical energy. The second aspect is related to how to efficiently connect the WEC farm with the on-shore power grid. This is because the variability and intermittency of wave energy can affect the stability of the power grid. This second problem can be encompassed within a broader conceptual framework, which is common to all massive renewable energies (REs). In this wider framework, the Smart Grid (SG) paradigm aims at integrating the current growing number of distributed renewable energy-based generators, without significantly affecting the stability of the power grid. The novelty of our approach is twofold, in the sense of optimizing the robustness of a distribution SG (connecting nodes that generate, consume or store electricity) against "abnormal operating conditions" –for instance, the breakdown or the operation stop of a WEC (or a set of them) caused by a storm– by (1) using an Evolutionary Algorithm, (EA) that optimizes the structure of the SG modeled by (2) applying concepts from Complex Networks (CN) Science.

Our approach takes advantage of some important properties of the SG paradigm: a smart grid allows for the bidirectional exchange of electric energy at the local scale and aims at supplying reliable and safe electric power by efficiently integrating distributed RE generators using smart sensing and communication technologies. Thanks to the efficient integration of distributed REs in the grid, electricity consumers can also become producers ("prosumers"), helping end-users obtain economic benefits by selling the energy generated in excess. In a similar abstraction, a Smart Wave Farm (SWF), formed by WECs and energy storing devices, can be viewed as a set of nodes that exchange electric energy at local scale. In this context, we have modeled the SG as an undirected graph so that each link (electric cable) allows for the bidirectional exchange of electric energy between nodes.

Aiming at optimizing the structure of such SG against abnormal conditions, we have proposed a novel objective function (to be minimized) that combines cost elements, related to the number of electric cables, and several metrics that quantify properties that are beneficial for the SG (energy exchange at the local scale and high robustness and resilience). The optimized SG structure is obtained by applying an EA in which the chromosome that encodes each potential graph (or individual) is the upper triangular matrix of its adjacency matrix. This allows for fully tailoring the crossover and mutation operators to such encoding. Since small-networks have been found to be beneficial for SGs, we have proposed a domain-specific initial population that includes both random networks and small-world networks. This assists the proposed EA to converge quickly.

The experimental work points out that the proposed method performs well and generates an optimum, synthetic, non-sparse-like small-world structure that leads to beneficial properties such as improving both the energy exchange at the local scale and the robustness and resilience. Specifically, the optimum topology fulfills a balance between moderate cost and robustness against abnormal conditions.

We would like finally to emphasize two aspects of the second publication of this Thesis:

- The proposed approach should be considered as a high level analysis and planning tool in the effort of estimating to what extent the smart grid topology can suffer from vulnerabilities. It cannot and does not intend to replace the conventional methods used by power engineers. In fact, the low level, detailed design must be carried out using electrical engineering techniques.

- The model is sufficiently general to be applied to any set of generators and loads (consuming energy) as well as to the Smart Wave Farm system formed by WECs, energy storing devices, and the connection(s) to power grid.

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List of Acronyms

AC: Alternating Current

AI: Artificial Intelligence

ANFIS: Adaptive-Network-Based Fuzzy Inference System

AR: autoregressive model

ARMA: auto regressive moving average

ARIMA: auto regressive integrated moving average

ARPU: Average Revenue Per User

BA: Barabási and Albert

CAPEX: Capital Expenditure

CN: Complex Netwok

CPS: Cyber-Physical System

CRO: Coral Reefs Optimization

DC: Direct Current

DS: Distribution Systems

EA: Evolutionary Algorithm

EC: Evolutionary Computing

EE: Electrical Engineering

ER: Erdős–Rényi

EV: Electric Vehicles

FC: Fuzzy Computation

FIS: Fuzzy Inference System

FL: Fuzzy Logic

FLC: Fuzzy Logic Controller

FS: Fuzzy Set

GPR: Gaussian Process Regression

IoT: Internet of Things

$\mu-$**Gs:** Micro-grids

ML: Machine Learning

NC: Neural Computation

NOAA: National Oceanic and Atmospheric Administration

OTEC: Ocean thermal energy converters

PV: Photovoltaic

RBF: Radial Basis Function

RE: Renewable Energy

RMSE: Root Mean Square Error

RS: Rough Set

SC: Soft Computing

SG: Smart Grid

SWF: Smart Wave Farm

SWAN: Simulating WAves Nearshore

TS: Takagi-Sugeno

WS: Watts–Strogatz

WAM: Wave Analysis Model

Chapter 1

Motivation and introduction

1.1 Motivation

Currently, the global electricity sector is facing a large-scale transition, driven basically by three inter-related and mutually reinforcing trends, which are impacting on both the production and demand of electric energy [1]. The first one is the so-called "de-carbonization" trend, in the effort of reducing CO_2 emissions by increasing at a great extent the use of renewable energies [2] along with the electrification of the mobility sector [3]. The second driving force is the "digitalization". This is based on a variety of impressive advances, which combine great innovations in microelectronics, communications technologies and novel soft computing techniques [4]. Digitalization is allowing to put into practice the concepts of Internet of Things [5] and "smart grids" [6]. These assist in optimizing the integration of an ever increasing number of distributed renewable energy generators, which can locally exchange the energy they produce in excess with others nodes that consume it ("prosumers" –consumers and producers of energy–) [7]. The third point, related to the latter, is the "decentralization" [8, 9], caused by the growing number of distributed renewable energies, the advances in energy storage [10] and the aforementioned emerging use of smart grids.

Indeed, this profound transformation of the energy sector worldwide is an *unavoidable necessity*: one of the biggest challenges humanity is facing today is how to use energy not only efficiently but also environmentally friendly. This is because of its essential influence on economy [11], global warming [12, 13], climate change [14–19], and ecosystems [20, 21]. These points are stimulating great research efforts not only in renewable electric energy systems [22] –including their integration in electric networks ("power grids") [10, 23, 24] and their influence on the power grid resilience [25]– but also in the design of algorithms and procedures to estimate the potential and exploitability of primary energy sources [26–29]. Among renewable energies, wind energy [2, 30–32], solar energy [2, 33] (both thermal [34] and photovoltaic (PV) [35–38]), and solar photovoltaic-wind hybrid energy systems [39] are currently playing a key role. Wind and photovoltaic energy systems are attracting currently a huge interest from both the industrial and scientific communities [2, 30, 33], the latter being focused mainly on the search for novel energy converters [40–43].

In addition to renewable wind and solar energies, which are already being used in a massive way in many countries [2, 30, 33], other renewable energy sources that show a clear potential for sustainable growth are those based on *marine energy*. Marine or ocean energy refers to any energy obtained from oceans by means of ocean waves, tidal movements (rise and fall), ocean (permanent) currents, and temperature gradients [2]. Among all of them [44–49], the two energies that exhibit the greatest potential are wave energy [50] and tidal energy [51]. These do not generate CO_2 and are potentially able to transform part of the huge energy of oceans (80,000 TWh a year [52]) into electricity [53–57] and, as a consequence, to reduce oil imports, a critical geo-economical concern. These are the causes why many governments throughout the world, international institutions and companies are increasingly interested in the development and deployment of marine energy systems [58–62], and, in particular, in wave energy. The most representative examples of these scientific, technological and industrial interests are the European Commission [2], the Nordic Countries, Ireland and the UK, in which a number of public institutions and companies [62–64] are aiming at exploiting their tremendous wave energy resource [55, 57]. For instance, the total amount of wave energy in UK and Ireland is equivalent to approximately 50% of the total European wave energy resource [59]. The UK marine energy resource has the potential to provide about 20% of demanded electricity, preventing the yearly emission of 30 million tonnes of CO_2. The positive influence of marine energy on economy is increasingly [65]: more than 1500 people work in the marine energy sector of the UK, with almost £450 million economic value in the British industry [58]. Another illustrative examples in which marine energy can have a key role are *offshore islands*. This is because wave energy has the potential to provide the clean electric energy demanded without significant environmental impact, an important concern in offshore islands, committed to the protection of ecological systems [66]. In addition, wave energy has continued to progress very favorably in 2017 with novel pilot and demonstration projects in Spain, Sweden, the United States, the Republic of Korea and China [2]. For further details about the current situation of marine energy, the interested reader is referred to [2, 67–71].

The previous paragraphs suggest that the conversion of ocean energy into electricity could play a key role in meeting the rising worldwide energy demand, along with mitigating climate change, diversifying the energy supply and strengthening the economic activity in those countries with high marine energy potential [72]. However, as will be shown in the present chapter, only a small number of marine energy deployments are currently being operated commercially [2]. Some of the causes lie in the high costs of some marine technologies, the negative environmental impacts on ecosystems (modifying the natural movement of water, in the case of tidal energy), or the electric connection to the on-shore power grid without affecting its stability (in the case of wave energy, because of its stochastic and intermittent nature), among others. In fact, there are many important and challenging aspects from the technological and scientific point of view that remain to be solved and that should be studied [71]. Specifically, some recent interesting reviews focus on integrating wave energy at large-scales [73], strategies to reduce the cost of array of converters [74], the potential applications of small scale wave energy installations [75], the cost-based study of marine energy farms [44], the research on novel concepts for wave energy converters [53, 76–78], the durability and control of wave energy converters [79, 80], the modeling of ocean wave energy converters [81–83], storage prototypes for offshore wave and tidal energy systems [84], general aspects about the generation of electricity from oceans [71, 85–87], a novel methodology to estimate the long-term power performance of wave converters [88], related ecological issues [89, 90], the potential of a number of ocean regions worldwide to be exploited [70, 91–104], the combined use of wave and offshore wind energy [56], the economics of wave energy [45, 105], its social acceptance [46, 49], and political and legal aspects in the emerging marine energy industry [106].

Thus wave energy involves a good number of issues to be researched. Although wave energy systems do not suffer from the problem of affecting marine ecosystems they do have two different problems related mainly to 1) the prediction of wave phenomena, which have a stochastic nature, and 2) the effective connection to the electricity grid without appreciably affecting its quality. As will be shown in this thesis, these are the two problems the research carried out focuses on, by using novel approaches based on soft computing methods (for the first problem [107]), and a combination of soft computing, smart grids, and complex networks concepts (for the second one [108]). The question that arises now is why we have focused on wave energy to the detriment of others. This is just the purpose of the following section.

1.2 Introduction: Why wave energy?

Despite the vast potential of marine energy, not all available technologies to transform the different types of marine energies into electricity have the same efficiency, feasibility and applicability. This is because of the ever-growing importance of environmental concerns [89, 90], which along with economical [44, 45, 73, 109], social [46,49] and technical considerations [67–71] make the decision for one or another technology be sometimes complicated. These latter technical points are based on the *class of energy conversion* involved [51, 110].

In this respect, a marine energy technology may be feasible from a technical viewpoint [71], but *not adequate* from an ecological standpoint (for instance, if it adversely affects a coastal ecosystem) [111]. Regarding this, there are several technologies to transform ocean energy into electrical energy. Among them, the most important are wave energy conversion, tidal energy conversion, and ocean thermal energy conversion. Very briefly, these technologies consist of [71, 112]:

- Ocean thermal energy converter (OTEC) is a technology that takes advantage of the fact that there are some ocean regions with large temperature gradients ($>$ 15 degree Celsius) between the surface and waters less than 1 km deep [113–116]. Regions with this property are rather scarce, and thus, the contribution of ocean thermal energy is much smaller than that of tidal and wave energies. However, ocean thermal energy could be useful on a small scale in combination with other renewable energies. For instance, a novel multi-generation system based on an OTEC system combined with photovoltaic and thermal solar collectors and a reverse osmosis desalination unit has been proposed to produce desalinated water [71, 117].

- Tidal energy is a technology that is based on tidal flow and reflux. During rising tides, a barrier traps sea water, while, during low tides, such water accumulated by the barrier flows through a turbine, which generates electric power [51]. The problem is that it is only suitable for those ocean regions having high tides ($>$ 5 meters) [71]. Although this is a simple and feasible technology [118], however, their full-scale use could be *problematic* because of the potentially severe environmental impact of modifying tides and their related costal ecosystems [119]. See [71] for further details.

- Wave energy technology, however, does not cause significant environmental problems. Wave energy converters (WECs) transform the kinetic energy of wind-generated waves into electricity by means of either the vertical oscillation of waves or the linear motion of waves [110, 120, 121]. They exhibit some important advantages when compared to the other converters [120, 122, 123], namely: 1) WECs usually cause much lower environmental impacts on ecosystems than tidal devices; 2) There are ideal areas (in the sense of having considerable wave power density *near* populated regions demanding energy) in north and west coast of Europe (Norway, UK, Ireland, Portugal), north coast of US and Canada, southern cost of Australia, northern coast of New Zealand, Japan, and India [102]; 3) Wind-generated wave energy (hereafter, wave energy) is the densest renewable energy (about 1000 times more concentrated than wind energy) and is less changing on an hourly basis than wind energy [79]. More details about these and other beneficial properties of WEC-based technologies can be found in [47, 53, 54, 88, 111, 124–130].

Albeit wave energy exhibits the aforementioned advantages when compared to tidal energy, however, it suffers, in addition to the disadvantage of intermittency, the problem of being more difficult to characterize than tides because of the stochastic nature of waves [131–133] (although they are less variable on an hourly basis than wind). Furthermore, wave energy flux can exhibit nonlinear variability, with irregular extreme events [134]. This complex variability also emerges in other weather and climate processes, and has been characterized as multifractal [135]. As a consequence of this complexity, both the design, deployment, and control of WECs [79, 136–139] become key points that require a characterization of the resource as accurate as possible.

The characterization of the oceanic energy resource can be carried out essentially through two families of techniques: *physical models* or *data-driven models*. Although they will be reviewed in Chapter 3, we advance here some basics:

1. Physical models are based on the *wave energy balance equation* [140], a differential equation which is solve numerically. There are several *numerical wave models* depending on the numerical methods and the physical parameterizations adopted [141], as will be shown in Chapter 3.

2. Data-driven models. Data from wave stochastic processes can be basically obtained from radars, satellites or buoys, which generate time data series. Data-driven models use such data to forecast, for instance, wave parameters. There are basically two data-based approaches in this field:

   2.1. Statistical regressive methods [142, 143] like autoregressive (AR) model, auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA) [144]. See [71] for further details.

   2.2. Soft Computing (SC) approaches, also known, computational intelligence (CI) methods (neural, fuzzy, evolutionary methods) [145]. Although it will be shown in more detail in Chapter 3, in which their current state of the art will be reviewed, we mention here in advance that SC techniques [145] are artificial intelligence (AI) methods that may be useful in wave energy problems. SC techniques have already proven to be very useful and feasible tools in many fields of Science and Engineering, and include Neural Computation (Neural Networks [146], Extreme Learning Machines [147, 148], Support Vector Machines [149]), Evolutionary Computing [150] (Genetic Algorithms [151], Genetic Programing [152]), and Fuzzy Computation [153]. In spite of the fact that there are more SC approaches, the aforementioned groups of techniques mentioned are the only ones that have been applied to wave energy problems till now, to the best of our knowledge.

   As shown in [71], data-driven methods have some advantages over numerical models: simple modeling, smaller computational effort, lack of errors arising out of wind-to-wave conversion, and absence of exogenous data (except the wave time series themselves) [154]. However, numerical models, which take into account a great variety of physical phenomena, are more accurate over large spatial and temporal domains. This analysis will be carried out in greater depth in Chapter 3.

Within this context, in this thesis we have focused on exploring the use of SC approaches in wave energy applications, as will be shown in the next section.

1.3 Purpose and contributions

The *purpose* of this thesis is to investigate the use of SC techniques applied to wave energy. Specifically, we have focused on two case studies, whose research contributions have been published in [107] and [108], respectively. Very briefly, these contributions are:

1. We have proposed in [107] a novel approach in wave energy applications that combines a Genetic Algorithm (GA) [155] hybridized to an Extreme Learning Machine (ELM) [156], called henceforth GA-ELM. It is able to select those wave parameters that maximize the reconstruction of the significant wave height, H_s, one of the most used parameters in wave energy applications. Data have been obtained from public databases, based on buoys measurements. Typically, a scalar buoy located at a point $\mathbf{r} = (x, y)$ on the sea surface is able to measure, at each time instant t, the vertical water surface elevation, $\eta(\mathbf{r}, t)$, leading thus to time series. Using Fourier analysis, the spectral wave density $S(f)$ can be computed, and, in turn, based on $S(f)$, a number of "integrated wave parameters", such as the spectral moments, the significant wave height H_s, or the mean wave period, to name a few, can also be estimated [71,157]. Specifically, our GA-ELM selects (in the set of available wave parameters in the neighbor buoys) a smaller subsets $\mathcal{F}_{n_{SP}}$ with n_{SP} parameters that will help an algorithm reconstruct H_s at the target buoy.

2. We have proposed in [108] a novel SC-based approach that aims at tackling –in a general framework common to all *intermittent* renewable energies (mostly, solar, wind and wave energies)– the problem of integrating them into the power grid. The smart grid (SG) concept is a feasible technology able to efficiently *integrate* into the power grid a quickly increasing number of intermittent generators, with the target of affecting as slight as possible the stability and robustness of the grid [158]. Within this state-of-the-art framework, we have proposed in [108] an approach whose novelty is twofold, in the sense of optimizing the robustness of a distribution SG –connecting nodes that generate (regardless of whether this is a WEC, or photovoltaic generator or a wind turbine), consume or store electricity– against "abnormal operating conditions" –for instance, the breakdown or the operation stop of a WEC (or a set of them) within a WEC farm caused by a storm, or by intermittent generation– by (1) using an Evolutionary Algorithm (EA) that optimizes the structure of the SG [158] modeled by (2) applying concepts from the Complex Networks (CN) Science.

Once the general purpose and the particular contributions have been specified, the structure of this thesis will be as described in the following section.

1.4 Thesis structure

Taking into account all the aspects mentioned above, we have structured the rest of this thesis as follows:

- Chapter 2 focuses on providing a solid foundation the remaining chapters are based on. In particular, Chapter 2 pursues the twofold objective of 1) characterizing wave processes and 2) introducing the basic concepts of WECs.

All of them are necessary to understand and motivate the use of SC techniques in wave energy.

- Chapter 3 describes the methodology and state of the art of SC techniques in the field of wave energy, in the effort of showing the novelty of our research. The reason why we focus on wave energy is because it is the most relevant marine energy, as previously explained in Chapter 2. The reason why we address the review from the viewpoint of SC techniques is because, as will be shown throughout the chapter, they perform (accuracy, computational effort) mostly as well (or even better) than traditional techniques. The review chapter includes not only those works that study wave parameters (to characterize the wave resource) but also others that focus on the design and control of WECs using SC methods.

- Chapter 4 focuses on explaining our GA-ELM approach [107], which is able to select those wave parameters that maximize the reconstruction of the significant wave height at a missing buoy's location by using wave data from nearest buoys. The method and the results described in this chapter have been published in [107].

- Chapter 5 has been motivated by two important, mutually interrelated points that, until such a chapter, had not yet been addressed in this thesis: 1) how several WECs should have to be electrically interconnected to each other (forming a WEC farm), and 2) how the WEC farm should be connected to the electric network (or "power grid") [159–161].

  - With respect to the first point, the main reason why WECs are electrically connected with each other is that a single standalone WEC cannot generate sufficient electric power for commercial-scale grid integration. Although linked WECs help soften the fluctuation of electric power associated to wave variability, such fluctuation is still important and can affect the quality of the power grid. A feasible solution consists in using electric energy storage systems, embarked on-board or shared among WECs in the farm, aiming to smooth the produced electric power without reducing energy efficiency [161, 162]. Thus, conceptually, a WEC farm can be considered as a set of nodes (either generating or absorbing electricity) connected following certain design criteria [159, 161, 163].

  - Regarding the second aspect, the electric connection of WEC farms to on-shore power grid [159–163], aims at seamlessly integrating it into the power grid. To do this, wave farms should become into "smart wave farms" (SWFs). The SWF approach allows for predicting waves using in-ocean sensors and forecasting algorithms. These predictions in turn can be used to: 1) adapt the WECs' energy capture, 2) make efficient energy storage decisions [164], and 3) control the quality of the power that the SWF injects into the on-shore power grid. The final goal is to integrate them smoothly to the electric grid [159, 161, 163]. The variability and intermittency of wave energy can be encompassed within a broader conceptual framework, which is common to all massive renewable energies. In fact, variability and intermittency are the two most serious problems that the emerging SG technology [158] aims to face. The SG concept is able to efficiently *integrate* into the power grid a rapidly increasing number of intermittent generators, with the target of affecting as slight as possible the stability and robustness of the grid [158].

The SWF and its connection to the on-shore power grid can be viewed as a SG whose structure needs to be optimized against random failures or abnormal operating conditions –for instance, intermittent generation or the breakdown or the operation stop of a WEC (or a set of them) within a WEC farm caused by a storm–. The novelty of Chapter 5 is twofold, in the sense of optimizing the robustness of such SG (connecting nodes that generate, consume or store electricity) against abnormal operating conditions by (1) using an EA that optimizes the structure of the SG modeled by (2) applying concepts from the Complex Networks Science. The model and results of this chapter have been published in [108].

◦ Chapter 6 finally summarizes the main results and suggests future research lines.

A final aspect that we would like to emphasize here is that the structure of this doctorate thesis has been designed so that the reader can study each chapter separately, according to his/her interests and/or previous background. Figure 1.1 represents the structure of chapters in which we have organized this thesis and indicates possible reading sequences. For example, a reader who is an expert in wave energy can go directly from the motivation and introduction in Chapter 1 to Chapter 4. This sequence has been represented by a solid line in Figure 1.1. Conversely, if the reader is an expert in SC but it is not in wave energy, he/she needs to read Chapter 2 (dashed line) before going directly to the chapter to Chapter 4 or to Chapter 5.

That is, the thesis structure represented in Figure 1.1 helps the reader specialized in wave energy or in SC leap directly to Chapter 4 (GA-ELM approach to H_s reconstruction) or to Chapter 5 (EA optimizing the structure of the SWF combining SG and CN concepts) without necessarily having read Chapter 2 (wave energy and WECs characterizations) or Chapter 3 (review and background of SC methods in wave energy applications).

With this approach, each of the chapters has been designed to *stand by itself* as far as possible.

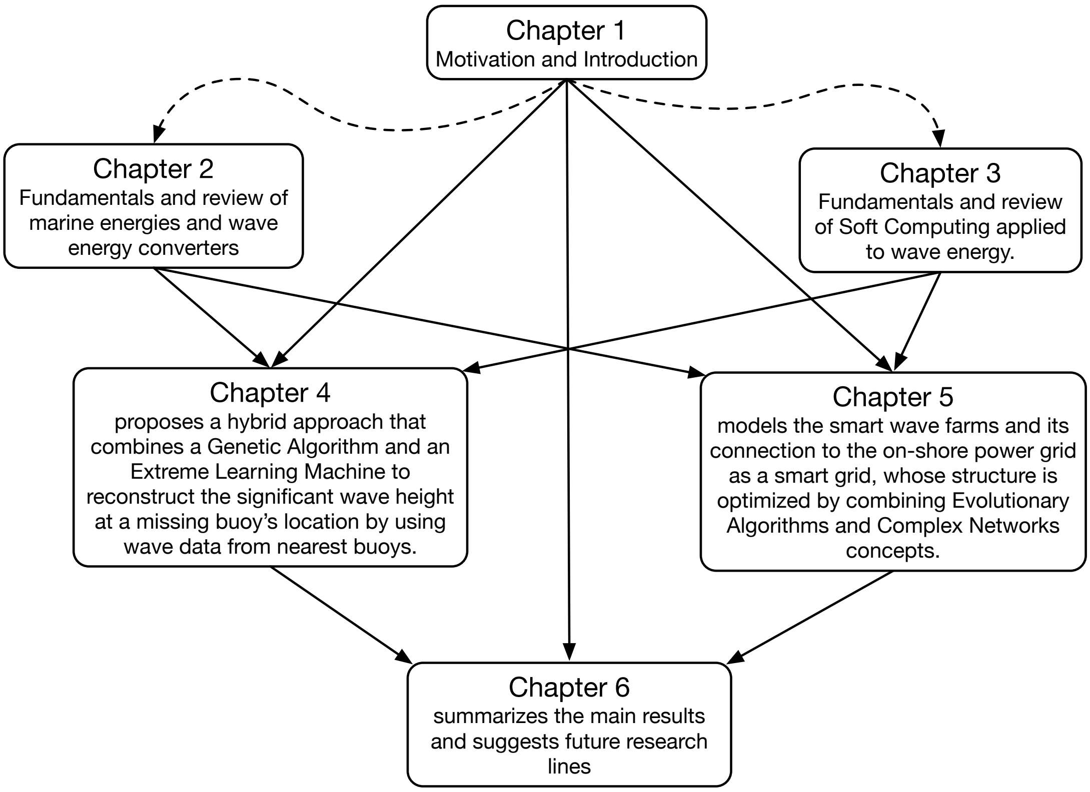


Figure 1.1: Representation of the structure of the thesis. The dashed lines represent optional reading sequences. In those cases in which the reader is an expert in either wave energy or in soft computing algorithms, he/she can read directly Chapter 4 or Chapter 5 without having read before the Chapter 2 or Chapter 3.

Chapter 2

A Brief Introduction to Wave Energy

2.1 Introduction

As motivated in Chapter 1, nowadays there is a serious concern worldwide about the efficient and ecological use of energy because of its key effect on economy [11], global warming [12, 13], climate change [15–19], and ecosystems [20, 21]. These elements are fostering great research efforts not only in renewable electric energy systems [22] – including their integration in power grids [10, 23, 24] and influence on grid resilience [25] – but also in the design of algorithms and methods to estimate the potential and exploitability of primary energy sources [26–29]. Among renewable energies, wind energy [31, 32], solar energy (both thermal [34] and photovoltaic (PV) [35–38]), and solar photovoltaic-wind hybrid energy systems [39] are currently playing a key role. Wind and photovoltaic energy approaches attract a huge interest from both the industrial and scientific community, the latter being focused on the search for novel energy converters [40–43].

However, we have also discussed in Chapter 1 that there are other renewable energies that despite their great potential are not being used with the same intensity as wind and photovoltaic energies. This is just the case of marine energies [44–49], especially, wave [50] and tidal [51] energies. Marine energies could become very important because they do not generate CO_2, are potentially able to transform part of the huge energy of oceans (80,000 TWh a year [52]) into electricity [53–57], and reduce oil imports, a crucial geo-economical issue. These are the reasons why many governments, international institutions and companies are increasingly interested in the development and deployment of marine energy systems [58–62], and, in particular, in wind-generated wave energy. The most representative example of this technological and *industrial interest* is occurring in the British islands, where a number of public institutions and companies [62–64] are aiming at exploiting their tremendous wave energy resource [55, 57]. The total amount of wave energy in UK and Ireland is estimated is equivalent to approximately 50% of the total European wave energy resource [59]. The UK marine energy resource has the potential to provide 20% of demanded electricity, preventing the yearly emission of 30 million tonnes of CO_2. The positive influence of marine energy on economy is increasingly (specially in Scotland [65]): over 1500 people work in the UK marine energy sector, with almost £450 million economic value in the British industry [58]. Another illustrative examples in which marine energy can have a key role are offshore islands. This is because marine energy has the potential to provide the clean electric energy demanded without significant environmental impact, an important concern in offshore islands, committed to the protection of ecological systems [66]. For further details about the current situation of marine energy, the interested reader is referred to [67, 69, 71].

These features illustrate the growing magnitude of marine energy, from both scientific, technological, and socio-economical viewpoints [71]. Specifically, there are many recent interesting works focused on integrating wave energy at large-scales [73], strategies to reduce the cost of array of converters [74], the potential applications of small scale wave energy installations [75], the cost-based study of marine energy farms [44], the research on novel concepts for wave energy converters [53, 76–78], the durability and control of wave energy converters [79, 80], the modeling of ocean wave energy converters [81–83], storage prototypes for offshore wave and tidal energy systems [84], general aspects about the generation of electricity from oceans [71, 85–87], a novel methodology to estimate the long-term power performance of wave converters [88], related ecological issues [89, 90], the potential of a number of ocean regions worldwide to be exploited [70, 91–104], the combined use of wave and offshore wind energy [56], the economics of wave energy [45, 105], its social acceptance [46, 49], and political and legal aspects in the emerging marine energy industry [106].

Despite the booming of publications in marine energy, however we have mentioned in Chapter 1 that not all the available technologies have the same feasibility and applicability [71]. This is because of the key role that environmental concerns [89, 90], and economical [44, 45, 73, 109] and social aspects [46, 49] play along with technical considerations [71]. These latter are related to the class of energy conversion involved [51, 110]. A conversion technology may be feasible from a technical viewpoint [71], but *not adequate* from an ecological standpoint (for instance, if it adversely affects a coastal ecosystem) [111].

As explained in more detail in Chapter 1, each of the marine energy converters has advantages and disadvantages [71], and its potential use is a balance between pros and cons. On the one hand, ocean thermal energy converters –which take advantage of the fact that there are ocean regions with large temperature gradients ($>$ 15 degree Celsius) between the surface and waters less than 1 km deep– cannot be used massively because regions with this property are scarce. On the other hand, tidal energy, based on tidal flow and reflux, is only suitable for those ocean regions having high tides ($>$ 5 meters) [71]. As described in Chapter 1, during rising tides, a barrier traps sea water, while, during low tides, such water accumulated by the barrier flows through a turbine, generating thus electric power [51]. Although this is a feasible technology [118], however, its mass use could modify tides and currents and, consequently, affect negatively their related costal ecosystems [71, 119]. So, among the three main marine technologies, wave energy is the one that exhibits the greatest potential for practical application, taking into account a global positive balance between advantages and disadvantages.

Wave energy thus exhibits a good balance between efficiency and environmental protection since it does not cause significant environmental problems. Wave energy converters (WECs) transform the kinetic energy of wind-generated waves into electricity by means of either the vertical oscillation of waves or the linear motion of waves [110, 120, 121]. They exhibit some important advantages when compared to the other converters [120,122,123]: 1) WECs usually cause much lower environmental impacts on ecosystems than tidal devices; 2) There are ideal areas (in the sense of having considerable wave power density *near* populated regions demanding energy) in north and west coast of Europe (Norway, UK, Ireland, Portugal), north coast of US and Canada, southern cost of Australia, northern coast of New Zealand, Japan, and India [102]; 3) Wave energy (hereafter, wave energy) is the densest renewable energy (about 1000 times more concentrated than wind energy) and is less changing on an hourly basis than wind energy [79]. More details about these and other beneficial properties of WEC-based technologies can be found in [47, 53, 54, 88, 111, 124–130].

Though wave energy has the aforementioned advantages when compared to tidal energy, however the problem is that waves are more difficult to characterize than tides because of the stochastic nature of waves [131–133] (although they are less variable on an hourly basis than wind). Furthermore, wave energy flux can exhibit nonlinear variability, with irregular extreme events [134]. This complex variability also emerges in other weather and climate processes, and has been characterized as multifractal [135], which are outside the scope of this thesis. As a consequence of such complexity, both the design, deployment, and control of WECs [79, 136–139] become key points that require a characterization of the resource as accurate as possible.

As pointed out in the previous paragraphs, marine energy encompasses a considerably extensive set of very different aspects that require a strong background. This is the reason why the motivation of the present chapter consists in providing a solid foundation on which the remaining chapters can be supported. In particular, this chapter pursues the twofold objective of 1) characterizing wave processes and 2) introducing the basic concepts of WECs. With these considerations in mind, and in the effort of making this chapter stand by itself, its structure is as follows. Section 2.2 starts by presenting the wave energy resource and some key wave parameters. The *significant wave height* (H_s) and *wave energy period* (T_e) are the most important in wave energy applications. Understanding the physical meaning of these and other parameters will assist us in better explaining the operation of WECs (Section 2.3), and in motivating the need for using SC strategies, whose main concepts, for the sake of clarity, will be postponed and introduced in Chapter 3. Finally, Section 2.4 completes the chapter with a summary of the main conclusions.

2.2 Wave energy resource: a short introduction

Put it simple, when planning the deployment of a WEC (and arrays of WECs [165, 166]), it is essential to previously characterize, as accurately as possible, the amount of wave energy available *in such particular location*. The underlying fundamentals are as follows.

2.2.1 Wave energy resource: fundamentals

The wave energy resource in a region is caused by both local and far winds blowing over the ocean *surface*, which transports the wave energy (up to 95% of the this energy is between the water surface and one-quarter of its wavelength below it [167]). Focusing thus our attention on the water *surface*, and within the framework of the *linear wave theory*, the vertical wave elevation, $\eta(\mathbf{r}, t)$, at a point $\mathbf{r} = (x, y)$ on the sea surface at time t can be assumed as a superposition of different monochromatic wave components [157, 168–170]. This model is appropriate when the free wave components do not vary appreciably in space and time (that is, statistical temporal stationarity and spatial homogeneity can be assumed [170]).

In this model, the concept of "sea state" refers to the sea area and the time interval in which the statistical and spectral characteristics do not change considerably (statistical temporal stationarity and spatial homogeneity). The total energy of a sea state is the combined contribution of all energies from different sources. The "wind sea" occurs when the waves are caused by the energy transferred between the local wind and the free surface of the sea. The "swell" is the situation in which the waves have been generated by winds blowing on another far area (for instance, by storms), and propagate towards the region of observation. Usually, sea states are the composition of these two pure states, forming multimodal or mixed seas.

In a given sea state, the wave elevation $\eta(\mathbf{r}, t)$ with respect to the mean ocean level can be assumed as a zero-mean Gaussian *stochastic process*, with statistical symmetry between wave maxima and minima. A buoy at a point $\mathbf{r}_B$ can take samples of this process, $\eta(\mathbf{r}_B, t_j)$ $j = 1, 2, \cdots, t_{\mathrm{MAX}}$, generating thus a time series of empirical vertical wave elevations. The Discrete Fourier Transform (DFT) of this sequence, using the Fast Fourier Transform (FFT) algorithm, allows for estimating the *spectral density* $S(f)$. Its spectral moments of order n can be computed as

$$m_n = \int_0^\infty f^n S(f) df, \tag{2.1}$$

and help compute many wave parameters, as will be shown in Subsection 2.2.3

Once $S(f)$ has been estimated, *wave energy flux*, a first indicator of the amount of wave energy available in a given area for WECs deployment, can also been estimated. This is just the purpose of the next section.

2.2.2 Resource: Wave energy flux

Wave energy flux or power density per meter of wave crest [171–177] can be computed as

$$P = \frac{\rho g^2}{4\pi} \int_0^\infty \frac{S(f)}{f} df = \frac{\rho g^2}{4\pi} m_{-1} = \frac{\rho g^2}{4\pi} H_s^2 \cdot T_e \tag{2.2}$$

where ρ is the sea water density (1025 kg/m^3), and g the acceleration due to gravity. Expression (2.2), for H_s in meters and T_e in seconds, leads to $P = 0.49 \cdot H_s^2 \cdot T_e$ kW/m, and helps engineers estimate the amount of wave energy available when planning the deployment of WECs at a given location.

The significant wave height H_s and the wave energy period T_e can be computed as shown in Subsection 2.2.3.

2.2.3 Computing some useful wave parameters

The objective of this section is to present, in a coherent and organized way, the parameters that will be used in this thesis. The main wave parameters are:

- The significant wave height,

  $$H_s = 4(m_0)^{1/2}, \tag{2.3}$$

  is the parameter related to the wave height that is most used in wave energy (in combination with T_e) and in the design of ships and marine structures (dams, oil platforms, etc.) and coastal protection (beaches, etc.).

- The wave energy period, which can be computed by using, among others, the estimator $T_{-1,0}$ [171] as

  $$T_e = T_{-1,0} = \frac{m_{-1}}{m_0}, \tag{2.4}$$

  is an estimate of the average period used in the design of turbines for wave energy conversion.

- The spectral moments m_{-1}, m_0, m_1, and m_2, whose general definition has been stated by Expression (4.4). They provide information on different statistical and physical characteristics of waves. For instance, m_0 is the variance of the wave elevation.

- The peak period is defined as

  $$T_p = 1/f_p, \tag{2.5}$$

  where f_p is the spectral peak frequency (the frequency where the spectrum $S(f)$ reaches its maximum value).

- The average zero-cross wave period:

$$T_z = \sqrt{\frac{m_0}{m_2}} \tag{2.6}$$

- The mean periods T_{m01}, T_{m02} and T_{m-10} are defined as

$$T_{mxy} = \frac{m_x}{m_y}, \tag{2.7}$$

  m_x and m_y being spectral moments (Expression (4.4)). These mean periods are important because:

  1. T_{m01} is an estimator of the mean period used in the study of the *giant waves* and wave forecast.
  2. T_{m02} is an estimate of the mean period used in the design of marine structures.
  3. T_{m-10} has already been defined in (2.4) and is one of the feasible estimators for T_e, the wave energy period. It is an estimation of the mean period used in turbine design calculations for wave energy extraction.

- The Goda's peakedness parameter [178], which can be computed as [170]

$$Q_p = \frac{2}{m_0^2} \int_0^\infty f \cdot S^2(f) \cdot df, \tag{2.8}$$

  has the potential to describe the statistical features of consecutive wave heights [178].

- The Longuet-Higgins spectral bandwidth (or spectral narrowness parameter), ν, defined as [179]

$$\nu = \sqrt{\frac{m_2 \cdot m_0}{m_1^2} - 1}, \tag{2.9}$$

  quantifies the degree to which spectral energy spreads over the frequency range.

- The spectral width parameter [180]

$$S_p = \epsilon = \sqrt{\frac{m_0 m_4 - m_2^2}{m_0 m_4}} \tag{2.10}$$

- The wave height correlation coefficient, γ, is a parameter that measures waves grouping properties (a property in which the waves tend to propagate forming high waves groups followed by lower waves). It can be computed using [179, 181, 182]

$$\gamma = \frac{\mathcal{E}(\kappa) - (1-\kappa^2)\mathcal{K}(\kappa)/2 - \pi/4}{1-\pi/4} \tag{2.11}$$

where $\mathcal{E}(\kappa)$ and $\mathcal{K}(\kappa)$ are the complete elliptic integrals of first and second kind, respectively, and κ parameter can be estimated [179] as

$$\kappa = \left| \frac{1}{m_0} \int_0^\infty S(f) \cdot e^{i2\pi f T_C} df \right|, \tag{2.12}$$

T_C being a characteristic time that can be estimated by using either the T_{m01} or T_{m02}.

In this work, $\gamma_{01}(\gamma_{02})$ and $\kappa_{01}(\kappa_{02})$ represent the values of γ and κ when using $T_{m01}(T_{m02})$, respectively.

Understanding the need for applying SC techniques to the design, deployment and control of WECs (to maximize power conversion) requires to have some knowledge about the way they work. This is just the purpose of the following subsection.

2.3 Wave energy converters

2.3.1 Classification and description

As pointed out in [71, 112], there are many different WECs [54, 79, 88, 111, 125–128, 130, 137, 167, 183]: there are more than 1000 WEC-related patents and about 100 projects at different degree of development. However, only a small fraction of these projects have been deployed and tested in oceans. Since there is a great variety of WECs, their classification can be tackled from different viewpoints and complexity levels, and there is *no* unanimity of what is the most appropriate one [71, 167].

A simple, first classifying viewpoint is related to water depth and location, leading to "shoreline", "near-shore", and "offshore" WECs. Shoreline WECs, situated near the electric grid, are the easiest to maintain, and exhibit the lowest probability of being destroyed under extreme conditions, because waves have usually lower energy near the coast than offshore. However, this also leads to the disadvantage of producing lower electric power. The second class corresponds to nearshore devices. They are located in relatively shallow waters (a depth of less than one-quarter wavelength [167] is one of the criteria used, although, again, there is no general agreement), and produce less energy than offshore devices. Finally, offshore WECs are in deep waters, and can generate more energy because of the greater energy of deep waters. The negative counterpart is that offshore WECs have to be designed to endure the most extreme waves, being thus considerably more difficult to construct/manufacture and maintain.

A second viewpoint to classify WECs is based on the size of the mechanical part that is moved by waves, absorbing their energy: "large" absorbers (flag-like), as the one shown in Figure 2.1 (a), and "point absorbers" (Figure 2.1(b)).

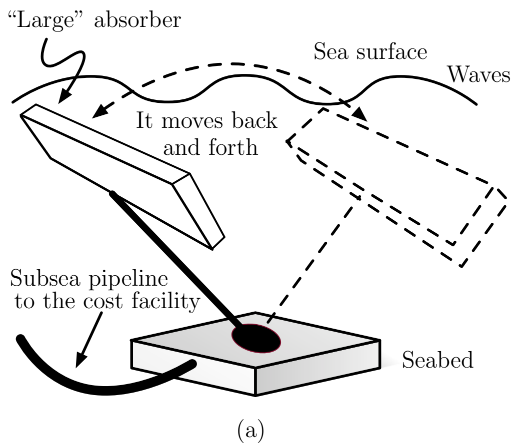


Figure 2.1: Illustration of the second classifying criterium for WECs: large (a) *vs* point (b) absorbers.

Finally, the third approach to classify WECs is based on the relative position of the device with respect to the predominant wave direction: parallel or "attenuator" (Figure 2.2.(a)), perpendicular or "terminator" (Figure 2.2.(b)), and "point absorber" (Figure 2.2 (c)), which absorbs energy from all directions.

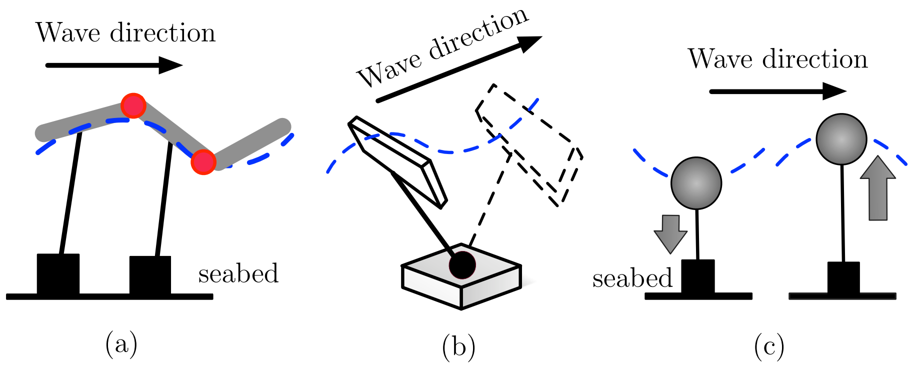


Figure 2.2: A simple representation of the third classifying criterium: (a) Attenuator WEC: parallel to the predominant wave direction. (b) Terminator WEC: perpendicular to the predominant wave direction. (c) Point absorber: it captures energy from all directions.

As mentioned, there is no consensus about what can be considered the most adequate classification. In this respect, it is illustrative to see, for instance, the classifications in [47, 130, 167, 183, 184] and the different approaches the authors adopt.

In the present chapter, we have considered a combination of viewpoints, similar to that of [60], which will assist us in clearly describing those WECs for which SC technologies are currently being used. The description below (Subsections 2.3.2, 2.3.4, 2.3.5,2.3.7, 2.3.8, and 2.3.6) is *not* exhaustive (contains only the most used WECs), and only pursues to make the thesis stand by itself and to motivate the need for SC techniques. A comprehensive description of these devices can be found in [130]. Other illustrative tutorials on WECs are [167, 183, 185]. There are recent works that study electrical topics of WECs [128, 166, 186], general techniques issues [111], control techniques [79, 138, 139], and models for oscillating-water-column WECs [129]. All these aspects, extremely technical, are out of the scope of this thesis. In this regard, the sections that follow only seek to introduce the concepts of the most used WECs that are strictly necessary for the achievement of the purposes of this thesis. The reader interested in more in-depth details of WECs can refer to the references listed above.

2.3.2 Attenuator WEC

As shown in Figure 2.2 (a), an attenuator is a “large” floating WEC that works *parallel* to the (predominant) wave direction. It works as follows [60, 167]: as the waves pass, the device absorbs energy from the relative movement between the different components it consist of. The “Pelamis” WEC, illustrated in Figure 2.3, is the most representative example of attenuator WEC. It is made up of semi-submerged cylindrical structures, which are attached by joints that allow them flexing in the represented two different directions: vertical (Figure 2.3 (a)) and horizontal (Figure 2.3 (b)). As waves go along this structure, its sections fold, and the relative movement between its parts is converted into electricity by means of hydraulic power take-off systems housed inside each joint [60, 130, 167]. The generated electric power is transmitted to shore by using subsea cables [71].

2.3.3 Oscillating Wave Surge Converter

Figure 2.1 (a) shows an Oscillating Wave Surge Converter (OWSC). It consists of a large, flag-like absorber hinged to the seabed (at depths of between 10 and 15 meters), and placed perpendicular to the prevailing wave direction (Figure 2.2 (b)). The hinged absorber swings backwards and forwards in the waves, driving two pistons. Thanks to a subsea pipeline, these pistons inject high pressure water to the shore-based electric generator. This simple concept exhibits some important advantage [71]: 1) The mechanical and the electric components are separated from each other, what makes the shore-based electricity generation be extremely reliable. 2) The mechanical part exhibits a superb survivability and is able to work even under extreme storms. 3) It has a minimal ecological impact, which is becoming of greatest importance. Finally note that, according to the third classification mentioned (Figure 2.2.b), the OWSC is a terminator WEC since its mechanical component is perpendicular to the predominant wave direction.

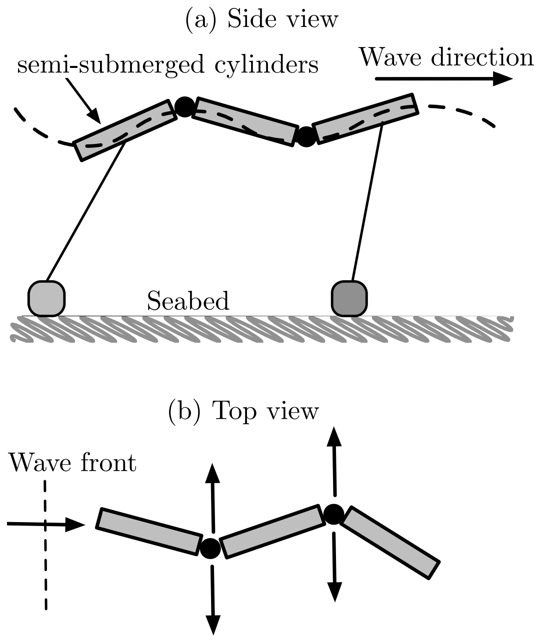


Figure 2.3: Simplified structure of the attenuator WEC called Pelamis. (a) Side view: vertical flexing as it surfs the passing wave. (b) Top view: horizontal flexing.

2.3.4 Point absorber

A point absorber WEC is a device that has small dimensions when compared to the incident wavelength. As represented in Figure 2.1 (b), a point absorber WEC is a *floating* structures that heaves up and down on the sea surface. Because of its small size, wave direction is not important for it [167], or alternatively, it is able to absorb energy from all directions via its movements at the water surface (Figure 2.2 (c)).

2.3.5 Submerged pressure differential WEC

A submerged pressure differential WEC consists of a structure *submerged* near the sea surface, like the Archimedes Wave Swing (AWS) represented in Figure 2.4. It works as follows. The motion of waves makes the sea level move up and down, producing a changing differential of pressure through the device. The varying pressure thus pumps a fluid through a system to generate electricity. They are usually located nearshore and are attached to the seabed.

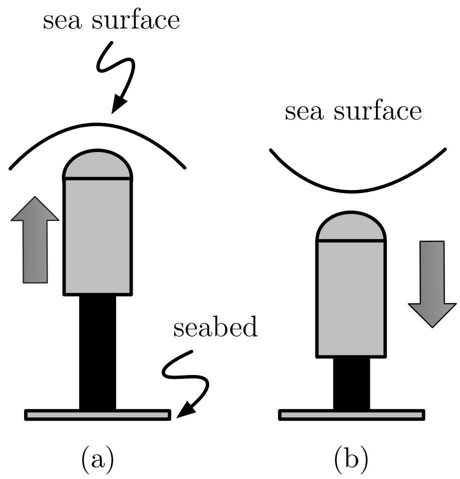


Figure 2.4: Representation of the way the AWS works. Sea level move up (a) and down (b), producing a changing differential of pressure through the device.

2.3.6 Rotating mass-based WECs

According to [71], Figure 2.5 will assist us in explaining how these WECs work. In these devices, the swaying motion caused by waves induces the rotation of a gyroscope (or an eccentric weight) inside the device (positions (a) and (b) in Fig. 2.5).

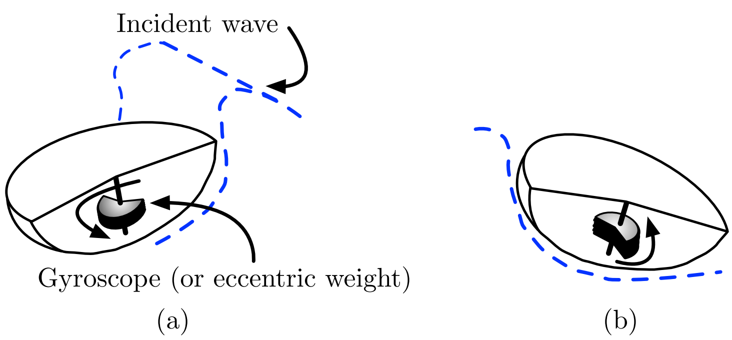


Figure 2.5: Rotating mass-based WEC. The swaying motion produced by waves ((a) and (b)) makes rotate an eccentric weight, which drives an electric generator housed within the structure.

The rotating component drives an electric generator housed within the partially hollow structure. A representative instance, with an overall efficiency of up to 90%, is the Salter's duck (nodding duck or Edinburgh duck), in which the wave motion makes it sway, what, in turn, induces the rotation of a gyroscope, an electric generator transforming its rotation into electricity. It is also an example of "terminator" device because it has its principal axis perpendicular to the predominant wave direction, intercepting thus waves [167].

2.3.7 Oscillating water column

Figure 2.6 will assist us in explaining how this WEC works. As illustrated in this figure, an oscillating water column is an empty structure, built on the seabed, that is partially submerged. It is open to the sea below the water surface so that waves entering the chamber make the water column move up and down. This movement makes the air on top of the water column be compressed and decompressed. This, in turn, makes the air flow to and from the atmosphere via a turbine, which generates electricity [129].

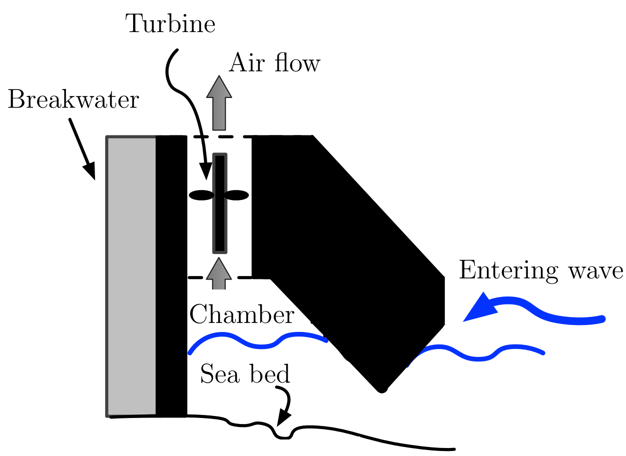


Figure 2.6: Simplified representation of the concept the Oscillating Water Column is based on.

2.3.8 Overtopping/Terminator device

As shown in Figure 2.7, an overtopping WEC stores sea water as waves enter the storage reservoir. The trapped water goes back to the sea through a conventional turbine which generates electric power.

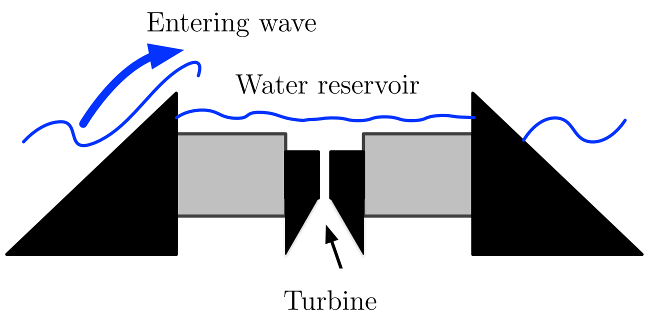


Figure 2.7: Simplified representation of the concept of Overtopping/Terminator device.

2.3.9 Comments: WECs and wave resource

According to [71, 112], there are some important points that should be highlighted:

1. Because of design restriction and fundamental thermodynamical issues, only a fraction of the energy flux available at a site can be captured and converted into electricity [71]. This fraction is not yet well established because there is no consensus on the optimum conversion mechanism [110, 120].
2. Regardless limiting performance considerations, there are some very recent papers that study WECs' performance in real conditions. In this respect, the work [82] provides an excellent review of the performance of the most important, state-of-the-art WECs in those worldwide locations having the highest wave power resource. Similarly, [187] has recently compared the performance of floating and fully submerged quasi-point absorber WECs.
3. Another important factor to consider from an engineering point of view is the effect of the *resource variability* on WEC performance. This is because sea states with power larger than a threshold are unexploitable and even can destroy the WEC. This power threshold depends on the WEC hydrodynamics and is a complex issue. In [188] the WEC power threshold has been estimated as four times the mean incident wave power.
4. In this respect, WECs' *survivability* depends on *extreme* sea states [189] and winds [190]. The probability density function of significant wave heights is very useful because H_s is the most significant parameter related to the *intensity of extreme loads* [189].
5. Besides having to be able to withstand long term and extreme distributions of H_s, floating WECs require *bivariate* distributions of significant wave height

and characteristic (mean or peak) periods [189]. The dynamic response of a floating WEC depends on the sea states defined by H_s and associated peak period T_p [191]. That is, while WEC survivability depends on the extreme sea states, their operational performance depends mostly of the wave period.

6. This is why the operation of many WECs have to be controlled to work as efficient as possible. Its control should ideally help a floating WEC operate in its *resonance mode*. Thus it is necessary for most WECs to tune the oscillating mechanical part to the wave period. This is the reason why many works aims at characterizing wave periods, as will be shown in the survey. Improving wave energy competitiveness requires better resource analysis in terms of periods [192].

7. Finally, although a given WEC has a range of significant wave heights in which it can perform, its efficiency mostly depends on the response amplification factor [189], which is governed only by the mean wave period. This is why it is necessary for improving WEC efficiency to have a probability distribution of characteristic wave periods. Controlling WECs is a very difficult task. Recent reviews in this subject are [124, 125].

As shown, the design, survivability, efficiency and control of WECs depend strongly on the knowledge that we have of sea states. This can be acquired using SC techniques, whose fundamentals will be introduced in the following chapter.

2.4 Conclusions

In this chapter we have introduced two groups of concepts the rest of the chapters (and the research work described in them) are based on. The first set of concepts is related to the characterization of the waves, while the second focuses on introducing the basic issues of the converters that transform wave energy into electricity.

Regarding the first, wave energy flux or power density per meter of wave crest, P, –stated by Expression (2.2)– depends on two important parameters: the significant wave height, H_s, and the wave energy period T_e. These can be calculated from statistics obtained from series of wave measurements, carried out, basically, by buoys. Oceanographic buoys are, and have been, probably one of the most used measuring instruments to characterize wind-generated wave properties [193]. In particular, a scalar buoy located at a point $\mathbf{r} = (x, y)$ on the sea surface is able to measure, at each time instant t, the vertical water surface elevation, $\eta(\mathbf{r}, t)$, leading thus to time series. Using Fourier analysis, the spectral wave density $S(f)$ can be computed, and, in turn, based on $S(f)$, a number of integrated wave parameters, such as the spectral moments, the significant wave height H_s, or mean wave period, to name just a few, can also be estimated [157]. As will be shown in Chapter 3, there are many SC techniques that can be used to estimate H_s and T_e. After certain mathematical operations, this expression ends up being $P \propto H_s^2 \cdot T_e$. This helps engineers estimate the amount of wave energy available when planning the deployment of WECs at a given location.

The second group of notions described in this chapter, and which are strongly related to the former, focus on the essential concepts of WECs. In this respect, we have shown that there are many different WECs, at a greater or lesser degree of development. Despite this, only a small fraction of them have been deployed and tested in oceans. Since there is a great variety of WECs, their classification has been tackled from different viewpoints and complexity levels, and we have shown that there is no unanimity of what is the most appropriate one.

- The simplest, first classifying viewpoint is related to water depth and location, leading to shoreline, near-shore, and offshore WECs. Shoreline WECs, located near the electric grid, are the easiest to maintain, and exhibit the lowest probability of being destroyed under extreme conditions (since waves have usually lower energy near the coast than offshore). However, this also leads to the disadvantage of generating lower electric power. The second class corresponds to nearshore devices. They are located in relatively shallow waters (a depth of less than one-quarter wavelength [167] is one of the criteria used, although, again, there is no general agreement), and generate less energy than offshore devices. These last ones are in deep waters, and are able to generate much more electric energy because of the greater energy of deep waters. The negative counterpart is that offshore WECs have to be designed to resist the most extreme waves, being thus considerably more difficult to manufacture and maintain.
- A second viewpoint to classify WECs is based on the size of the mechanical part that is moved by waves, absorbing their energy: "large" absorbers (flag-like), as the one shown in Figure 2.1 (a), and "point absorbers" (Figure 2.1(b)).
- Finally, the third approach to classify WECs is based on the relative position of the device with respect to the predominant wave direction: parallel or "attenuator" (Figure 2.2.(a)), perpendicular or "terminator" (Figure 2.2.(b)), and "point absorber" (Figure 2.2 (c)), which absorbs energy from all directions.

In this chapter, we have considered a combination of viewpoints, similar to that of [60, 112], which will assist us in clearly describing those WECs for which SC technologies are currently being used.

Regardless of the classification considered, what does seem certain is that the efficiency, control and survivability of WECs depend strongly on sea states:

- Resource variability has great influence on WEC performance from a purely operational point of view. This is because sea states with power larger than a threshold are unexploitable and even can destroy the WEC. This power threshold depends on the WEC hydrodynamics and is a complex issue. In [188] the WEC power threshold has been estimated as four times the mean incident wave power.

- WECs' *survivability* depends on *extreme* sea states [189] and winds [190]. The probability density function of significant wave heights is very useful because H_s is the most significant parameter related to the *intensity of extreme loads*

The analysis of the different wave parameter and WECs that we have carried out points out that the design, survivability, efficiency and control of WECs depend strongly on the knowledge that we have of sea states. This can be acquired using SC techniques, whose fundamentals will be introduced in the following chapter.

Chapter 3

Soft Computing Techniques in Wave Energy: Methodology and State of the Art

3.1 Introduction

As shown in Chapter 2, among all the available marine technologies, wave energy is the one that exhibits the best future potential because, in addition to being efficient from a technical viewpoint, it does not cause significant environmental problems. We have explained in Chapter 2 that wave energy converters (WECs) transform the kinetic energy of wind-generated waves into electric energy by means of either the vertical oscillation of waves or the linear motion of waves [71, 110, 120, 121]. WECs have some key advantages when compared to the other converters [120, 122, 123], namely:

- Wave energy is the densest renewable energy (about 1000 times more concentrated than wind energy) and is less changing on an hourly basis than wind energy [79]. More details about these and other beneficial properties of WEC-based technologies can be found in [47, 53, 54, 88, 111, 124–130].
- There are ideal areas (in the sense of having considerable wave power density *near* populated regions demanding energy) in north and west coast of Europe (Norway, UK, Ireland, Portugal), north coast of US and Canada, southern cost of Australia, northern coast of New Zealand, Japan, and India [2, 71, 72, 102];
- WECs usually cause much lower environmental impacts on ecosystems than tidal devices.

Despite exhibiting these advantages, that have been discussed in more detail in Chapter 2, wave energy nevertheless has some serious practical problems: waves are more difficult to characterize than tides because of the stochastic nature of waves [131–133] (although they are less variable on an hourly basis than wind), and are intermittent (as are solar and wind energy). Furthermore, wave energy flux can exhibit nonlinear variability, with irregular extreme events [134]. This complex variability also emerges in other weather and climate processes, and has been characterized as multifractal [135]. As a consequence of this complexity, both the design, deployment, and control of WECs [79, 136–139] become key points that require a characterization of the resource as accurate as possible.

The characterization of the oceanic energy resource can be carried out essentially through two families of techniques: *physical models* or *data-driven models* [71]:

1. Physical models are based on the *wave energy balance equation* [140], a differential equation which is solve numerically. There are several *numerical wave models* depending on the numerical methods and the physical parameterizations adopted [71, 141]. Some important numerical models are WAM (Wave Analysis Model), SWAN (Simulating WAves Nearshore) [194–197] and WAVEWATCH III [198, 199]. In the SWAN model, waves vary their shape, height, and direction as a consequence of wind action, wave breaking, energy transfer between waves, white capping, and variations in the seabed and currents [140, 195, 200]. The initial wave conditions (wave height, wave direction and wave period) are inputs to the model, which computes the aforementioned wave changes as these move toward shore. The results are numerically computed on a 500-m × 500-m grid. The model provides output information (wave height, wave speed, and wave direction) in each cell of the grid. SWAN accounts for the following physics [188, 194, 201]: 1) Wave generation by wind. 2) Wave propagation in time and space, refraction due to current and depth, shoaling, frequency shifting due to currents and non-stationary depth. 3) Three- and four-wave interactions. 4) Whitecapping, bottom friction and depth-induced breaking. 5) Dissipation caused by aquatic vegetation, turbulent flow and viscous fluid mud. 6) Reflection (specular and diffuse) against obstacles, and diffraction. While WAN and WAVEWATCH III are used at global scale for offshore locations, linking meteorological parameters to the generation of ocean wave states, SWAN is used to accounts for the wave transformations that occur near the coast (whitecapping, bottom friction and depth induced wave breaking, as mentioned) [188]. As shown, *numerical wave models* are very powerful but demand a huge amount of meteorological and oceanographic data and *computational effort*. Numerical models are more useful for forecasting over a large spatial and temporal domain (within a window of a few days) [202]

2. Data-driven models. Data from wave stochastic processes can be basically obtained from radars, satellites or buoys, which generate time data series. Data-driven models use such data to forecast, for instance, wave parameters. There are basically two data-based approaches in this field [71, 112]:

   2.1. Statistical regressive methods [142, 143] like autoregressive (AR) model, auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA) [144], etc.

2.2. Soft Computing (SC) methods (neural, fuzzy, evolutionary methods) [145]. As will be shown throughout this chapter, SC techniques [145] are artificial intelligence (AI) methods that may be useful in wave energy problems. SC techniques have already proven to be very useful and feasible tools in many fields of Science and Engineering, and include Neural Computation (NC) –Neural Networks [146], Extreme Learning Machines [147, 148], Support Vector Machines [149]–, Evolutionary Computing (EC) [150] (Genetic Algorithms [151], Genetic Programing [152]), and Fuzzy Computation (FC) [153]. Albeit there are more SC approaches, the techniques mentioned below are the only ones that have been applied to wave energy problems till now, to the best of our knowledge [71, 112].

Data-driven methods have some advantages over numerical models: simple modeling, smaller computational effort, lack of errors arising out of wind-to-wave conversion, and absence of exogenous data (except the wave time series themselves) [154]. However, numerical models, which take into account a great variety of physical phenomena, are more accurate over large spatial and temporal domains [71].

Taking into account the framework described in the previous paragraphs, the *purpose* of this chapter is to review the use of SC techniques in the field of *wave energy*. The reason why we focus on wave energy is because it is the most relevant one, as mentioned before. The reason why we address the review from the viewpoint of SC techniques is because, as will be shown throughout this survey, they perform (accuracy, computational effort) mostly as well (or even better) than traditional techniques. The review includes not only those works that study wave parameters (to characterize the wave resource) but also others that focus on the design and control of WECs using SC techniques.

Note that there are many works dealing with WECs issues, wave resource characterization, and related topics (economic, social, environmental issues), as shown in this Introduction. In this chapter, we *only* focus on those that tackle wave energy problems by using SC techniques (which is the target of our work), and discard, with few exceptions, those works that do not use SC techniques. The *methodological approach* that we have adopted consist in [71, 112]:

1. Explaining how each technique can be applied to tackle problems in the field of wave energy, discussing its advantages, disadvantages and limitations.

2. Comparing their results to those obtained from traditional approaches.

3. Discussing them in terms of accuracy and computational effort. Many of the papers evaluated do not use the same measures to assess the efficiency of the methods (which can be very different, as will be shown). As a comparison criterium, we will use the statistical measures that follow. If $\mathcal{P}$ represents the observed wave parameter, which in general has stochastic nature ($\mu_{\mathcal{P}}$ and $\sigma_{\mathcal{P}}$

being its mean value and its standard deviation), and $\hat{\mathcal{P}}$ labels an estimate of it, them:

3.1. The root mean square error (RMSE) between $\hat{\mathcal{P}}$ and $\mathcal{P}$ is

$$\mathrm{RMSE}(\hat{\mathcal{P}}) = \sqrt{E\left[(\hat{\mathcal{P}} - \mathcal{P})^2\right]}, \tag{3.1}$$

$E[\cdot]$ being the mean value operator.

3.2. The correlation coefficient (R) between $\hat{\mathcal{P}}$ and $\mathcal{P}$ is

$$R = \rho_{\mathcal{P},\hat{\mathcal{P}}} = \frac{E\left[(\mathcal{P} - \mu_{\mathcal{P}})(\hat{\mathcal{P}} - \mu_{\hat{\mathcal{P}}})\right]}{\sigma_{\mathcal{P}}\sigma_{\hat{\mathcal{P}}}} \tag{3.2}$$

The main *contributions* of this chapter are:

1. Explaining the essential concepts of the SC techniques that will appear later on in our review;

2. Discussing their advantages, disadvantages, limitations and usefulness;

As shown in Chapter 2, the design, survivability, efficiency and control of WECs depend strongly on the knowledge that we have of sea states. This can be acquired using SC techniques, whose fundamentals will be introduced in the following section.

In this present chapter, we have adopted a point of view similar to that of the reference [71, 112], which combines the use of SC techniques in wave energy within an unified framework including both converters and resource characterization issues (which have already been presented in Chapter 2 of this thesis). There are some papers, which inspired by [71], have recently explored partial aspects related to the use of SC techniques for obtaining medium-to long-term predictions of global wave energy resources [203, 204], or optimal wave parameter relationships [205].

The rest of this chapter has been organized as follows. Sections 3.2, 3.3 and 3.4 focus on summarizing the main concepts that NC, EC and FC are based on. Section 3.5 reviews and analyses the use of SC approaches in different fields of wave energy, ranging from estimations of wave resources to control of WECs. Finally, Section 3.6 summarizes the main contributions of this chapter.

3.2 Neural Computation approaches: fundamentals

Neural Computation is inspired by the way human brain works in the sense it is able to generalize, that is, it is able to learn from representative examples, and to solve a similar problem never seen before [71, 112].

In the particular case of ANN, this is achieved by mimicking the human brain connectivity. An ANN neural network is a parallel and distributed information processing system based on single processing units, which, for analogy, are called "neurons". Multi-Layer Perceptrons (MLPs), a particular implementation of neural network, are by far the most used Neural Computation technique in wave parameter estimation, as will be shown later on.

In this paper, we consider Neural Computation in a broad sense, including also kernel methods such as Support Vector Machines (SVMs), which, strictly, are not ANNs. The following subsections, 3.2.1 and 3.2.2, introduce, respectively, the basic concepts these approaches are based on.

3.2.1 Multi-Layer Perceptron (MLP)

The MLP concept

Figure 3.1 will assist us in introducing the MLP concept. It represents a network in which their neurons are organized forming layers. The input layer, on the leftmost part of Figure 3.1, is the one that receives the input data vector $[x_1, \cdots, n_N]$. The output layer, on the rightmost part, is one that provides the result, z, for instant, a prediction.

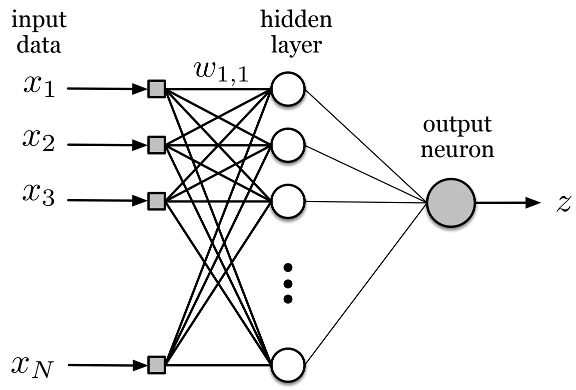


Figure 3.1: Simplified structure of a single hidden layer perceptron. It consists of a number of simple computing units (neurons) connected forming an input layer, a hidden layer and an output layer.

For simplicity we have represented only one output neuron, although in a more general case, the network could have multiple output neurons. The layer in between the input and output layers is called "hidden" layer [206]. Note that neurons are connected by links. Any link is associated to a weight $w_{i,j}$, which quantifies to what extent a connection is important. The particular values of weight $w_{i,j}$ are adjusted in a *learning process*.

In the learning or design process, an MLP is trained and validated by using, respectively, a “training set” (for which the input and the corresponding outputs are known), and a “validation set” (whose samples have not been used in the training process). The final performance is computed over a “test set”, not used during the design stage [206, 207]. The MLP is able to learn in the sense it will be able to predict (or classify) samples *different* from those used in the aforementioned design process. This is the so-called “ability to generalize”, and is the capability why MLPs are known to be universal approximators of many functions. MLPs have been successfully applied to a great amount of nonlinear prediction and classification problems [206, 207].

The way the neurons are linked to each other during the design stage is the key property that makes the complete network exhibit the mentioned beneficial properties. The relationship between the input signals (x_j, for $j = 1, 2, \ldots, n$) and the output (y_k) of a given *neuron* k is

$$y_k = \varphi\left(\sum_{j=1}^{n} w_{j,k} \cdot x_j - \theta\right), \tag{3.3}$$

where $w_{j,k}$ is the weight associated to the j-th input, θ is a threshold, and φ is a transfer function. Although there are several functions, the logistic function

$$\varphi(x) = \frac{1}{1 + e^{-x}}. \tag{3.4}$$

is a widely used.

Generally, as will be shown, in wave energy problems, the Levenberg-Marquardt method is the most used algorithm to train the MLP [208]. This algorithm is based on the Jacobian matrix, which can be computed via a standard back-propagation method, much less complex than computing the Hessian matrix [208]. The Levenberg-Marquardt algorithm works by using the following Newton-like update,

$$\mathbf{x}_{k+1} = \mathbf{x_k} - \left(\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}\right)^{-1}\mathbf{J}^T\mathbf{e}, \tag{3.5}$$

where $\mathbf{J}$ is the Jacobian matrix, $\mathbf{e}$ is a vector of network errors, and μ is a parameter which controls the process: when $\mu = 0$, it becomes the Newton’s method, while when μ is large, it leads to a gradient descent method with small step size.

A novel and much faster learning method based on the MLP structure is the so-called Extreme Learning Machine (ELM) [209–213].

The ELM concept

The key characteristic of the ELM training consists in randomly setting the network weights and computing then the inverse of the hidden-layer output matrix [147]. The main benefits of this technique are its simplicity, which makes the training algorithm extremely fast, and its exceptional efficiency, usually superior to other more conventional approaches such as classical MLPs or Support Vector Machines. Additionally, the universal approximation capability of ELMs, along with its classification ability, have been already proven [147, 148, 211–213].

Given a training set $\aleph = \{(\mathbf{x}_i, \mathbf{t}_i) | \mathbf{x}_i \in \mathbb{R}^n, \mathbf{t}_i \in \mathbb{R}^m, i = 1, \cdots, N\}$, an activation function, $g(x)$, and and number of hidden nodes, $\tilde{N}$, the ELM algorithm works as follows:

1. It assigns at random inputs weights $\mathbf{w}_i$ and bias b_i, i being $i = 1, \cdots, \tilde{N}$.

2. It computes the hidden layer output matrix, $\mathbf{H}$,

$$\mathbf{H} = \begin{bmatrix} g(\mathbf{w}_1 \cdot \mathbf{x}_1 + b_1) & \cdots & g(\mathbf{w}_{\tilde{N}} \cdot \mathbf{x}_1 + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(\mathbf{w}_1 \cdot \mathbf{x}_N + b_1) & \cdots & g(\mathbf{w}_{\tilde{N}} \cdot \mathbf{x}_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \tag{3.6}$$

3. It computes the output weight vector β as

$$\beta = \mathbf{H}^{\dagger}\mathbf{T}, \tag{3.7}$$

   where $\mathbf{H}^{\dagger}$ stands for the Moore-Penrose inverse of matrix $\mathbf{H}$ [209], and $\mathbf{T}$ is the training output vector, $\mathbf{T} = [\mathbf{t}_1, \cdots, \mathbf{t}_N]^T$.

Note that the number of hidden nodes ($\tilde{N}$) is a free parameter to be computed. In general, scanning a range of $\tilde{N}$ values is a useful approach to this problem.

3.2.2 Support Vector Machines for regression problems

A second important method for prediction, we have included in this work within the broadly considered Neural Computation paradigm, is the Support Vector Machine for regression problems (SVMr) [149]. Although there are different implementations of the SVMr concept, the classic model, ϵ-SVMr, described in [149], will assist us in explaining the basic concepts as follows.

Given a set of training vectors $\mathcal{C} = \{(\mathbf{x_i}, y_i), i = 1, \ldots, l\}$, where $\mathbf{x_i}$ is a feature vector of the input space with dimension N, and y_i labels the output value to be estimated, the ϵ-SVMr algorithm for regression consists in training a model

$$y(\mathbf{x}) = f(\mathbf{x}) + b = \mathbf{w}^T \phi(\mathbf{x}) + b \tag{3.8}$$

that aims at minimizing a risk function

$$R[f] = \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{l} L\left(y_i, f(\mathbf{x})\right) \tag{3.9}$$

where, in Expressions (3.8) and (3.9), $\mathbf{w}$ controls the smoothness of the model, $\phi(\mathbf{x})$ is a function of projection of the input space into the feature space, b represents a bias parameter, and $L(y_i, f(\mathbf{x}))$ labels a loss function. For instance, an ϵ-insensitive loss function [149],

$$L(y_i, f(\mathbf{x})) = |y_i - f(\mathbf{x_i})|_\epsilon, \tag{3.10}$$

leads to an L1-SVMr (L1 support vector regression) [149].

Aiming at training this model, it is required to solve the following optimization problem [149]

$$\min \left(\frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \right), \tag{3.11}$$

subject to the constraints:

$$y_i - \mathbf{w}^T \phi(\mathbf{x_i}) - b \leq \epsilon + \xi_i, \quad i = 1, \ldots, l \tag{3.12}$$

$$-y_i + \mathbf{w}^T \phi(\mathbf{x_i}) + b \leq \epsilon + \xi_i^*, \quad i = 1, \ldots, l \tag{3.13}$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, \ldots, l. \tag{3.14}$$

It is useful to formalize this optimization problem in a dual form as

$$\begin{aligned} \max \Bigg(& -\frac{1}{2} \sum_{i,j=1}^{l} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(\mathbf{x_i}, \mathbf{x_j}) - \\ & -\epsilon \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i (\alpha_i - \alpha_i^*) \Bigg) \end{aligned} \tag{3.15}$$

subject to

$$\sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0 \tag{3.16}$$

$$\alpha_i, \alpha_i^* \in [0, C] \tag{3.17}$$

In addition to these constraints, the Karush-Kuhn-Tucker conditions must be fulfilled, the bias parameter b having to be obtained too. See [149] for further details.

In the dual formulation of the problem, function $K(\mathbf{x_i}, \mathbf{x_j})$ is the kernel matrix, which is formed by the evaluation of a kernel function, equivalent to the dot product $\langle \phi(\mathbf{x_i}), \phi(\mathbf{x_j}) \rangle$. An common choice for this kernel function is a Gaussian function

$$K(\mathbf{x_i}, \mathbf{x_j}) = exp(-\gamma \cdot \|\mathbf{x_i} - \mathbf{x_j}\|^2). \tag{3.18}$$

The final form of function $f(\mathbf{x})$ depends on the Lagterm multipliers α_i, α_i^* as follows:

$$f(\mathbf{x}) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(\mathbf{x_i}, \mathbf{x}) \tag{3.19}$$

In this way it is possible to get an SVMr model by means of the training of a quadratic problem for given hyper-parameters C, ϵ and γ. Nevertheless, computing these parameters is not simple, being necessary to implement search algorithms to compute the optimal values or an estimation for them [214].

3.3 Evolutionary Computation

While Neural Computation is inspired by the human brain paradigm, Evolutionary Computation (EC) is inspired by both the biological principles of Genetics and Natural Selection associated to the very varied relationships of predation, reproduction, etc., that occur in long populations. Within the framework of wave energy, the most representative approaches belonging to Evolutionary Computation are Evolutionary Algorithms (EAs), Genetic Algorithms (GAs) and, more recently, the so-called Coral Reefs Optimization (CRO) algorithm. All of them are population-based algorithms inspired by biological concepts. For the sake of clarity, we start our description by the GA, whose concepts are more intuitive.

3.3.1 The concept of Genetic Algorithm

A GA [155, 215], an optimization and search technique that does not require derivative information, is able to deal with a large number of variables, to provide a global solution for multi-local extrema problems, to optimize functions with continuous or discrete variables, and to optimize variables with extremely complex cost surfaces.

Put it simple, a GA is based on three key points [155, 215]:

1. Encoding the candidate solutions (individuals).
2. Generating an initial population of candidate solutions.
3. Applying genetic operators (selection, recombination or crossover, and mutation).

These points emulate the way Nature works. Encoding a candidate solution is analogous to the way Nature represents the external characteristics of a living being by means of chromosomes (genetic information). In Nature, the creation of novel chromosomes (via mutations or reproduction) may lead to the ability to survive:

the better an individual is adapted to the environment, the higher its probability of survival is, and thus the higher its chances of having descendants. Analogously, in a GA, the selection operator evaluates fitness of individuals and selects the one (the candidate solution to the problem) that best solves it (with the lowest error). In the procreation process in Nature (crossover or recombination, in GA terminology), the parent chromosomes are combined to generate a novel chromosome. Sporadically, and because of inevitable errors in copying genetic information (or external factors, for instance, radiation), mutations (random variations) can occur, leading to the appearance of individuals with some novel characteristics, different from those of their parents. If the novel attribute makes the progeny better suited to the environment (or equivalently, it solves better the problem at hand), the probabilities of survival and of having descendants also increase. Part of the offspring could inherit the novel chromosomes, and thus the corresponding external characteristic codify by them.

In this way, the initial population of individuals evolves and, for a number of generations, the described process results in the creation of individuals better adapted to the environment (better solutions to the problem) and in the extinction of those worse suited.

3.3.2 The concept of Evolutionary Algorithm

An EA is an optimization, population-based algorithm, inspired by the principles of natural selection and genetics, which is able to tackle complex problems [150, 216] such as the one formulated. Among these advantages, EAs do not require derivative information and are able to optimize functions with a large number of continuous or discrete variables, finding the global solution for multi-local extrema problems [217].

Although GA and EA are sometimes used interchangeably in many works, in this thesis, we prefer to use the term EA since, as will be explained in a practical and detailed way in Section 5.7 of Chapter 5 (focused on integrating wave energy in power grids by combining EA and CN concepts), we have encoded each feasible solution as a binary triangular matrix, instead of a bit-string. For further details about different encodings, the interested reader is referred to [218].

The underlying concepts of EAs and the way they are computationally implemented are inspired by the way Nature finds out solutions to extremely complex problems, such as the "survival of the fittest" individual in a evolving ecosystem [216, 217]. Aiming at better explaining our approach, it is convenient to introduce here two biological phenomena from which EAs are inspired: (1) the external characteristics ("phenotype") of living beings are encoded (represented) using genetic material ("genotype"); and (2) evolution is the result of the interaction between the random creation of new genetic information and the selection of those living beings that are best adapted to the environment [217].

Genotype-Phenotype Relationship

As mention, in natural evolution, genotype is the genetic information that encodes and causes the phenotype (all external characteristics) of a living being (or "individual"). Specifically, each characteristic is encoded by a "gene", a "chromosome" being the set of these genes [217]. Each gene is located at a particular position on the chromosome and can exhibit different values ("allele").

Natural Evolution

The random creation of new genetic information in Nature may lead to a better (or sometimes, worse) ability to survive. The better a living being is adapted to its environment, the higher its probability of survival is. This is called "survival of the fittest". In turn, the longer the individual's life is, the higher its probability of having descendants. In the procreation process, the parent chromosomes are crossed or combined ("recombination") to generate a new chromosome (which encodes the offspring). With very small probability, "mutations" (or random variations in genes) can occasionally occur, caused by external factors (for instance, radiation) or simply by unavoidable errors when copying genetic information. This leads to offspring with new external properties, which are different from those of their predecessors. If such arising external characteristic makes the offspring better adapted to the environment, its probability of survival and having descendants increases. In turn, part of the offspring can inherit the mutated genes (and thus the corresponding external characteristic), which can be passed from generation to generation. These natural processes make the population evolve, resulting in the emergence of individuals better adapted to the environment and in the extinction of those less fitted. For deeper details about the main similarities and differences between natural evolution and evolutionary algorithms, the interested reader is referred to [216].

Please note that these brief paragraphs are only intended to be an introduction to the essential concepts to understand the review we have carried out in Section 3.5 of the present chapter. We postpone the details of our particular implementation of the EA explored in this thesis to Section 5.7. As mentioned in Chapter 1, Chapter 5 will explore the feasibility of an approach that models a farm of WECs connected to the on-shore grid as a smart grid, whose complex network structure is optimized by using an EA.

3.3.3 The Coral Reefs Optimization algorithm

The Coral Reefs Optimization (CRO) algorithm is a very novel algorithm [219–223] which has been recently used in renewable energy [224] and related topics [225–227].

The CRO algorithm is a meta-heuristic approach inspired by corals' reproduction and coral reefs formation, proposed recently in [219]. Basically, the CRO is based on the artificial modeling of a coral reef, Λ, consisting of a $N \times M$ square grid. It is assumed that each square (i, j) of Λ is able to allocate a "coral" (or colony of corals), $\Xi_{i,j}$, representing a "solution" to a given optimization problem. This candidate solution $\Xi_{i,j}$ is *encoded* as a string of numbers in a given alphabet $\mathcal{I}$.

For instance, in the problem described in [71], which consists in selecting, among the 60 wave-describing features, those that maximize H_s reconstruction, each candidate solution $\Xi_{i,j}$ is encoded using the string

$$\mathcal{I}_{i,j} = [c_1, \cdots, c_{60}], \tag{3.20}$$

whose elements represent whether the i wave-describing feature in the candidate vector will be used or not: $c_i = 1$ codifies that i-th feature has been selected, while $c_i = 0$ means that this is not the case.

The CRO algorithm is then first *initialized* at random: some squares in the Λ grid are occupied by corals (i.e. solutions to the problem) while other squares in the grid remain empty. Non-occupied squares or *holes* in the reef are sites where new corals can freely settle and grow in the future. The rate between free/occupied squares in Λ at the beginning of the algorithm is an important parameter of the CRO algorithm. It is denoted as ρ, and fulfills that $0 < \rho_0 < 1$.

Each coral is then associated to a *health* function $f(\Xi_{i,j}) : \mathcal{I} \to \mathbb{R}$, that represents the problem's objective function. $f(\Xi_{i,j})$ quantifies the extent to which coral $\Xi_{i,j}$ (or trial solution) accurately solves the problem.

In [71], the *healthiest* coral $\Xi_{m,n}$ represents the best solutions in the sense that its encoding vector $\mathcal{I}_{m,n}$ –Expression (3.20)– makes the estimating algorithm (an ELM) minimize the root-mean-square error RMSE($\hat{H}_s$) –Expression (3.1)– between the estimated value $\hat{H}_s$ and the real H_s sample available in the data base. That is, coral $\Xi_{m,n}$ represents the best H_s reconstruction.

The CRO algorithm –like other evolutionary, population based ones– is based on the fact that the reef will progress (or evolve in time), as long as healthier (stronger) corals (which represent better solutions to the problem at hand) survive, while less healthy corals perish.

This is why, after the reef initialization described above, a second phase, "reef formation", is artificially simulated in the CRO algorithm. It consist of the simulation of the corals' reproduction and novel larvae sitting in the reef by *sequentially applying different operators* until a given stop criteria is met.

There are several operators to mimic corals' reproduction and novel larvae sitting. Some of them are: a modeling of corals' sexual reproduction (*broadcast spawning* (*external* sexual reproduction) and *brooding* (*internal* sexual reproduction)), a model of asexual reproduction (*budding*), and also some catastrophic events in the reef, i.e. polyps *depredation*. After the sexual and asexual reproduction, the *set of larvae* formed (*new solutions* to the problem), try to find a place to grow in the reef. It could be in a free space, or in an occupied once, by *fighting* against the coral actually located in that place. If larvae are not successful in locate a place to grow in a given number of attempts, they are depredated in this phase. Some important details about the implementation of these mechanisms are:

1. *Broadcast Spawning* (external sexual reproduction). It consists of two steps:

   1.a. In a given step k of the reef formation phase, select uniformly at random a fraction of the existing corals ρ_k in the reef to be broadcast spawners. The fraction of broadcast spawners with respect to the overall amount of existing corals in the reef will be denoted as F_b. Corals that are not selected to be broadcast spawners (i.e. $1 - F_b$) will reproduce by brooding later on, in the algorithm.

   1.b. Select couples out of the pool of broadcast spawner corals in step k. Each of such couples will form a coral larva by sexual crossover, which is then released out to the water. Note that, once two corals have been selected to be the parents of a larva, they are not chosen anymore in step k (i.e. two corals are parents only once in a given step).

2. *Brooding* (internal sexual reproduction). As previously mentioned, at each step k of the reef formation phase in the CRO algorithm, the fraction of corals that will reproduce by brooding is $1 - F_b$. The brooding modeling consists of the formation of a coral larva by means of a random mutation of the brooding-reproductive coral (self-fertilization considering hermaphrodite corals). The produced larva is then released out to the water in a similar fashion than that of the larvae generated in step 1.b.

3. *Larvae setting*. Once all the larvae are formed at step k either through broadcast spawning (1.) or by brooding (2.), they will try to set and grow in the reef. First, the health function of each coral larva is computed. Second, each larva will randomly try to set in a square (i, j) of the reef. If the square is empty (free space in the reef), the coral grows therein no matter the value of its health function. By contrast, if a coral is already occupying the square at hand, the new larva will set only if its health function is better than that of the existing coral. A number κ of attempts for a larva to set in the reef is defined: after κ unsuccessful tries, it will be depredated by animals in the reef.

4. *Asexual reproduction*: in the modeling of asexual reproduction (budding or fragmentation), the overall set of existing corals in the reef are sorted as a function of their level of healthiness (given by $f(\Xi_{ij})$), from which a fraction F_a duplicates itself and tries to settle in a different part of the reef by following the setting process described in Step 3. Note that a maximum number of identical corals (μ) will be allowed in the reef.

5. *Depredation in polyp phase*: corals may die during the reef formation phase of the CRO algorithm. At the end of each reproduction step k, a small number of corals in the reef can be depredated, thus liberating space in the reef for next coral generation. The depredation operator is applied with a very small

probability P_d at each step k, and exclusively to a fraction F_d of the worse health corals in Λ.

The algorithm applies iteratively the aforementioned operators until the stopping criterium is reached or if the lowest RMSE value remains unchanged for a given number of iterations.

3.3.4 Genetic Programming: concept

Genetic Programming (GP) is similar to GA in the sense it evolves *computer programs* and finally leads to a program able to solve a problem without having had "telling" it how to do it [228, 229]. It starts from a high-level description of the problem at hand ("what needs to be done" instead of "how to do it"), and iteratively evolves a population of computer programs into a novel generation of computer programs by applying operators. Its steps are usually [230, 231]: 1) Generation of the initial population of computer programs (individuals), usually represented as a tree graph. 2) Evaluation of the fitness of the individuals. 3) Selection of the best individuals as parents. 4) Creation of novel individuals (off-spring) via the genetic operations (crossover, mutation). 5) Replace parents in the current population by those best-suited off-springs. 6) Iterate steps 2-5 until a stop criterion is fulfilled (either a number of generations or fitness criterion such as minimum error). A more exhaustive description of GP can be found in [228, 229], while its particular application to prediction in time-series can be found in [232].

3.4 Fuzzy Computation

Fuzzy Computation (FC) is inspired by the fact that humans exhibit the outstanding ability to reason in an environment of incomplete information, uncertainty, and partiality of class membership. Fuzzy Logic (FL) and Rough Set (RS) theories are the two principal FC approaches applied to wave energy problems, as will be shown later on.

3.4.1 Fuzzy Logic

Its original concept, proposed by Zadeh [233], is based on the concept of "fuzzy set" (FS), which plays a key role in fuzzy logic. In conventional set theory, an element either belongs to a set or it does not. However, in FS theory, an element can belong to a set with a certain degree ("partial membership"). The degree of membership is referred to as the "membership value", and is commonly represented by a real value in $[0, 1]$, where 0 and 1 correspond, respectively, to "full non-membership" and "membership".

Based on these ideas, predicates in FL can exhibit partial degrees of truth, in the same way as elements can have partial membership in FS, the grade of truth being represented by using a real number in $[0, 1]$. These concepts will assist us in introducing two key ideas in FL: "graduation" and "granulation" [234, 235]. In FL, everything is allowed to be graduated, that is, be a matter of degree. In FL, everything is allowed to be granulated: for example, the concept "size" is granulated when its values are described as "small", "medium" and "big". In this respect, the key contributions of FL are the concept of "linguistic variable" (that is, using words instead of numbers) [235], the fuzzy "if-then" rules, and the ability to compute with information described in natural language. These are the fundamental concepts of Fuzzy Inference Systems (FIS), whose details can be found in the review [235]. Recent applications of fuzzy logic in renewable energy systems are [236, 237].

3.4.2 Rough Set

One of the Rough Set (RS) characteristics is its explicative nature, that is, the generated model explains the knowledge hidden in the dataset, and is relatively easy to understand. Put it very simple, RS theory is a mathematical method envisaged [238–240] to deal with the vagueness or uncertainty in decision making. However, unlike other different methods that deal with uncertainty (such as statistical probability or FS theory), RS theory deals with the uncertainty generated when indistinguishable elements (described by the same data or knowledge) can be classified into different classes. This fact prevents them from being precise assigned to a set. Thus, the classes in which the elements are classified are vague, but they can be approximated with precise sets [241].

RS works by finding out dependencies between attributes, and simplifying the set of attributes by eliminating those that are not necessary to properly characterize the knowledge. The concept of "reduct" arises thus as the minimal attribute subset that gives the same quality of classification as the initial set containing all the attributes. The reduct leads to "if-then" rules of the form "if conditions then decisions". These rules stipulate what decisions should be taken up in the case in which some conditions are fulfilled. The if-then rules can also be used to allocate novel elements to a class by matching the condition part of one of the decision rule to the description of the element.

3.5 State of the art. Review of SC approaches in wave energy applications

3.5.1 The importance of applying SC algorithms to estimate wave parameters

Not all the wave parameters have the same practical importance in wave energy applications. Among all the wave parameters that we have defined in Chapter 2 [P (Exp. (2.2)), H_s (Exp. 2.3), T_e (Exp. 2.4), T_p (Exp. 2.5), T_z (Exp. 2.6), Q_p (2.8), ν (2.9), ϵ (Exp. 2.10) or γ (Exp. 2.11)], the parameter that has appeared most times in the bibliographic review that follows is H_s. This is because two important reasons:

1. It is necessary to compute the *available resource* at a location prior to WEC deployment.

2. WEC *survivability* depends on *extreme* sea states, H_s being the most significant parameter related to the intensity of sea states [189].

Other parameters that, although important, have appeared less often in the revision of the literature are T_e, T_p, T_{m01} and T_{m02}.

- T_e is useful to estimate P and in the design of turbines for wave energy conversion.

- T_p is useful because the dynamic response of a floating WEC depends on it [191].

- T_{m01} is used in the study of the giant waves and wave forecast.

- T_{m02} has applicability in the design of marine structures, including Oscillating Water Column WECs (Figure 2.6) and overtopping WECs (Figure 2.7).

For further details about the state of the art in the use of SC techniques applied to wave energy problems, the interested reader is referred to [71] and [203], this latter being focused on medium-to long-term predictions of wave energy resources. Reference [205], which has been published just when the writing of this thesis was being completed, explores relationships between wave parameter.

The following sections analyze the main conclusions of our literature review.

3.5.2 The use of neural networks in wave energy problems: state of the art

MLP in wave energy

The MLP approach is the SC method that has appeared most often in our review. There are some important conclusions about the applicability and usefulness of NNs to estimate the mentioned wave parameters:

1. All papers [144,154,242–252] agree on the fact that MLPS are able to *accurately predict* H_s with prediction intervals up to 12 hours, with high correlation coefficient up to $R \approx 0.97$. MLPs achieve in general better results than statistical methods (AR, ARMA, ARIMA) for prediction intervals up to 12 h [144, 249]. For instance, $R_{\text{MLP}} = 0.964 > R_{\text{ARIMA}} = 0.824 > R_{\text{ARMA}} = 0.808$ [144, 249]. Besides this higher performance, neural networks exhibit other practical advantages (model-free, flexibility, adaptability).

2. Even, a few studies [154, 248, 252] have reported on the fact that MLP models are able to forecast H_s with good accuracy up to 24 h –with a correlation coefficient R ranging from 0.99 (3h lead time) to 0.95 (24h)–. The latter two works combine wavelets and artificial neural network. The key idea behind this SC approach is that H_s samples are first decomposed through discrete wavelet transformation to obtain wavelet coefficients, which are then used as inputs to the NN.

3. MLPs have also proven to be useful to *reconstruct* missing H_s values [250, 251] with very high correlation coefficient $R = 0.98$ [250]. In [251] H_s is also reconstructed with high accuracy: the minimum mean square error is $\text{MMSE}_{\text{MLP}} = 0.0217$ m ($\text{RMSE}_{\text{ARX}} = 0.0235$ m) in short-term predictions, while for long-term predictions (48h) was found $\text{RMSE}_{\text{MLP}} = 0.0252$ m, slightly superior to $\text{RMSE}_{\text{ARX}} = 0.0238$ m.

4. Although H_s is the most studied parameter through MLPs, there are also a few works [243,246] that have estimated values of other parameters of less utility in wave energy. The main conclusion regarding the estimation of the remaining parameters using MLPs is that they can be estimated with *high accuracy* in the short-term [243, 246], with correlation coefficients: $R_{H_s} = 0.947$, $R_{T_z} = 0.945$, $R_{Q_p} = 0.953$, $R_{S_p} = 0.883$, $R_{E_{\max}} = 0.901$, $R_{T_p} = 0.891$. Please see [243, 246] for further details.

5. Another interesting conclusion that can be obtained from [243] is the feasibility of MLPs to construct relationships between H_s and other wave parameters such as the average zero-cross period T_z (Exp. (2.6)), the spectral peak period T_p (Exp. 2.5), the spectral peak energy E_{max}, the maximum wave high H_{max}, and in between spectral narrowness parameter ν (Exp. 2.9) and spectral width parameter ϵ (Exp. 2.10), two measures of the spectral width. The underlying

motivation behind this work is that it is often necessary for some applications to identify interrelationships between different parameters describing a short-term sea state. For instance, obtaining the structural response of marine structures [170] (platforms, ships, WECs such as OWSC or Oscillating Water Column, whatsoever) requires to estimate the peak energy density $E_{\max}$ for a given design value of H_s. The works [244, 245] have explored a similar methodology to predict the significant wave height and zero-up-crossing wave periods T_{02}.

6. MLPs have been used to estimate the significant wave height H_s and other wave parameters [246]: zero crossing period (T_z), spectral peakedness parameter (Q_p), spectral width parameter (S_p), maximum spectral energy (E_{max}), and time period corresponding to maximum spectral energy (T_p). In particular, the correlation coefficients of the MLP designed with empirical data (field wave analysis) were (over the test set): $R_{H_s} = 0.947$, $R_{T_z} = 0.945$, $R_{Q_p} = 0.953$, $R_{S_p} = 0.883$, $R_{E_{\max}} = 0.901$, $R_{T_p} = 0.891$. The authors concluded that the ocean wave parameters can be directly obtained from the measured spectra using trained NN.

7. The MLP approach has also been exploited to estimate wave spectra [253] from average values of some key wave parameters (significant wave height, average zero-cross wave period, spectral width and peakedness parameter). The main finding of this work is that the ANN approach helps estimate the spectral shapes more accurately than those provided by some spectrum theoretical models –JONSWAP and Scotts–. The correlation coefficients over the test set was found as high as $R = 0.97$. In [254] the performance of the NN approach is even better than that achieved by SWAN model ($R_{\mathrm{NN}} = 0.94 > R_{\mathrm{SWAN}} = 0.89$) with the exception of the most powerful peak.

8. Wave energy flux can be estimated with errors ranging from 16 to 20 percent at an hourly horizon, and 28-29 percent at a daily resolution [255]. Finally, [254] shows that ANNs are a powerful tool to forecast the wave energy potential at particular coastal site with great accuracy. The performance of the NN is even better than that achieved by SWAN model ($R_{\mathrm{NN}} = 0.94 > R_{\mathrm{SWAN}} = 0.89$) with the exception of the most powerful peak [254].

9. Finally, an ANN to control an Archimedes Wave Swing WEC has been successfully proven to increase the yearly average electricity production about 160% over the performance of the conventional controller [256].

ELM in wave energy

The use of ELMs in wave energy is very recent, and has been used in combination with population-based approaches, such as GAs [107] and CRO [71] algorithms:

1. The recent work [107] has proposed the use of a ELM-based approach to reconstruct H_s at a given buoy. Specifically, this study combines a GA and an ELM

(hybrid GA-ELM algorithm) that selects wave parameters from surrounding buoys in the effort of minimizing the reconstruction error at the buoy under study. The approach has been satisfactory proven using real data from two locations near the Caribbean Islands. The GA-ELM selects the best parameters (7 among 60) that make an *optimized* ELM estimator to reconstruct H_s with an RMSE of 0.48 m.

2. In [71], the authors have proposed a hybrid CRO-ELM algorithm to reconstruct the missing value of the significant wave height H_s at a given buoy by using a number of wave parameters available at other surrounding buoys. The explored CRO-ELM algorithm selects those parameters that make the ELM estimator work optimally. In particular, the CRO-ELM proposed reconstruct H_s at a buoy by using wave data from surrounding buoys in the Caribbean Sea, and achieves a small error (Root Mean Square Error, RMSE$[\hat{H}_s]$ = 0.455 m) after selecting, among the 60 wave-describing features, those 7 that maximize the ELM performance.

3.5.3 SVM approach in wave energy

1. The SVM with Radial Basis Function (RBF) kernel predicts H_s slightly better ($R = 0.96$) than the ANN approach ($R = 0.94$) with the added bonus of requiring less computational time [257].
2. Wave spectrum has been estimated in [258] by using SVM for regression, and has been found to be able to estimate the spectral shape with low values of mean square error, RMSE(Hz/m^2)= 0.03 and relative high correlation coefficient $R = 0.78$.
3. The newly work [259] makes use of a SVR machine to estimate H_s using the "shadowing effect" of X-band marine radar images, avoiding the radar calibration. The mean square error has been found to be 0.0154 m, lower that that of the MLP (0.0176 m).

3.5.4 Fuzzy approaches in wave energy

With the technical standpoint we have stated in the Introduction, the second class of SC techniques, Fuzzy Computation, has also been applied to predict wave parameters, although at a lesser extent than the Neural Computation approach, as will be shown in the paragraphs that follow. They include Fuzzy Inference System (FIS), Takagi-Sugeno (TS) fuzzy method, and Adaptive-Network-Based Fuzzy Inference System (ANFIS). The main conclusions are:

1. The ANFIS approach is a feasible tool for modeling wave parameters [260]: the scatter index of the ANFIS model in H_s prediction is less than that of the CEM method.

2. The TS fuzzy approach overcomes the classical ARMAX method [261–263] when predicting H_s.

3. The ANFIS method exhibits a slightly higher accuracy than conventional ones when estimating the parameters H_s and T_p [264].

4. The fuzzy logic controller (FLC) of a point absorber WEC help increase the energy capture in about 16% [265]. An advanced version of this FLC, which includes a particle swarm optimization algorithm [266], increases the average power in 15%.

5. The combination of FL and GA assists in increasing the energy conversion of a floating point absorber WEC in irregular waves compared to the case in which this control is not applied [267, 268].

3.5.5 Evolutionary approaches in wave energy

Among the Evolutionary Computation techniques applied to estimate wave energy resource parameters, the Genetic Programming (GP) approach is the most used. They have been successfully used in:

1. Filling up missing values in wave time series provided by buoys [269, 270]. An example of its successful application is the problem of filling up missing values in wave time series provided by buoys [269], in which particular GP models on spatial correlation with neighboring values have been carried out. The results suggest that GP achieves slightly better results than the ANNs explored by the authors in previous works: $R_{\text{GP}} = 0.95 > R_{\text{ANN}} = 0.94$, $\text{RMSE}_{\text{GP}} = 0.22 < \text{RMSE}_{\text{ANN}} = 0.25$ m. In a similar scientific standpoint, [270] leads to the conclusion that gaps of missing values are slightly better computed by the GP algorithm than those estimated by the ANN designed for comparative purposes. Specifically, if the gaps of missing values are small: $R_{\text{GP}} = 0.99 > R_{\text{ANN}} = 0.98$, $\text{RMSE}_{\text{GP}} = 0.14 < \text{RMSE}_{\text{ANN}} = 0.32$ m.

2. Estimating wind data from wave data [271], with slightly more accurate results than those computed by ANNs ($R_{\text{GP}} = 0.95 > R_{\text{ANN}} = 0.94$).

3. Predicting H_s at short term [272]. The significant wave height predictions have been made over time intervals of 3, 6, 12 and 24 hours, and the experiments have pointed out that the GP approach is a feasible tool for short term prediction with $R = 0.9$ for 12 h.

GAs have also been used:

1. Predicting wave significant height and peak spectral period, by using a hybrid GA-adaptive network-based FIS (GA-ANFIS) model [273]. The key point in

this work is that both clustering and rule-based parameters are jointly computed by using GAs and ANNs. The prediction accuracy of the proposed approach has been compared to that of conventional ANFIS and Shore Protection Manual (SPM) methods, leading to the conclusion the proposed GA-ANFIS model works better.

2. Optimizing the shape of wave energy collectors [274]. A collector is described in this work by using a parametric model of its geometry, based upon bicubic B-spline surfaces. The cost functions are formulated using estimates of the weighted mean power based on data from a site on the West Shetland Shelf (North East Atlantic Ocean). The results show that the selected shapes perform better than a comparable box-shaped collector. The authors suggest that optimizing the collector shape with respect to its size as well as the overall mean power delivery could improve its performance substantially. More work need to be done in this respect.

3.6 Conclusions

In this chapter we have reviewed the use of Soft Computing (SC) techniques (Neural, Fuzzy, and Evolutionary Computation) in the field of wave energy. The benefits of applying SC techniques to wave energy problems resides on their great potential to work with a huge amount of imprecise or missing data. This is just the case of the design, deployment, and even control of (some) wave energy converters (WECs), whose fundamentals have been summarized in Chapter 2 to make this thesis stand by itself. In this regard, a first indicator prior to the deployment of WECs at a given location is the amount of wave energy flux available. This magnitude can be estimated by using the significant wave hight H_s and the wave energy period T_e, which, in turn, can be computed from espectral magnitudes of buoy data. These and other wave parameters have been found to be estimated in our review by means of a variety of SC techniques. In particular:

- Most of the applications of Neural Computation techniques, considered in this paper in a broad sense, have been found to focus on the prediction of a number of wave energy parameters by means of Multilayer Perceptrons (MLPs) and, at a lesser extent, by Support Vector Machines (SVMs). Neural Computation techniques have been applied to: *a*) Predict a variety of wave parameters, in particular, H_s and T_e; *b*) Estimate missing data in wave time series; *c*) Estimate the wave spectrum; *d*) Forecast wave energy flux; and *e*) Control WECs, in particular Archimedes Wave Swing WECs.
- The second class of SC techniques, Fuzzy Computation, has been found to be applied: 1) To predict wave parameters, although at a lesser extent than the Neural Computation approach; 2) To control WECs, by using a combination of Fuzzy Computation and GAs, in particular a floating point (buoy-based) absorber WEC.

- Evolutionary Computation algorithms have been applied to: 1) Fill up missing values in wave time series; 2) Predict H_s; and 3) Optimize the shape of wave energy collectors.

These SC techniques have proven to reach similar and even superior results than other data-driven models like statistical methods (AR, ARMA, ARIMA,...) in short term estimations (up to 24 h). Data-driven methods have some advantages over numerical models: simple modeling, smaller computational effort, and lack of errors arising out of wind-to-wave conversion. However, numerical models, which take into account a great variety of physical phenomena, are more accurate over large spatial and temporal domains.

Chapter 4

A Hybrid Genetic Algorithm – Extreme Learning Machine approach for Significant Wave Height Reconstruction

Up to this point of the thesis, we have presented in Chapter 2 the main concepts of both wave resources and wave energy converters (WECs), whereas Chapter 3 has presented and reviewed the use of soft computing (SC) techniques in the field of wave energy, in the effort of showing the novelty of our research.

Thus we are already now able to present our first research case in which we have used SC algorithms in an innovative way to solve problems in marine energy. This is just the purpose of the present chapter in which we summarize our approach to reconstruct the significant wave height H_s by applying a hybrid approach that combines a Genetic Algorithm (GA) and an Extreme Learning Machine (ELM). The method and the results of this chapter have been published in [107].

Note that, as mentioned in Chapter 1, we have organized the structure of this thesis so that the reader can study each chapter separately, according to his/her interests and/or previous background. This helps the reader specialized in wave energy or in SC leap directly to the present chapter without necessarily having read Chapter 2 (wave energy and WECs characterizations) or Chapter 3 (review and background of SC methods in wave energy applications). In this respect, this chapter has been written in the effort of standing by itself as far as possible.

4.1 Introduction

Oceanographic buoys are, and have been, probably one of the most used measuring instruments to characterize wind-generated wave properties [193]. In particular, a scalar buoy located at a point $\mathbf{r} = (x, y)$ on the sea surface is able to measure, at each time instant t, the vertical water surface elevation, $\eta(\mathbf{r}, t)$, leading thus to time series. Using Fourier analysis, the spectral wave density $S(f)$ can be computed, and, in turn, based on $S(f)$, a number of integrated wave parameters, such as the spectral moments, the significant wave height H_s, or mean wave period, to name just a few, can also be estimated [157].

The availability and accuracy of wave data play a crucial role in the better understanding of numerical [275, 276] and statistical wave models [277, 278], and in a number of marine-related activities such as the design of vessels and marine structures (oil platforms, breakwaters [279, 280], wave overtopping volumes [281], ports, etc.), wave forecasting for safe ship navigation, or the design and operation of wave energy converters [48] to generate renewable electricity without CO_2 emission. Thus the topic has a clear impact on human safety, economics, clean energy production, and ecology (since the modification of coastal streams by ports may alter marine ecosystems).

However, a number of unexpected events can make buoys break down (such as storms [282], navigation accidents, or other incidents), often causing *missing data gaps*, lasting from the causing event until the buoy is repaired. Considering the great importance that wave data have in the aforementioned marine-related activities, the reconstruction of missing wave data becomes a key topic. Just in this respect, in this chapter, we tackle the problem of reconstructing the missing values of H_s at a "target buoy", based on a number of wave parameters of neighbor buoys. The novelty of our approach is twofold:

1. We propose a hybrid evolutionary algorithm that selects those wave parameters that maximize the H_s reconstruction. It consist of a Genetic Algorithm (GA) [155] hybridized to an Extreme Learning Machine (ELM) [156], called henceforth GA-ELM. It selects (in the set of available wave parameters in the neighbor buoys) a smaller subsets $\mathcal{F}_{n_{SP}}$ with n_{SP} parameters that will help an algorithm reconstruct H_s at the target buoy.

2. We explore to what extent the selected parameters are useful in helping other regression algorithms reconstruct H_s. In this respect we compare the accuracy achieved by three Learning Machine (ML) methods −ELMs, Support Vector Regression (SVR) [149], and Gaussian Process Regression (GPR) [283]− leading to the conclusion that they all achieve very good results in reconstructing H_s.

Although other ML techniques have been applied to fill missing wave data gaps (see next section of related work), to the best of our knowledge, our hybrid GA-ELM approach is novel in the context of coastal engineering, although GAs have been applied before to the modeling of wind waves at sea [284]. After reviewing the related work in Section 4.2, the structure of the rest of this chapter is as follows: While Section 4.3 summarizes the regression methods used, Section 4.4 describes in detail the wave parameters and the database used. Section 4.5 centers on the description of the proposed GA-ELM algorithm. Section 4.6 shows and discusses the results achieved by ELMs, SVRs, and GPRs when using the parameters selected by the GA-ELM. Finally, Section 4.7 summarizes the main findings and conclusions of this work.

The results on this chapter have been published in [107].

4.2 Related work

As mentioned in Introduction section, this chapter tackles the problem of filling up missing H_s data at a target buoy by using a hybrid GA-ELM algorithm that selects those parameters at neighboring buoy locations that help alternative ML regressors (either ELM, SVR, or GPR) reconstruct H_s. A detailed description of all the techniques used in this chapter is far beyond the scope of the work, however, we would like to comment on several previous approaches that have been applied to missing data reconstruction in the past, and also to provide some references of the main techniques that will be applied in this chapter.

Among ML techniques, the Neural Network (NN) approach [285] has been applied to compute missing wave data in time series measured at the station Europlatform, placed in the North Sea [250]. This approach has been found to be specially reliable to reach accurate estimations of missing wave data [251]. In that work, feed forward Multi-Layer Perceptrons (MLPs) and recurrent neural networks were trained by the steepest descent with momentum algorithm and the conjugate gradient algorithm, and their estimations were compared to those computed by using conventional stochastic models. The recurrent neural network approach trained by the conjugate gradient algorithm was found to predict wave height, period, and direction more accurately than the feed forward MLP one. In [286] a NN coupled to a numerical prediction model was used to obtain wave height prediction/reconstruction values. Results in buoys located at lake Superior and in the Pacific Ocean were used to validate the model. In [287] a NN with k-nearest neighbor algorithm has been applied to a problem of wave estimation using significant heights in previous hours. Results in two buoys located at Caspian sea have shown a good agreement of the prediction with real data. NNs and Genetic Programming (GP) [230] were successfully applied in [288] to estimate missing wave heights from neighbouring stations heights measurements. Six buoys from Gulf of Mexico were used, and results obtained showed a good reconstruction of weight heights using these techniques. GP and NNs have also been applied to wave forecast from wind data in [289], obtaining good results in data from the east coast of the USA and India. Also using the data from adjacent buoys, significant wave height values at a buoy location have been estimated by means of a Neuro-Fuzzy approach [262] based on Sugeno-type fuzzy inference. In that paper, the antecedent and consequent part parameters of the fuzzy IF-THEN rules have been inferred after training the fuzzy inference system by the Adaptive Neuro Fuzzy Inference System (ANFIS) methodology [290]. The experimental work was also carried out by using data measured by buoys located at the Gulf of Mexico. NN and ANFIS methods were tested in a problem of wave parameters estimation in [264], over lake Ontario data obtained from a deep-water buoy. In [269], particular GP models based on spatial correlation with neighboring values have been applied to wave height estimation. The results suggest that GP achieves slightly better results than the NNs explored by the authors in previous works. In a similar scientific standpoint, [270] leads to the conclusion that gaps of missing values are slightly better computed by the GP algorithm than those estimated by the NN designed for comparative purposes, in particular if the gaps of missing values are small. Radial basis functions (RBF) have also been applied to similar problems like in [291], where this class of neural network was applied to a problem of down-scaling waves data to shallow waters. There have been alternative approaches that hybridize physical/numerical methods with statistical or ML approaches, such as [278], where different predictive variables from numerical models are hybridized with linear regression for wave height estimation, or [292], that used predictive variables from numerical methods hybridized with different ordinal classifiers for discrete wave height estimation in the gulf of Alaska.

In this chapter we also apply alternative ML algorithms to the reconstruction of missing data at target buoys. Specifically, we use Extreme Learning Machines [156, 213] hybridized with evolutionary algorithms [155, 293], and also Support Vector Regression algorithms (SVR) [149,294] and Gaussian Process Regression (GPR) [283, 295] to improve the data reconstruction in buoys. Specific details on the proposed GA-ELM algorithm will be given in a posterior section.

4.3 Methods: Machine Learning techniques used

As mentioned in Section 4.1, this chapter tackles the problem of filling up missing H_s data at a target buoy by using a hybrid GA-ELM algorithm that selects those neighbor's parameters that help ML regressors (either ELM, SVM, or GPR) reconstruct H_s.

The fundamentals of ELM and SVM have already been explained in Sections 3.2.1 and 3.2.2 in Chapter 3. The only algorithm that remains to be explained is GPR.

Gaussian Process (GP) Regression have recently attracted a lot of attention because of their good performance in regression tasks [283]. We give here a short description of Gaussian Process Regression (GPR), the interested reader being referred to the more exhaustive reviews [295] or [296].

Given a set of N multi-dimensional inputs $\mathbf{x}_n$ and their corresponding scalar outputs y_n, that is, the data set $\mathcal{D}_S \equiv \{\mathbf{x}_n, y_n\}_{i=1}^{m}$, the regression task consists in obtaining the predictive distribution for the corresponding observation y_* based on $\mathcal{D}_S$ given a new input $\mathbf{x}_*$.

The GPR model assumes that the observations can be modeled as some noiseless latent function of the inputs plus independent noise, $y = f(\mathbf{x}) + \varepsilon$, and then sets a zero-mean GP prior on the latent function $f(\mathbf{x}) \sim \mathcal{GP}\ (0, k(\mathbf{x}, \mathbf{x}'))$ and a Gaussian prior on $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ on the noise, where $k(\mathbf{x}, \mathbf{x}')$ is a covariance function and σ^2 is a hyperparameter that specifies the noise power.

The covariance function $k(\mathbf{x}, \mathbf{x}')$ specifies the degree of coupling between $y(\mathbf{x})$ and $y(\mathbf{x}')$, and it encodes the properties of the GP such as power level, smoothness, etc. One of the best-known covariance functions is the anisotropic squared exponential. It has the form of an unnormalized Gaussian, $k(\mathbf{x}, \mathbf{x}') = \sigma_0^2 \exp\left(-\frac{1}{2}\mathbf{x}^T \boldsymbol{\Lambda}^{-1}\mathbf{x}\right)$ and depends on the signal power σ_o^2 and the length-scales $\boldsymbol{\Lambda}$, where $\boldsymbol{\Lambda}$ is a diagonal matrix containing one length- scale per input dimension. Each length-scale controls how fast the correlation between outputs decays as the separation along the corresponding input dimension grows. We will collectively refer to all kernel parameters as $\boldsymbol{\theta}$.

The joint distribution of the available observations (collected in $\mathbf{y}$) and some unknown output $y(\mathbf{x}_*)$ is a multivariate Gaussian distribution, with parameters specified by the covariance function:

$$\begin{bmatrix} \mathbf{y} \\ y_* \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} \mathbf{K} + \sigma^2 \mathbf{I}_N & \mathbf{k}_* \\ \mathbf{k}_*^T & k_{**} + \sigma^2 \end{bmatrix}\right), \tag{4.1}$$

where $[\mathbf{K}]_{nn'} = k(\mathbf{x}_n, \mathbf{x}_{n'})$, $[\mathbf{k}_*]_n = k(\mathbf{x}_n, \mathbf{x}_?)$ and $k_{**} = k(\mathbf{x}_*, \mathbf{x}_*)$. $\mathbf{I}_N$ is used to denote the identity matrix of size N. The notation $[\mathbf{A}]_{nn'}$ refers to entry at row n, column n' of $\mathbf{A}$. Likewise, $[\mathbf{a}]n$ is used to reference the n-th element of vector $\mathbf{a}$.

From (4.1) and conditioning on the observed training outputs we can obtain the predictive distribution

$$\begin{aligned} &p_{GP}(y_*|\mathbf{x}_*, \mathcal{D}) = \mathcal{N}(y_*|\mu_{GP*}, \sigma^2_{GP*}) \\ &\mu_{GP*} = \mathbf{k}_*^T(\mathbf{K} + \sigma^2\mathbf{I}_N)^{-1}\mathbf{y} \\ &\sigma^2_{GP*} = \sigma^2 + k_{**} - \mathbf{k}_*^T(\mathbf{K} + \sigma^2\mathbf{I}_N)^{-1}\mathbf{k}_*, \end{aligned} \tag{4.2}$$

which is computable in $\mathcal{O}(N^3)$ time, due to the inversion of the $N \times N$ matrix $\mathbf{K} + \sigma^2\mathbf{I}_N$.

Hyperparameters $\{\boldsymbol{\theta}, \sigma\}$ are typically selected by maximizing the marginal likelihood (also called "evidence") of the observations, which is

$$\log p(\mathbf{y}|\boldsymbol{\theta}, \sigma) = -\frac{1}{2}\mathbf{y}^T(\mathbf{K} + \sigma^2\mathbf{I}_N)^{-1}\mathbf{y} - \frac{1}{2}|\mathbf{K} + \sigma^2\mathbf{I}_N| - \frac{N}{2}\log(2\pi). \tag{4.3}$$

If analytical derivatives of (4.3) are available, optimization can be carried out using gradient methods, with each gradient computation taking $\mathcal{O}(N^3)$ time. GP algorithms can typically handle a few thousand data points on a desktop PC.

When dealing with multi-output functions, instead of a single set of observations $\mathbf{y}$, D sets are available, $\mathbf{y}_1 \cdots \mathbf{y}_D$, each corresponding to a different output dimension. In this case we can assume independence across the outputs and perform the above procedure independently for each dimension. This will provide reasonable results for most problems, but if correlation between different dimensions is expected, we can take advantage of this knowledge and model them jointly using multi-task covariance functions [297].

4.4 Measured data, wave parameters, and database

Figure 4.1 will assist us in explaining the two case studies we have considered to evaluate the performance of the reconstruction method we propose.

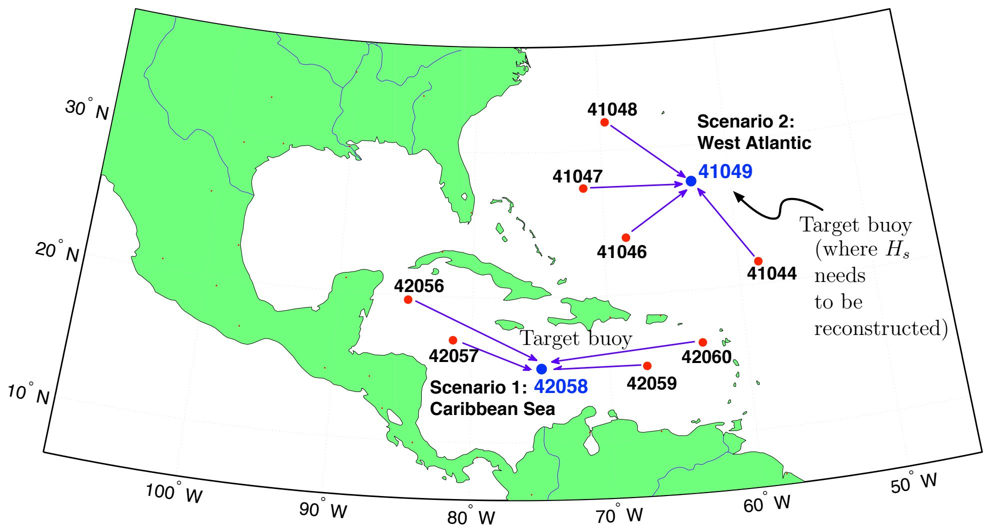


Figure 4.1: Map representing the locations of the buoys involved in the case studies considered. A blue dot represents the target buoy where H_s needs to be reconstructed by using wave data from the corresponding neighbor buoys, represented by red dots.

The first scenario represented in Figure 4.1, labeled "Caribbean Sea", shows the location of five buoys: "42056", "42057", "42058", "42059", and "42060" (National Oceanic and Atmospheric Administration (NOAA) [298]). The arrows aim at schematically illustrating the goal of reconstructing H_s at the buoy "42058" (or "target", represented by a blue dot) based on wave-describing parameters of the other four neighbor red-dot buoys ("42056", "42057", "42059", and "42060", respectively). These wave-describing parameters have been computed from the spectral wave density measured hourly by NOAA at each buoy during 2011. Similarly, the second scenario, "West Atlantic", involves data from buoys 41044, 41046, 41047 and 41048 [298], which will be used to reconstruct H_s at the target buoy 41049. We have used these two different locations in the effort of exploring the feasibility of the proposed method in different sea conditions. The Caribbean Sea is almost enclosed and therefore the wave developed is affected by the fetch limitation. On the contrary, in the chosen Atlantic location other population of different wave fields can be found, such as swell that present a more regular behavior in the spatial propagation than short-crested and high directional spreading wind sea.

4.4.1 Wave parameters and data structure

As mentioned, based on the hourly spectral wave density data at these buoys, we have computed, for each buoy, 15 integrated sea state parameters, which will be used to reconstruct H_s. Regarding the definition of those parameters used, and as mentioned in the Introduction made in Chapter 1, this thesis report has been organized so that each chapter is self-contained, with the aim that the reader can focus exclusively on the chapter of interest. In this respect, the aforementioned wave-describing parameters have been described in the paragraphs below to make this chapter stand by itself.

Section 2.2.3 in Chapter 2 contains a broad description of wave parameters. For simplicity, we summarize in the present section only those parameters that have been used in the problem at hand. For more details the interested reader is referred to Section 2.2.3. In this respect, the selection of wave parameters that can describe sea states, which have been studied in the last twenty years [299], are the following:

- The wave spectral moments m_{-1}, m_0, m_1, and m_2, whose corresponding mathematical definitions can be obtained from that of the spectral moment of order n,

$$m_n = \int_0^\infty f^n \cdot S(f) \cdot df, \tag{4.4}$$

  $S(f)$ being the spectral wave density data from a given buoy, and $n = -1, 0, 1, 2, \cdots$

- The significant wave height, computed as

$$H_s = 4 \cdot (m_0)^{1/2} \tag{4.5}$$

- The peak period, defined as $T_p = 1/f_p$, f_p being the spectral peak frequency, that is, the frequency where the spectrum $S(f)$ reaches its maximum value.

- The mean periods T_{m01}, T_{m02} and T_{m-10}, defined as

$$T_{mxy} = \frac{m_x}{m_y} \tag{4.6}$$

  m_x and m_y being spectral moments computed by Expression (4.4).

- The Goda's peakedness parameter [178], which can be computed as [170]

$$Q_p = \frac{2}{m_0^2} \int_0^\infty f \cdot S^2(f) \cdot df, \tag{4.7}$$

  has the capability to describe empirically the statistical parameters of consecutive wave heights [178].

- The Longuet-Higgins spectral band-width, ν, defined as [179]

$$\nu = \sqrt{\frac{m_2 \cdot m_0}{m_1^2} - 1}, \tag{4.8}$$

indicates the degree of the spectral energy spreading over the frequency range.

- The wave height correlation coefficient, γ, firstly introduced by Kimura [181], and that, after the contributions of Battjes and van Vledder [182] and Longuet-Higgins [179], can be computed as

$$\gamma = \frac{\mathcal{E}(\kappa) - (1-\kappa^2)\mathcal{K}(\kappa)/2 - \pi/4}{1 - \pi/4} \tag{4.9}$$

where:

1. κ parameter can be estimated by using the expression [179, 193]

$$\kappa = \left| \frac{1}{m_0} \int_0^\infty S(f) \cdot e^{i2\pi f T_c} df \right|, \tag{4.10}$$

T_c being a characteristic time that we have computed by using either the estimator T_{m01} or the estimator T_{m02}. Thus, we use the notation, $\kappa(T_c = T_{m01}) \equiv \kappa_{01}$, which represents the value of κ parameter computed by using T_{m01} as an estimator of T_c, while $\kappa(T_c = T_{m02}) \equiv \kappa_{02}$ is the one estimated with T_{m02}.

2. $\mathcal{E}(\kappa)$ and $\mathcal{K}(\kappa)$ are the complete elliptic integrals of 1st and 2nd kind, respectively.

As in the case of κ parameter, γ_{01} represents the value of γ parameter computed by using T_{m01} as an estimator of T_c, while γ_{02} is the one estimated by means of T_{m02}.

For more details the interested reader is referred to Section 2.2.3.

4.4.2 Database $\mathcal{D}$

With the wave data described in Subsection 4.4.1, we have, for any buoy in both scenarios, a wave-describing vector with 15 components (H_s, m_{-1}, m_0, m_1, m_2, T_p, T_{m-10}, T_{m01}, T_{m02}, Q_p, ν, κ_{01}, γ_{01}, κ_{02}, γ_{02}), computed hourly, during year 2011.

These data vectors are just those that form the initial database $\mathcal{D}$, which has been randomly divided into a training set, $\mathcal{S}_{training}$ (containing 80% of the samples), and a test set, $\mathcal{S}_{test}$ (with the remaining 20% saved for testing and not used during the design stage), so that $\mathcal{D} = \mathcal{S}_{training} \bigcup \mathcal{S}_{test}$.

In the effort of preventing our algorithm from overfitting $\mathcal{S}_{training}$ (what could reduce its ability to reconstruct the objective variable), we have used a k-fold cross validation process, whose details will be better understood in Subsection 4.5.3, just after our algorithm have been explained.

4.5 The proposed GA-ELM algorithm for wave parameter selection

Since our purpose is to reconstruct H_s at a target buoy using input vectors with 15 components (H_s, m_{-1}, m_0, m_1, m_2, T_p, T_{m-10}, T_{m01}, T_{m02}, Q_p, ν, κ_{01}, γ_{01}, κ_{02}, γ_{02}) for each of the four neighbor buoys in any scenario, the number of input variables are thus $4 \times 15 = 60$. Or, in other words, the input vector $\mathbf{X} = [x_1, \cdots, x_{60}]$ has 60 components. Note that, aiming at estimating as fast and accurately as possible, it is important to properly reduce the input vector dimensionality in the effort of: 1) Reducing the computational complexity of the reconstruction system; 2) Removing those wave parameters that could provide non-useful information and even degrade the estimation accuracy. Thus, the problem consists in selecting those wave-describing parameters, from a more general point of view) that make the system work as accurately as possible.

With this in mind, the method we propose is based on a GA that computes the fitness of any candidate solution by using an ELM. The reason why we have not hybridized the GA with either the SVR or the GPR, as we have done with the ELM, is because of their higher computational complexity. This is of the greatest importance because, for any generation, the algorithm has to evaluate the fitness of the trial candidate solutions (that is, to what extent, the wave-parameter vector help the classifier work accurately), and the SVRs and GPRs require a training time that make them unsuitable to form part of the fitness function of the GA.

The basic concepts GAs are based on, have already been introduced in Section 3.3, these being:

1. Encoding the candidate solutions (individuals).
2. Generating an initial population of candidate solutions.
3. Applying genetic operators (selection, recombination or crossover, and mutation).

The following subsections summarize the main details of the encoding, the initial population, and the genetic operators we have implemented.

4.5.1 Encoding and initial population

Before applying the genetic operators it is crucial to properly codify the candidate wave-describing vector. The chromosome that encodes any individual (candidate solution) is a string $\mathbf{C} = [c_1, \cdots, c_i, \cdots, c_{60}]$ whose elements represent whether the i wave-describing feature in the candidate vector will be used or not: $c_i = 1$ codifies that feature x_i has been selected, while $c_i = 0$ means that this is not the case.

The size of the initial population is a key point for the GA performance. On one hand, a large initial population could lead to more diversity (and thus, a higher search space, and slower convergence). On the other hand, a very small population leads to a smaller search space to be explored, at the expense of increasing the risk of prematurely converging to a local extreme. After a number of experiments, the optimal size of the initial population has been found to be 100 individuals.

4.5.2 Applying genetic operators

The hybrid GA-ELM we propose evolves the initial population of candidate solutions through successive generations by means of the application of three genetic operators (selection, crossover and mutation) in a loop until a stopping criterium is fulfilled (either a maximum number of generations is reached or if the algorithm converges to a stable solution after a number of generations).

- The selection operator selects a subpopulation of individuals to become parents to crossover. Among the number of selection operators −roulette wheel selection, tournament selection, Boltzman selection, rank selection [300]−, the implemented GA makes use of a tournament selection which involves running several "tournaments" among a few individuals chosen at random from the population. For each individual, its fitness value is evaluated as the root-mean-square error (RMSE) between the reconstructed (estimated) value ($\hat{H}_s$) and the real (measured) one (H_s) available in the data base:

$$\mathrm{RMSE}(\hat{H}_s) = (E[(\hat{H}_s - H_s)^2])^{1/2}, \tag{4.11}$$

  E being the mean value operator. The winner of each tournament (the one with the best fitness) is finally selected for crossover.

- The crossover operator exchanges parts of two selected individuals, leading to novel chromosomes (which codify novel candidate solutions). Among various crossover operators (one-point, two-point, multi-point [301]...), the proposed GA makes use of an one-point crossover operator in which a point on both parents' chromosomes is selected so that genes beyond such point are swapped between the two parent chromosomes. The crossover probability has been set to $p_c = 0.6$ after a number of experiments.

- The mutation operator randomly changes (mutates) an offspring chromosome with a mutation probability, p_m. This has been done by flipping the bits from 0 to 1. The main goal of the mutate operator is to increase diversity within the population, and prevent the GA from prematurely converging to local extrema. The mutation probability has been set to $p_m = 0.01$ after a number of experiments.

The algorithm iterates until a maximum number of generations (50) is reached or until the lowest RMSE value remains unchanged for a given number of iterations (20). These values have been found to be large enough to allow the algorithm to properly converge in our experiments.

4.5.3 k-fold cross validation methodology

As mentioned before, aiming at preventing our GA-ELM from overfitting $\mathcal{S}_{training}$, we have made use of a k-fold cross validation process [302, 303] with $k = 5$. The goal of this cross validation method is to properly define a data subset to "test" the ELM estimator in the *training* phase (that is, a *validation* subset). $\mathcal{S}_{training}$ is thus randomly divided into 5 equal-size subsets so that four of them are used to train the ELM estimator, while the remaining one is saved as the validation set for testing the performance of the system in terms of its RMSE. The cross-validation process is then repeated $k = 5$ times (folds), with each of the k subsets used once as the validation subset ($\mathcal{S}_{validation,i}$, $i = 1, \cdots, 5$). Finally, the five results from the folds have been averaged to produce a single estimation: that is, for each individual, its fitness value is computed as the mean value of the 5 estimation errors obtained during this process.

Once the GA-ELM algorithm has converged, the best individual found has been used to feed an ELM-based estimator $\hat{H}_s$, which has been trained by using $\mathcal{S}_{training}$, and tested with $\mathcal{S}_{test}$ ($\mathcal{S}_{training} \cup \mathcal{S}_{test} = \mathcal{D}$).

4.6 Results and discussion

4.6.1 Result from the feature selection process

As mentioned before, the RMSE of a certain H_s reconstruction algorithm is characterized by Expression (4.11). First of all, and as a baseline result to compare with, we have applied the ELM algorithm with all input parameters available (60), obtaining RMSE values of 0.668m and 0.809m for Scenario 1 (Caribbean Sea) and Scenario 2 (West Atlantic) buoys, respectively. The proposed GA-ELM and alternative methodologies should beat these results for both Scenarios. We also provide here the results of the ELM considering as input parameters $m_{-1}, m_0, m_1, m_2, \kappa_{02}$ in all buoys (20 input parameters). In this case, the RMSE obtained was 0.592 and 0.788, for Scenario 1 and 2, respectively. Figure 4.2 shows RMSE($\hat{H}_s$), for both scenarios, as a function of the number of the best selected parameters, n_{SP}. For the sake of clarity, we have represented only those reconstruction values corresponding to $5 \leqslant n_{SP} \leqslant 10$, since this interval has been found to be the one in which the best reconstruction (lower RMSE($\hat{H}_s$)) is achieved. This is because, on the one side, a higher number of parameters degrades the reconstruction accuracy since some of the parameters behave as noise. On the other side, smaller feature subsets do not have enough information for properly reconstruction.

A key point to note in Figure 4.2 is that the proposed GA-ELM algorithm works well in the sense that it selects a very reduced subset of parameters ($n_{SP} = 10$ parameters) among the available 60 parameters we had at the beginning of the process. Note that using only 10 selected parameters lead to reduced reconstruction errors: RMSE$(\hat{H}_s)_{\text{Caribbean}} \lesssim 0.50$ m, and RMSE$(\hat{H}_s)_{\text{Atlantic}} \lesssim 0.75$ m, obtaining an improvement over the case of not considering a feature selection mechanism. Furthermore, using only five parameters leads approximately to the same RMSE, that is, there is no operational benefit in using more than 5 parameters. The question arising here is which such best wave-describing parameters are. Tables 4.1 and 4.2 aim at answering this question.

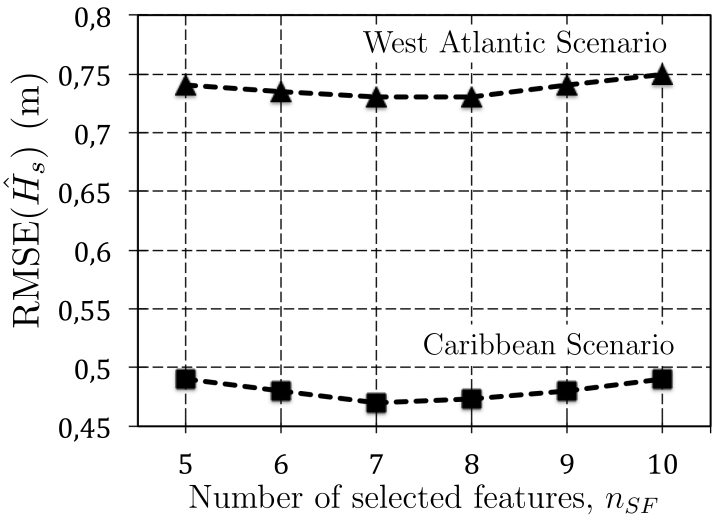


Figure 4.2: Root mean square error of H_s reconstruction, RMSE($\hat{H}_s$), computed over $\mathcal{S}_{test}$, as a function of the number of parameters selected (n_{SP}) by the GA-ELM method, in both scenarios.

Table 4.1, related to H_s reconstruction in Scenario 1, consists of four sub-tables, each corresponding to any of the considered buoys (42056, 42057, 42059, 42060) whose data are used to reconstruct H_s in buoy 42058. In any sub-table, the columns represent *all* the available wave parameters, while the rows represent the number of parameters n_{SP} that the GA-ELM algorithm has selected.

To clearly explain what this Table 4.1 means, it is convenient to focus first on the cells marked by stars ($\star$) in the rows labeled "5". The marker "$\star$" has been used to univocally identify the parameters that have been selected when the GA-ELM algorithm searches for the best 5 parameters ($n_{SP} = 5$). These best 5 parameters scored by "$\star$" are: κ_{02} (from buoy 42056), H_s, m_0, m_1 (from buoy 42057), and m_2 (buoy 42059). No feature has been selected from buoy 42060 (there is no $\star$ in row "5" of the sub-table corresponding to buoy 42060). Similarly, and in the effort of better understanding Table 4.1, we have used different symbols ($\circ$, $\bullet$, $\oplus$, $\otimes$, $\odot$) to mark the parameters that have been selected when the GA-ELM algorithm searches for the best $n_{SP} = 6, 7, 8, 9$ and 10 parameters, respectively.

Table 4.1: Parameters selected by the GA-ELM algorithm for each buoy in the Caribbean Sea case study. There is a sub-table for each buoy involved. While the columns contain all the available parameters (wave-describing parameters), the rows represent the number of parameters (n_{SP}) that the GA-ELM algorithm has selected. The symbols $\star$, $\circ$, $\bullet$, $\oplus$, $\otimes$, and $\odot$ mark the parameters that have been selected for $n_{SP} = 5, 6, 7, 8, 9$ and 10, respectively.

	Wave parameters of buoy 42056 (1185 km away from the target buoy 42058)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5														$\star$	
6					$\circ$										
7				$\bullet$											
8				$\otimes$											
9				$\oplus$											
10				$\odot$											

	Wave parameters of buoy 42057 (740 km away from the target buoy 42058)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5	$\star$		$\star$	$\star$											
6	$\circ$	$\circ$										$\circ$	$\circ$		
7	$\bullet$		$\bullet$					$\bullet$		$\bullet$					$\bullet$
8	$\otimes$	$\otimes$									$\otimes$				
9	$\oplus$	$\oplus$		$\oplus$	$\oplus$						$\oplus$				
10	$\odot$		$\odot$				$\odot$			$\odot$	$\odot$				$\odot$

	Wave parameters of buoy 42059 (799 km away from the target buoy 42058)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5					$\star$										
6					$\circ$										
7					$\bullet$										
8			$\otimes$	$\otimes$	$\otimes$			$\otimes$							
9					$\oplus$						$\oplus$				
10				$\odot$					$\odot$						

	Wave parameters of buoy 42060 (1260 km away from the target buoy 42058)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5															
6															
7															
8															
9												$\oplus$			
10									$\odot$						

At this point, the results in Table 4.1 will assist us now in understanding better the results shown in Figure 4.2, in which we had mentioned that only 5 parameters contain enough information to reconstruct H_s. This has physical meaning in the sense that the selected wave parameters (H_s, κ_{02}, and spectral moments m_0, m_1, m_2 of closest buoys, those marked by stars ($\star$) in rows "5" of Table 4.1) have a close relation to H_s, since it is a function of m_0.

Regarding the second case study (West Atlantic), Table 4.2 list the parameters selected by the GA-ELM in this scenario. We have used in Table 4.2 the same notation as in the previous case. Regarding this previous analysis on the important parameters selected by the GA-ELM algorithm, note that ELMs are highly non-linear predictive tools. This means that a direct physical explanation of the different parameters' effect in the prediction in not possible, or at least, is not straightforward. In other words the better performance of some algorithms versus other, or the better performance of different sets of parameters is partly due to the data structure of the problem. Of course, physical properties may emerge in the algorithms' performance, but not always. Thus, it is in general not possible a direct interpretation of the predictive variables chosen and the algorithms' performance on the basis of physical parameters interpretation.

Table 4.2: Wave parameters selected by the GA-ELM algorithm for each buoy in the West Atlantic case study. Again, there is a sub-table for each buoy. Columns contain all the available parameters (wave-describing parameters), and rows represent the number of parameters (n_{SP}) that the GA-ELM algorithm has selected. The symbols $\star$, $\circ$, $\bullet$, $\oplus$, $\otimes$, and $\odot$ mark the parameters that have been selected for $n_{SP} = 5, 6, 7, 8, 9$ and 10, respectively.

	Wave parameters of buoy 41044 (793 km away from the target buoy 41049)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5								$\star$							
6							$\circ$				$\circ$				
7							$\bullet$								
8								$\oplus$							
9			$\otimes$		$\otimes$	$\otimes$	$\otimes$								
10						$\odot$		$\odot$							

	Wave parameters of buoy 41046 (677 km away from the target buoy 41049)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5		$\star$													
6		$\circ$													
7		$\bullet$													
8	$\oplus$	$\oplus$								$\oplus$					
9	$\otimes$										$\otimes$				
10		$\odot$								$\odot$					

	Wave parameters of buoy 41047 (841 km away from the target buoy 41049)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5	$\star$														
6	$\circ$														
7	$\bullet$		$\bullet$										$\bullet$		
8	$\oplus$														
9	$\otimes$														
10	$\odot$		$\odot$									$\odot$			$\odot$

	Wave parameters of buoy 41048 (800 km away from the target buoy 41049)														
	H_s	m_{-1}	m_0	m_1	m_2	T_p	T_{m-10}	T_{m01}	T_{m02}	Q_p	ν	κ_{01}	γ_{01}	κ_{02}	γ_{02}
5			$\star$	$\star$											
6	$\circ$			$\circ$											
7			$\bullet$										$\bullet$		
8	$\oplus$			$\oplus$											$\oplus$
9			$\otimes$	$\otimes$											
10	$\odot$			$\odot$											

There are two final remarks we would like to note here:

1. The first one is related to the fact that, in both scenarios, H_s of one of the closest buoys to the target is always selected, while those parameters from the farthest buoy are rarely selected. This is very clear in Table 4.1, where the parameters of buoy 42057 (740 km away from the target buoy 42058, the closest

one) have been selected the most. In the second scenario, West Atlantic, this trend can not be found, due probably to the different oceanographic conditions of the area, that is more open than Caribbean sea, and therefore a number of different wave fields can be found, such as swell that show a higher spatial correlation than wind sea.

2. The second comment is that the most popular parameters, besides H_s, are the spectral moments, which, as mentioned before, have a very close relation to the significant wave height. Without using these spectral moments, and only H_s is used, we have observed that the results obtained are worse. A possible explanation for this is that there are many sea states for the same value of H_s (i.e. wind sea, swell, bimodal sea states, etc). Since the different spectral moments weight different regions of the frequency domain, it seems that the system has more information on the sea state.

Once the best wave-describing parameters have been selected, the question arising is to what extent they still operate accurately when they are used by other regression methods to reconstruct H_s. This is just the purpose of the next section.

4.6.2 Exploring the quality of the selected parameters in different ML regression methods

We have compared the performance of ELM, SVR and GPR for reconstructing H_s, in both scenarios, using the parameters selected by the proposed GA-ELM. As in the previous case, we provide here the RMSE for SVR and GPR, i.e, 0.523m (SVR) and 0.498m (GPR) in Scenario 1, and 0.654 (SVR) and 0.628 (GPR) in Scenario 2. The results of the SVR and GPR considering $m_{-1}, m_0, m_1, m_2, \kappa_{02}$ as input parameters in all buoys (20 input parameters) are 0.502m (SVR) and 0.591m (GPR) for Scenario 1, and 0.634m (SVR) and 0.591m (GPR), for Scenario 2, respectively.

The experimental work we have carried out, in any scenario, is as follows:

1. The GA-ELM algorithm searches for the best n_{SP} parameters, and constructs the subset $\mathcal{F}_{n_{SP}}$. For instance, $\mathcal{F}_5$ represents the 5-feature subset $\{\kappa_{02}$ (from buoy 42056), H_s, m_0 (buoy 42057), m_1 (42057), m_2 (42059)$\}$, which we had marked by $\star$ in Table 4.1.

2. Training any of the regression methods (ELM, SVR, GPR) with the samples in $\mathcal{S}_{test}$ driven by the methodology stated in Subsection (4.5.3).

Figures 4.3 and 4.4 show, for the first and second scenario, respectively, the RMSE($\hat{H}_s$)(m) that any of the regression methods make as a function of the subset parameters used ($\mathcal{F}_{n_{SP}}$), provided by the GA-ELM when searching for the best n_{SP} reconstructing parameters.

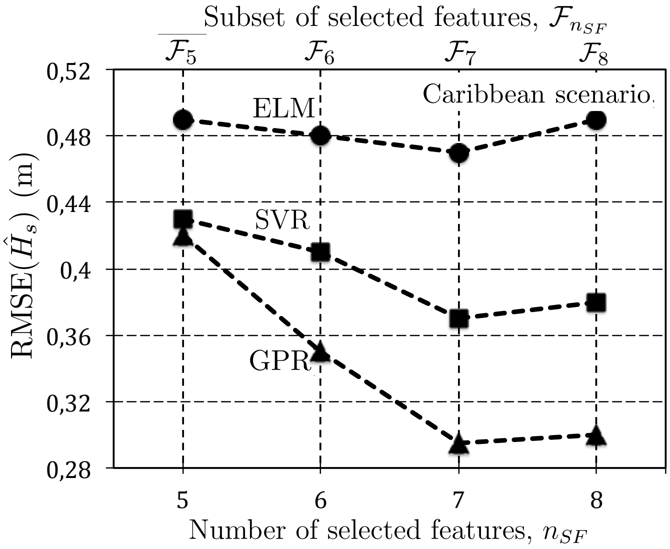


Figure 4.3: Reconstruction error, RMSE$(\hat{H}_s)(m)$, computed over $\mathcal{S}_{test}$, in the Caribbean scenario, made by any of the method explored (ELM, SVR, GPR), as a function of the subset of parameters ($\mathcal{F}_{n_{SP}}$) selected by the GA-ELM ($n_{SP} = 5, 6, \cdots, 8$).

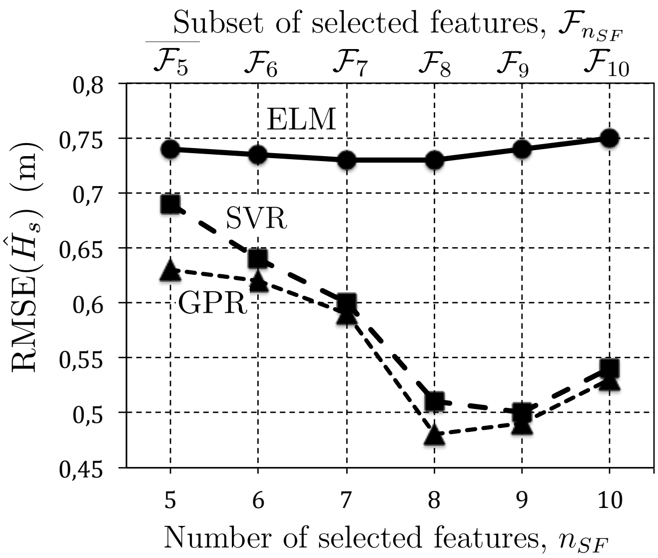


Figure 4.4: Reconstruction error, RMSE$(\hat{H}_s)(m)$, computed over $\mathcal{S}_{test}$, in the West Atlantic scenario, made by any of the method explored (ELM, SVR, GPR), as a function of the subset of parameters ($\mathcal{F}_{n_{SP}}$) selected by the GA-ELM ($n_{SP} = 5, 6, \cdots, 10$).

Figures 4.3 and 4.4 provide the following information:

1. The results show that all the ML methods explored are able to reconstruct H_s values in the two different locations studied (Caribbean Sea and West Atlantic).

2. The best results (smallest error) are given by the Gaussian Process Regressors:

   - $\text{RMSE}(\hat{H}_s)^{\text{GPR}}_{\text{Carribean}} \approx 0.30$ m in Figure 4.3, when using the 7 parameters in $\mathcal{F}_7$ (see Table 4.1 for the list of the 7 best wave parameters selected),
   - $\text{RMSE}(\hat{H}_s)^{\text{GPR}}_{\text{Atlantic}} \approx 0.48$ m, in Figure 4.4, for $\mathcal{F}_8$ (Table 4.2).

We complete the discussion by using Figures 4.5 and 4.6. These figures show the $\text{RMSE}(\hat{H}_s)(m)$ computed over $\mathcal{S}_{test}$ by the GPR method versus the measured available $H_s(m)$ values in the Caribbean Scenario (Figure 4.5, by using the obtained optimal feature subset $\mathcal{F}_7$), and in the West Atlantic Scenario (Figure 4.6, using $\mathcal{F}_8$), respectively.

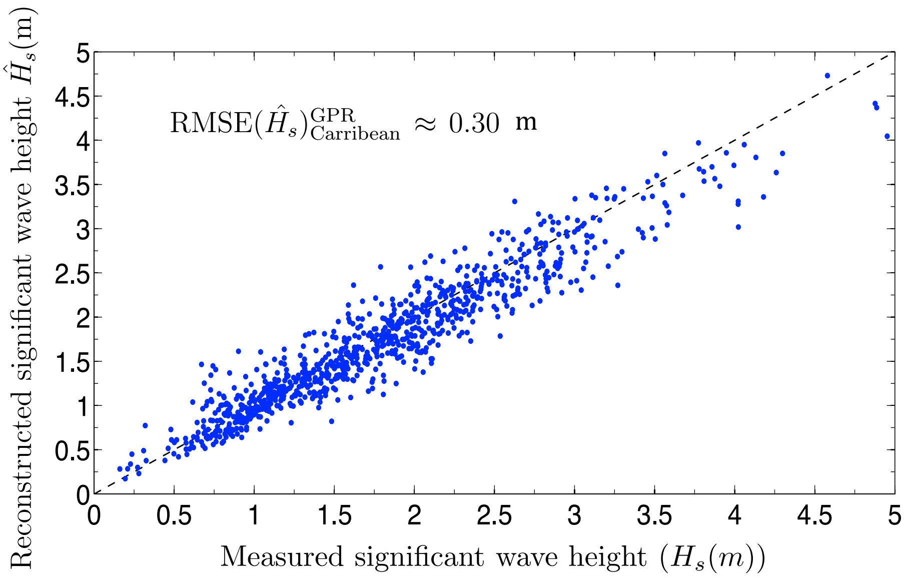


Figure 4.5: Reconstructed significant wave height ($\hat{H}_s$(m)) computed over $\mathcal{S}_{test}$ by the GPR (using the feature subset $\mathcal{F}_7$) vs. measured real values of the significant wave height (H_s(m)) in the Caribbean Scenario.

Finally, note that Figures 4.5 and 4.6 show that the GPR method works well when using the selected feature subset ($\mathcal{F}_7$ and $\mathcal{F}_8$, respectively). In the case of the West Atlantic scenario, the higher error occur for large values of the significant wave height (larger than 6m). This may be due to the fact that the amount of samples for high values of the significant wave height ($H_s \geqslant 6$ m) is very reduced compared to the case of $H_s \leqslant 6$ m. (Since their probability of occurrence is low). The algorithm thus tends to underestimate the H_s value because it has been trained with more smaller values than larger values.

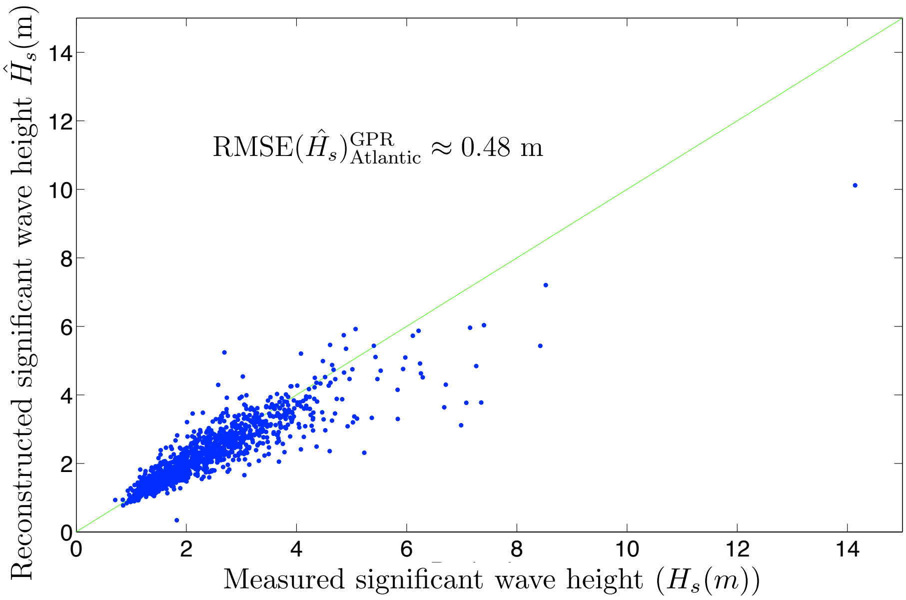


Figure 4.6: Reconstructed significant wave height, $\hat{H}_s(m)$, computed over $\mathcal{S}_{test}$ by the GPR vs. measured significant wave height, $H_s(m)$, in the West Atlantic case study (Scenario 2), using the feature subset $\mathcal{F}_8$.

4.7 Summary and conclusions

In this chapter we have tackled a problem of significant wave height H_s missing values reconstruction (at the location of an out-of-operation measuring buoy) by using wave parameters from nearby buoys. This reconstruction is important from several view points, because such wave parameters play a key role in coastal engineering (design of vessels, oil platforms, breakwaters, etc.), forecasting for ship navigation, and in the design and operation of wave energy converters. We have faced the problem of filling up missing H_s values within the framework of Machine Learning (ML) in a two-step process, which has led to two contributions. The first one has consisted in designing a hybrid evolutionary algorithm that selects, among the available wave parameters (from the nearby buoys), a smaller subset $\mathcal{F}_{n_{SP}}$ with n_{SP} parameters that minimizes the H_s reconstruction error. For doing this, we have proposed a novel approach in marine applications consisting of a Genetic Algorithm (GA) that computes the fitness of the candidate individuals (trial solutions) in each generation by using an Extreme Learning Machine (ELM). In this context, the key advantage of the ELM when compared to other ML approaches (Neural Networks, Support Vector Machines, for instance) is that ELMs learn very fast, this being essential in population-based evolutionary algorithms such as GAs. This is why we have hybridized the ELM with the GA in detriment of alternative ML regressors. The proposed hybrid GA-ELM method generates a subset $\mathcal{F}_{n_{SP}}$ of n_{SP} parameters that minimizes the root mean square error of H_s reconstruction, RMSE$(\hat{H}_s)(m)$. In the effort of testing its performance in two different coastal regions, we have explored two case studies: one in the Caribbean Sea, and the other, in the West Atlantic coast nearby Florida. The results suggest that:

- The proposed GA-ELM algorithm works very well in the sense that it selects a very reduced subset of parameters ($n_{SP} = 10$ parameters) among the available 60 parameters. Using $5 \leqslant n_{SP} \leqslant 10$ parameters lead to small reconstruction errors: RMSE$(\hat{H}_s)_{\text{Caribbean}} \lesssim 0.50$ m, and RMSE$(\hat{H}_s)_{\text{Atlantic}} \lesssim 0.75$ m.
- From an operative view point there is no practical benefit in using more than 5 parameters, in the sense that more parameters increase the computation time without significantly improving the reconstruction accuracy.
- This has physical meaning in the sense that most of the selected wave parameters in $\mathcal{F}_5$ (H_s, and spectral moments m_0, m_1, m_2 of closest buoys) have a close relation to the way H_s is defined.

The second contribution has consisted in evaluating to what extent the selected wave parameters in subset $\mathcal{F}_{n_{SP}}$ assist other ML regressors −Extreme Learning Machines, Support Vector Regression (SVR), and Gaussian Process Regression (GPR)− in reconstructing H_s. The results show that:

- All the ML method explored have H_s reconstruction errors below 1m in the two different locations studied (RMSE$(\hat{H}_s) < 0.5$ m in the Caribbean Sea, and RMSE$(\hat{H}_s) < 0.75$ m in the West Atlantic scenario).
- In particular, the GPR method is the one that reaches the smallest error: RMSE$(\hat{H}_s)^{\text{GPR}}_{\text{Caribbean}} \approx 0.30$ m for $\mathcal{F}_{n_7}$ (see Table 4.1 for the list of the 7 best wave parameters selected), and RMSE$(\hat{H}_s)^{\text{GPR}}_{\text{Atlantic}} \approx 0.48$ m for $\mathcal{F}_8$ (Table 4.2).

As a general conclusion, the twofold approach presented seems to be a feasible tool to fill missing wave values from neighbor buoys.

Chapter 5

Integrating Wave Energy in Power Grids: A Complex Networks Approach with Evolutionary Algorithms

Until the present chapter, we have explored throughout this thesis some issues related to the characterization of wave resources and wave energy converters (WECs) (Chapter 2), the corresponding use of soft computing (SC) techniques in these goals (Chapter 3) along with a practical application of a novel SC approach for the accurate reconstruction of significant wave heights (Chapter 4).

There are, however, some important, mutually interrelated aspects that have not yet been addressed in this thesis: 1) how several WECs should be electrically interconnected to each other (forming a WEC farm), and 2) how the farm should be connected to the electric network (or "power grid") [159–161].

With respect to the first point, the main reason why many WECs have to be electrically connected with each other is that usually a single standalone WEC cannot generate sufficient electric power for commercial-scale grid integration. The problem is difficult since WECs in a farm also interact with each other [159, 161]: besides generating electricity, individual WECs also modifies and reflects waves, which have an impact on how much energy can be captured by neighboring WECs, and vice-versa [159, 162]. There is another reason to use WEC farms: many linked WECs help soften the fluctuation of electric power associated to wave variability. Even so the problem of electric power variability associated to wave variability is still essential. This is of practical importance since such electric power fluctuation affects the quality of the power grid [304]. A feasible solution consists in using electrical energy storage systems, embarked on-board or shared among WECs in the farm, aiming at smoothing the generated electrical power without reducing energy productivity [161,162]. Although it is not yet clear, the point to be highlighted here is that a WEC farm can be considered as a set of nodes (either generating WECs or absorbing storage devices) connected following certain design criteria [159,161,163].

Regarding the second aspect –the electric connection of WEC farms to on-shore power grid [159–163]– there are several points that must be taken into account:

- Aiming at harnessing wave energy as much as possible and at seamlessly integrating it into the power grid, wave farms should become into "smart wave farms" (SWFs). A SWF should contain not only the necessary number of WECs (to deliver enough energy) but also energy storage devices, sensors, communication systems, and computational resources. This SWF can be considered as a "cyber-physical system" [305, 306]. A CPS is a system that consists of a set of sensing, computing, actuating, and communication resources (hardware/software) which aim at *monitoring* (from physical to cyber) and *controlling* (from cyber to physical) the *real, physical* world [307–311].

- The SWF approach allows for predicting waves using in-ocean sensors and forecasting algorithms. These predictions in turn can be used to: 1) adapt the WECs' energy capture, 2) make efficient energy storage decisions [164], and 3) control the quality of the power that the SWF injects into the on-shore power grid. The final goal is to integrate them smoothly to the electric grid [159, 161, 163].

The variability and intermittency of wave energy can be encompassed within a broader conceptual framework, which is common to all massive renewable energies. Although intermittent, wave energy is more consistent and predictable than wind or solar generation [164]. In fact, variability and intermittency are the two most serious problems that the emerging smart grid (SG) technology [158] aims to face. The SG concept is able to efficiently *integrate* into the power grid a rapidly increasing number of intermittent generators, with the target of affecting as slight as possible the stability and robustness of the grid [158]. It is specifically within the broader framework of distribution SGs and, in particular, within that of the integration of intermittent renewable energies, where this chapter is focused on.

The novelty of our approach is twofold, in the sense of optimizing the robustness of a distribution SG (connecting nodes that generate, consume or store electricity) against "abnormal operating conditions" –for instance, the breakdown or the operation stop of a WEC (or a set of them) within a WEC farm caused by a storm, or the aforementioned intermittent generation– by (1) using an EA that optimizes the structure of the SG [158] modeled by (2) applying concepts from the Complex Networks Science.

The model and results of this chapter have been published in [108].

5.1 Introduction

5.1.1 Motivation

The rising contribution of renewable energy (RE) sources in the current energy mix is crucial to decrease the economic and geopolitical dependence on fossil fuels and to reduce the emission of CO_2, one of the causes of climate change [312] and global warming [313]. Efficiently integrating distributed RE generation systems [314–316] is a key research topic because the most used renewable energies—photovoltaic (PV) solar energy [40, 317], wind energy [318, 319] and marine energy [71, 320]—are intermittent and more difficult to store [321] and integrate without affecting the quality of the electrical network (usually called "power grid") [322] or the electricity prices [323]. Technical, specific details about the design of smart power grid renewable energy systems can be found in the updated book [324]. In particular, the present proliferation of small-scale urban PV in buildings [325] and urban wind generators [326] can help home electricity consumers become also producers ("prosumers") [7] using the SG [327, 328] and micro-grids ($\mu-$Gs) [329] concepts.

On the one hand, $\mu-$Gs exhibit the potential to cost-efficiently increase the use of RE along with the power supply reliability, as studied by Wang and Huang [330–332]. Specifically, [330] focuses on an optimization methodology that can efficiently integrate distributed energy resources by leveraging complementary resources, such as, solar and wind REs and energy storage. Using real data, [331] proposes a framework for planning micro-grid systems that aims at increasing the use of RE along with the reliability of power supply. Even more, the method proposed in [332] aims at enabling the bidirectional exchange of power among interconnected micro-grid, increasing the global efficiency. As long as the increasing penetration of distributed RE resources is one of the driving forces for micro-grids deployments [330–332], other catalysts for change are some new loads such as electric vehicles (EV) [3], data centers [333] and home RE-prosumers [334]. In this context, distribution systems (DSs) involve complex issues such as modeling their sensitivity with respect to distributed RE sources [335], the efficient control of distributed generation [315] or scheduling problems [336].

On the one hand, the SG paradigm is a relatively novel conception of the electric power network that, based on hi-tech monitoring, control and communication technologies [6, 337, 338], aims not only to efficiently integrate RE sources [108], but also to supply reliable and safe electric power. As mentioned, thanks to the efficient integration of distributed REs via the SG [339], electricity consumers can also become prosumers. The SG approach allows for the bidirectional exchange of electric energy at the local scale, which is very positive because it stimulates the local production (small-scale photovoltaic systems and small-wind turbines) and consumption, helping end-users obtain economic benefits by selling the energy generated in excess [338]. Integrating small-scale renewable energies is thus one of the driving forces that is fueling the evolution of conventional grids to smart grids. The second driving force, inter-related with the RE integration, is the pressure for unbundling the energy sector (as occurred in access telecommunication networks). Ideally, unbundling the electric sector would allow everyone to generate electricity, becoming a seller on a free energy market [338]. The distribution medium and low voltage parts of the power grid are the best candidates for unbundling the electric market. In this respect, smart grids are now becoming the enabling technology for not only the unbundling of electric sector through the integration of small-scale renewable energies, but also for the efficient integration of electric vehicles [3], which are increasingly important in the effort of reducing air pollution in big cities [312].

In this complex context, abnormal operating conditions in SGs with RE generation can be caused by the occurrence of: (1) random failures (such as, the breakdown or the operation stop of a WEC, imbalances between generation and consumption, the presence of overloads or failures arising from the inherent SG complexity [340], which can cause cascading failures); and (2) targeted or intentional attacks [6, 337, 341].

The vulnerability to abnormal operating conditions can be studied from different viewpoints that include methods from both the Electrical Engineering (EE) and the complex network (CN) fields. In turn, vulnerability in power grids using CN concepts is a broad research area that involves two different approaches [341]. The first one is based solely on "topological" concepts and use metrics such as the mean path length, the clustering coefficient or the betweenness centrality, among many others [341]. Aiming at enhancing the topological approach, the second "hybrid" methodology consists of introducing concepts arising from EE into the CN framework and takes advantage of novel electric metrics, such as those belonging to the "extended topological model" [342]. Regarding the first topological approach, there is a controversy [342,343] about whether or not it is able to give physical insights into all aspects of real power grids. The CN community argues that its approach does not aim to focus on the detailed operation, but to find out the unexpected emergence of collective behavior (for instance, the synchronization in smart grids [344]). Conversely, part of the EE community asserts that this leads to an unreasonable simplification [341–343]. This controversy, not yet resolved and recently discussed in [341], is the reason why we devote Section 5.5 to clarifying this and other issues, after introducing the necessary background.

Regardless of this debate, smart grids have been studied very recently by Pagani et al. [7,338,343,345,346], on the basis of real data extracted from low and medium voltage power grids. These works propose successful strategies to evolve the already deployed conventional grids into smart grids. Instead of grid evolution, the research line explored in [347–349] has adopted the different approach of generating synthetic smart grid structures.

5.1.2 Purpose and contributions

Within the aforementioned context, the two-fold purpose of this chapter consists of: (1) modeling the topological structure of distribution SGs with RE generation using CN concepts; and (2) minimizing the negative effects of abnormal events by maximizing the grid robustness by using an evolutionary algorithm (EA) tailored for this goal. The SG is represented by a graph, a set of nodes (generators, storing devices, and loads) that are connected to each other by means of links (equivalently, electric cables). With this in mind, the contributions of our chapter are:

1. We model a smart grid with RE generators, storing devices, and loads as an undirected graph $\mathcal{G}$ so that each link allows for the bidirectional exchange of electric energy.

2. Our model can be applied indistinctly to the set of elements that make up the WEC farm (nodes: WECs and storing elements), or it can be applied to the set formed by a cluster of farms and the points of interconnection with the on-shore power grid (nodes: WECs, storing elements, and on-shore loads).

3. We propose an objective function to be optimized that combines cost elements (related to the number and average length of links and also to the number of nodes with many links) and several properties that are beneficial for the SG (such as energy exchanges at local scale and high robustness and resilience). Our optimization problem includes some restrictions used in [338] and also others that help our EA find optimal synthetic structures for the SG, starting from scratch. This is a "greenfield" strategy, used by companies in those zones where they do not have infrastructure, deploying thus the new grid starting from scratch. This is another difference when compared to [338], in which the authors have just adopted a "brownfield" approach aiming at evolving the conventional low voltage power grid into a smart grid.

4. We use an EA with a problem representation in which the chromosome $\mathbf{c}_{\mathcal{G}}$, which encodes each potential graph $\mathcal{G}$ (or individual), is the upper triangular matrix of its "adjacency matrix", $\mathbf{A}_{\mathcal{G}}$. In this formulation, $\mathbf{A}_{\mathcal{G}}$ is a square, symmetric and binary matrix in which any element a_{ij} encodes whether node i is linked to node j ($a_{ij} = 1$) or not ($a_{ij} = 0$) [350]. Since there is no self-connected node, the adjacency matrix has zeros on its main (principal) diagonal ($a_{ii} = 0$). These are the reasons why the connection information in graph $\mathcal{G}$ is stored by its upper triangular matrix $\mathcal{T}_{\mathcal{G}}$. Thus, chromosome $\mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$ encodes in a compact form the graph $\mathcal{G}$. As will be shown in detail in Section 5.2, this encoding is different from others found in the literature using EAs on graphs, such as, for instance, a chromosome formed by a one-dimensional array with N elements (the number of graph nodes) [351], N-length chromosome of two-dimensional elements [352] (where a node is specified by its location in the graph) or a set of vectors in which each allele (or gene value) represents a community [353]. The mutation and crossover operators are fully adapted to our encoding. This approach could be generalized by considering the strength of the connection between node i and j in terms of its link weight w_{ij}.

5.1.3 Practical perspectives

There are several research works that have applied EA and CN concepts to smart grids problems, which are partially related to our proposal and whose detailed discussion we postpone to Section 5.2 for clarity. There are also many research papers that focus on studying the smart grid from the point of view of CNs and graph theory and others that study graph problems using evolutionary computation (EC) techniques, in general, and EAs, in particular. However, a combined EA-CN approach to optimize the topology of smart grids, based on a variety of design constrains, has not yet been carried out to the best of our knowledge.

Our approach should be considered as a high level analysis, planning and decision-making tool to gain insights into how to design robust structures for smart grids and does not attempt and cannot replace the well-founded techniques of EE. Because of its importance and to make this chapter stand by itself, we devote Section 5.5, as mentioned before, to justify the consistency of our proposal. The synthetic structure provided by our EA can be taken as a starting point to test whether or not it fulfills all of the electrical requirements. In this sense, our approach can be considered as a complementary high-level tool, so that the low level detailed design is carried out by using EE techniques.

5.1.4 Chapter organization

The rest of this chapter is organized as follows: Section 5.2 reviews those works that are related to our approach to a greater or lesser extent. Sections 5.3 and 5.4 introduce, respectively, topological and hybrid CN concepts that will assist us in better explaining our method, while Section 5.5 discusses to what extent these CN approaches are useful in power grids. Sections 5.6 and 5.7 state, respectively, the SG topology optimization problem and the particular EA we propose to solve it. Section 5.8 discusses the experimental work we have carried out. Finally, Section 5.9 summarizes the key findings and conclusions.

For the sake of clarity, Table 5.1 lists the symbols used in this chapter.

5.2 Related Work

For the sake of clarity, we have divided this section into two subsections: Section 5.2.1 and Section 5.2.2.

Table 5.1: List of symbols used in this chapter.

Symbol	Definition or Meaning
$\mathbf{A}_\mathcal{G}$	Adjacency matrix of graph $\mathcal{G}$.
a_{ij}	Element of the adjacency matrix $\mathbf{A}_\mathcal{G}$ that encodes whether node i is linked to node j ($a_{ij} = 1$) or not ($a_{ij} = 0$).
$\bar{b_1}$	Mean value of betweenness b_1 or multi-scale vulnerability of order 1.
$\bar{b_2}$	Mean value of of the multi-scale vulnerability of order 2.
b_l^p	Betweenness centrality of link l.
$b_p(\mathcal{G})$	Multi-scale vulnerability of order p of a graph $\mathcal{G}$. It is defined by Equation (5.9)
$\mathcal{C} = \bar{\mathcal{C}}$	Mean clustering coefficient of a network. It is defined by Equation (5.4).
$\mathbb{C}$	Set of all chromosomes.
$C_B(v)$	Betweenness centrality of node v. It quantifies how much a node v is found between the paths linking other pairs of nodes. It is defined by Equation (5.5).
$\mathbf{c}_\mathcal{G}$	Chromosome that encodes the graph $\mathcal{G}$.
C_i	Clustering coefficient of node i. It is defined as the ratio between the number M_i of links that exist between these k_i vertices and the maximum possible number of links ($C_i \doteq 2M_i/k_i(k_i - 1)$.
$\mathcal{C}_{\text{RG}}$	Clustering coefficient of a random graph
$\mathbf{D}$	Node degree matrix: $\text{diag}(k_1, \cdots, k_N)$. It is the diagonal matrix formed from the nodes degrees.
$d_E(n_i, n_j)$	Euclidean distance between any pair of nodes n_i and n_j in a spatial network.
d_{ij}	Distance between two nodes i and j. It is the length of the shortest path (geodesic path) between them, that is, the minimum number of links when going from one node to the other.
Δ_{b_1}	Coefficient of variation for betweenness. It is defined by Equation (5.10).
$f_{\text{OBJ}}(\mathcal{G})$	$= f_\zeta(\mathcal{G}) =$ objective function to be minimized. It is defined by Equation (5.11).
$\bar{f_\zeta}$	Mean value of the objective function f_ζ.
$\mathcal{G}$	Graph representing a network.
$\mathbf{G}$	Set of all possible connected graphs $\mathcal{G}$ with N nodes and $M = \mathcal{N}_l$ links.
$\mathbb{G}$	Set containing all of the candidate graphs.
$\mathcal{G}_\zeta$	Optimum graph that solves the objective function with combination parameter ζ.
$\langle k \rangle$	Average node degree: $\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i$.
k_i	Degree of a node i. It is the number of links connecting i to any other node. It is defined by Equation (5.2).
k_{MAX}	Maximum node degree.
ℓ	Average path length of a network. It is the mean value of distances between any pair of nodes in the network. It is defined by Equation (5.3).
$\mathcal{L}$	Set of links (edges) of a graph.
$\mathbf{L}_\mathcal{G}$	Laplacian matrix (or Kirchhoff matrix) of graph $\mathcal{G}$. It is defined by Equation (5.14).
ℓ_{RG}	Average path length of a random graph.
$\lambda_2(\mathcal{G})$	Algebraic connectivity of graph $\mathcal{G}$.
M	Size of a graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$. It is the number of links in the set $\mathcal{L}$. It is defined by Equation (5.1).
$\mathcal{N}$	Set of nodes (or vertices) of a graph.
N	Order of a graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$. It is the number of nodes in set $\mathcal{N}$, that is the cardinality of set $\mathcal{N}$: $N = \lvert\mathcal{N}\rvert \equiv \text{card}(\mathcal{N})$.
$P(k)$	Probability density function giving the probability that a randomly selected node has k links.
p_{cross}	Crossover probability.
p_{mut}	Mutation probability.
p_{selec}	Selection probability.
$\mathcal{P}_{\text{size}}$	Population size.
$\bar{\mathcal{S}}$	Average entropic degree.
$\mathcal{S}_i$	Entropic degree of node i defined by Equation (5.6).
σ_{b_1}	Standard deviation of betweenness.
$\mathcal{T}_\mathcal{G}$	Upper triangular matrix of graph $\mathcal{G}$.
T_{size}	Tournament size.
$\mathcal{W}$	Set of weight elements w_{ij}.
w_{ij}	Weight of link l_{ij}. It models the strength of the connection between node i and j.
ζ	Parameter that controls the linear combination between components with opposing trends in the objective function to be minimized given by Equation (5.11).

On the one hand, Section 5.2.1 discusses the research papers that focus on studying the smart grid from the viewpoint of complex networks and graph theory. On the other hand, Section 5.2.2 reviews those articles that tackle graph problems using evolutionary computation techniques, and EAs, in particular. To the best of our knowledge, there is no work combining both branches of knowledge for the problem of optimizing the structure of smart grids.

5.2.1 The Smart Grid as a Complex Network: Related Work

The SG paradigm has been modeled very recently as a complex network in a series of papers by Pagani et al. [7, 9, 338, 343, 354–360]. The approach adopted in these works is based on the need for improving the low voltage power grid, motivated in Section 5.1, and aims to analyze and adapt the already deployed distribution power grids on the basis of complex network approaches [338].

The ultimate goal of such a series of papers [7, 9, 338, 343, 354–360] consists of putting into practice a decision support system to guide operators, utilities and policy makers to evolve the current grid to a more efficient smart grid.

These works cover a significant variety of research topics appearing in smart grids: the study of the potential of the SG to generate big data [355], the search for topological vulnerabilities [357], the study of the optimal spatial distribution [356], the use of agent-based systems for deregulated smart grids [359], the modeling of dynamic prices [358], the study of the last mile of the SG [354] and other technological aspects of SGs as CNs [7, 9, 338]. With regard to the latter, the authors carried out a topological analysis of some representative medium and low voltage power grids [9] and obtained a set of metrics based on topological properties in the effort of including their influence on the cost of electricity distribution. In the next step in this line of research, [7] has studied complex models to evaluate to what extent these allow for local electricity exchange, finding out that: (1) increasing the connectivity from the current value of the average degree ($\langle k \rangle \approx 2$) to higher values is beneficial; and (2) the small-world complex network with average degree $\langle k \rangle \approx 4$ fulfills a feasible balance between performance enhancement and cost. The key, more recent work [338] explores a variety of feasible evolution strategies towards the SG and applies them to the real Dutch distribution system. An interesting finding in [338] is that increasing the connectivity leads to a topology that could lead to a more efficient and reliable electric grid.

While the aforementioned research line [7,9,338,343,354–360] proposes successful strategies to evolve the already deployed conventional grids into smart grids, the research line [347–349] has a different approach that consists of generating synthetic structures for smart grids. In these papers, the so-called "RT-nested-small world" model, based on analyses of real grid topologies and their electrical properties, has been proposed to create a large number of synthetic power grid test structures, with scalable size and the similar small-world topology and electrical features found in some real power grids [348].

As will be shown later on, our method has some aspects in common with both approaches. On the one hand, we state an optimization problem with some of the design constraints proposed in [338] (and with additional ones that we propose in this chapter). On the other hand, our method generates synthetic structures, similar to the approach [347–349], but with the difference that we find the optimum synthetic structure by using an evolutionary algorithm.

5.2.2 Evolutionary Computation in Graph Approaches: Related Work

The use of evolutionary computation in the broad field of graphs has been carried out with different purposes and approaches. Aiming at discussing these within the goal of this chapter, we use the encoding strategy adopted in each work as the comparative criterion. The reason is that the way candidate solutions are represented in EAs has a crucial influence on the design of evolutionary operators and on the algorithmic efficiency.

One of the most fertile areas of research combining graph theory and EC is focused on clustering in graphs. Cluster analysis is a key technique used for splitting a set of N objects into a number k of comparatively-homogeneous groups (clusters) based on their similarities [361]. The number of different attainable partitions in a clustering problem is given by the Stirling number of second kind, $S(N, k)$, and is known to be NP-hard when $k > 3$ [361, 362]. For instance, in a relative small graph with 50 nodes and five clusters, $S(50, 5) \approx 7.4 \times 10^{32}$, which makes it convenient to use approximate methods such as those of evolutionary computation. In this respect, the approach in the recent work [351] consists of converting probabilistic datasets into probabilistic graphs with the purpose of clustering by using an EA. The genetic representation of this problem in this research work is a one-dimensional array having N elements, the number of graph nodes. This representation has been found to be feasible to extract neighborhood node information and uses such information to process probabilities on their links [351]. Graph partitioning via a multi-objective EA has been studied in [352] by encoding the problem with a chromosome that is a set of N (number of nodes) two-dimensional elements, in which any node is represented by its location in the graph. Instead of using EAs, the problem of optimal non-hierarchical clustering has been tackled in [361] by using a novel algorithm that combines differential evolution and k-means algorithms. Centered on social networks, the problem of community detection using graph-based information is tackled in [353] by applying graph clustering algorithms based on its topology information. Since any candidate solution should contain a group of communities, a chromosome encoding an individual in [353] is a set of vectors of binary values in which each allele represents a community composed by a set of binary values, one for each node in the social network. Partially related to the latter work, the paper [363] explores the feasibility of a spectrum optimization algorithm for community detection based on selecting those links to be removed by minimizing the algebraic connectivity metric. In the effort of making it applicable to large-scale networks, a greedy heuristic method has been tested to get the lower bound of optimal value. The problem of community detection, either disjoint or overlapping, has been tackled using a multi-objective EA [364] in which an individual consists of two components: the first one is a permutation of all nodes, while the second component is the set of communities. Another recent method that is gaining impulse is spectral clustering [365], which builds a similarity graph and applies spectral analysis to retain the data continuity in the cluster. The approach in [365] has proposed a novel algorithm inspired by the spectral clustering algorithm, the co-evolutionary multi-objective genetic graph-based clustering algorithm, which includes a variable number of clusters [365]. The encoding here is a simple label-based representation [365] inspired by the conventional integer encoding of genetic algorithms. Each individual is a q-dimensional vector (q being the number of data examples) with integer values between one and the number of clusters of the sub-population to which it is assigned. Very recently, reference [366] has explored a multi-objective EA for detecting overlapping communities. This differs from most other articles (focus on disjoint communities) in which each gene of the chromosome is an integer number that encodes the community label of the corresponding clique node of the maximal-clique graph. Also within the approach of maximum clique-finding problem, reference [367] explores an EA able to tackle the problems such as maximum independent set, set packing, set partitioning, set cover, minimum vertex cover, subgraph and double subgraph isomorphism. In the proposed approach, each problems is first mapped onto the maximum clique-finding problem, which is later tackled by an evolutionary strategy that represents each subgraph with a binary string.

Another important research field that combines CNs and EC consists of analyzing and/or generating CN structures [368–370]. On the one hand, reference [368] focuses on optimizing the structure of complex networks based on a memetic algorithm. Its problem encoding consists of an array containing the node number and the number of the node with which such a node is connected. On the other hand, the problem of automatically generating complex network models is tackling using genetic programming (GP) [369]. In this proposal, the goal is to find out those more appropriate network measures that capture as much as possible their structure, and the used tool is a GP that generates automatically CNs on which such measures can be tested. Similarly, the feasibility of a GP for the automatic inference of graph models for complex networks has also been explored in [370].

The graph coloring problem has also recently been tackled using an EA [371,372]. It aims at finding the minimum number of colors where each node dominates at least one non-empty color class and is an NP-complete for general graphs. In [372], the EA approach makes use of an encoding in which an individual is represented by a two-dimensional array with k columns, k being the number of colors used to color the nodes.

An interesting, partially related to our approach is the work carried out in [373], which focuses on a hybrid evolutionary graph-based multi-objective algorithm for the layout optimization of truss structures. The encoding of each candidate solution is composed of three matrices (the adjacency matrix of the simple graph model, the adjacency matrix corresponding to the weighted graph model and the coordinate matrix of nodes) along with two Boolean vectors (representing restricted nodes, which cannot be left out, and those movable ones, respectively). This approach is related to a certain degree with [374, 375], which use a matrix representation based on the graph concept in truss topology optimization.

Finally, the main conclusion of the reviews carried out in Sections 5.2.1 and 5.2.2 is that, to the best of our knowledge, there is no work combining complex network/graph theory and evolutionary algorithms in the effort to optimize the structure of smart grids starting from scratch, which is useful not only from a modeling and theoretical perspective, but also from the practical viewpoint as a high level tool for analysis, planning and decision-making.

5.3 Background: Complex Networks Concepts

The purpose of this section is to introduce basic definitions (Section 5.3.1) along with the concept of "small network" that, as will be shown, has important advantages for the network robustness (Section 5.3.2).

5.3.1 Some Useful Definitions in Complex Network

Any network can be mathematically represented by using a graph, $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ represents the set of nodes (or vertices) and $\mathcal{L}$ denotes the set of links (edges) [350]. The interested reader is referred to [350]; a very lucid and comprehensive description of complex networks, with many examples of their existence in a great variety of natural and artificial systems, can be found in [350]. The following list contains only those definitions that are important to understand our work [341, 350, 376, 377]:

- An "undirected" graph is a graph for which the relationship between pairs of nodes are symmetric, so that each link has no directional character (unlike a "directed graph"). Unless otherwise stated, the term "graph" is assumed to refer to an undirected graph.

- A graph is "connected" if there is a path from any two different nodes of $\mathcal{G}$. A disconnected graph can be partitioned into at least two subsets of nodes so that there is no link connecting the two components ("connected subgraphs") of the graph.

- A "simple graph" is an unweighted, undirected graph containing neither loops nor multiple edges.

- The "order" of a graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ is the number of nodes in set $\mathcal{N}$, that is the cardinality of set $\mathcal{N}$, which we represent as $|\mathcal{N}|$. We label the order of a graph as N, $N = |\mathcal{N}| \equiv \text{card}(\mathcal{N})$.

- The "size" of a graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$ is the number of links in the set $\mathcal{L}$, $|\mathcal{L}|$, and can be defined ($\doteq$) as:

$$M \doteq \sum_i \sum_j a_{ij} = \mathcal{N}_l, \tag{5.1}$$

  where $a_{ij} = 1$ if node i is linked to node j and $a_{ij} = 0$ otherwise. As mentioned before, a_{ij} are the matrix elements of the adjacency matrix.

- The "degree" of a node i is the number of links connecting i to any other node and is simply:

$$k_i \doteq \sum_j^N a_{ij} \tag{5.2}$$

- The node degree is characterized by a probability density function $P(k)$ giving the probability that a randomly-selected node has k links.

- A "geodesic path" is the shortest path through the network from one nodes to another; or in other words, a geodesic path is the path that has the minimal number of links between two nodes. Note that there may be and often is more than one geodesic path between two nodes [350].

- The "distance" between two nodes i and j, d_{ij}, is the length of the shortest path (geodesic path) between them, that is the minimum number of links when going from one node to the other.

- The "average path length" of a network is the mean value of distances between any pair of nodes in the network [350]:

$$\ell \doteq \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}, \tag{5.3}$$

  where d_{ij} is the distance between node i and node j.

- The "clustering coefficient" is a local property capturing the density of triangles in a network. That is, two nodes that are connected to a third node are also directly connected to each other. Thus, a node i in a network has k_i links that connects it to k_i other nodes. The clustering coefficient of node i is defined as the ratio between the number M_i of links that exist between these k_i vertices and the maximum possible number of links ($C_i \doteq 2M_i/k_i(k_i-1)$. The clustering coefficient of the whole network is [341]:

$$\mathcal{C} \doteq \frac{1}{N} \sum_i C_i, \tag{5.4}$$

  that is, for a given node, we compute the number of neighboring nodes that are connected to each other and average this number over all of the nodes in the network.

- The "betweenness centrality" quantifies how much a node v is found between the paths linking other pairs of nodes, that is,

$$C_B(v) \equiv \mathcal{B}_v \doteq \sum_{s \neq v \neq t \in \mathcal{V}} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{5.5}$$

  where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through v. A high C_B value for node v means that this node, for certain paths, is critical to support node connections. The attack or failure of v would lead to a number of node pairs either being disconnected or connected via longer paths.

5.3.2 Small-World Property and its Importance in Robustness

There is a property of some complex networks that has been found to be especially beneficial for smart grids [7, 338]: "small world". Some properties of small-world networks that are interesting for the purpose of this chapter are:

- A small-world network is a complex network in which the mean distance or average path length ℓ is small when compared to the total number of nodes N in the network: $\ell = \mathcal{O}(\log N)$ as $N \to \infty$. That is, there is a relatively short path between any pair of nodes [378, 379]. The term "small-world networks" is often used to refer Watts–Strogatz (WS) networks, first studied in [379]. It can be generated by the "rewiring" method shown in Figure 5.1a: Link l_{13}, which was connecting Node 1 to Node 3, is disconnected (from Node 3) and rewired to connect Node 1 to Node 9. In the resulting network, going from Node 1 to Node 9 only requires one jump via the rewired link (and thus, $d_{1,9}^{\text{new}} = 1$). However, in the original regular network, going from Node 1 to Node 9 through the geodesic or shortest path ($1 \to 3 \to 5 \to 7 \to 9$) involves four links ($d_{1,9} = 4$). This leads to networks with small average shortest path lengths between nodes ℓ, and high clustering coefficient $\mathcal{C}$. Figure 5.1b shows the aspect and $P(k)$ of a WS we have generated with $N = 100$ nodes and "rewiring probability" $p = 0.2$. It has a short mean distance, $\ell \simeq 6.04$, and high clustering, $\mathcal{C} \approx 0.274$. Most of the small-world networks have exponential degree distributions [380].

- Figure 5.1b ($N = 100$ and $p = 0.2$) also illustrates that the architecture of real small-world networks is extremely heterogeneous: the vast majority of the elements are poorly connected, but simultaneously, few have a large number of connections [381]. The robustness of small-world network has been explored in [382, 383] leading to the conclusion that, in a non-sparse WS network ($M \sim 2N$), simultaneously increasing both rewiring probability and average degree ($\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i$) improves significantly the robustness of the small-world network.

- An interesting variation of the WS model is the one proposed by Newman and Watts [384] (NW small-world model) in which one does not break any connection between any two nearest neighbors, but instead, adds with probability p a connection between a pair of nodes. It has been found that for sufficiently small p and sufficiently large N, the NW model is basically equivalent to the WS model [385]. At present, these two models are together commonly termed small-world models.

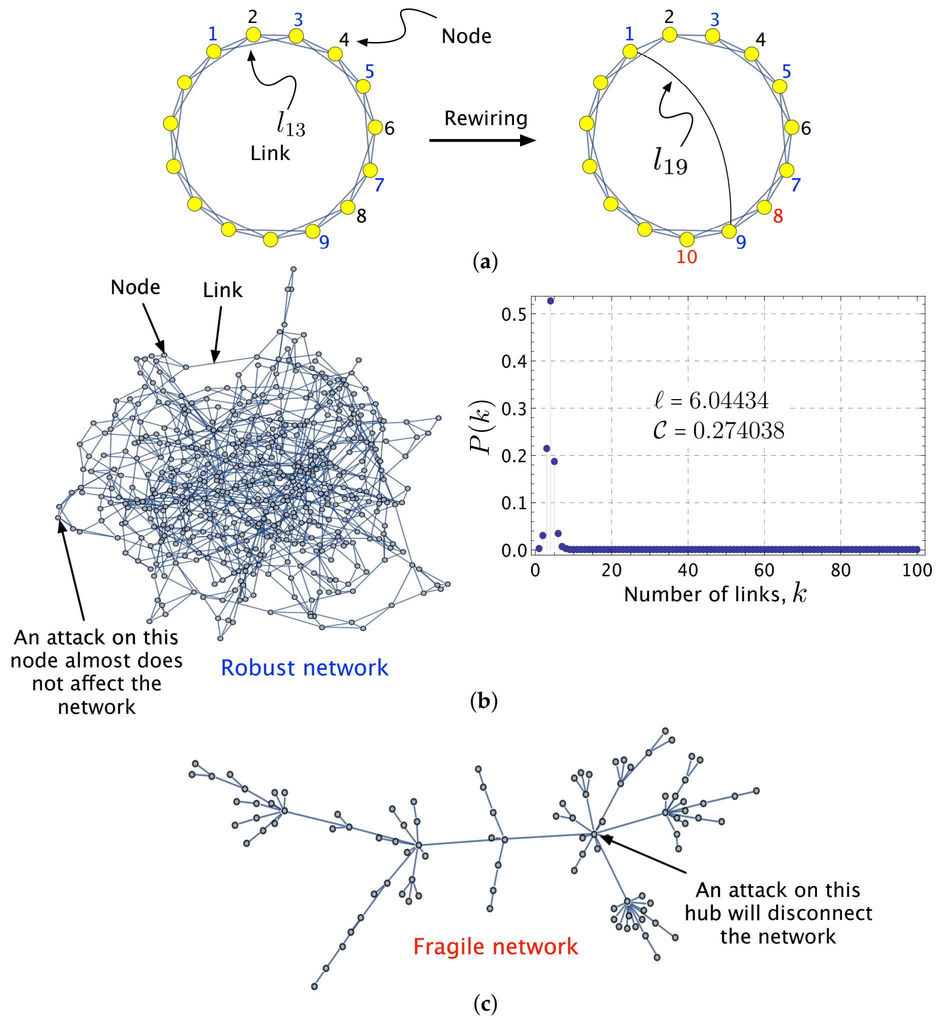


Figure 5.1: (**a**) First step in the creation of a small-world Watts–Strogatz (WS) network; (**b**) example of a WS network and its node degree distribution; (**c**) scale-free network. See the main text for further details.

Figure 5.1b also helps us introduce the concept of network robustness (or its inverse concept, vulnerability). It is related to the degree to which a network is able to withstand an unexpected event without degradation in its performance. It quantifies how much damage occurs as a consequence of such unexpected perturbation.

Intuitively, the random failure of the marked link in Figure 5.1b does not affect the network functionality, while the targeted attack on the marked node in Figure 5.1c will make the network disintegrate in many unconnected parts before recovery. Figure 5.1b,c represent, respectively, a very robust network and another very fragile one. In particular, note in Figure 5.1c that, as most nodes have only a few connections and only a few nodes ("hubs") have a high number of links, then the network is said to have no "scale" [386]. This is why they are called "scale-free" networks. A scale-free network can be generated by progressively adding nodes to an existing network by introducing links to nodes with "preferential attachment" [387, 388] so that the probability of linking to a given node i is proportional to the number of existing links k_i of the node. This is the so-called Barabási and Albert (BA) model.

As mentioned in Section 5.1, there are however some authors arguing that this topological approach should be enriched by adding electrical concepts. The following section introduces only those concepts that will assist us in explaining our proposal. For a more complete and in-depth discussion, which is beyond the scope of this chapter, the interested reader is referred to [341, 342].

5.4 Background: Hybrid Approaches Combining Complex Networks and Electric Engineering Concepts

As shown in detail in the review paper [341], there are some selected works [342, 345] that emphasize that the topological approach may lead to inaccurate results because it does not capture some of the properties of power grids described by Kirchoff's laws. Regarding this, there are some basic concepts that compel engineers to include electrical power engineering concepts [341]. The first one, in contrast to general purpose CNs, is that a power grid is a flow-based network in which electric power flowing between two nodes can involve many links. From the EE viewpoint, the topological distance metric in CN theory should be substituted by an "electrical distance", involving line impedances [342]. The second cause is that, in conventional CN analysis, all elements are usually identical. This is not often the case in power transmission grids because of the existence of different types of nodes such as generation and load buses. Additionally, in power grids, transmission lines have flow limits. Based on these concepts, reference [342] argues that, when applying to power grids, the graph must be weighted (impedance, maximum power) and directed (since electric power flows from generators to loads). However, since smart grids are bidirectional; the corresponding graphs are undirected.

Thus, aiming at overcoming the mentioned limits of pure topological approaches, hybrid approaches combine CN and EE concepts [341]. An interesting research line belonging to hybrid approaches is the extended topological approach [342, 389–392]. It includes in the CN methodology novel metrics such as the "entropy degree". The entropic degree of a node i, denoted as $\mathcal{S}_i$, aims at including three elements in the topological definition of node degree when computed over a weighted network [389]: (1) the strength of the connection between node i and j in terms of link weight w_{ij}; (2) the number of links connected with such node; and (3) the distribution of weights among the links. The entropic degree of node i is defined as [389]:

$$\mathcal{S}_i \doteq \left(1 - \sum_j p_{ij} \log p_{ij}\right) \sum_j w_{ij}, \tag{5.6}$$

where $p_{ij} \doteq \frac{w_{ij}}{\sum_j w_{ij}}$ is the normalized weight of the link between nodes i and j.

The question arising here is whether or not applying CN approaches on the power grid is useful.

5.5 Discussion: Is the CN Approach Useful in Power Grids?

There are some selected papers [9,341,393–397] that point out that CN science is a unifying, powerful technique that enables one to analyze, within the same conceptual framework, a great variety of very different systems whose constituent elements are organized in a networked way. The CN community, including part of the electrical engineering community [398], argue that the CN approach does not aim to reflect the detailed operation of a given grid, but to discover the possible emergence of a systemic or collective behavior, beyond that of its single components. This is supported by a number of high-impact works [393,399–404]. An interesting example of its feasibility is the appearance of synchronization in smart grids [344]. However, the opposing community asserts that the pure topological CN approach loses the details of the physics behind Kirchhoff's laws and fails at predicting important aspects of power grids. In this respect, as mentioned, hybrid approaches include concepts from EE [389–391, 403, 405–409]. Nonetheless, the CN approach with purely topological analysis (or even with extended ones to take into account minimal electrical information [342]) has been found to be useful to detect critical elements and to assess topological robustness [343, 404, 410]. Specifically, Luo and Rosas-Casals have recently reported studies [404, 410] that aim at correlating electric-based vulnerability metrics (based on the extended topological approach) with real malfunction data corresponding to some European power transmission grids (Germany, Italy, France and Spain). The results, validated and proven by empirical reliability data, are statistically significant (Kolmogorov–Smirnov test) and suggest the existence of a relationship between structure (described by extended topological metrics) and dynamical empirical data.

Although much research must be carried out, the evidence in [404, 410] opens a research line to find a more meaningful link between CN-based metrics and the real empirical data of power grids. The CN approach could be useful to make vulnerability assessment and to design specific actions to reduce topological fragility

[342]. The analyses of [341, 343, 404, 410] suggest that there is a connection between the topological structure and operation performance in a power grid because the structural change could disturb its operational condition and, as a consequence, degrade its operation performance. As a result, there is an increasing interest in analyzing structural vulnerability of power grids by means of the CN methodology. A deeper discussion on these issued can be found in [341] or in [343], where a lucid introduction to complexity science in the context of power grids is provided.

Regardless of which of the two confronting options is more accurate (or useful, depending on their purpose), there are some important practical issues related to whether or not there is a predominant power grid structure (and, in particular, whether there is an optimal topology for smart grids; Section 5.5.1) and whether or not it is better to model them with weighted graphs (Section 5.5.2).

5.5.1 Power Grids: Is There a Dominant Topology?

There are several graph structures aiming at abstracting the real power grid topology. For instance, the research in [379] points out that the U.S. western power grid seems to have a small-world network. However, the works by Cotilla-Sanchez et al. [411] and Hines et al. [407] show that (a) the explored power grid does not exhibit a small-world nature and that (b) a spatial approach to connectivity and distance fails in setting up a graph model representing the electrical properties of the grid. Furthermore, the research [387] suggested that the degree distribution of the power grid seemed to be scale-free following a power law distribution function, although not all of the subsequent works have agreed on this [341]. In this respect, some other works have also found that there are exponential cumulative degree functions, for instance in the Californian power grid [380] and in the whole U.S. power grid [412]. This notwithstanding, on the other hand, reference [413] has shown that the topologies of the North American eastern and western electric grids can be analyzed based on the Barabasi–Albert network model, with good agreement with the values of power system reliability indices previously obtained from standard power engineering methods. This suggests that scale-free network models are applicable to estimate aggregate electric grid reliability [342]. In addition to [379], there are also several works that report on power grids with small world nature: the Shanghai Power Grid (explored with a hybrid CN Direct Current (DC) and Alternating Current (AC) power flow models) [414], the Italian 380-kV, the French 400-kV and the Spanish 400-kV grids [415] or the Nordic power grid [416]. Rosas-Casals et al. [417], using data from thirty-three different European power grids, found that, although the different explored grids seem to have an exponential degree of distributions and most of them lack the small-world property, these grids showed however a behavior similar to scale-free networks when nodes are removed, concluding that this behavior is not unique to scale-free networks. This could suggest similar topological constraints, mostly associated with geographical restrictions and technological considerations [342]. Thus, the existence of several topologies in high-voltage transmission power grids suggest that there is no predominant structure, except for the fact that many grids have a heterogeneous nature [342] and that they are vulnerable to fails/attacks on the most connected nodes and robust against random failure.

However, in the particular case of smart grids, the small-world model seems to be beneficial. As pointed out in [7], the exchange of electric energy at the local scale could be very positive because it stimulates the local production and consumption of renewable-based electric energy (small-scale photovoltaic systems and small-wind turbines), helping the end-user obtain economic benefit by selling the energy produced in excess. Using real data from Dutch grids, and within the CN framework, the key contribution of [7] is to propose the use of CN theory (combined with global statistical measures) as a design tool to synthesize the best smart grid structures, in terms of performance and reliability (for a local energy exchange) and cabling cost. The authors in [7, 9, 338, 343, 354–360] made the conclusion that the small-world model seems to have many feasible features, not only structural, but also economic, related to electricity distribution.

Finally, and although not conclusive, power grids with a small network structure seem to be the most robust (except random networks) or, at least, seem to be those with the highest potential to improve robustness in a feasible way. In particular, the research work [382] has compared the robustness of random networks (ER), small-world (WS) and scale free (BA). Random networks are the most robust and scale-free the most vulnerable. Among the structures found in power grids (scale-free, small-world, as mentioned before), non-sparse small-world networks ($M \sim 2N$) are the most robust. According to [383], non-sparse small-world networks have also the beneficial property of increasing easily their robustness by a feasible method that consists of simultaneously increasing both the rewiring probability and the average degree ($\langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} k_i$), which improves significantly the robustness of the small-world network.

5.5.2 Unweighted and Weighted Graphs: Which Is the Best?

An interesting point of discussion is whether the graph representing the particular grid under consideration uses either weighted or unweighted links. The review [341] points out that many works [9, 393, 396, 397, 412, 413, 415–419] have in common that each power grid has been represented using the simplest graph model: undirected and unweighted. This is because these approaches do not include any characterization of the link weights. Unweighted graphs are by far the most used representation in the group of references that tackle robustness in power grids from the pure topological CN viewpoint. On the contrary, most of the hybrid approaches, which include power flow models and/or electric-based metrics, made use of weighted graphs [341]. A deeper insight into the role of weighted links is given in [342], where it is noted that in power grids, transmission lines have power flow limits, which must be represented by weights w_{ij} standing for the flow limit on line $l_{ij} \equiv l(i, j)$ linking nodes i and j. The authors in [342] argue that when applying CN analysis to power grids, the electrical power grid must be represented as a weighted and directed network graph $\mathcal{G} = (\mathcal{N}, \mathcal{L}, \mathcal{W})$, where $\mathcal{W}$ is the set of weight elements w_{ij}.

5.6 Proposal: Metrics, Objective Function and Problem Statement

5.6.1 Metrics to Construct the Objective Function

We have mentioned that in a smart grid made up of prosumer nodes, there should be a bidirectional interchange of energy at the local scale. Aiming at achieving this goal, the following features are beneficial:

1. It is necessary for the SG to have a structure with reduces losses in the electric cables used to transport electric power from one node to another. This electrical restriction can be modeled using the condition:

$$\ell \leqslant \log N, \tag{5.7}$$

   which, as pointed out in [338], is related to giving a reduced path when moving from one node to another in a general purpose complex network. In the particular case of a smart grid, this may lead to a topology with limited losses in the circuits used to transfer electricity from one node to another. That is, it is a requirement related to the efficiency of the network. Along with the high clustering coefficient, this is also one of the properties of small-world networks, in which the mean distance or average path length ℓ is small when compared to the total number of nodes N in the network: $\ell = \mathcal{O}(\log N)$ as $N \to \infty$. A small value of ℓ is also important from the economic viewpoint since it may lead to smaller cost.

2. The entropic degree of a node i, $\mathcal{S}_i$, defined by Equation (5.6), has the advantage of providing a quantitative measurements of the importance of buses [389] in power grids by including the involved link weights and their number and distributions.

3. Since the node degree k_i of a node i is the number of links connecting i to any other node, its maximum value gets an upper limit related to the maximum power that a node can support:

$$\max(k_i) \leq k_{\text{MAX}}. \tag{5.8}$$

   The value of k_{MAX} is related to the maximum power that a node is able to support and is directly related to its economic cost. In [338], average degree values $\langle k \rangle$ ranging from ≈ 3 to ≈ 4 lead to a good balance between performance and cost.

4. The clustering coefficient defined by Equation (5.4) of a smart grid $\mathcal{C}_{\text{SG}}$ should be higher than that of the corresponding random network (RN) with the same order (number of nodes) and size (number of links). This aims at assuring a local clustering among nodes because it is more likely that electricity exchanges occur in the neighborhood in a scenario with many small-scale distributed RE generators [338].

5. We measure the network vulnerability by using the concept of multiscale vulnerability of order p of a graph $\mathcal{G}$ [420, 421],

$$b_p(\mathcal{G}) \doteq \left(\frac{1}{\mathcal{N}_l} \sum_{l=1}^{\mathcal{N}_l} b_l^p \right)^{1/p}, \tag{5.9}$$

where b_l^p is the betweenness centrality of link l. The multi-scale vulnerability b_p of a graph $\mathcal{G}$ measures the distribution of shortest paths when links are failing (or attacked) [421] and is very useful when comparing the vulnerability of networks because it helps distinguish between non-identical although very similar network topologies [420]. As shown in [421], if we want to distinguish between two networks with graphs $\mathcal{G}$ and $\mathcal{G}^*$, one first computes b_1. If $b_1(\mathcal{G}) = b_1(\mathcal{G}^*)$, then one takes $p > 1$ and computes b_p until $b_p(\mathcal{G}) \neq b_p(\mathcal{G}^*)$. Using this approach, we have considered $b_2(\mathcal{G})$. A network represented by a graph $\mathcal{G}$ is less vulnerable (more robust) than another $\mathcal{G}^*$ if $b_2(\mathcal{G}) < b_2(\mathcal{G}^*)$. Please see [420, 421] for further details.

6. A coefficient of variation for betweenness [338],

$$\Delta_{b_1} = \frac{\sigma_{b_1}}{\bar{b_1}}, \tag{5.10}$$

where σ_{b_1} is the standard deviation of betweenness (b_1) and $\bar{b_1}$ is the mean value of betweenness. Distributions with $\Delta_{b_1} < 1$ are known as low-variance ones. This requirement leads to network resilience by providing distributions of shortest paths that are more uniform among all nodes. See [338] for further details.

5.6.2 Proposed Objective Function

We propose an objective function (to be minimized), which is a combination of different functions related to topological and hybrid CN metrics mentioned before in Lists 1–6 in Section 5.6.1. The objective function is:

$$f_{\text{OBJ}}(\mathcal{G}) = f_\zeta(\mathcal{G}) = \zeta \cdot (\mathcal{N}_l + \ell + \frac{1}{\bar{\mathcal{C}}}) + (1 - \zeta) \cdot (b_2 + \frac{\sigma_{b_2}}{\bar{b_2}}), \tag{5.11}$$

where $\mathcal{N}_l$ is the number of links, ℓ is the average path length, $\bar{\mathcal{C}}$ is the mean clustering coefficient and b_2 is the multi-scale vulnerability of order 2. The rest of the components have already been defined before. Note that f_{OBJ} is only one of the possible functions among several ones that aim at:

- Reducing $\mathcal{N}_l$ in the effort of decreasing the economic cost and the electric losses in the links used to transport electricity from one node to another. Reducing $\mathcal{N}_l$ makes the network less robust. This is because the minimum value of b_2, $b_{2,\min} = 1$ [420], is reached for the "fully-connected network" or "completely-connected graph" in which any node is connected with all of the others. As the number of links decreases, the network becomes increasingly fragile and $b_2 > 1$. Reducing $\mathcal{N}_l$ to a great extent leads to an inexpensive, but very fragile structure ($b_2 \gg 1$ [420, 421]). Thus, the decrease of the number of links and the increase of the robustness have opposite tendencies. This is why we propose a balance between $\mathcal{N}_l$ and b_2 via the weight parameter ζ, which controls the linear combination between constituents with opposing trends.
- Reducing b_2 (approaching one from above) to increase robustness and also $\frac{\sigma_{b_2}}{\bar{b}_2}$ to improve resilience.
- Reducing ℓ along with maximizing $\bar{\mathcal{C}}$ leads to a small-world structure.
- Increasing $\bar{\mathcal{C}}$ aiming to stimulate the local electricity exchanges in scenarios with many small-scale distributed RE generators.

5.6.3 Problem Statement

Let N be the "order" or the number of nodes (generators, loads) of the graph representing a smart grid. The number of links ($M = \mathcal{N}_l =$ network size) to connect the N nodes and the specific way in which these nodes connect to each other are two of the aspects to be determined. Let $\mathbf{G}$ be the set of all possible connected graphs $\mathcal{G}$ with N nodes and $M = \mathcal{N}_l$ links. A graph is connected if there is at least a path between every pair of nodes.

The problem consists of finding the topological structure (the network, or equivalently, the optimum graph $\widehat{\mathcal{G}}$) that minimizes the objective function f_{OBJ} stated by Equation (5.11),

$$\widehat{\mathcal{G}} = \arg\min_{\mathcal{G}\in\mathbf{G}} f_{\mathrm{OBJ}}(\mathcal{G}), \tag{5.12}$$

subject to a the condition that the graph $\mathcal{G}$ must be connected,

$$\lambda_2(\mathcal{G}) > 0. \tag{5.13}$$

Parameter λ_2 is called "algebraic connectivity" (or the Fiedler eigenvalue) [420] and, in graph theory, is one of the available parameters that can be used to mathematically measure to what extent a graph is connected. The algebraic connectivity λ_2 is a positive real number whose magnitude quantifies the level of connectivity in the graph. Larger values of algebraic connectivity represent higher robustness against efforts to break the graph into isolated parts. In the opposite limit, $\lambda_2 = 0$

means that the network has been broken into several disconnected parts. The algebraic connectivity λ_2 is computed as the second smallest eigenvalue of the "Laplacian matrix" of a graph $\mathcal{G}$, $\mathbf{L}_\mathcal{G}$. The Laplacian matrix, sometimes also called the admittance matrix or Kirchhoff matrix, is an $N \times N$ symmetric matrix defined by: [420]

$$\mathbf{L}_\mathcal{G} = \mathbf{D}_\mathcal{G} - \mathbf{A}_\mathcal{G}, \tag{5.14}$$

where $\mathbf{D}_\mathcal{G} = \mathrm{diag}(k_1, \cdots, k_N)$ is the node degree matrix, which is the diagonal matrix formed from the nodes degrees, and $\mathbf{A}_\mathcal{G}$ is the adjacency matrix of graph $\mathcal{G}$.

5.7 Proposed Evolutionary Algorithm

5.7.1 Basic Concepts

An EA is an optimization, population-based algorithm, inspired by the principles of natural selection and genetics, which is able to tackle complex problems [150, 216] such as the one formulated. Among these advantages, EAs do not require derivative information and are able to optimize functions with a large number of continuous or discrete variables, finding the global solution for multi-local extrema problems [217]. As discussed in Section 5.2.2, although GA and EA are sometimes used interchangeably in the reviewed works, in this chapter, we prefer to use the term EA since, as will be explained in Section 5.7; we have encoded each feasible solution as a binary triangular matrix, instead of a bit-string. For further details about this, the interested reader is referred to [218].

The underlying concepts of EAs and the way they are computationally implemented are inspired by the way Nature finds out solutions to extremely complex problems, such as the "survival of the fittest" individual in a evolving ecosystem [216, 217]. Aiming at better explaining our approach, it is convenient to introduce here two biological phenomena from which EAs are inspired: (1) the external characteristics ("phenotype") of living beings are encoded (represented) using genetic material ("genotype"); and (2) evolution is the result of the interaction between the random creation of new genetic information and the selection of those living beings that are best adapted to the environment [217].

The relationship between genotype and phenotype

As mention, in natural evolution, genotype is the genetic information that encodes and causes the phenotype (all external characteristics) of a living being (or "individual"). Specifically, each characteristic is encoded by a "gene", a "chromosome" being the set of these genes [217]. Each gene is located at a particular position on the chromosome and can exhibit different values ("allele").

Biological Evolution

The random creation of novel genetic information in Nature may lead to a better (or sometimes, worse) ability to survive. The better a living being is adapted to its environment, the higher its probability of survival is. This is called "survival of the fittest". In turn, the longer the individual's life is, the higher its probability of having descendants. In the procreation process, the parent chromosomes are crossed or combined ("recombination") to generate a new chromosome (which encodes the offspring). With very small probability, "mutations" (or random variations in genes) can occasionally occur, caused by external factors (for instance, radiation) or simply by unavoidable errors when copying genetic information. This leads to offspring with new external properties, which are different from those of their predecessors. If such arising external characteristic makes the offspring better adapted to the environment, its probability of survival and having descendants increases. In turn, part of the offspring can inherit the mutated genes (and thus the corresponding external characteristic), which can be passed from generation to generation. These natural processes make the population evolve, resulting in the emergence of individuals better adapted to the environment and in the extinction of those less fitted. For deeper details about the main similarities and differences between natural evolution and evolutionary algorithms, the interested reader is referred to [216].

5.7.2 Evolutionary Algorithm Used

The analogy of our problem with the biological metaphor described is that we are looking for the "best graph" $\widehat{\mathcal{G}}$ that minimizes the objective function f_{OBJ} in Equation (5.12). In this search, a very large number of possible graphs $\mathcal{G}$ has to be evaluated aiming at computing the corresponding value $f_{\mathrm{OBJ}}(\mathcal{G})$. Each possible graph is a candidate, trial solution or "individual". The complete set of individuals is called the "population". The extent to which a candidate solution is able to solve our problem is the "fitness of the individual". The smaller the f_{OBJ} value of an individual, the better the fitness of the individual.

Just like in natural evolution, each individual or candidate solution is encoded using a chromosome, a kind of representation that eases the problem solution because it transforms the real search space into another in which working is much easier. The population is evolved via the application of genetic operators that mimic the natural processes of reproduction, mutation and selection.

Encoding Method

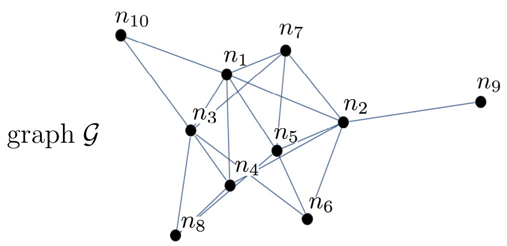
In our problem, the chromosome $\mathbf{c}_{\mathcal{G}}$, which encodes each potential graph $\mathcal{G}$ (or individual), is the upper triangular matrix of its adjacency matrix $\mathbf{A}_{\mathcal{G}}$. In this formulation, $\mathbf{A}_{\mathcal{G}}$ is a square, symmetric and binary matrix whose elements encode whether a node is linked ($a_{ij} = 1$) to another adjacent one in the graph or not ($a_{ij} = 0$). Since there is no node self-connected, the adjacency matrix has zeros on its main (principal) diagonal (($a_{ii} = 0$)). These are the reasons why all of the information of link connections of graph $\mathcal{G}$ is stored by the upper triangular matrix $\mathcal{T}_{\mathcal{G}}$. Thus, chromosome $\mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$ encodes in a compact form the information of the adjacency matrix $\mathbf{A}_{\mathcal{G}}$ of graph $\mathcal{G}$ (or individual).

For illustrative purposes, Figure 5.2a shows a simple random graph with 10 nodes and 20 links, while Figure 5.2b,c represents its corresponding adjacency matrix ($\mathbf{A}_{\mathcal{G}}$) and its upper triangular matrix ($\mathcal{T}_{\mathcal{G}}$ or chromosome $\mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$ encoding the information of individual $\mathcal{G}$), respectively.

In the discussions that follow, the terms "individual" and "chromosome" are used interchangeably because each chromosome uniquely represents each solution in the actual search space. This strategy can be considered as transforming the actual search space into another in which the computational working is much easier. From a mathematical point of view, if $\mathbb{G}$ is the set containing all of the candidate graphs and $\mathbb{C}$ is the set of chromosomes that encodes each of them ($\mathbf{c}_{\mathcal{G}}$), this representation is equivalent to defining a bijection,

$$\Xi : \mathbb{G} \longleftrightarrow \mathbb{C} \tag{5.15}$$

so that any candidate graph is represented by a unique chromosome $\Xi(\mathbf{A}_{\mathcal{G}}) = \mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$.



(a)

adjacency matrix $\mathbf{A}_{\mathcal{G}}$

$$\begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

(b)

chromosome $\mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$

$$\begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

(c)

Figure 5.2: Simple example illustrating the encoding process. (**a**) Small random graph $\mathcal{G}$ (or individual) with 10 nodes and 20 links; (**b**) adjacency matrix $\mathbf{A}_{\mathcal{G}}$ of graph $\mathcal{G}$; (**c**) upper triangular matrix $\mathcal{T}_{\mathcal{G}}$ or chromosome $\mathbf{c}_{\mathcal{G}} = \mathcal{T}_{\mathcal{G}}$ encoding the information of individual $\mathcal{G}$.

Initial Population

The size of the initial population (number of chromosomes), $\mathcal{P}_{\text{size}}$, is a crucial parameter for EA performance [218]. On the one hand, a large population could cause more diversity of candidate solutions (and thus, a higher search space), leading to a slower convergence. On the other hand, too small a population leads to reduced diversity: only a limited part of the search space will be explored. This increases the risk of prematurely converging to a local extreme. In our specific problem, after a number of experiments, the initial population has been chosen as $\mathcal{P}_{\text{size}} = 50$ individuals, as a tradeoff between computational complexity and performance.

As important as the population size is the way in which such an initial population is generated. Usually, the initial population is initialized at random. This strategy is appropriate for those problems in which there is no information about how the solution will be. However, there are problems in which a non-random, domain-specific initial population is more suitable [422]. This is the case of our problem since we have information about a suitable (although non-optimum) solution: small-world networks have been found to exhibit beneficial properties in some smart power grids. See [338] for a more detailed explanation. In our preliminary work, we have found that the EA works better if the initial population is generated as follows:

- Fifty percent of $\mathcal{P}_{\text{size}}$ are Watts–Strogatz random graphs (with small-world properties, including short average path lengths and high clustering) with rewiring probability ranging from 10^{-2} to one.
- Fifty percent of $\mathcal{P}_{\text{size}}$ are Erdős–Rényi (ER) random graphs with N nodes and $N \times 5$ links.

Figure 5.3 shows some examples of four graphs belonging to the initial population.

An important point is to ensure that any graph $\mathcal{G}$ in the initial population is connected by checking that it fulfills the condition $\lambda_2(\mathcal{G}) > 0$ [420].

This approach to generate an SG domain-specific aims to reduce the number of searches within the solution space and to assist operators in finding the global minimum quickly.

Implementation of Evolutionary Operators

Selection Operator

Selection operators can be basically classified into two classes [218]: fitness proportionate selection (such as roulette-wheel selection and stochastic universal selection) and ordinal selection (tournament selection and truncation selection) [218]. After a number of experiments, we have selected as the selection operator the tournament selection. This strategy is one of the most widely-used selection operators in EAs since it performs well in a broad variety of problems, is susceptible to parallelization and can be implemented efficiently [218, 423]. A very clear description of its key concepts and further details can be found in [423].

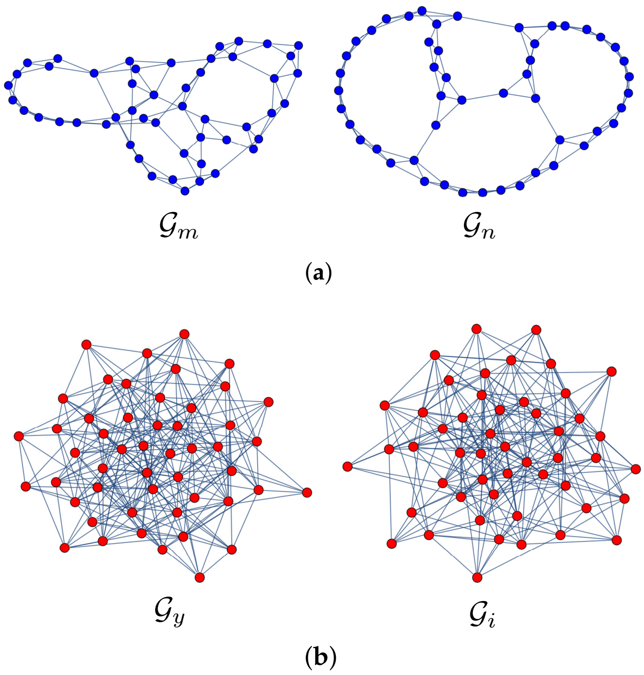


Figure 5.3: Examples of four graphs belonging to the initial population. (**a**) Watts–Strogatz random graphs; (**b**) Erdős–Rényi (ER) random graphs.

Tournament selection basically aims at selecting individuals based on the direct comparison among their fitness. In our problem, a candidate solution, a graph $\mathcal{G}$, encoded by chromosome $\mathbf{c}_\mathcal{G}$ is more fit than another, $\mathbf{c}_\mathcal{H}$, if the corresponding objective function f_{OBJ} is better (lower):

$$f_{\mathrm{OBJ}}(\mathbf{c}_\mathcal{G}) < f_{\mathrm{OBJ}}(\mathbf{c}_\mathcal{H}). \tag{5.16}$$

The simplest tournament selection operator consists of picking out at random two individuals (contenders) from the population and carrying out a combat (tournament) to elucidate which one will be selected. In particular, each combat involves the generation of a random real number $n_{\mathrm{tour}} \in [0, 1] \subset \mathbb{R}$ to be compared to a prearranged selection probability, p_{selec}. If $n_{\mathrm{tour}} \leq p_{\mathrm{selec}}$, then the stronger (fitter or best) candidate is selected, otherwise the weaker candidate is selected. The probability parameter p_{selec} gives a suitable strategy for adjusting the selection pressure. To favor best (fittest) candidates, p_{selec} is usually set to be $p_{\mathrm{selec}} > 0.5$ [423].

This simplest implementation of tournament with only two competitors (tournament size = 2) can be generalized to involve more than two individuals. As shown in [423], the selection pressure can be adjusted by changing the tournament size. If the tournament size increases, weak individuals have a smaller probably of being selected. That is, the more competitors, the higher the resulting selection pressure.

Regarding this, the tournament selection operator we have implemented has a tournament size of $T_{\text{size}} = \mathcal{P}_{\text{size}} = 50$ contenders (that is, all individuals are fighting each other) and a selection probability, $p_{\text{selec}} = 0.8$. As mentioned, $p_{\text{selec}} > 0.5$ favor best (fittest) candidates [423]. The individual that accumulates the most wins is selected as the one that pass to the next generation in the selection process.

Crossover Operator

The crossover operator works as follows:

1. Select at random (p_{cross}) two individuals from the population (father and mother).
2. Select at random the same row in the parents.
3. Exchange the selected rows between the father and the mother, which leads to two child chromosomes.

Mutation Operator

Mutation operators are designed to generate diversity in each generation and aim at exploring the whole search space by introducing local changes with very small probability. Specifically, the implemented mutation operator selects at random an individual with a given probability p_{mut}. The mutation operator then picks out at a random row (of the upper triangular matrix representing such an individual). Note that row "i" encodes how node i is connected to others: element $a_{ij} = 1$ means that there is a link between nodes i and j. The next step that the operator makes is to select at random two elements of the row and to perform a permutation. This is equivalent to rewiring the links of node i to other nodes and ensuring that: (1) node i is not disconnected from the rest of the network and (2) that the degree of node i remains unchanged, despite having made the mentioned rewiring.

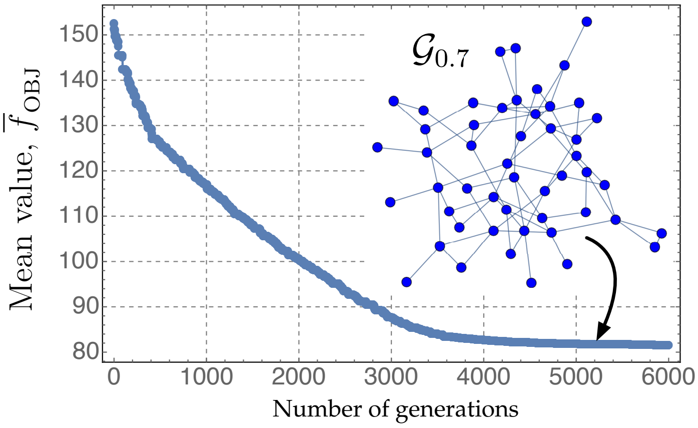
5.8 Experimental Work

5.8.1 Methodology

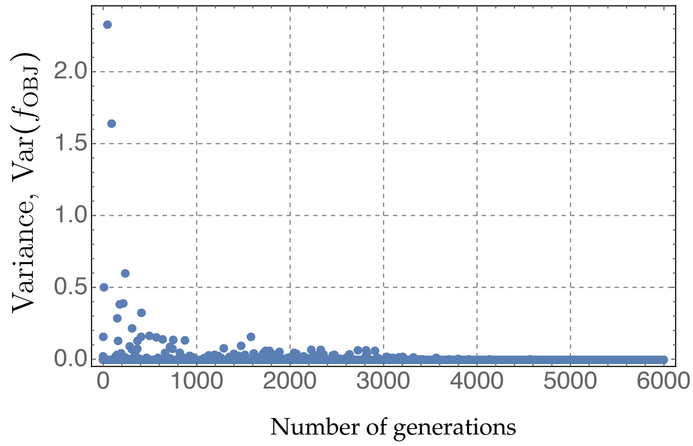
The EA is stochastic as it begins with a population randomly generated (see Section 5.7), and then evolutionary probabilistic operators are applied to the population in each generation. The result gets better (f_{OBJ} is reduced) quickly with the first iterations (generations) until it ends up stagnating, converging to a near-optimal result. As the EA is stochastic, obtaining statistical values is compulsory. This is the reason why the EA has been repeated 20 times, which have been found long enough.

The values for the EA parameters that we have considered in the experimental work described below are: $T_{\text{size}} = \mathcal{P}_{\text{size}} = 50$ graphs (50% being WS small-world graphs, with rewiring probability ranging from 10^{-2} to 1, and 50% being ER random graph with N nodes and $N \times 5$ links), $p_{\text{selec}} = 0.8$, $p_{\text{mut}} = 0.09$ and $p_{\text{cross}} = 0.2$.

For illustrative purposes, Figure 5.4 shows the mean value (a) and variance (b) of $f_{\text{OBJ}} = f_{0.7}$ as a function of the number of generations.



(a)



(b)

Figure 5.4: Mean value (**a**) and variance (**b**) obtained by the proposed EA when minimizing the objective function stated by Equation (5.11) for $\zeta = 0.7$ and constrained to Equation (5.13), as a function of the number of generations.

5.8.2 Results: Optimizing the Structure

Figure 5.5 shows some selected results obtained by the proposed EA when minimizing the objective function stated by Equation (5.11) constrained to Equation (5.13). For each value of ζ, the parameter that controls the linear combination of opposing constituents in Equation (5.11), the problem consists of finding the optimum network (or, equivalently, the optimum graph) that minimizes $f_\zeta(\mathcal{G})$. The results represented correspond to the mean value (over 20 realizations of the EA). Figure 5.5 consists of several subfigures. On the left part of Figure 5.5, we have represented, as a function of ζ, the following values: (a) the mean value of the objective function, $\bar{f}_\zeta$; (b) the multi-scale vulnerability of order two, b_2; (c) the average path length, ℓ; (d) the clustering coefficient, $\mathcal{C}$; and (e) the average node degree, $\langle k \rangle$.

On the right part of Figure 5.5, we have represented some interesting graphs. All of these figures are necessary to properly understand the result. Regarding this, note that:

1. The optimum value of $\bar{f}_\zeta$ in Figure 5.5a is achieved for $\zeta = 0.7$. This corresponds to the optimum graph $\mathcal{G}_{0.7}$ shown in Figure 5.5h. This graph has $b_2 = 63$ (Figure 5.5), which is an intermediate robustness between the one of $\mathcal{G}_{0.0}$ (Figure 5.5f) and that corresponding to $\mathcal{G}_{1.0}$ (Figure 5.5j). $\mathcal{G}_{0.7}$ arises from the tradeoff between having a reasonable robustness and efficient power exchange at the local scale (high $\mathcal{C}$ and low ℓ) with a limited number of links ($74 \ll 300$, the number of links of $\mathcal{G}_{0.0}$). $\mathcal{G}_{0.0}$ represents a network with high number of links, very interconnected, and thus, potentially very expensive, and with very high robustness (smallest fragility, $b_2 \approx 1$). On the contrary, $\mathcal{G}_{1.0}$, which has $b_2 \approx 200$, is thus very fragile: note in Figure 5.5j that the occurrence of abnormal conditions on the marked link will completely disconnect the power grid. In this limiting case ($\zeta = 1$), the optimum network $\mathcal{G}_{1.0}$ has only 51 links (very low economical cost), but at the expense of being very vulnerable to targeted attacks on hubs.

2. A key point to note in Figure 5.5a is that, in the interval $0.6 \leq \zeta \leq 0.8$, the objective function has a slight variation $80 \leq \bar{f}_\zeta \leq 81$, in which the corresponding optimum graphs $\mathcal{G}_{0.6}$, $\mathcal{G}_{0.7}$ and $\mathcal{G}_{0.8}$ exhibit some beneficial properties for the SG:

    2.1. Intermediate robustness, ranging from 50 to 80 in Figure 5.5b.

    2.2. A small average path length, $\ell < \ell_{\mathrm{RG}}$ (Figure 5.5c). This is related to the efficient power flow between nodes [338].

    2.3. Clustering coefficient considerably higher than that of the random graph (with the same number of nodes and links), $\mathcal{C} > \mathcal{C}_{\mathrm{RG}}$ (see Figure 5.5d). This is related to the local exchange of power between neighbor nodes [338]. These two latter conditions are topological features that help the power grid be a smart grid. Furthermore, the two latter features show that the graphs in $0.6 \leq \zeta \leq 0.8$ have the small-world nature. In particular, these graphs with $M \sim 1.66N$ approach non-sparse small-world networks (with $M \sim 2N$), which, according to [383], are the most robust.

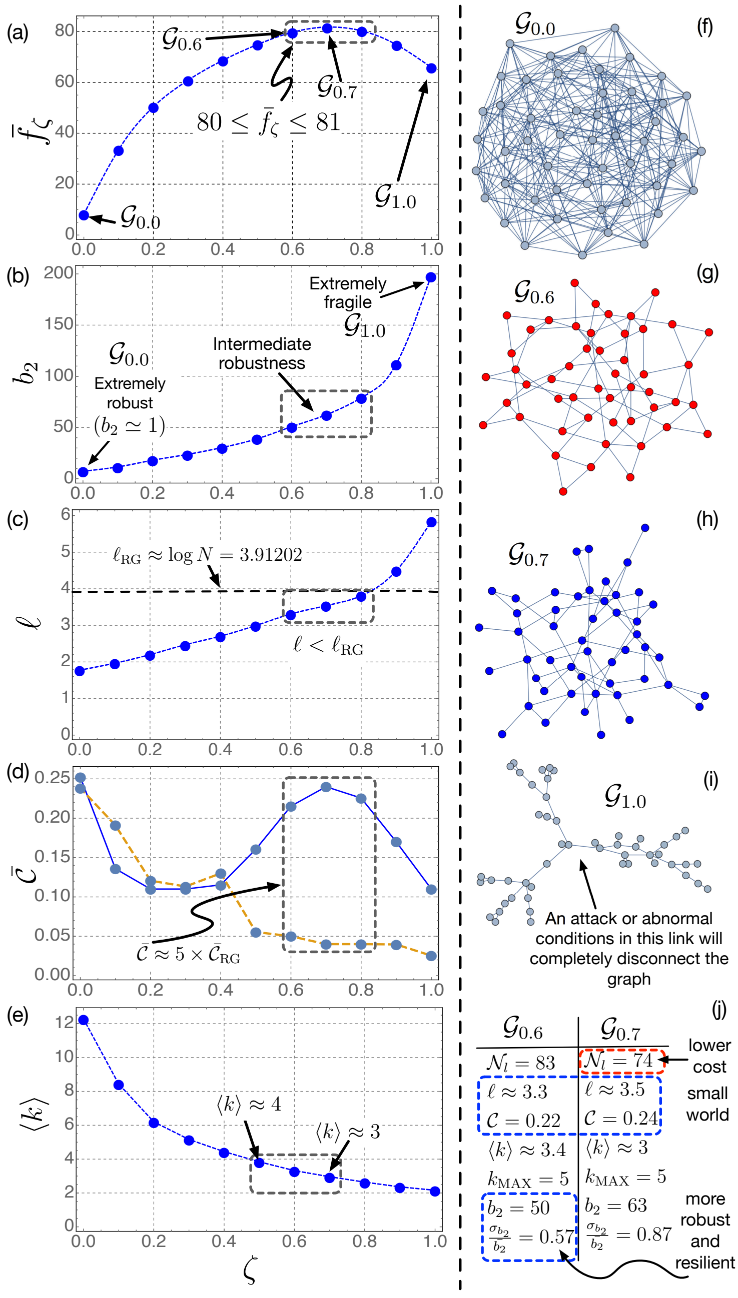


Figure 5.5: Result reached by the proposed EA when minimizing the objective function stated by Equation (5.11) as a function of ζ: (a) Mean value of the objective function, $\bar{f}_\zeta$; (b) Multi-scale vulnerability of order two, b_2; (c) Average path length, ℓ; (d) Clustering coefficient, $\mathcal{C}$; (e) Average node degree, $\langle k \rangle$. On the right side, (f), (g), (h) and (i) show, respectively, optimum structures for several values of ζ: $\mathcal{G}_{0.0}$, $\mathcal{G}_{0.6}$, $\mathcal{G}_{0.7}$ and $\mathcal{G}_{1.0}$. (j) Summary of illustrative results for $\mathcal{G}_{0.6}$ and $\mathcal{G}_{0.7}$.

2.4. Additionally, in $0.6 \leq \zeta \leq 0.8$, $\mathcal{C} \approx 5 \times \mathcal{C}_{\mathrm{RG}}$, in good agreement with the properties described in [338].

2.5. The average node degree $\langle k \rangle$ has values ≈ 3, which has been proven to be beneficial in [338].

2.6. k_{MAX} ranges between ≈ 5 and ≈ 7, which limits the existence of nodes with many links, and therefore, with high capacity ($\approx$ more expensive).

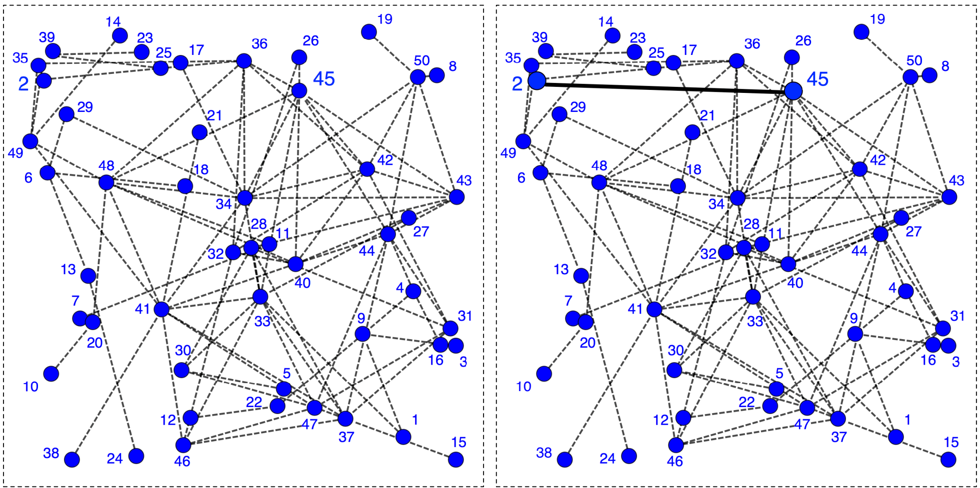
5.8.3 The Benefits of Adding Links

In this case, we assume that the SG is a network whose nodes are embedded in space ("spatial network" (SN)). This is a realistic condition that appears in some real power grids: the Florida high-voltage power grid, which has been found to be a spatial network with strong geographical constrains that embeds it in space [424], or the Italian power grid [418]). Furthermore, the recent work [425] assumes that a power grid is well described by a two-dimensional, spatially-embedded, connected network. To make the study as general as possible, we assume that the SG is a spatial network whose 50 nodes are located at positions that have been generated at random inside the unit square, with the restriction that the normalized Euclidean distance between any pair of nodes fulfills $d_E(n_i, n_j) \leq d_{\mathrm{MAX}} = 0.5$.

The purpose of our example is to study the beneficial properties of adding links. In this respect, Figure 5.6 shows the network obtained by minimizing the number of links constrained to a limit, small algebraic connectivity $\lambda_2^{\mathrm{OBJ}} = 0.01$, which prevents the network from being disconnected. An initially completely-connected network is the most robust network having the maximum number of links. However, in a real-world infrastructure (such as the power grid), this is unrealistic because of not only economic considerations, but also from a technical viewpoint (substations having many connections). Figure 5.6 shows the beneficial properties of adding links. By adding only one link between Node 2 and Node 45, the algebraic connectivity increases up to $\lambda_2 = 0.1005$, almost by a factor of $\times 100$, while ℓ increases up to $\ell = 3.9 \lnapprox 3.91 = \log(50)$, reaching the corresponding small-world feature.

This results is in good agreement with others found in the literature. The smart addition of links in power grids may lead to the small-world property, making networks more robust [400,403]. Specifically, the survey in [341] shows that the addition of links improves robustness in real grids in Spain, France and Italy [418]. Under the assumption of a small-world WS network model, it is observed that line congestion decreases as the density of shortcuts rises. By rewiring shortcut lines under a certain probability, the mean load in lines results in being lower and so does the number of congested lines. A similar result has been found in [400], which in turn reinforces the suitability of small-word network models when it comes to robustness [380,426–429].

The advantages arising from small-world diameters has been recently emphasized in [403], in which the system has been modeled as a network of networks, leading to two important conclusions that could help increase robustness (reduce vulnerability).



(a) (b)

Figure 5.6: (**a**) Spatial network with minimum algebraic connectivity; (**b**) addition on a link between Node “2” and Node “45”.

The first one, as mentioned, is that networks with a small diameter are very robust. This has very important practical implications from an engineering viewpoint. In wireless networks, this helps reduce power consumption. In electric grids, this means that generators should be placed near consumers, which can be attained by means of distributed renewable energy generation. This strategy could reduce the investment of deploying or upgrading power transmission grids. The second key conclusion is that adding links is, in general, beneficial until a critical number of lines is reached, beyond which adding more links could increase cascading failures [393]. Note that not all models are consistent regarding the beneficial aspects of adding lines, although it is true that the vast majority of them agree on the conclusion that this strategy is advantageous [341].

Small-sized, small-world topologies for SGs, like those previously obtained, exhibit an additional bonus of helping the intentional islanding. This is a strategy that aims to stop the initial failure occurring in a small part of a power grid [430–432] and to prevent it from propagating through the rest of the system, causing thus a larger blackout. In [417,433], the authors suggest that a feasible method to prevent the propagation of disturbances would be to design the network so as to allow for intentionally separable, stable, small islands or “micro-grids”. In the case of emergency, a micro-grid is simply a subset of the grid that can be islanded and which is able to supply electric energy to all or most of its users when an emergency is triggered [341,434]. In this regard, the SG concept can be a good strategy to put this into practice. In a broader approach, a “hybrid” grid is understood as the coexistence of largely interconnected grids with central control and smaller, decentralized areas that could be operated as micro-grids, in the case of emergency. In this context, small, distributed, smart grids as complex networks are on the rise [7,339,355,357], towards an electric grid characterized by a very considerable influence of prosumers, which will have a considerable influence on the electricity distribution infrastructure in the near future.

5.8.4 Comparison with an Evolution Strategy

The use of an evolutionary algorithm to jointly minimize the link density and the average distance in complex networks was studied in the pioneering, seminal work [435], generating different topologies of general application. This algorithm consists basically of an evolution strategy (ES). The simplest ES works on a population of size two: the current single parent and the result of its mutation. This is the so-called (1+1)-ES [436]. The (1+1)-ES starts with a single individual ($\mathcal{P}_{\text{size,initial}} = 1$), a graph generated at random. This single progenitor is then evolved by applying a mutation algorithm, which flips an element a_{ij} and generates a new individual. The only constraint is that the resulting mutated network is connected. The objective function is then evaluated with the novel individual. If this value is lower than that of the single progenitor, the new individual is accepted, and the ancestor is removed. Otherwise, the mutant individual is eliminated. This minimization algorithm is iterated until convergence is reached. Figure 5.7 will assist us with comparing this $(1+1)$-ES to the proposed EA.

Figure 5.7 shows the mean value of $\mathcal{N}_l$ as a function of the number of generations, computed, respectively, by using the proposed EA (a) and the $(1+1)$-ES (b). In this case study, we have considered the number of links (or network size) $\mathcal{N}_l$ as the objective function to be minimized because: (1) it is a function in which the exact solution is known; and (2) it is a simple function that requires a much lower computational burden than the one studied above. These two properties make this simple case study allow for obtaining a feasible comparison between the efficiency of the proposed EA and that of the $(1+1)$-ES. We use as the comparative criterion the number of generations necessary for each algorithm to converge to the exact, known solution $\mathcal{N}_{l,\min} = M - 1$. The results have been represented in Figure 5.7 for a network with order $M = 50$ nodes.

Figure 5.7 reveals that the $(1+1)$-ES needs a much longer convergence time than that of the proposed EA. Using the number of generations as the comparative criterion, the proposed EA converges to the exact solution (a graph with 49 links) after 900 generations, while the $(1+1)$-ES requires about 8100 generations to converge to a connected graph with the minimum number of links (49 links). That is, the proposed EA is more efficient in the sense that it needs a number of generations $\approx$ 9-times lower than that of the simplest $(1+1)$-ES. This is because the latter performs a completely random search ($p_{\text{mut},(1+1)-\text{ES}} = 1$) and starts with an initial population with a single progenitor, as long as the EA starts with a larger population (50 individuals) with greater variability and takes advantage of applying a crossover operator (with probability $p_{\text{selec}} = 0.8$) in addition to a mutation operator with small probability ($p_{\text{mut}} = 0.09$), preventing thus a completely random search.

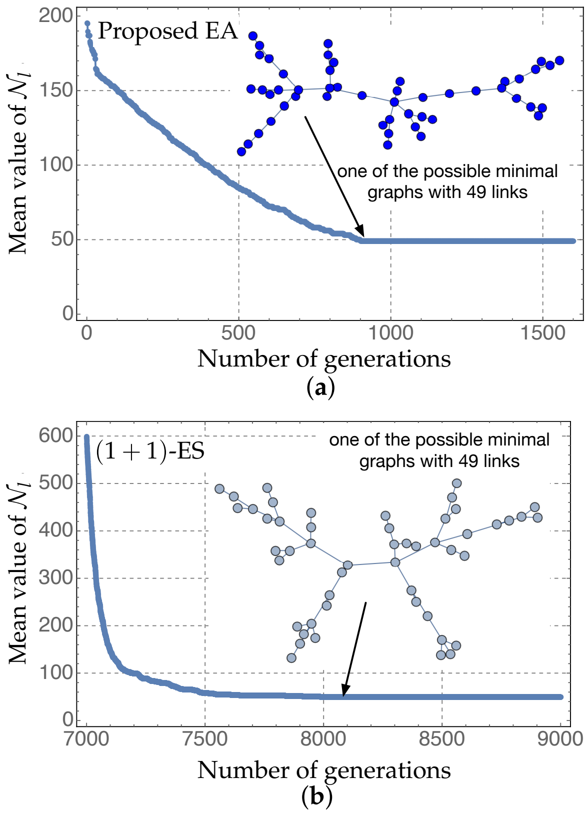


Figure 5.7: Mean value of the number of links ($\mathcal{N}_l$) as a function of the number of generation using, respectively, the proposed EA (**a**) and the (1 + 1)-evolution strategy (ES) (**b**). The number of nodes is $M = 50$.

5.9 Summary and conclusions

This chapter has been motivated by two important, mutually interrelated points: 1) how several WECs should have to be electrically interconnected to each other (forming a WEC farm), and 2) how the WEC farm should be connected to the power grid. The main reason why WECs are electrically connected with each other is that a single standalone WEC cannot generate sufficient electric power for commercial-scale grid integration. Although linked WECs help soften the fluctuation of electric power associated to wave variability, such fluctuation is still important and can affect the quality of the power grid. A feasible solution consists in using electric energy storage systems aiming at smoothing the produced electric power without reducing energy efficiency [161, 162]. Thus, conceptually, a WEC farm can be considered as a set of nodes (either generating or absorbing electricity) connected according to certain design criteria [159,161,163]. In turn, the electric connection of a WEC farm to on-shore power grid [159–163] aims at seamlessly integrating it into the power grid. To do this, wave farms should become into "smart wave farms" (SWFs). The

SWF approach allows for predicting waves using in-ocean sensors and forecasting algorithms. These predictions in turn can be used to: 1) adapt the WECs' energy capture, 2) make efficient energy storage decisions [164], and 3) control the quality of the power that the SWF injects into the on-shore power grid. The variability and intermittency of wave energy is common to other mass renewable energies, such as wind and solar energies, and can be tackled within the unifying framework of smart grids (SGs). The emerging SG concept is able to efficiently *integrate* into the power grid a rapidly increasing number of intermittent generators, with the target of affecting as slight as possible the stability and robustness of the grid [158].

Thus in this chapter we have considered the SWF and its connection to the on-shore power grid as a SG whose structure needs to be optimized against random failures or abnormal operating conditions –for instance, intermittent generation or the breakdown or the operation stop of a WEC (or a set of them) within a WEC farm caused by a storm–. The novelty of this chapter is twofold, in the sense of optimizing the robustness of such SG (connecting nodes that generate, consume or store electricity) against abnormal operating conditions by (1) using an EA that optimizes the structure of the SG modeled by (2) applying concepts from the Complex Networks Science. The approach is general in the sense that allows for optimizing the structure of any SG with renewable energy (RE) generation against abnormal conditions (imbalances between generation and consumption, overloads or failures arising from the inherent SG complexity) by combining the complex network (CN) and evolutionary algorithm (EA) concepts. The model and results of this chapter have been published in [108].

Our approach takes advantage of some important properties of the SG paradigm being based on: a smart grid allows for the bidirectional exchange of electric energy at the local scale and aims at supplying reliable and safe electric power by efficiently integrating distributed RE generators using smart sensing and communication technologies. In this context, we have modeled the SG as a undirected graph so that each link (electric cable) allows for the bidirectional exchange of electric energy between nodes (WECs and storing devices, for instance). Because of its flexibility, the model is also applicable to the efficient integration of distributed REs (small-scale photovoltaic systems and small-wind turbines) in the low voltage grid, so that electricity consumers can also become producers ("prosumers"), helping end-users obtain economic benefits by selling the energy generated in excess.

Aiming at optimizing the structure of such SG against abnormal conditions, we have proposed a novel objective function (to be minimized) that combines cost elements, related to the number of electric cables, and several metrics that quantify properties that are beneficial for the SG (energy exchange at the local scale and high robustness and resilience, as shown in [338]). The optimized SG structure is obtained by applying an EA in which the chromosome that encodes each potential graph (or individual) is the upper triangular matrix of its adjacency matrix. This allows for fully tailoring the crossover and mutation operators to such encoding. Since small-networks have been found to be beneficial for SGs [338], we have proposed a domain-specific initial population that includes both random networks and small-world networks. This assists the proposed EA to converge quickly.

The experimental work points out that the proposed method works well and generates an optimum, synthetic, non-sparse-like small-world structure that leads to beneficial properties such as improving both the energy exchange at the local scale and the robustness and resilience. Specifically, the optimum topology fulfills a balance between moderate cost and robustness against abnormal conditions. We have also explored the benefits of adding links to improve the robustness of smart grids, in good agreement with [380, 426–429]

We would like finally to emphasize that the proposed approach should be considered as a high level analysis and planning tool in the effort of estimating to what extent the smart grid topology can suffer from vulnerabilities. It cannot and does not intend to replace the conventional methods used by power engineers. In fact, the low level, detailed design must be carried out using electrical engineering techniques. In this respect, a deep discussion about the controversy still unresolved between the complex network and electrical engineering communities can be found in [341,343,404,410], reference [343] being a clear introduction to complexity science in the context of power grids.

Chapter 6

Conclusions and Future Work

6.1 Summary and conclusions

In this thesis we have explored the use of Soft Computing (SC) approaches in wave energy problems. The reason we have focused on wave energy to the detriment of other marine energies is that, among all the available marine technologies, wave energy is the most used because, in addition to being efficient from a technical viewpoint, it does not cause significant environmental problems. Its efficient conversion is based on a variety of wave energy converters (WECs), which transform the kinetic energy of wind-generated waves (or simply, wind energy) into electric energy by means of either the vertical oscillation of waves or the linear motion of waves. Wave energy exhibits some significant advantages when compared to the other marine energies (tidal and ocean thermal energies):

- Wave energy is the densest renewable energy (about 1000 times more concentrated than wind energy) and is less changing on an hourly basis than wind energy.
- There are many ideal regions (in the sense of having substantial wave power density *near* populated regions demanding electric and clean energy) in the North and West coast of Europe (Nordic countries, UK, Ireland, Portugal), North coast of US and Canada, Southern cost of Australia, Northern coast sof New Zealand, Japan, and India.
- WECs usually cause much lower environmental impacts on ecosystems than tidal devices.

Despite exhibiting these advantages, which have been discussed in detail in Chapter 2, wave energy suffers from some serious practical problems: 1) waves are more difficult to characterize than tides because of the stochastic nature of waves (although they are less variable on an hourly basis than wind), and 2) wave energy is intermittent. Furthermore, wave energy flux can exhibit nonlinear variability, with irregular extreme events. As a consequence of this complexity, both the design, deployment, and control of WECs become key points that require a *resource characterization* as accurate as possible. Such characterization can be carried out essentially through two families of techniques: physical models and data-driven models:

1. Physical models are based on the wave energy balance equation, a differential equation which is solve numerically. There are several *numerical wave models* depending on the numerical methods and the physical parameterizations adopted. Numerical wave models are very powerful but require a huge amount of meteorological and oceanographic data and *computational effort*. Numerical models are more useful for forecasting over a large spatial and temporal domain (within a window of a few days).

2. Data-driven models made use of data measured from wave stochastic processes by means of buoys, radars, or satellites, which generate time data series. Data-driven models use such data to forecast, for instance, wave parameters. There are basically two data-based approaches in this family of models:

   2.1. Statistical regressive methods like autoregressive (AR) model, auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA), and so on.

   2.2. SC methods (neural, fuzzy, and evolutionary methods).

The reason why we have focus in this thesis on SC approaches in wave energy is that SC techniques have proven to reach similar and even superior results than other data-driven models such as statistical methods (AR, ARMA, ARIMA,...) in short term estimations (up to 24 h). SC methods have some advantages over numerical models: simpler modeling, smaller computational cost, and lack of errors arising out of wind-to-wave conversion.

Aiming at exploring the use of novel SC approaches in wave energy problems, we have introduced in Chapter 2 two groups of concepts that the rest of the chapters (and the research work described in them) make use of. The first set of concepts is related to a basic characterization of wave stochastic processes, while the second one focuses on introducing the fundamentals of the most used WECs that transform wave energy into electricity.

- Regarding wave resource characterization, the wave energy flux (or power density per meter of wave crest), P, depends of two important parameters: the significant wave height, H_s, and the wave energy period, T_e. These can be calculated from statistics obtained from series of wave measurements, carried out, basically, by buoys. Oceanographic buoys are one of the most used measuring instruments to characterize wind-generated wave properties. In particular, a scalar buoy located at a point $\mathbf{r} = (x, y)$ on the sea surface is able to measure, at each instant of time t, the vertical water surface elevation, $\eta(\mathbf{r}, t)$, leading thus to time series. Using Fourier analysis, the spectral wave density

$S(f)$ can be computed, and, in turn, based on $S(f)$, a number of integrated wave parameters, such as the spectral moments, the significant wave height H_s, or mean wave period, to name just a few, can also be estimated. There are many SC techniques that can be used to estimate H_s and T_e. After certain mathematical operations, this expression ends up being $P \propto H_s^2 \cdot T_e$. This helps engineers estimate the amount of wave energy available when planning the deployment of a WEC or farm of WECs at a given location since a first indicator is the amount of available wave energy flux, $P \propto H_s^2 \cdot T_e$. Thus, the significant wave height H_s and the wave energy period T_e are, among all others, the most important wave parameters in the design of both WECs and WEC farms.

- The second group of concepts we have described in Chapter 2, and which are strongly related to the former, focuses on the essential concepts WECs are based on. In this respect, we have shown that there are many different WECs, in greater or lesser degree of development. Despite this, only a small fraction of them have been deployed and tested in oceans. Since there is a great variety of WECs, their classification has been tackled from different viewpoints and complexity levels, and we have shown that there is no unanimity of what is the most appropriate one. The simplest classifying viewpoint is related to water depth and location, leading to shoreline, near-shore, and offshore WECs. Offshore WECs are in deep waters and are able to generate much more electric energy because of the greater energy of deep waters. The negative counterpart is that they have to be designed to survive the most extreme waves, being thus considerably more difficult to manufacture and maintain. In turn, regardless their location, WECs can also classified on the basis of their relative position with respect to the predominant wave direction: parallel or "attenuator", perpendicular or "terminator", and "point absorber", which absorbs energy from all directions. The analysis of the different wave parameter and WECs that we have carried out points out that the design, survivability, efficiency and control of WECs depend strongly on the characterization of sea states. These can be carried out by using SC techniques.

Just in this respect, Chapter 3 has centered on presenting and analyzing the state of the art of SC techniques (Neural, Fuzzy, and Evolutionary Computation) in the field of wave energy. The benefits of applying SC techniques to wave energy problems lies in their potential to work with a huge amount of imprecise or missing data. This is just the case of the design, deployment, and even control of (some) WECs. Regarding this, and as mentioned before, a first indicator prior to the deployment of WECs at a given location is the amount of wave energy flux available. This magnitude can be estimated by using the significant wave hight H_s and the wave energy period T_e, which, in turn, can be computed from spectral magnitudes of buoy data. These and other wave parameters have been found to be estimated in our review by means of a variety of SC techniques:

- Most of the applications of Neural Computation techniques, considered in a broad sense, have been found to focus on the prediction of a number of wave energy parameters by means of Multilayer Perceptrons (MLPs) and, at a lesser extent, by Support Vector Machines (SVMs). Neural Computation techniques have been applied to: *a*) Predict a variety of wave parameters, in particular, H_s and T_e; *b*) Estimate missing data in wave time series; *c*) Estimate the wave spectrum; *d*) Forecast wave energy flux; and *e*) Control WECs, in particular Archimedes Wave Swing WECs.

- The second class of SC techniques, Fuzzy Computation, has been found to be applied: 1) To predict wave parameters, although at a lesser extent than the Neural Computation approach; 2) To control WECs, by using a combination of Fuzzy Computation and GAs, in particular a floating point (buoy-based) absorber WEC.
- Evolutionary Computation algorithms have been applied to: 1) Fill up missing values in wave time series; 2) Predict H_s; and 3) Optimize the shape of wave energy collectors.

The aforementioned SC techniques have proven to reach similar and even superior results than other data-driven models like statistical methods (AR, ARMA, ARIMA,...) in short term estimations (up to 24 h).

Based on the results of the literature review and on the previously stated background, the second part of this thesis has focused on two novel research proposals that use SC in wave energy problems and that have been published in [107] and [108], respectively.

The first of these case studies has been explored in Chapter 4, in which we have tackled a problem of significant wave height H_s reconstruction (at the location of an out-of-operation measuring buoy) by using wave parameters from nearby buoys. This reconstruction is important because such wave parameter plays a key role in the design and operation of WECs, in coastal engineering (design of vessels, oil platforms, breakwaters, etc.), and in forecasting for ship navigation and WECs' control. We have faced the problem of filling up missing H_s values within the framework of Machine Learning (ML) in a two-step process, which has led to two contributions. The first one has consisted in designing a hybrid evolutionary algorithm that selects, among the available wave parameters (from the nearby buoys), a smaller subset $\mathcal{F}_{n_{SP}}$ with n_{SP} parameters that minimizes the H_s reconstruction error. For doing this, we have proposed a novel approach in marine energy applications consisting of a Genetic Algorithm (GA) that computes the fitness of the candidate individuals (trial solutions) in each generation by using an Extreme Learning Machine (ELM). In this context, the key advantage of the ELM when compared to other ML approaches (Neural Networks, or Support Vector Machines, for instance) is that ELMs learn very fast, this being essential in population-based evolutionary algorithms such as GAs. This is why we have hybridized the ELM with the GA in the detriment of other alternative ML regressors. The proposed hybrid GA-ELM method generates a subset $\mathcal{F}_{n_{SP}}$ of n_{SP} parameters that minimizes the root mean square error of H_s reconstruction, RMSE($\hat{H}_s$)(m). In the effort of testing its performance in two different coastal regions, we have explored two case studies: one in the Caribbean Sea, and the other, in the West Atlantic coast nearby Florida. The results, published in [107], suggest that:

- The proposed GA-ELM algorithm works very well in the sense that it selects a very reduced subset of parameters ($n_{SP} = 10$ parameters) among the available 60 parameters. Using $5 \leqslant n_{SP} \leqslant 10$ parameters lead to small reconstruction errors: RMSE$(\hat{H}_s)_{\text{Caribbean}} \lesssim 0.50$ m, and RMSE$(\hat{H}_s)_{\text{Atlantic}} \lesssim 0.75$ m.
- From an operative view point there is no practical benefit in using more than 5 parameters, in the sense that more parameters increase the computation time without significantly improving the reconstruction accuracy.

The second contribution of Chapter 4 has consisted in evaluating to what extent the selected wave parameters in subset $\mathcal{F}_{n_{SP}}$ assist other ML regressors −Extreme Learning Machines, Support Vector Regression (SVR), and Gaussian Process Regression (GPR)− in reconstructing H_s. The results show that:

- All the ML method explored have H_s reconstruction errors below 1m in the two different locations studied: RMSE($\hat{H}_s$) < 0.5 m in the Caribbean Sea, and RMSE($\hat{H}_s$) < 0.75 m in the West Atlantic scenario.
- In particular, the GPR method is the one that reaches the smallest error: RMSE$(\hat{H}_s)^{\text{GPR}}_{\text{Caribbean}} \approx 0.30$ m for $\mathcal{F}_{n_7}$, and RMSE$(\hat{H}_s)^{\text{GPR}}_{\text{Atlantic}} \approx 0.48$ m for $\mathcal{F}_8$.

As a general conclusion, the twofold approach presented seems to be a feasible tool to fill missing wave values from neighbor buoys.

Chapter 5 has finally focused on the second novel research line we have published in [108]. This has been motivated because of two mutually interrelated issues: 1) how several WECs are electrically interconnected to each other (forming a WEC farm); and 2) how the farm is connected to the electric network or power grid. The variability and intermittency of wave energy can affect the stability of the power grid and can be encompassed within a broader conceptual framework, which is common to all massive renewable energies (REs). In this respect, the Smart Grid (SG) paradigm aims at integrating a growing number of distributed renewable energy-based generators, without significantly affecting the stability of the power grid. The novelty of our approach is twofold, in the sense of optimizing the robustness of a distribution SG (connecting nodes that generate, consume or store electricity) against "abnormal operating conditions" –for instance, the breakdown or the operation stop of a WEC (or a set of them) caused by a storm– by (1) using an Evolutionary Algorithm, (EA) that optimizes the structure of the SG modeled by (2) applying concepts from Complex Networks (CN) Science. The model and results of this chapter have been published in [108].

Our approach in Chapter 5 takes advantage of some important properties of the SG paradigm: a smart grid allows for the bidirectional exchange of electric energy at the local scale and aims at supplying reliable and safe electric power by efficiently integrating distributed RE generators using smart sensing and communication technologies. Thanks to the efficient integration of distributed REs (small-scale photovoltaic systems and small-wind turbines) in the low voltage grid, electricity consumers can also become producers ("prosumers"), helping end-users obtain economic benefits by selling the energy generated in excess. In this context, we have modeled the SG as a undirected graph so that each link (electric cable) allows for the bidirectional exchange of electric energy between nodes (prosumers).

Aiming at optimizing the structure of such SG against abnormal conditions, we have proposed a novel objective function (to be minimized) that combines cost elements, related to the number of electric cables, and several metrics that quantify properties that are beneficial for the SG (energy exchange at the local scale and high robustness and resilience). The optimized SG structure is obtained by applying an EA in which the chromosome that encodes each potential graph (or individual) is the upper triangular matrix of its adjacency matrix. This allows for fully tailoring the crossover and mutation operators to such encoding. Since small-networks have been found to be beneficial for SGs, we have proposed a domain-specific initial population that includes both random networks and small-world networks. This assists the proposed EA to converge quickly.

The experimental work points out that the proposed method works well and generates an optimum, synthetic, non-sparse-like small-world structure that leads to beneficial properties such as improving both the energy exchange at the local scale and the robustness and resilience. Specifically, the optimum topology fulfills a balance between moderate cost and robustness against abnormal conditions.

We would like finally to emphasize two aspects:

1. The proposed approach should be considered as a high level analysis and planning tool in the effort of estimating to what extent the smart grid topology can suffer from vulnerabilities. It cannot and does not intend to replace the conventional methods used by power engineers. In fact, the low level, detailed design must be carried out using electrical engineering techniques. In this respect, a deep discussion about the controversy still unresolved between the complex network and electrical engineering communities can be found in [341, 343, 404, 410], reference [343] being a clear introduction to complexity science in the context of power grids.

2. The model is sufficiently general to be applied to any set of generators and loads (consuming energy) as well as to the Smart Wave Farm (SWM) system formed by WECs, energy storing devices, and the connection(s) to power grid.

6.2 Future work

Regarding the first research line, explored in Chapter 4, as a future line of work, the proposed GA-ELM method could be also applied to reconstruct other missing wave parameters besides significant wave height, such as wave period and direction. Note that the research work explored in Chapter 4 is centered on using only scalar information because often this is the only information available in many location throughout the world. Using directional information would probably help to improve the results.

Finally, with respect to the approach described in Chapter 5, a future research line could consists in optimizing the interconnection between the WECs that form a farm. This, to the best of our knowledge, has not been studied yet from the combined CN-EA that we have proposed in this thesis. A possible approach to the problem could be to optimize a fitness function consisting of a balance between the costs associated to the connections between the linked WECs and the robustness of the resulting complex network.

List of Publications

1. Alexandre, E., Cuadra, L., Nieto-Borge, J. C., Candil-García, G., **Del Pino, M.** and Salcedo-Sanz, S. (2015). "A hybrid genetic algorithm-extreme learning machine approach for accurate significant wave height reconstruction". *Ocean Modelling*, 92, 115-123. **Impact Factor: 3.341**.

2. Cuadra, L., **Del Pino, M.**, Nieto-Borge, J. C., and Salcedo-Sanz, S. (2017). "Optimizing the Structure of Distribution Smart Grids with Renewable Generation against Abnormal Conditions: A Complex Networks Approach with Evolutionary Algorithms". *Energies*, 10(8), 1097; doi:10.3390/en10081097. **Impact Factor: 2.262**.

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