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Dr. D. Sancho Salcedo Sanz, Profesor Titular de Universidad del Área de Conocimiento de Teoría de la Señal y Comunicaciones de la Universidad de Alcalá, y Dr. D. Javier Del Ser Lorente, Director Tecnológico del Área Óptima de Tecnalia Research & Innovation,

CERTIFICAN

Que la tesis "Advanced Meta-heuristic Approaches and their Application to Operational Optimization in Forest Wildfire Management", presentada por Dña. Miren Nekane Bilbao Marón y realizada en el Departamento de Teoría de la Señal y Comunicaciones bajo nuestra dirección, reúne méritos suficientes para optar al grado de Doctor, por lo que puede procederse a su depósito y lectura.

Alcalá de Henares, Diciembre 2013.

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Dña. Miren Nekane Bilbao Marón ha realizado en el Departamento de Teoría de la Señal y Comunicaciones y bajo la dirección del Dr. D. Sancho Salcedo Sanz y del Dr. D. Javier Del Ser Lorente, la tesis doctoral titulada "Advanced Meta-heuristic Approaches and their Application to Operational Optimization in Forest Wildfire Management", cumpliéndose todos los requisitos para la tramitación que conduce a su posterior lectura.

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MEMORIA DE TESIS DOCTORAL

ADVANCED META-HEURISTIC APPROACHES AND THEIR APPLICATION TO OPERATIONAL OPTIMIZATION IN FOREST WILDFIRE MANAGEMENT

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Abstract

In the last decade the number and frequency of large-scale disaster events has increased sharply, mainly due to the devastating phenomena derived from worldwide climatological paradigms (e.g. global warming). Floods, hurricanes and earthquakes are among those disasters whose severity has grown significantly during this period: as to mention, in 2001 more than 20.000 casualties resulted from a massive earthquake in the state of Gujarat (India), whereas this fatal indicator went up to approximately 230.000 and 316.000 casualties in the earthquakes occurred in Indonesia and Haiti in 2004 and 2010, respectively.

The scope of this Thesis focuses on a particular class of disasters with an equally concerning increase of its severity and frequency in the last few years: wildfire events, understood as those large-sized fires not voluntarily initiated by the human being. Despite the variety of initiatives, procedures and methods aimed at minimizing the impact and consequences of wildfires, several fatalities occurred in the last few years have put to question the effectiveness of current policies for the allocation of firefighting resources such as aircrafts, vehicles, radio communication equipment, supply logistics and fire brigades. A clear, close exponent of this noted deficiency is the death of eleven firefighters occurred in a 130 km^2 forest wildfire in Guadalajara (Spain) in 2005, which was officially attributed to a proven lack of coordination between the command center and the firefighting crew on site, ultimately resulting in radio isolation among the deployed teams. The reason for this missed coordination in the management of firefighting resources can be questioned by authorities and involved stakeholders, but it undoubtedly calls for the study and development of algorithmic tools that help operations commanders optimally perform their coordination duties.

Unfortunately, the economical crisis mostly striking on countries from the Southern Europe has reduced significantly national budgetary lines for wildfire prevention and suppression to the benefit of deficit-reduction programs. As a consequence of these budget cuts, cost aspects have lately emerged as necessary, relevant criteria in operations planning: from an optimization perspective, firefighting resources are allocated so as to achieve the maximum effectiveness against wildfires, subject to the available budget upper bounding the overall economical cost associated to the decisions taken by commanders and decision makers. Although the cost constraints in this problem are obvious and well-reasoned, in practice management procedures for firefighting resources do not follow cost-aware strategies, but are instead driven by the limited capacity of the human being to dynamically perform decisions in complex, heterogeneous scenarios.

This Thesis builds upon the above rationale to propose modern meta-heuristic algorithms for solving optimization problems modeling different firefighting resource allocation paradigms. This family of solvers efficiently explores the solution space of a

given problem by iteratively applying intelligent explorative and exploitative mechanisms, yielding solutions that trade optimality for a reduced computational complexity with respect to exhaustive search methods. In particular, the dissertation gravitates on the adoption of Harmony Search algorithm as the meta-heuristic technique lying at the core of the proposed resource allocation schemes, which are contextualized in two different scenarios:

- The first studied setup addresses the optimum design of wireless relayed communication networks deployed over large-scale disaster areas. In this scenario the so-called dynamic relay deployment problem consists of finding the optimum number of deployed communication relays and their location aimed at simultaneously maximizing the number of nodes covered and minimizing the cost of the deployment. This problem formulation is further extended by considering diverse relay models characterized by different coverage radii and associated costs. To efficiently tackle this problem a novel hybrid scheme is derived comprising 1) a Harmony Search based global searching procedure; and 2) a modified version of the K-means clustering algorithm as a local search technique. Single- and bi-objective approaches are proposed for emergency and strategic communications planning, respectively. Numerical experiments are run over an emulated scenario based on real statistical data from the Castilla La Mancha region (center of Spain) to show that the proposed scheme provides an intelligent tool capable of simultaneously determining the number and models of the relays to be deployed.

- The second scenario focuses on the optimal deployment of aerial firefighting aircrafts based on predictive fire risk estimations over a certain geographical area. The underlying optimization problem can be formulated as how to properly allocate firefighting resources to capacity-constrained aerodromes in such a way that the utility of the deployed resources with respect to fire forest risk predictions is maximized and the overall cost of performing the resource allocation is minimized. The problem formulation is further complemented by considering the relative distance between the aerodrome, the wildfire and water pump resources (sea, rivers and lakes) in the metric definition. From the algorithmic standpoint, single- and bi-objective Harmony Search heuristics are proposed jointly with a greedy local method that accounts for the imposed capacity constraints. The performance of the developed solvers is assessed through experiments run in synthetic scenarios and a realistic setup over the Spanish peninsula, including practical estimations of the Fire forest Weather Index (FWI) and real geographical locations of water resources and aerodromes. The satisfactory results obtained therefrom shed light on the applicability of the derived techniques to the preemptive management of aerial resources under cost and effectiveness criteria.

To sum up, this Thesis elucidates, from a case-based approach, that modern meta-heuristics embody a computationally efficient algorithmic solution for solving cost-constrained communications and firefighting resource allocation paradigms arising from the management of wildfire events.

Resumen

La última década ha sido testigo de un aumento vertiginoso de la cantidad y frecuencia de desastres a gran escala, principalmente debido a los fenómenos devastadores derivados de paradigmas climatológicos y ambientales a gran escala como el calentamiento global. De entre ellos son las inundaciones, huracanes y terremotos los desastres de mayor frecuencia de aparición y fatales consecuencias durante este período, tal como certifican los más de 20.000 muertos a consecuencia de un terremoto en la región de Gujarat (India) en 2001, o las 230.000 y 316.000 pérdidas humanas de los terremotos de Indonesia y Haití en 2004 y 2010, respectivamente.

En este contexto, el enfoque de esta tesis se centra en una casuística concreta de desastre a media-gran escala cuya frecuencia y severidad han crecido de manera igualmente preocupante en los últimos tiempos: los incendios, definidos como un fuego de grandes dimensiones no voluntariamente iniciado por el ser humano, y que afecta a aquello que no está destinado a quemarse. Pese a la diversidad de iniciativas, campañas y procedimientos orientados a la minimización del impacto y las consecuencias de los incendios, varios sucesos fatales acontecidos en los últimos años han puesto en duda la efectividad de las políticas actuales de gestión de recursos contra incendios como aeronaves, vehículos terrestres, equipamiento de comunicaciones radio, logística de abastecimiento y las brigadas desplegadas en el área afectada. Un ejemplo manifiesto de esta falta de eficacia es la muerte de once bomberos ocurrida en un incendio de 130 kilómetros cuadrados en la zona de Guadalajara (España) en 2005, oficialmente atribuida a una deficiente coordinación entre el puesto de mando y los equipos de extinción debida, fundamentalmente, a problemas de cobertura en los sistemas de radiocomunicación. Aunque la causa de esta falta de coordinación ha sido cuestionada por las autoridades y los agentes involucrados desde entonces, lo cierto es que este suceso supone un ejemplo evidente de la necesidad de estudiar y desarrollar herramientas algorítmicas que ayuden al personal de comandancia a ejecutar óptimamente sus tareas de coordinación y control.

Desafortunadamente la coyuntura de crisis económica mundial que azota con especial fuerza los países del Sur de Europa ha mermado dramáticamente las partidas presupuestarias para la prevención y extinción de incendios en beneficio de programas nacionales de reducción de déficit. A consecuencia de estos recortes, el coste ha irrumpido con fuerza como un criterio de extrema relevancia en la planificación operativa de este tipo de desastres: desde la perspectiva de un problema de optimización, los recursos contra incendios son actualmente gestionados con el objetivo fundamental de maximizar su efectividad contra incendios, sujeto a la restricción de que el coste agregado asociado a las decisiones tomadas no supere un determinado umbral presupuestario. Pese a que estas restricciones de coste están bien acotadas, en la práctica la mayoría de los procedimientos de gestión de recursos contra incendios están fuertemente determinados por la capacidad limitada del ser humano para tomar decisiones ágiles en escenarios de elevada complejidad y heterogeneidad.

Por los motivos anteriormente expuestos, la presente Tesis doctoral propone la adopción de algoritmos meta-heurísticos para solventar eficientemente problemas de optimización que modelan procesos de gestión de recursos contra incendios. Esta familia de algoritmos de optimización es capaz de explorar el espacio solución de un problema dado merced a la aplicación iterativa de mecanismos inteligentes de búsqueda explorativa y explotativa, produciendo soluciones que sacrifican calidad por una complejidad computacional menor en comparación con la resultante de procesos determinísticos de búsqueda exhaustiva. En particular la Tesis plantea la búsqueda por harmonía (del inglés *Harmony Search*) como la técnica meta-heurística de optimización común a las herramientas diseñadas para la gestión de recursos en dos escenarios diferentes:

- El primer escenario analizado contempla el despliegue óptimo de redes de comunicación inalámbrica para la coordinación de equipos de extinción en incendios forestales de gran escala. Desde el punto de vista formal, el problema del despliegue dinámico de retransmisores que caracteriza matemáticamente este escenario consiste en estimar el número y localización de los retransmisores radio que deben ser desplegados en el área afectada por el incendio, de tal modo que el número de nodos móviles (i.e. recursos) con cobertura radio es maximizado a un coste mínimo del despliegue. A fin de reflejar la diversidad de equipamiento de retransmisión radio existente en la realidad, este problema es reformulado para considerar modelos de retransmisor con diferentes características de cobertura y coste. El problema resultante es resuelto de manera eficiente mediante sendos algoritmos mono- y bi-objetivo que conjugan 1) la Búsqueda por Harmonía como método de búsqueda global; y 2) una versión modificada del algoritmo de agrupación K-means como técnica de búsqueda local. El desempeño de los métodos propuestos es evaluado mediante experimentos numéricos basados en datos estadísticos reales de la Comunidad de Castilla la Mancha (España), merced a cuyos resultados queda certificada su practicidad a la hora de desplegar infraestructura de comunicación en este tipo de desastres.

- El segundo escenario bajo estudio se concentra en el despliegue y planificación óptima de vehículos aéreos de extinción de incendios basados en estimaciones predictivas del riesgo de incendio de una cierta área geográfica. De manera enunciativa, el problema subyacente busca la asignación de recursos a aeródromos y aeropuertos con restricciones de capacidad que maximice la utilidad de dichos recursos en relación al riesgo de incendio y minimice, a su vez, el coste de ejecutar dicha asignación. La formulación de este problema también considera, dentro de la definición de dicha función de utilidad, la distancia relativa entre aeropuerto, punto de potencial riesgo de incendio y el recurso acuífero (lago, río o mar) más cercano. Para su resolución eficiente se propone el uso de algoritmos de optimización basados, de nuevo, en la Búsqueda por Harmonía, incorporando además métodos voraces de reparación capacitiva. La aplicabilidad práctica de estos métodos es validada mediante experimentos numéricos en escenarios sintéticos y un caso práctico que incluye valores reales del riesgo de incendio, posiciones de recursos acuíferos e instalaciones aeroportuarias.

En resumen, esta Tesis evidencia, desde un punto de vista práctico, que la meta-heurística moderna supone una solución algorítmica computacionalmente eficiente para tratar problemas de gestión de medios y recursos contra incendios sujetos a restricciones de coste.

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List of Acronyms and Symbols

Chapter 1:

$\mathbf{R}$	Vector of generic resources
R_k	k-th generic resource
$\mathcal{R}_k$	Vocabulary of R_k
Ω	Generic resource allocation strategy
$f_\Omega(\mathbf{R},\mathbf{S})$	Effectiveness metric, fitness or objective function of Ω
$\mathbf{S}$	set of static variables involved in $f_\Omega(\cdot)$
$g_i(\mathbf{R},\mathbf{S})$	i-th generic constraint imposed on $\mathbf{R}$ and $\mathbf{S}$
N_c	Imposed number of generic constraints
HS	Harmony Search
$\mathbb{R}$	Set of all real numbers
$\mathbb{Z}$	Set of all integers

Chapter 2:

$\mathbf{X}$	Generic set of optimization variables
$\mathcal{X}$	Alphabet for $\mathbf{X}$
K	Number of generic optimization variables
$h_i(\mathbf{X})$	Generic constraint of an optimization problem
H_i	Upper or lower bound of $h_i(\mathbf{X})$
$f(\mathbf{X})$	Generic objective or fitness function
$|\cdot|$	Cardinality of a given set
L	Number of fitness functions in a multi-objective problem
N	Number of solutions conforming an estimated Pareto front
$\bar{\mathbf{X}}$	Vector comprising N Pareto-optimal solutions
GA	Genetic Algorithm
MLP	Multi-Layer Perceptron
ELM	Extreme Learning Machine
FL	Fuzzy Logic
FS	Fuzzy Sets
PSO	Particle Swarm Optimization
DE	Differential Evolution
EDA	Estimation of Distribution Algorithm

$\mathcal{F}$	Generic set of all feasible solutions in an optimization problem
$\mathcal{G}$	Set of chromosomes in a GA
$\zeta : \mathcal{F} \mapsto \mathcal{G}$	Chromosome encoding of $\mathcal{F}$ in $\mathcal{G}$
Ψ	Population (GA) or memory (HS) size
p_ψ	Probability of selecting the ψ individual in the GA selection stage
VEGA	Vector Evaluation Genetic Algorithm
WBGA	Weight-based Genetic Algorithm
MOGA	Multi-Objective Genetic Algorithm
NPGA	Niched Pareto Genetic Algorithm
NSGA	Non-Dominated Sorting Strategy
PAES	Pareto Archived Evolution Strategy
MOEA	Multi-Objective Evolutionary Algorithm
SA	Simulated Annealing
ACO	Ant Colony Optimization
CRO	Coral Reefs Optimization
$X_k(\psi)$	k-th note in ψ-th harmony vector within the HM
$\mathbf{X}(\psi)$	ψ-th harmony vector within the HM
HM	Harmony Memory
ω_{HMCR}	Auxiliary variable for the definition of the HMCR operator
β	Pitch adjustment bandwidth
VRP	Vehicle Routing Problem
CVRP	Capacitated VRP
VRPPD	VRP with Pick-up and Deliveries
MDVRP	Multiple Depot VRP
PVRP	Periodic VRP
SDVRP	Split Delivery VRP
TS	Tabu Search
GRASP	Greedy Randomized Adaptive Search Procedure
VNS	Variable Neighbor Search

Chapter 3:

VSAT	Very Small Aperture Terminal
2G	2nd Generation of Cellular Networks (e.g. GSM or GPRS)
3G	3rd Generation of Cellular Networks (e.g. UMTS)
4G	4th Generation of Cellular Networks (e.g. WiMax, HSPA+ or LTE)
PMR	Private Mobile Radio
WLAN	Wireless Local Area Network
DRDP	Dynamic Relay Deployment Problem
TVSC	Two-vertex Square Covering algorithm
BIP	Binary Integer Programming algorithm
MDRDP	Modified Dynamic Relay Deployment Problem
A	Disaster area
N	Number of emergency teams deployed
$\{\mathbf{p}_i\}_{i=1}^{N}$	Positions of the deployed emergency teams
$\mathcal{D}$	Set of parameters defining a relay deployment over A
M	Number of relays
M_{min}	Minimum value assumed for M

FWI_z	Risk of grid point z
$B(m)$	Budget of airport m
$R(n)$	Coverage radius of aircraft n
$d_{m,z}$	Distance from airport m to grid point z
$\lambda^{-1}(\cdot)$	Inverse function for $\lambda()$
$J(d_{m,z})$	Distance dependent risk weighting function
$\lambda(\psi,n)$	Airport assigned to aircraft n in harmony ψ
τ	Number of aircraft models
$\vartheta(n)$	Model of aircraft n
Q_t	Fuel consumption rate of aircraft model t
$d_{m,m'}^{ra}$	Distance traveled by an aircraft reallocated from airport m to m'
$W_F(\cdot)$	Fuel expenditure associated to a reallocation strategy
$\lambda_0(n)$	Airport initially assigned to aircraft n
p_c	Unitary price of a fuel litre
ΔW_F	Refueling cost penalty
$W_R(\cdot)$	Interregional airport usage fee
$W_C(\cdot)$	Compensation to non-military airports
$\Upsilon(\cdot)$	Firefighting potentiality function
V_t	Water tank capacity of aircraft model t
$d_{z,t}^{wr}$	Distance from grid point z to the closest water resource compliant with model t
$V(n,z)$	Amount of water eventually dropped by an aircraft n over point z
$N_r()$	Number of water recharges without refueling
γ_t	Distance penalty due to water reloading and carrying maneuvers
$\text{rep}(x,t)$	Auxiliary function for building sets with multiple value repetitions

Appendix:

CFS	Canadian Forest Service
LST	Local Standard Time
FFMC	Fine Fuel Moisture Code
T	Temperature [Celsius]
H	Relative humidity [%]
W	Wind speed [km per hour]
r_0	Rainfall measured in an open environment [mm]
m_0	Fine fuel moisture content
F_0	Value of the FFMC code in the previous 24 hours
r_f	Effective rainfall for the FFMC [mm]
EMC	Equilibrium Moisture Content
E_d	EMC for drying
E_w	EMC for wetting
κ_o	Log drying rate
κ_1	Log wetting rate
m_{ad}	Fine fuel moisture content after drying
DMC	Duff Moisture Content
r_e	Effective rainfall for the DMC [mm]
M_0	Duff moisture content from the day prior to the computation
P_0	Value of the DMC code in the previous 24 hours
M_r	Duff moisture content after rain

b	Slope variable
L_e	Effective length of the day for the DMC computation
DC	Drought Code
V	Evapotranspiration measured in 0.254 mm water units per day
L_f	Day length factor for the DC computation
r_d	Effective rainfall for the DC [mm]
D_0	Value of the DC code in the previous 24 hours

INTRODUCTION

"The key to growth is the introduction of higher dimensions of consciousness into our awareness."

- Lao Tzu

In its unstoppable race towards levels of more advanced development, evolution has gravitated on several aspects of the human kind. To begin with, it is of undoubted certainty that human beings have undergone severe biological changes due to several interrelated reasons, ranging from the essential survivability of the species themselves to the inherent complexity of different challenges encountered during History. Examples are clear as evidenced by consecutive speed and height records in Olympics, and significantly decreased occurrence rates of diseases that more than a century ago were known to be epidemic and fatal partly as a consequence of an enhanced resilience of human organisms. Such evolutionary changes also spread to the behavioral patterns shown up by humans either in isolation or more remarkably, when collaboratively connect to each other towards a certain goal. No matter if human kind has collectively worked towards colonization, organization, exploration or conquest: socio-cultural models have evolved dramatically to yield a humankind strongly upheld on the purpose of survivability, sustainability, efficiency, freedom, leadership or progress. Most archaeologists and cultural anthropologists work within the framework of modern theories of sociocultural evolution in an attempt at unifying diverse approaches and beliefs on this matter.

A common factor featured by both biological and socio-cultural evolution lies on the exploitation of the available natural resources as a necessary substrate to support the evolution itself. Worthy is to mention the relevance and impact of wood and steel furnishing, land ownership, fishing, silicon fabrics and outer space navigation in several episodes of History featuring significant advances towards higher levels of prosperity. By natural resource it is meant any asset derived from undisturbed environments that offer potentiality to be exploited for the survival or profit of the humankind, such as land, water, soil, plants and animals. Beyond their primary use, many other criteria are often utilized to classify natural resources: their bioticity (if it arises from living, organic material) their potentiality, availability and timeliness. This Thesis will be particularly concerned with the renewability of any given natural resource, understood as its ability to replenish naturally and seamlessly when consumed or exploited by the human being. Luckily, Nature has been generous in what relates to the renewability of natural resources with a strong impact on the survivability of the humankind such as wood, sunlight, wind or water. Other natural resources with more technological implications such as fossil fuels or silicon are nowadays exploited at the pace dictated by their low, almost null renewability.

Among such renewable natural resources wood will grasp the thematic scope of this Thesis. In essence wood is made of a composite of cellulose fibers embedded and strongly compressed into a matrix of lignen. This naturally appearing combination of substances and elements gives rise to a robust, durable material traditionally employed in construction and organic propelling, with further uses in transport, furniture fabric and medicine, among others. Wood is obtained from forests from which, once it has been collected, is taken to lumber camp so as to elaborate boards, frames and other finished products alike. However, the motivation of this Thesis does not ground on the multiplicity of applications and uses of this natural resource, but rather capitalizes on the vulnerability of wood against fires and the technical and operational difficulties when extinguishing them in such a flammable environment. Due to its composition, wood is by itself a highly propagative material for fire which, in case of a massive forest fire event, requires strict yet quick preemptive countermeasures to minimize its impact and ultimately, avoid deforestation and soil desertification. Needless to highlight that such countermeasures are necessitated for a far more primary rationale than the importance of wood in different industrial sectors: forests – and plants in general – play a crucial role as a catalyst of the natural conversion from light to chemical energy and oxygen therefrom, which is of utmost necessity and a sine qua non condition for life in planet Earth.

Risk consequences in forest fire management also scale down to smaller, albeit equally avoidable granularities. Unfortunately, in addition to the fire itself, firefighting brigades deployed on site also undergo diverse life-threatening hazards ranging from heat stress to fatigue, smoke, dust and other injuries including burns, cuts and scrapes. Part of these hazards arise as a direct consequence of the work developed by the brigades for extinguishing the fire. However, in some other cases the promptness and urgency under which decisions are taken in these situations cause a lack of coordination between sparsely deployed teams, which may ultimately lead to isolated individuals and groups subject to carbon monoxide or direct exposition to flames. In regards to the former, carbon monoxide can be found at the highest concentration at close proximity to slow burning fires. This fact reveals that health hazards are not only a matter of wide-area disasters, but also underlie latently beneath smoldering, apparently low-risk fire events.

From an operational perspective, health risks should be reason enough to allocate as much financial resources as available so as to minimize its likelihood and severity. However, the worldwide economical context of the last few years has restricted stringently national budget items allocated to fire prevention strategies and disaster management methodologies by institutions and governments. This being remarked and in light of several evident facts discussed in forthcoming sections, there is a noted necessity for explicitly considering cost aspects in the management of firefighting resources in such a way that expenditure is properly balanced with respect to the available budget and the risk level of the scenario itself. Therefore, the design and adoption of cost-efficient processes, tools and methods to preserve the integrity of forests by increasing their resilience against fires and minimizing their catastrophic effects, as exposed in the remainder of this introducing Chapter.

1.1   Motivation and Research Hypothesis

Any formulated research hypothesis finds its raison d'être in facts and evidences extracted from reality. Accordingly, the above claimed need for cost efficiency when managing firefighting resources against forest fires emerges from a noted lack of correlation between the expenditure and

resources allocated to a certain fire disaster and the life and economic losses resulting therefrom. Intuitively, leaving aside other factors such as the characteristics of the soil one could intuitively expect a clear correspondence between such indicators, in such a way that a forest fire should be assigned enough financial and firefighting resources so as to minimize the risk of suffering casualties subject to a positive balance between economic losses and expenditure. This eventual correspondence would pinpoint an efficient management of the resources allocated to the event at hand.

However, data do not unveil a so clear correlation between such factors. This assertion is supported by the indicators on the forest fire events over one hundred hectares of devastated woodland occurred in Spain registered and published by the Ministry of Agriculture, Nutrition and Environment (*Ministerio de Agricultura, Alimentación y Medio Ambiente*) in the period 2001-2011 [1]. In this data set several attributes and factual aspects related to such fire events are listed, including the area affected by every registered fire event, the number of fatalities and wounded individuals and the used resources (personnel, vehicles and aircrafts), among several other features. These factors are depicted in Figure 1.1 by scattering the devastated area versus the amount of firefighting resources with markers directly proportional to the number of human casualties due to every such fire event.
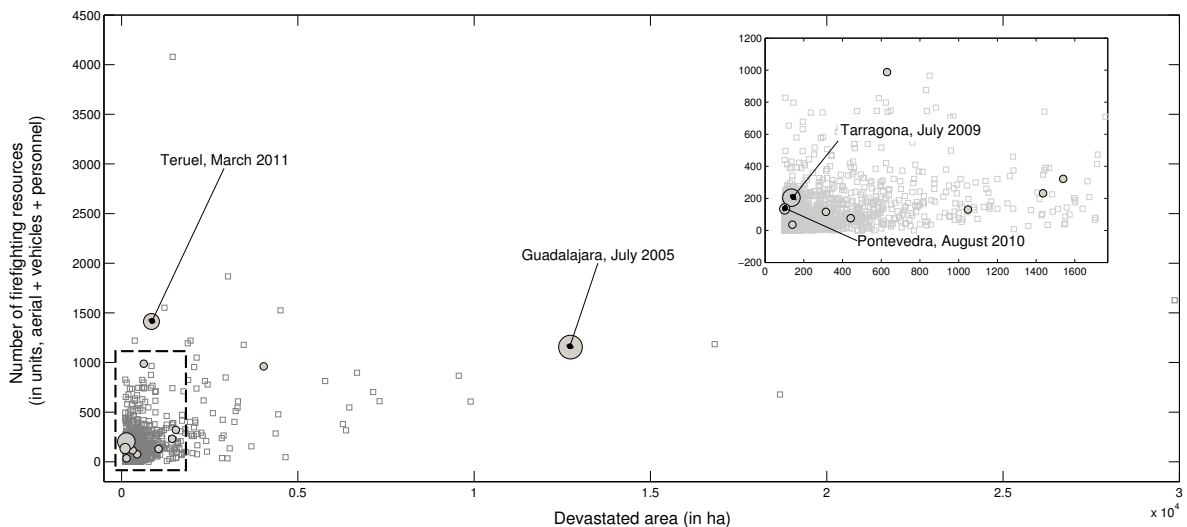
Figure 1.1: Number of firefighting resources versus devastated area for all wildfires over 100 ha occurred in Spain from 2001 to 2011. Square gray markers correspond to those wildfires with no casualties, whereas the radii of circled markers are set proportional to the number of casualties of the fire they represent. The embedded plot magnifies the region bounded by a dashed rectangle.

Several conclusions of significant relevance in the scope of this Thesis stem from its analysis. First of all, notwithstanding what could have been intuitively expected, the plot evinces no apparent correlation between the number of allocated resources and the casualties for the wildfire event involved in the figure. It can be observed that there are wildfire events with few allocated extinguishing resources and varying number of personal losses, whereas an increase of the number of allotted resources does not guarantee a consequent minimization of the number of casualties, as clearly exemplified by the wildfires in *Teruel* and *Guadalajara* occurred in 2011 and 2005, respectively.

This noted lack of correlation between casualties and dedicated resources is not be insightful by itself if the study focuses only in these two features, as none of them results to be representative of its intensity and extension. This is the reason why the plot considers in its horizontal axis the area devastated by every wildfire measured in hectares. Intuitively one expects that the area affected by any given fire results to be inversely proportional to the number of resources dedicated to its extinction, i.e. the more resources are allocated, the smaller the affected are by the fire will be. However, the same conclusion holds: data does not support this expected inverse relationship between both variables.

Although other hidden factors (i.e. weather conditions) may also play their role when wrapping up conclusions from the depicted data, the study so far suggests that the allocated resources have not been managed properly in all the fire events under consideration. This last statement becomes further buttressed when the three depicted variables are jointly analyzed: there are no means to infer from the data the amount of casualties from the number of allocated resources and the devastated area of a given wildfire. In other words: the number of casualties is not related anyhow to the amount of resources and the devastated area by the fire.

Summarizing, this data-based study puts to question the effectiveness of decisions taken to assign and deploy resources for the extinction of wildfires. Decisions in this context are driven by well-specified procedures and protocols based on the passive reaction triggered by circumstantial conditions (e.g. a given number of firefighting resources for every hectare of terrain affected by the fire). Unfortunately, there are three evidences for which these resource management procedures result to be far from optimal:

- Governmental investments for the acquisition, renewal and maintenance of firefighting resources are progressively decreasing as a result of the worldwide economical context. For instance, the environmental forum of the *Castilla La Mancha* region (center of Spain) denounces, in their report published in October 2013 [2], that there are only 5 light vehicles in the region with the legally required equipment to combat wildfires (one per province), which incur in delays and an increased risk when performing their duty. Besides, in this same report it is claimed that regional firefighting brigades have undergone significant reductions – reaching up to 50% – in the number of effective hours dedicated to the prevention, surveillance and extinction of wildfires. More exemplifying datum: at a national level the Spanish firefighting campaign for 2013 has dedicated 267 aircrafts for the extinction of wildfires during summertime, 8 units less than in 2012 as a consequence of the funding reductions in the Ministry for Agriculture, Fisheries and Food. Cost, therefore, is called to play an essential role when allocating resources nowadays and in the present future. Current resource allocation procedures, on the contrary, do not take into account any cost related criteria in decision making.

- Decisions to combat wildfires are not made pro-actively nor preventively, but rather reactively in the form of countermeasures to taken risks. Examples of this lack of strategic preemption when organizing firefighting resources abound in practice, such as the wildfires occurred in the Spanish regions of *Levante* (*Cortes de Pallás* and *Andilla*, June 2012 [3]) and *Galicia* (*Fragas do Eume*, March-April 2012 [4]). In these examples wind bursts hindered significantly the coordination of the resources involved in extinguishing tasks, even though weather forecasts had anticipated this risk several days in advance. Consequently, reports made by expert committees highlighted the need for more effective preventive initiatives so as to minimize the impact of side eventualities on the management of resources. Weather

also took a fatal role in the death of 11 members of the brigades involved in the wildfire that took place in *Guadalajara* in July 2005 [5]: an outdoor temperature of 33 Celsius, turbulent wind blowing at 20 kilometers per hour heading South east, a relative air humidity of 22 %, and 50% less rainfall than the same period of 2011. It is true that this wildfire has been proven to be human caused (i.e. a barbecue in a forbidden area); but equally certain is to state that more resources could have been allocated to this region should weather forecasts had been taken into account by authorities and decision makers.

- An underlying potential risk in the management of resources is the human intervention itself[1]. In disasters such as wide area wildfires commanders must assess and weight lots of data received from different means so as to effectively yet safely organize and deploy the firefighting brigades on site. However, cases such as the wildfire happened in a brush-choked canyon north of Phoenix (Arizona, USA) in June 2013 shows up the fact that human decision making is subject to errors and assumptions that may lead to fatalities: in this wildfire 19 elite firefighters perished while commanders thought the crew was in a safe place [6]. No extreme had heard each other for 33 minutes until just before the fire overwhelmed the brigade. Certainly decision support tools would have been extremely useful to deploy communication resources in a more effective, active, monitored fashion, discarding any non-supported assumptions from the commanding forces.

Based on these observations, the research scope of this Thesis gravitates on designing algorithmic tools that help decision makers and commanders allocate firefighting resources in a optimal yet cost-efficient manner. To this end, it is essential to understand beforehand how the allocation of resources breaks down into the formal mathematical statement of a optimization problem, as done in the following subsection.

1.1.1 General Formulation of Resource Allocation Problems

Generally speaking, resource can be defined as any asset that can be exploited so as to yield some measure of benefit for a given process. If *process* is mapped to *fire extinction* and *measure of benefit* corresponds to any positive metric quantifying effectiveness when extinguishing fire, it should be clear that resource may refer to a wide spectrum of assets reactively (vehicles, brigades, aircrafts, hoses, axes, water, etc) or preventively (surveillance patrols, bulldozers for opening firebreaks, forest cleaning teams) operating on the purpose of suffocating fire.

From a mathematical standpoint, resources can be modeled as variables whose values determine their joint effectiveness when combating a wildfire. At a first approach one could intuitively think of an allocation strategy where each variable (namely, resource) is optimized to its best effectiveness disregarding how the rest of assets have been allocated. Nonetheless, the overall effectiveness of all assets against a given wildfire does not decompose into the individual contributions of each of such resources; all become mutually correlated since they are used in the same scenario and share underlying variables such as time, space, cost or any other alike. For example, one could not command bulldozers and forest cleaning teams to operate on the same geographical area since 1) there is a risk for the human crew; and 2) cleaning forest areas next to firebreaks is

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[1]Interestingly this third point is succinctly linked to the concept of integrative complexity, which stands for a protocol to measure how complexly people think about an issue, and how every person recognizes complex connections among different dimensions of an issue [7].

not as effective against eventual wildfires as distributing geographically the available resources. In summary: the allocation of resources must be challenged from a global perspective, by casting effectiveness metrics implicating all the resources to be managed in a non-necessarily decomposable fashion.

Technically the above argued metric function is also referred to as *objective function*, which is to be maximized or minimized by varying the values of the participating variables (correspondingly, resources). Let the set of resources be denoted as a K-dimensional vector $\mathbf{R} \triangleq \{R_1, \ldots, R_K\}$, where $R_k \in \mathcal{R}_k$ is the variable representing the k-th resource to be optimized. The composition itself and alphabet $\mathcal{R}_k$ for R_k depend roughly on both the parameter of the resource to be allocated (position, time, capacity, etc) and the encoding approach used for its representation, which is strongly linked to the characteristics of the algorithm used for its solving. Having these definitions in mind, a resource allocation strategy Ω establishes an effectiveness metric, fitness or objective function $f_\Omega(\mathbf{R}, \mathbf{S})$ to be maximized (e.g. area covered by firefighting brigades) or minimized (e.g. attendance delay by ground vehicles, economical cost required for establishing the allocation policy Ω). Arranged as a single mathematical formulation, resource allocation can be formulated as

$$\underset{\mathbf{R}}{\text{Optimize}} \quad f_\Omega(\mathbf{R}, \mathbf{S}), \tag{1.1}$$

$$\text{subject to} \quad g_i(\mathbf{R}, \mathbf{S}) \gtreqless G_i, \, i = 1, \ldots, N_c, \tag{1.2}$$

$$R_k \in \mathcal{R}_k, \, k = 1, \ldots, K, \tag{1.3}$$

i.e. as the conventional formulation of an optimization problem where Expression (1.2) corresponds to the N_c equality or inequality constraints set by the scenario at hand or the resource allocation strategy itself. For instance, in cost-constrained policies for wildfire prevention the commander may set a maximum monetary cost for the allocation process due to budget restrictions. Likewise, optimal positioning strategies for firefighting brigades can be subject to geographical constraints (e.g. very steep slopes in mountains or rocky wastelands where fires is not likely to propagate). In reference to the above expression $\mathbf{S}$ denotes the set of static variables involved in the definition of the metric that are not to be optimized, e.g. fixed costs, nominal coverage of radio communication devices or water tank capacity in firefighting crafts.

1.1.2   Complexity Aspects and Algorithmic Alternatives

Once the mathematical formulation of resource allocation problems has been exposed, the *leitmotiv* of this Thesis is in the position to show that the challenges arising from the efficient solving of large-scale optimization paradigms also apply in the context of asset coordination in wildfire extinction campaigns. Inherent properties of this scenario such as the erratic fire dynamics and the heterogeneity of firefighting resources get further involved by the ever-increasing scales of wildfire events and the need for inter-agency coordination in a scenario demanding fast, reliable, multi-criteria optimization tools. Several clarifying facts and data from studies follow:

- A number of studies have quantitatively predicted the scales, magnitudes and consequences of wildfires based on weather forecasts, soil dryness, vegetation and other related factors, for which analytical indices and long-term climate models have been developed and used as a measure of the possibility of fires of a certain severity occurring in an area [8]. In this

context exemplifying is to highlight the recent report presented at the annual meeting of the American Geophysical Union in *San Francisco* (USA) in late 2012, where the burned area from wildfires in the USA was predicted to double in size by 2050 due to warmer and drier conditions in coming decades [9]. Besides this envisaged increase of wildfire scales, the record of incidences in such a year of intense activity as 2012 (with massive fires affecting *Colorado* and *New Mexico* [10]) suggests that fire events take place in nearby locations and very close in time, i.e. they are strongly correlated in both time and space. This ultimately leads to the certainty that commanders will encounter higher difficulties in the future when allocating their managed resources due to simultaneous, co-located and necessarily interconnected wide-area wildfires, ultimately heading to an increased complexity of the optimization problem that models the decision making.

- As explained before in this chapter, there is an increasing concern by authorities and governments about the cost implications of fire prevention and suppression. In particular, the case of USA has gained visibility in the last decade, with expenditures regularly beyond 10000 millions dollars per year in this period [11]. In light of this expended budget history and its growing trend, the Federal Land Assistance, Management and Enhancement Act (FLAME Act) of 2010 enforced the national stakeholders in charge for managing firefighting resources (specifically, the U.S. Department of Agriculture, the U.S. Department of the Interior, and the U.S. Department of Homeland Security) to coordinately elaborate a Cohesive Wildfire Management Strategy to derive cost-effective, sustainable policies for allocating and managing fire resources [12]. When transferred to the algorithmic realm, the consideration of cost-driven criteria in the management of fire assets gives rise to an optimization problem subject to additional cost-related constraints that jeopardize the application of straightforward, deterministic solvers. Alternatively the problem might be reformulated by including a second cost-representative objective function in Expression (1.1) to be simultaneously minimized along with $f_\Omega(\mathbf{R}, \mathbf{S})$. However, this bi-objective optimization model calls for advanced optimizers capable of efficiently balancing both interrelated metrics and incorporating further methods to deal with the rest of constraints.

- When issuing commands from decision makers to the firefighting crew deployed on site, the heterogeneity of fire extinguishing resources may unchain suboptimal decisions due to the pattern-driven way of thinking of human beings when facing problems of this nature. In such cases human reasoning tend to oversimplify the decision making by searching for patterns among the assets. However, not all e.g. ground vehicles feature the same water and transporting capacity, autonomy and distance from their actual location to the wildfire at hand. By way of illustration INAER, a Spanish private company specialized in aerial emergency services and aircraft maintenance for mission critical operations has a portfolio of more than 150 aircrafts corresponding to 18 different helicopter models and 7 airplanes [13]. Differences become obviously more acute when comparing firefighters to each other, as physical conditions arise as a fundamental factor to drive any person's potential performance to extinguish fires. In conclusion, the heterogeneity of resources becomes one of the most challenging issues for making decisions in wildfire management procedures, and is envisaged to become specially unmanageable as the scales of the wildfire at hand increase.

Thus, there is a need for algorithmic tools to allocate limited yet heterogeneous resources so as to cost-efficient mitigate wildfire events of increased scales, intensity and propagability. As a consequence of the high dimensionality of the optimization problems modeling such scenarios, black-box techniques result to be particularly suitable since they ground on a blind (or semi-blind)

trial-and-error learning strategy. Only the computation of values of the objective function and the constraints are required disregarding their mathematical structure, continuity, differentiability, convexity and/or analytical decomposability. Within this category, meta-heuristics have been traditionally utilized in a plethora of problem formulations arising in different disciplines characterized by complex, non-smooth search spaces. By virtue of specialized stochastically-driven operators, meta-heuristic solvers iteratively refine a candidate solution – or a set of them – with regard to a given quality measure by *learning from experience* and without making any assumptions about the optimization problem under consideration. Moreover, their searching procedure can be extended to address optimization paradigms where multiple, conflicting objective functions are to be optimized simultaneously. A byproduct of this class of black-box optimization techniques is the lack of guaranteed optimality on the produced solution: by filtering out bad intermediate solutions, meta-heuristics only certify that the likelihood of being trapped in local optima decreases along iterations, but nothing can be claimed about the metric-defined distance of the remaining solutions with respect to the global optimum.

All the above rationale considered, this Thesis hypothesizes meta-heuristic algorithms as suitable optimization techniques for the allocation and management of firefighting resources in large-scale wildfire events, and hinges on the proven search efficiency, flexibility and robustness of these solvers to conduct research towards assessing their performance in different use cases.

1.2 General and Specific Objectives

Bearing in mind the established research hypothesis and in light of the motivating facts exposed in the previous section, the main contribution of this Thesis focuses on studying and validating the applicability of modern meta-heuristic algorithms for the efficient solving of complex optimization problems lying underneath the allocation of firefighting resources in the management of wildfires. As claimed before, meta-heuristic solvers allow for a balanced trade-off between the optimality of the produced solutions and the computational complexity required during the search process. This property makes this class of algorithmic optimizers specially promising for solving combinatorial and mixed integer optimization paradigms subject to multiple constraints, and possibly involving several conflicting objectives. As will be shown throughout this research work, problem formulations featuring these characteristics arise when managing resources of different nature in wildfire extinguishing campaigns.

The above main objective of the Thesis breaks down into the following set of specific goals:

- First an insight on meta-heuristic algorithms, their general classification, searching principles is provided, along with a survey on their historical applicability to the management of disaster situations and in particular, wildfire events. The scope of this study will mainly concentrate on population-based evolutionary algorithms, since they have been shown to perform well in complex problems arising in fields as diverse as engineering, biology, economics, marketing, genetics, robotics, physics, chemistry and telecommunications, among many others. This will permit to properly put the contributions of the Thesis in context and to make the dissertation sufficiently self-contained. As a result of this analysis, the so-called Harmony Search (hereafter, HS [14]) algorithm will be selected as the core meta-heuristic solver of subsequent resource allocation approaches due to its proven flexibility and outperforming behavior with respect to other evolutionary schemes in the literature.

- Next the applicability of HS-based meta-heuristic optimization algorithms is exemplified in two different wildfire management scenarios. The first one essentially hinges on the so-called dynamic relay deployment problem, which consists of finding the optimum number of deployed relays and their location aimed at simultaneously maximizing the overall number of covered mobile nodes and minimizing the cost of the deployment. This problem is extended by considering relay models characterized by different coverage radii and associated costs. To efficiently tackle this problem a novel hybrid scheme will be derived comprising 1) a Harmony Search (HS) based global optimization procedure; and 2) a modified version of the well-known K-means clustering algorithm as a local search technique. Single- and bi-objective formulations of the algorithm will be sketched targeting emergency and strategic operational planning, respectively. Simulations will be performed over a emulated scenario based on real statistical data from the *Castilla La Mancha* region (center of Spain).

- The second scenario under study focuses on optimally deploying firefighting aircrafts on the existing aerodromes and airports over a certain geographical area based on predictive fire risk estimations. The problem will be mathematically formulated as 1) a capacity-constrained resource allocation problem where a measure of the utility or impact of the deployed resources with respect to fire forest risk predictions is to be maximized based on different aircraft and airport models; and 2) a multi-objective problem where cost and utility are to be jointly optimized and simultaneously considering their mutually conflicting nature. In the latter formulation, the initial location of airplanes and the operational cost of their reassignment is also taken into account. Likewise, the impact of the relative distance from the eventual wildfire to the closest water resource is also quantified and included in the definition of the utility function. On the purpose of efficiently tackling this optimization problem, a family of meta-heuristic solvers inspiring from the aforementioned HS algorithm will be derived, implemented and in a set of synthetically generated scenarios and a real case for the Iberian peninsula.

As can be guessed from the above description, both analyzed scenarios ground on the formulation of single- and bi-objective optimization problems subject to a set of constraints, which are then tackled via harmony search heuristics hybridized with local methods designed ad-hoc for the scenario at hand. This technological coherence throughout the Thesis is accomplished by virtue of a consistent, well-defined research methodology, as exposed in the next section.

1.3 Methodology

This Thesis will follow an example-based methodology by which two instances of such problems will be addressed, involving communication and aerial resources to be optimally allocated when combating a wide-area fire event. The procedure to address each of such studied cases departs from the high-level formulation of the research hypothesis contextualized in an specific optimization problem (e.g. radio communication relaying in field operations during wildfire extinction campaigns): to this end, related concepts, theories and literature are compiled, ordered and carefully examined towards finding meaningful connections to the application scenario at hand. This previous stage not only allows exploring the best algorithmic options for the formulated problem, but also permits to identify and highlight the novel ingredients of the proposed research.

Next, the problem under consideration is formally posed in conventional mathematical notation. Theretofore in this second stage the variables and parameters to be considered in the definition of the problem will be listed and described in detail. Once the formulation is completed jointly with the description of its participating variables, an insight on the complexity requirements of the problem itself will be discussed so as to argue the selection of meta-heuristic algorithms specially tailored to alleviate the computational burden of the search procedure at the possible cost of optimality. Modifications of the naive version of the Harmony Search meta-heuristic from which the proposed resource allocation procedures inspires will be thoroughly discussed, along with the local methods inserted in the algorithm thread to efficiently tackle possible constraints featured by the problem.
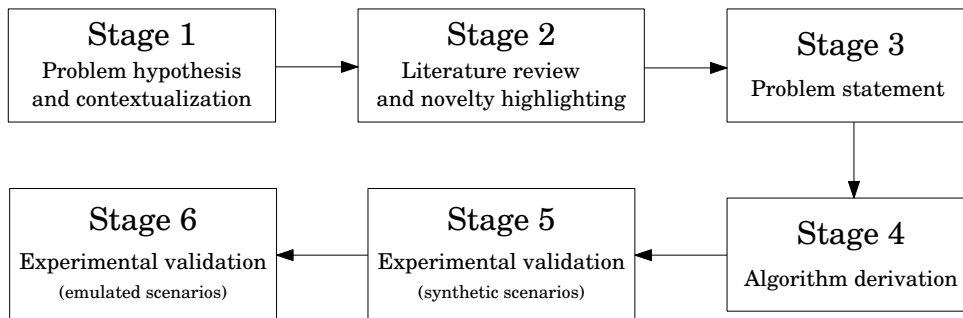
Figure 1.2: Methodology adopted in the Thesis.

As for the validation of the proposed algorithms, numerical computer experiments will be carried out over *synthetically generated* and *emulated* simulation scenarios. The first refers to setups which do not reflect any connection to real situations and scenarios, but instead are built up artificially by means of analytical functions. On the contrary, the latter stands for scenarios which, even if they are still computer-generated, the functions lying beneath the generation of scenarios rely on real statistical data for their definition. This permits to validate the performance of the derived algorithms in artificial hence controlled simulation setups, and to shed light on their applicability by emulating a real problem composition. In both cases a range of performance indicators will be averaged by means of a Monte Carlo simulation methodology [15], which consists of randomly sampling the space of possible realizations of the algorithm under study for inferring meaningful statistics about the optimality, stability and mean behavior of the provided solutions.

1.4   Structure of the Thesis and Notation Generalities

According to the specific research objectives enumerated before, this Thesis is structured in two different technical chapters, which are backgrounded by a third gravitating on essentials of meta-heuristics and their application to resource allocation in disaster events. Figure 1.3 illustrates the storyline undertaken in this dissertation: first, Chapter 2 corresponds to the aforementioned introduction to the fundamentals of optimization algorithms, which stresses on meta-heuristics as a family of computationally efficient, flexible solvers in the context of large-scale resource allocation. This technical backdrop serves as a solid starting point to Chapters 3 and 4, each including a literature review of the recent activity around the two resource allocation problems addressed

in this Thesis, together with their corresponding formal problem statements, derived algorithms and a discussion on the obtained results. Chapter 5 wraps up all the conducted research by drawing the main conclusions extracted therefrom and by motivating and sketching several lines of future research. Appendix A serves as a complementary yet insightful support to Chapter 4. The reader should notice that Chapter 2 is not deemed mandatory, but recommendable for grasping an overall outlook of the entire research work.
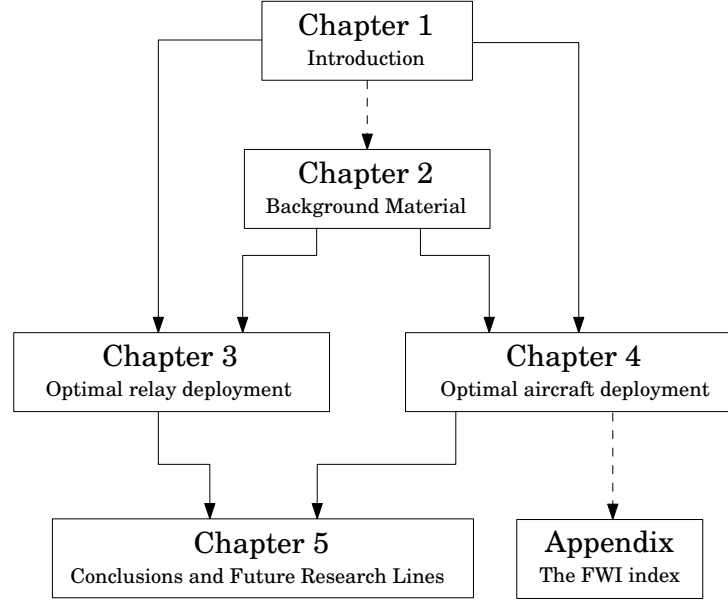
Figure 1.3: Structure of the Thesis. Dashed arrows indicating the optionality of the pointed chapter.

Unless otherwise stated, the following mathematical convention will be used: capitalized bold font (e.g. $\mathbf{X}$) will represent variable vectors, whereas sets will be typeset in calligraphic case (e.g. alphabets $\mathcal{X}$), except for the sets $\mathbb{Z}$ (integer numbers) and $\mathbb{R}$ (real numbers), respectively. Any given variable vector breaks down into its enumerated compounding variables as $\mathbf{X} = \{X_1, \ldots, X_K\}$, $\mathbf{X} = \{X_k\}_{k=1}^{K}$ or $\mathbf{X} = \{X(k)\}_{k=1}^{K}$. As can be noted from the previous convention, unity-starting indexing will be adopted for all enumerative variables and parameters. Greek letters will stand for user-defined parameters in the definition of the proposed algorithms. All acronyms and symbols are gathered at the beginning of the Thesis for the reader's perusal, which may be found redundant – yet understandable from the context – among different chapters of the dissertation.

BACKGROUND MATERIAL

"The proof of evolution lies in those adaptations that arise from improbable foundations."

- Stephen Jay Gould

As has been anticipated in Chapter 1, this dissertation mathematically formulates the allocation of resources in the management of large-area disaster situations (in particular, wildfires) as a conventional optimization problem which, from a general standpoint, can be understood as the discovery of the best among a set of possible solutions subject to certain fitness criteria and imposed constraints. Formally enunciating the different resource allocation paradigms resulting from the characterization of the scenarios under study comes along with a number of substantial benefits. To begin with, the computational effort required for its resolution can be assessed by analyzing the convexity and linearity of the considered metric(s) and constraints, as well as the combinatorial nature of the search space defined by the alphabet of the involved variables. Likewise, the inspection of all such peculiarities may unveil the family of solvers best suited to efficiently deal with the problem at hand, as well as the eventual need for punctual modifications in the nominal definition of such solvers to handle particularly involved *hard* constraints.

Based on the above rationale, an interested reader of the Thesis should conveniently feature a solid background on the foundations of optimization problems and related solving approaches, with an emphasis on stochastically-driven algorithms. For the sake of completeness this chapter provides a formal introduction of the basic concepts of single- and multi-objective optimization problems, followed by a justification of the need for stochastically driven approximative solving methods and a overview on meta-heuristic algorithms as one of the most widely used portfolios of approximative optimizers in the literature. This review ends by delving into the Harmony Search algorithm on which the resolution of the optimization problems described in subsequent chapters is based. At this point it should be made clear that the contents of this Chapter aim at overlooking different practical approaches used for solving continuous and discrete optimization problems. The reader interested in further details of approximative and exact solving techniques is referred to the recent yet thorough surveys and reviews by Glover, Boyd and Nocedal in [16, 17, 18].

2.1 Fundamentals of Optimization Problems

Optimization problems arise in many disciplines and various knowledge domains. Researchers, practitioners, companies and public institutions face with decision processes in a daily basis,

most involving tens or even hundreds of alternatives whose expected or estimated impact on the process at hand is in essence the evaluation criteria that permits to assess the benefit of choosing an option or another. Besides the inherent difficulty of handling lots of interrelated decision variables, in practice users and companies are not free to select any possible option, but instead those that fulfill constraints that restrict the number of available alternatives, as exemplified by political decision making processes being recently impacted by budgetary and law limitations. Therefore, a decision alternative must be selected that complies with all the existing constraints, and that maximizes (e.g. power saving, speed, time, efficiency) or minimizes (correspondingly, money, time, risk or error) a fitness evaluation function.

In this context, this Thesis builds upon the conception of the allocation of firefighting resources as an optimization problem, which can be formally defined as the paradigm of finding the best feasible solution – in terms of a certain measure of fitness that must be either maximized or minimized – over a possibly constrained search space. Such imposed constraints can be implicit in the definition of the vocabulary for each compounding variable of the candidate solutions or, alternatively, may be set explicit as bounded function set of such variables. From a more formal approach an optimization problem can be defined as to find the best solution

$$\mathbf{X}^* \triangleq \{X_1,\ldots,X_K\} \in \mathcal{X}, \tag{2.1}$$

with $\mathbf{X}^*$ denoting the solution of the problem, X_k its compounding decision variables, and $\mathcal{X} \triangleq \mathcal{X}^K$ the search space for $\mathbf{X}$, such that

$$\underset{\mathbf{X}}{\text{Optimize}} \quad f(\mathbf{X}), \tag{2.2}$$

$$\text{subject to} \quad h_i(\mathbf{X}) \gtreqless H_i, \, i = 1,\ldots,N_c, \tag{2.3}$$

where $f : \mathcal{X} \mapsto \mathbb{R}$ is the so-called *fitness* or objective function, and $\{h_i(\cdot), H_i\}$ establish the N_c constraints imposed on the problem formulation that restrict the search space $\mathcal{X}$ to a certain *feasible* subspace. The alphabet of the decision variables $\{X(k)\}_{k=1}^K$ constituting the solution vector $\mathcal{X}$ can be either continuous ($X_k \in \mathbb{R}$) or discrete ($X_k \in \mathbb{Z}$). Consequently, problem models for optimization paradigms are coined as continuous when the alphabet of all decision variables is defined on the real set, i.e. $\mathbf{X} \in \mathbb{R}^K$, as opposed to combinatorial problems where decision variables are drawn from a finite, discrete set $\mathbb{Z}$ such that $\mathbf{X} \in \mathbb{R}^K$. Mixed problem formulations combine real and discrete decision variables jointly related through the fitness function $f(\mathbf{X})$. For instance, the problem formulation tackled in Chapter 3 is mixed as the number of relays is a discrete integer variable, whereas their positions are regarded as continuous optimization variables.

It should be made clear that a problem formulation may render distinct *feasible* solutions, where feasibility must be understood as the thorough fulfillment of the N_c imposed constraints by the solution at hand. However, an optimization problem aims at achieving an optimum decision on the values for a set of variables in a global sense. In other words, any solving attempt at an optimization problem seeks the derivation of the globally optimum solution, which denotes the vector $\mathbf{X}$ that provides, among all feasible vectors in $\mathcal{X}$, the best value for the fitness function $f(\cdot)$. This statement does not imply that the global optimum is always unique, as the cardinality of this set of optimum solutions may be even infinite in problems characterized by a high modality of its fitness metric. Seen in another way: optimality requires feasibility, but the reciprocal statement does not necessarily hold.

In line with the above definition of global optimum, a locally optimal solution denotes a *feasible* vector $\mathbf{X}^{\wp} \in \mathcal{X}$ whose optimality holds for a certain subset of the solution space $\mathcal{X}$, i.e. a

feasible vector $\mathbf{X}^{\wp}$ will be locally minimum if there exists an open neighboring set $\mathcal{N}_{\mathbf{X}^{\wp}}$ of $\mathbf{X}^{\wp}$ such that $f(\mathbf{X}^{\wp}) \leq f(\mathbf{X}) \ \forall \mathbf{X} \in \mathcal{N}_{\mathbf{X}^{\wp}}$ (a clarifying bi-dimensional fitness function is depicted in Figure 2.1). When confronting a given optimization problem one of the most involved challenges from the algorithmic point of view is to avoid declaring a local optimum as the global solution to the problem under consideration: indeed, first-order gradient descent methods [19] are known to get trapped in local optima if no further adaptations are done. In such a case it is desirable to devise strategies for escaping from locally optimal regions of the search space towards areas of increased (and hopefully, dominating) optimality.
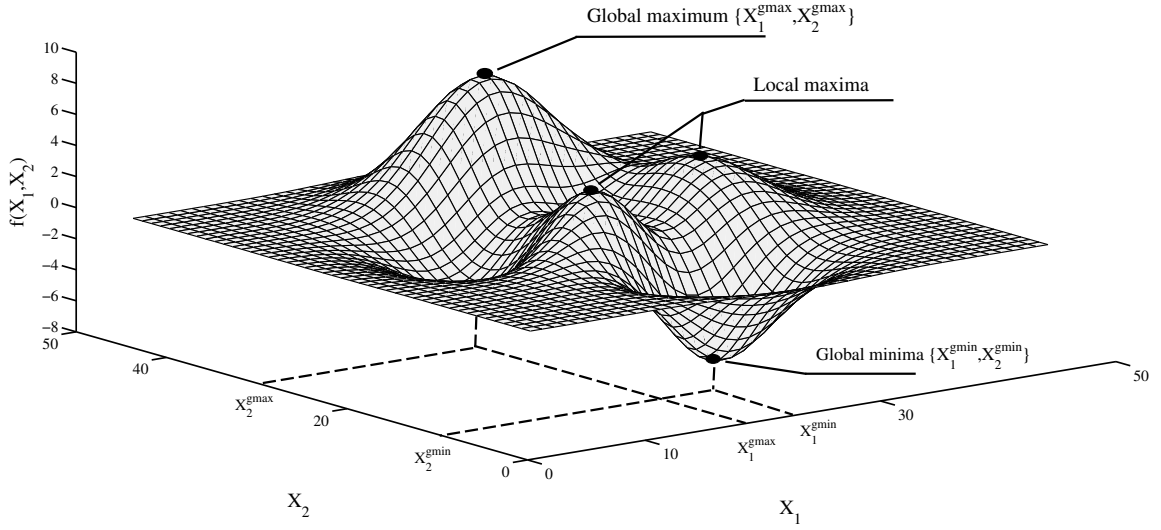
Figure 2.1: Example of a two-dimensional (i.e. $|\mathcal{X}| = 2$) function $f(\mathbf{X})$ with multiple local optima and isolated global optima $\mathbf{X}^{gmax} = \{X_1^{gmax}, X_2^{gmax}\}$ and $\mathbf{X}^{gmin} = \{X_1^{gmin}, X_2^{gmin}\}$. The function is built by translating, scaling and sampling an aggregation of 2-dimensional Gaussian distributions.

In this context it is important to point out the notion of optimality when tackling an optimization problem with a given solver. The term *optimality* stands for the relative quality of the produced solutions (which is given by their fitness value) with respect to the global optimum of the problem at hand. As such, near-optimal solutions will refer to those candidates which are potentially close to the overall optimum without any further guarantee that they may coincide. The relevance of the near-optimality concept is paramount in the literature related to meta-heuristics and in general, approximative optimization methods; due to their iterative search behavior (which often relies on stochastic processes), this class of optimization techniques does not guarantee that the globally optimum solution is ever achieved, but only ensures that progressively better fitness values are iteratively attained. Therefore, the optimality of any optimization algorithm depends roughly on its capability to efficiently examine the solution space $\mathcal{X}$ by combining explorative and exploitative search procedures, which will be later discussed in this Chapter in the scope of the Harmony Search optimization algorithm.

2.1.1 Multi-Objective Optimization

The introduction has heretofore inspected the formalities of optimization algorithms when their definition is based on a single fitness function $f(\mathbf{X})$, which may be driven by a single optimization variable – i.e. $|\mathbf{X}| = 1$ or, equivalently, $K = 1$ in Expression (2.1) – or a multidimensional candidate

vector, correspondingly $|\mathbf{X}| > 1$ or, equivalently, $K > 1$. However, in practice a myriad of optimization problems involve several fitness functions to be optimized. If such metrics are independent of each other by featuring orthogonal solution spaces, the problem formulation can be broken down into separate optimization problems that can be solved in isolation. However, it is often the case that many – if not all – such metric functions share a common set of optimization variables that makes the overall problem non decomposable. Notwithstanding the increased complexity derived from this non-decomposability, multi-objective optimization finds its rationale from the fact that such shared variables may drive the metric values towards different directions which, in some cases, may not be sought in the problem formulation. In words, the fitness functions involved in a multi-objective optimization problem may be conflicting through the values of their shared variables. For instance, in a conventional telecommunications deployment problem an area is to be covered by means of base stations with circular coverage and an associated economic cost.

One could establish a cost-constrained single-objective problem definition where the metric to be maximized is the area covered by the base stations, with their number and positions inside the area as optimization variables. Alternatively, an bi-objective formulation would consider the area covered and the overall economic cost of the deployment as the fitness functions to be maximized and minimized, respectively. It should be intuitively clear, however, that an increase of the covered area would come along with a worse (*higher*) economic cost, since in the limit where the base stations have been optimally positioned there is no other way to increase the area covered than to deploy another base station, which necessarily unchains a higher cost. Hence, "optimizing" a multi-objective problem must be conceived as finding a value for the solution vector $\mathbf{X}$ that renders values for all objective functions acceptable to the designer [20].
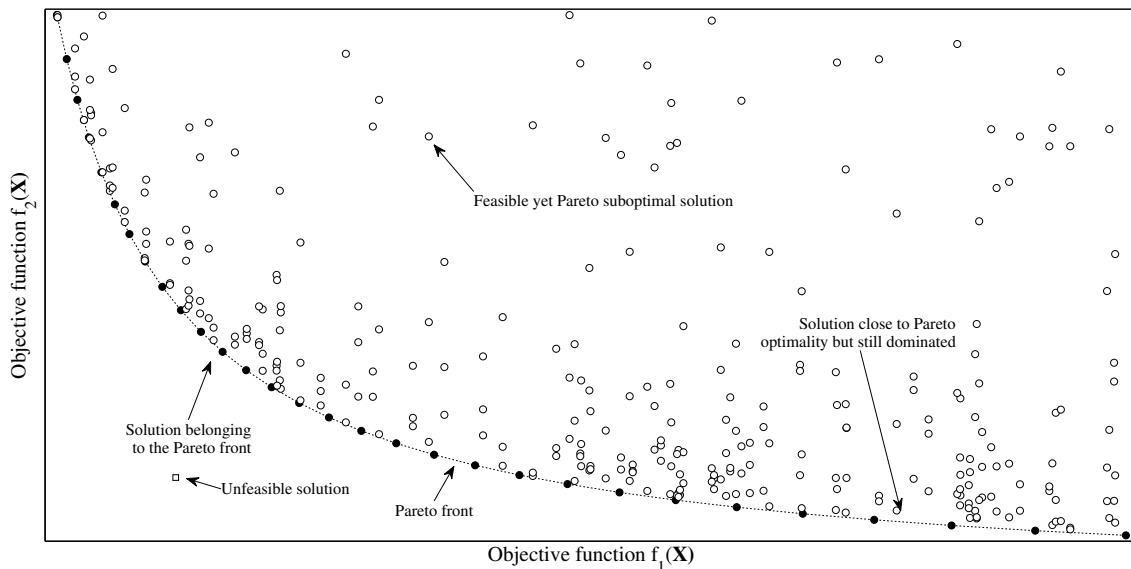
Figure 2.2: Example of the estimated Pareto front for a bi-objective minimization problem. In the plot bold circle markers ● correspond to Pareto optimal solutions, whereas the fitness values of Pareto suboptimal values of $\mathbf{X}$ are labeled with ○. An example of an unfeasible solution is marked with □: it happens to be Pareto dominating, but possibly by not fulfilling one or several imposed constraints.

This being said, there are different algorithmic ways to deal with a multi-objective optimization problem. The most straightforward approach is to properly normalize and aggregate the objective functions into a single one. However, most of the research done in the specific field of

meta-heuristic multi-objective optimization has gravitated on estimating the so-called Pareto set. Proceeding further with the technical particularities of Pareto-based methods, a multi-objective optimization problem under this approach can be formally defined as finding the vector of candidate solutions $\bar{\mathbf{X}}^* = \{\mathbf{X}_1^*, \mathbf{X}_2^*, \ldots, \mathbf{X}_N^*\}$ with $\mathbf{X}_n^* \in \mathcal{X} \; \forall n \in \{1, \ldots, N\}$ that optimizes the vector function

$$\mathbf{f}(\bar{\mathbf{X}}) = \{f_1(\bar{\mathbf{X}}), f_2(\bar{\mathbf{X}}), \cdots, f_L(\bar{\mathbf{X}})\}, \tag{2.4}$$

each of whose compounding candidate vectors $\mathbf{X}_n$ (with $n \in \{1, \ldots, N\}$) fulfills the constraints $h_i(\mathbf{X}_n) \gtreqless H_i$ for $i = 1, \ldots, N_c$. Expressed differently, the goal of a multi-objective optimization problem is to determine among all such solution sets satisfying the above N_c constraints, the specific set of solution vectors $\bar{\mathbf{X}}^*$ that attains the optimum value of the L objective functions defined in Expression (2.4). As opposed to its single-objective formulation counterpart the notion of *optimality* differs from the paradigm of achieving a unique solution that simultaneously meets the constraints and provides the best value for the objective function at hand. Multi-objective optimization coins the so-called Pareto optimality under which the aforementioned $\bar{\mathbf{X}}^* \in \mathcal{X}^N$ is declared *Pareto optimal* in a minimization problem if there does not exist another set of candidate solutions $\bar{\mathbf{X}}$ such that $f_l(\bar{\mathbf{X}}) \leq f_l(\bar{\mathbf{X}}^*) \; \forall i \in \{l, \cdots, L\}$ and $f_{l'}(\bar{\mathbf{X}}) < f_{l'}(\bar{\mathbf{X}}^*)$ for at least one $l' \in \{1, \ldots, L\}$. That is to say, $\bar{\mathbf{X}}^*$ is Pareto optimal if no feasible vector of decision variables can be found to decrease any metric function without causing a simultaneous increase in at least another criterion. Consequently, the union of the metric values for all non-dominated vectors in the optimal Pareto set is referred to as *Pareto front*, as shown in Figure 2.2 for a bi-objective minimization problem.

Operationally speaking, the multi-objective formulation of an optimization problem does not involve any dramatic change in the concepts of continuity of the solution space (i.e. combinatorial and continuous multi-objective optimization problems can be found throughout the literature). However, the optimality of multi-objective solvers changes radically as this concept must embrace Pareto dominance and solution diversity of the estimated front. To this end, several quality indicators have been developed in the literature to evaluate different multi-objective approaches [21, 22], among which it is worth to mention:

- The hypervolume indicator, which measures the volume of the objective function space covered by the members of a non-dominated set of solutions. For a two-objective optimization problem, it is given by the sum of all rectangular areas bounded by a reference point.

- The ϵ-indicator which, given two Pareto sets $\bar{\mathbf{X}}_A$ and $\bar{\mathbf{X}}_B$, quantifies the smallest amount $\epsilon \in \mathbb{R}$ that should be employed to shift the set $\bar{\mathbf{X}}_A$ so that every point in $\bar{\mathbf{X}}_B$ is covered.

To end with, it should be pinpointed that if a multi-objective formulation of a multiple-metric optimization problem is established, knowledge about the produced estimation of the Pareto optimal set helps designers and decision makers when choosing the compromise solution trading one metric function for another, i.e. solvers tackling a multi-objective formulation should recreate the set of optimal trade-offs between all metrics, which is the first step in design procedures arising in any discipline (from Telecommunications to Engineering, Medicine, Logistics and Economics).

2.2 A Rationale for Meta-Heuristics and Soft Computing

When dealing with optimization problems characterized by continuous search spaces $\mathcal{X}$, the cardinality of the solution space becomes infinite, hence increasing the computational complexity of

exhaustive search techniques focused on enumerating and sorting all the compounding solutions of the search space under exploration. What makes continuous-variable problems even more involved is the inclusion of constraints in the formulation: although a priori the search space becomes restricted by virtue of the feasibility imposed on the solution space, in practice the consideration of multiple constraints comes along with the need for further algorithmic derivations indeed devoted to ensuring that the solutions proposed by the primary solver are feasible. Consequently, off-the-shelf optimization algorithms specially prescribed for continuous problems (e.g. gradient descent methods) are not directly applicable, but instead demand for side *repair* procedures well suited to deal with constrained optimization. This approach comes along with either radically new analytical optimizers with a very sharp applicability after long research times, or an increased computational burden of the overall solver due to the incorporation of the aforementioned repair procedure in its algorithmic thread. This observation becomes critical when dealing with multi-modal fitness landscapes, term that stands for the presence of multiple local optima in the fitness functions involved in the problem definition. In these cases the aforementioned side procedures should also help the overall optimization algorithm avoid premature convergence to local optima.

Fortunately, it is often the practical case that fitness functions happen to feature low modality and reasonably analytical differentiability, the latter paving the way to the application of optimizers relying on derivative information (e.g. gradient and Hessian) for guiding their progression to the global optima. The convexity, decomposability and linearity of the fitness function at hand and its associated constraints also eases the relaxation and simplification of the problem towards its efficient solving by means of techniques such as linear programming and its variants [23], interior-point methods [24, 25], Lagrange multipliers [26] and least squares [27], among others. This empirical statement motivates the general thought that continuous problems are often solved more easily than their discrete counterparts. However, not all problem-solving methods exhibit a clear differentiability, nor are their fitness functions analytically stated in a closed-form expression. Constrained combinatorial problems are among the most clear exponents of the insufficiency of derivative-guided solving methods to cope with complex optimization paradigms with uncertain differentiability: despite the existence of techniques that can be used to solve this class of problems to optimality (e.g. the so-called cutting plane [28] or branch and bound [29] methods), their computational complexity and scalability becomes compromised with as few as a couple of dozens of variables.

In light of the above rationale, the interest in *derivative-free* optimization algorithms has lately resurrected in the research community as means to efficiently solve optimization problems by only requiring the fitness of a proposed solution to be evaluable, i.e. disregarding the derivability, linearity, convexity or decomposability of the problem at hand. This category of solvers do not approach an optimization problem in a principled, mathematically formal yet computationally costly way, but instead resort to iterative heuristic methods to yield solutions whose quality is satisfactory for problems where the global optimality of the solution is not critical (or even attainable, due to the scales of the problem and its solving complexity via analytical methods).

Within this class of computationally-efficient derivative-free schemes, meta-heuristic optimization algorithms have lately emerged as the primary subfield of stochastic optimization, which gather all such algorithms and techniques utilizing some degree of randomness through their search procedure to solve computationally hard problems. Following the argument in [30], meta-heuristic algorithms are applied to *I-know-it-when-I-see-it* problems: 1) paradigms when the designer possesses very few helpful information in advance; 2) problems where there is no a priori

intuition about what the optimal solution looks like; 3) problem instances whose analytical approach may lead to costly, involved and often inconclusive mathematical derivations; and 4) cases where brute-force schemes are impractical due to the large dimensionality of their search spaces. On this purpose, meta-heuristic algorithms imitate behaviors, processes and phenomena occurring in Nature and Social Sciences in the computer design of their searching procedure. Formally speaking and despite not unique, the literal definition of Stützle [31] may serve as a good baseline for the interpretation of meta-heuristics:

> *"Meta-heuristics are typically high-level strategies which guide an underlying, more problem specific heuristic, to increase their performance. The main goal is to avoid the disadvantages of iterative improvement and, in particular, multiple descent by allowing the local search to escape from local optima. This is achieved by either allowing worsening moves or generating new starting solutions for the local search in a more intelligent way than just providing random initial solutions. Many of the methods can be interpreted as introducing a bias such that high quality solutions are produced quickly. This bias can be of various forms and can be cast as descent bias (based on the objective function), memory bias (based on previously made decisions) or experience bias (based on prior performance). Many of the meta-heuristic approaches rely on probabilistic decisions made during the search. But, the main difference to pure random search is that in meta-heuristic algorithms randomness is not used blindly but in an intelligent, biased form."*

This procedure builds upon a set of intelligent stochastically-driven operators imitating different particularities of the observed process that allows controlling the degree of exploration (diversification) and exploitation (intensification) of the algorithm at hand. Optimization algorithms attaining improvements within the vicinity of their proposed solutions – by e.g. profiting from partial local gradient information – are known to be exploitative, whereas algorithms cruising randomly over the search space are referred to as explorative. Explorative strategies are necessary when handling large multi-modal search spaces, but exploitative algorithms permit to attract intermediately produced solutions closer to optimality. Indeed meta-heuristics are often hybridized with local methods that provide additional exploitative capabilities to the global search procedure for local optima avoidance and constraint handling, such as Iterated Local Search [32], Variable Neighborhood Search [33], Greedy [34], GreedyExp [35], Large Neighbourhood Search [36], Hill Climbing [37] or simplified meta-heuristics [38].

2.3 Soft Computing and Evolutionary Optimization

From a general perspective meta-heuristics belong to Soft Computing [39], a Computer Science field that tolerates and leverages imprecision, uncertainty, partial truth, and approximation to infer inexact solutions to computationally hard paradigms for which there is no algorithm that can compute an exact solution within a technologically affordable time. Soft Computing is a key part of Artificial Intelligence, and many of its methods also belong to the area of knowledge called *Natural Computing*, which refers to the spectrum of algorithms inspired by the way Nature solves extremely complex problems. It draws inspiration from Evolution (leading to Evolutionary Computation), Physics (Simulated Annealing), social living being networks (e.g. social insects, coining

the Ant Colony Optimization solver and the subfamily of Swarm Intelligence methods), Neural Networks (capitalizing on the capability of the human brain to perform reasoning in complex environments) and Immune Systems, among many others. This classification is flexible in the sense that some algorithms may belong simultaneously to different groups: for instance, a Genetic Algorithm (GA) is a population-based meta-heuristic optimization method (similar to Ant Colony Optimization), but it can also be regarded as an evolutionary algorithm. Another example: a fuzzy neural network or neuro-fuzzy system is a learning machine that finds the parameters of a fuzzy system (i.e. fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks. It thus belongs to the intersection between Neural Computation and Computation based on Fuzzy concepts.
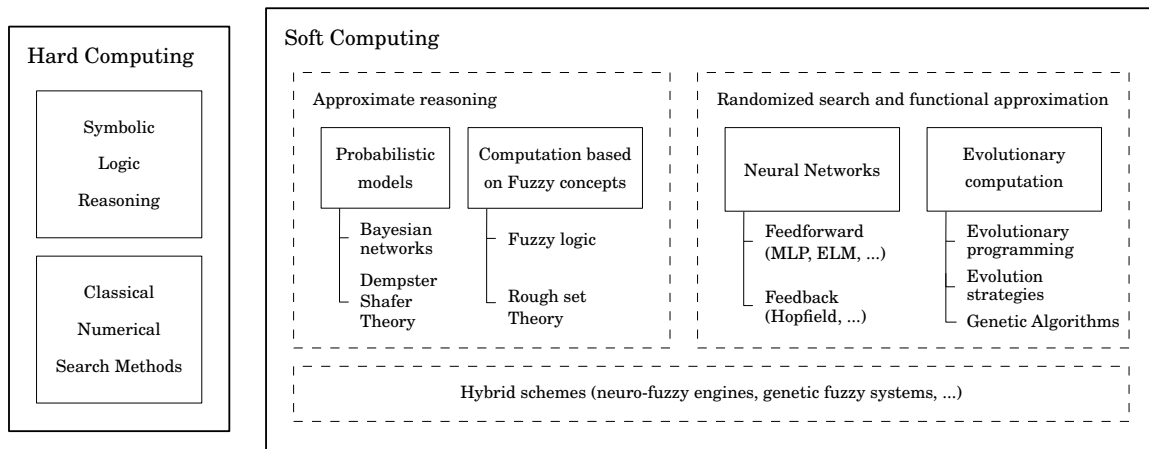
Figure 2.3: General taxonomy of Soft Computing approaches.

Figure 2.3 represents the four basic algorithmic pillars of Soft Computing, some of them exhibiting non-null intersection: Neural Computation, Computation based on Fuzzy Concepts, Probabilistic Reasoning and Evolutionary Computation. A brief introduction on these branches of Soft Computing will be next provided in an attempt at making this chapter self-documented and insightful on the roots of Soft Computing.

2.3.1   Neural Computation

Neural Computation is a branch of Soft-Computing which includes algorithms inspired by the human brain metaphor, and also other approaches, mainly devoted to classification and regression problems. The portfolio of neural computing techniques is huge, hence this section focuses on the most widely used Neural Computation approaches: the Multi-Layer Perceptron (MLP). The MLP is a particular kind of neural network, in essence a massively parallel and distributed information processing system that has been successfully applied to a large variety of nonlinear classification and regression problems [40, 41]. Put it simple, an MLP consists of an *input* layer, a number of *hidden* layers, and an *output* layer. The leftmost one represents the input layer, which receives data usually arranged as an input vector. On the other side, the rightmost ouput layer produces an output signal. Those layers between the input and output layers are the so-called *hidden* layers. In turn, all layers forming an MLP are basically composed of a number of especial processing units, called *neurons*, whose internal behavior will be described below. As important as the processing units themselves is their mutual connectivity: the neurons within a given layer

are connected to those of other layers by means of weighted links. These weights are just the parameters that determine to what extent a neuron is connected to other. In this respect, the value of each weight is related to one of the most important properties that an MLP can exhibit: the ability to learn and generalize from a sufficiently large number of examples under what is called a supervised learning process.

Such a learning process demands a database containing a variety of input examples (also referred to as patterns) and their corresponding known outputs. The weight values for the connection between neurons are those that minimize the error between the output generated by the MLP when fed with input patterns in the database and the expected one already contained in the database. In other words, the weights of the links are adjusted to learn the function relating the input samples to the corresponding known output in the database. In this regard, it is well known that MLPs (similarly to most of the neural networks) are universal approximators of a wide range of functions, which gives them a great versatility [42]. For instance, in many regression problems and the prediction of time series, MLPs with a single hidden layer are profusely used: as a matter of fact, the number of neurons in the hidden layer is a parameter to be optimized when using this type of neural networks [40, 41]. In what relates to the learning procedure of MLP, the well-known Levenberg-Marquardt algorithm is often used [43], which was originally designed to attain second-order training speed without having to compute the Hessian matrix. This matrix is estimated by using the Jacobian matrix, which can be computed through a standard back-propagation technique much less complexly than the Hessian matrix.

MLPs have been successfully applied to many different classification and regression problems in science and engineering applications. However, its main drawback is the lack of a general rule to come up with an optimal network structure to solve a given problem. Deriving the optimum number of hidden layers and the number and type of neurons in this layer for a given problem remains an open challenge, which has been tackled thoroughly in the literature. The training algorithm is another open question: though the existing approaches provide good results, research in this field is still active, yielding alternative training approaches – some of them hinging on metaheuristics – that have gained momentum in classification and regression paradigms. One of such training procedures is the Extreme Learning Machine (ELM), a fast learning method based on the structure of MLPs recently proposed in [44] and applied thereafter to a large number of classification and regression problems [45, 46, 47]. The ELM structure is similar to that of the MLP, but with the exception that neurons are trained just by randomly setting the network weights, and then obtaining the inverse of the hidden-layer output matrix. This makes the training algorithm extremely fast and simple, and results to perform better when compared to other established approaches such as classical multi-layer perceptrons or support vector machines. Moreover, the universal approximation capability of the ELM network, as well as its classification capability, have been already proven [48, 49]. Due to this noted outstanding performance and their extreme fast training time, ELMs are perfect for fast classification or regression tasks [50, 51, 52].

2.3.2 Computation based on Fuzzy Concepts

Fuzzy Logic (FL) based computation is inspired by the fact that humans exhibit the extraordinary capability to reason and make decisions in an environment of uncertainty, incomplete information, and partiality of class membership. The original concept of Fuzzy Logic was first proposed by Zadeh [53], and is based on the concept of *fuzzy sets*, which plays a central role in fuzzy logic. Classical set theory has a crisp concept of membership: an element either belongs to a set *or* it

does not. However, fuzzy set (FS) theory differs from the traditional one in the fact that *partial membership* is allowed (that is, an element can belong to a set with a certain degree). This *degree of membership* is commonly referred to as the *membership value* and is represented by using a real value in $[0,1]$, where 0 and 1 correspond to *full non-membership* and *membership*, respectively. Usually, triangular or trapezoidal functions are used as *membership functions* because of their simplicity, although, however, smoother or complex shapes can be used if necessary [54]. Based on these ideas, predicates in fuzzy logic can have *partial degrees of truth*, in the same way as elements can have partial membership in fuzzy set theory. The degree of truth of a predicate is represented using a real number in $[0,1]$. These ideas allow introducing two basic concepts in FL: *graduation* and *granulation* [55], which lie at the very core of FL, and are the mayor distinguishing properties of fuzzy logic [54] when comparing to classical reasoning schemes. In FL everything is allowed to be granulated: for example, the concept *size* is granulated when its values are described as "small", "medium" and "large". Thus, the principal contributions of fuzzy logic consist of the concept of a *linguistic variable* (using words instead of numbers [54]), the machinery of fuzzy "if-then" rules, and the capability to compute with information described in natural language. The interested reader is recommended the illustrative review in [54] for further details. Fuzzy logic makes it possible to construct better models of reality in human-centric science such as economics, medicine, psychology and linguistics [57, 58, 59, 60]. In particular, FL-based computation plays a relevant role in insurance-related problems [61].

2.3.3　Probabilistic Reasoning

Probabilistic Reasoning denotes those mechanisms used to update and guess the outcome of systems affected by randomness or other types of probabilistic uncertainty by conditioning it with newly available evidence. Probably one of the most evident exponents of this class of Soft Computing methods can be found in the so-called Bayesian Belief Networks, which build upon the well-known Bayes Law to graphically represent the probabilistic conditional relationships between different random variables by means of a graph [65, 66]. Based on this graphical representation algorithms such as Belief Propagation [67] and later evolved Sum-Product Algorithm [68] for cyclic graphs allow performing inference and learning efficiently over this family of probabilistic frameworks. Another trend in this Soft Computing subfield lies on the Dempster-Shafer theory [69, 70], whose original purpose was to compute the degree of belief of statements made by different sources from a subjective probability of the reliability of the sources themselves, hence establishing the theoretical foundations for data fusion schemes subject to communication failures or any other origin of uncertainty [71].

2.3.4　Evolutionary Computation

Techniques under the Evolutionary Computation category are inspired by the principles of Genetics and Natural Selection. The most representative strategy in this subset is the concept of Genetic Algorithm (GA, [72]), although there are also other paradigms that have been recently introduced such as the social computation by swarms as in e.g. the Particle Swarm Optimization approach (PSO, [73]). There is a plethora of optimization algorithms belonging to the family of evolutionary computation, as is next exemplified by an outlook on genetic evolutionary approaches, techniques inspiring from swarm intelligence and physics, and the solver mimicking

the music composition process of an orchestra that lies at the core of the algorithms proposed in this dissertation: Harmony Search.

2.3.4.1 Genetic and Evolutionary Algorithms

By inspiring on concepts borrowed from natural evolution and survival of the fittest individuals in Nature, Evolutionary Computation gained momentum in the research community by virtue of the seminal findings on Evolution Strategies by Rechenberg [74] and Schwefel [75], and evolution-based schemes stemming therefrom such as Evolutionary Programming [76], Differential Evolution (DE) [77] and Estimation of Distribution Algorithms (EDA) [78]. Generally speaking, this class of meta-heuristic optimization techniques has been widely used for solving combinatorial optimization problems[1] by encoding the problem through strings of numbers. All genetic and evolutionary algorithms are based on the evolution of a population of candidate solutions by applying an encoding strategy and a series of evolutionary operators, which are next outlooked in the context of the most frequently utilized evolutionary algorithm in the related literature, the Genetic Algorithm [62, 63]:

- Encoding of the candidate solutions: in nature, all of the genetic information which encodes and causes the external characteristics of a living organism (or individual) is referred to as *genotype*. Any particular characteristic produced by a piece of this genetic information is encoded by a *gene*, a *chromosome* being hence the set of these genes. Each gene is located at a particular position on the chromosome and may have different values, called *allele*. This strategy can be regarded as a transformation of the real search space into another where the exploration and exploitation is much easier. From a mathematical point of view, if $\mathcal{F}$ denotes the set containing all the candidate solutions and $\mathcal{G}$ is the set of chromosomes that encodes them, there is a bijection $\zeta : \mathcal{F} \mapsto \mathcal{G}$ such that any solution $\mathbf{X} \in \mathcal{F}$ is represented by an unique chromosome $\zeta(\mathbf{X}) \in \mathcal{G}$. Roughly speaking, the terms chromosome and individual are interchangeable.

- Generation of an initial population of candidate solutions: the size of the set of individuals to which the evolutionary operators are applied is a crucial issue for the search performance of the algorithm itself. On the one hand, a large population size Ψ may cause more genetic diversity (and thus, a higher search space[2]), and consequently suffer from slower convergence. On the other hand, with a very small population only a reduced part of the search space is potentially explored, thus increasing the risk of prematurely converging to a local extreme.

- Application of evolutionary mechanisms: in Nature, the random creation of new genetic information with respect to the ancestors of the individual at hand may lead to the ability to survive. The better an individual is suited to the environment, the higher its probability of survival results to be. This is the idea of the so-called *survival of the fittest* principle: the longer the individual's life is, the higher its chances of having descendants will be. In this procreation process, the parent chromosomes are combined (recombination) to produce

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[1]Despite their original application to combinatorial problems, evolutionary optimization approaches are also utilized for efficiently solving continuous problems by redefining their constituent evolutionary mechanism.

[2]Not to be misunderstood as *solution space*, which mainly depends on the problem definition and the alphabet characteristics of its compounding variables.

a novel chromosome. Sporadically, and because of unavoidable errors in copying genetic information or external factors (for instance, radiation), mutations (random variations) occur. The consequence is the creation of a generation of living beings with some novel characteristics that make them slightly different from those of their progenitors. If the new attribute makes the offspring better suited to the varying environment, the probabilities of both survival and procreation also increase. Part of the offspring could inherit the modified genes and the corresponding external characteristic. In this manner, the population of individuals evolves and, for a number of generations, the described process results in the creation of individuals better adapted to the environment and in the extinction of those worst suited.

This brief introduction on evolutionary computing enables a better understanding of the fundamentals of the standard genetic algorithm established in [64], which features crossover and mutation operators, binary encoding and selection by means of the Roulette Wheel method. As motivated before, the genetic algorithm is based on a number of evolution operators, which will be detailed below, implemented in a loop process. The algorithm starts by initializing the individuals – usually at random based on the alphabet of their constituent genes – and the calculation of fitness values associated with each individual. A loop is then entered in which evolution operators are applied until either a certain stopping condition is fulfilled: usually a predetermined number of generations (sequences of the loop) is used, but alternative criteria are also used, e.g. stop when no improvements are observed in the results after a number of generations set beforehand. The aforementioned evolution operators work as follows in reference to Figure 2.4:

- A selection operator aims at selecting those individuals (population components) that will be part of the population for the next generation. In the standard implementation of the algorithm, each individual has a probability of survival for the next generation proportional to its associated fitness value, which is given by the objective function to be optimized. Specifically, if $f(\mathbf{X}_\psi)$ denotes the fitness value of individual $\mathbf{X}_\psi$ in a Ψ-sized population, its probability p_ψ of being selected is given by

$$p_\psi = f(\mathbf{X}_\psi) \cdot \left(\sum_{\psi=1}^{\Psi} f(\mathbf{X}_\psi) \right)^{-1}, \tag{2.5}$$

with $\psi \in \{1, \dots, \Psi\}$. This particular selection procedure is referred to as the Roulette Wheel method [62], and is considered the most conventionally utilized selection procedure for Genetic Algorithms. However, other well-known selection methods are also utilized in the literature such as the probabilistic tournament [79], the ranking selection [80] and schemes inspired from Monte Carlo simulation [81] or statistical geometry [82].

- A crossover operator, whose goal consists in generating novel individuals from existing ones. In the standard implementation, individuals are paired at random, and crossed (by exchanging parts of the binary string) with a probability called *crossover probability*, which is usually around 60% (that is, 60% of pairs of individuals are crossed in each generation). Each pair then leads to another pair of offspring individuals, replacing parents in the next generation. There are different types of crossover methods: one point, two-point or multipoint, depending on whether the parents are crossed by exchanging parts in one, two or more points in their binary string.

- The mutation operator aims to mimic the following fact in Nature: the chromosomes (which contain genes that encode the physical characteristics of an individual - genotype -) can undergo random changes called mutations. They may be due to external causes (e.g. radiation)

or internal (a simple failure to copy the material). These mutations can generate individuals with novel external physical characteristics (phenotype) that may allow them (or not) adapt to the changing environment. If advantageous, the feature can be spread with a certain probability to later generations. In a Genetic Algorithm, the mutation operator generates a new individual from an existing one. This process is performed by changing at random certain bits from 0 to 1 and vice-versa, with very low probability (usually the mutation likelihood for a given individual is about 1%). It differs from the previous one in that the bits change occurs within the same individual and not with another of its generation.
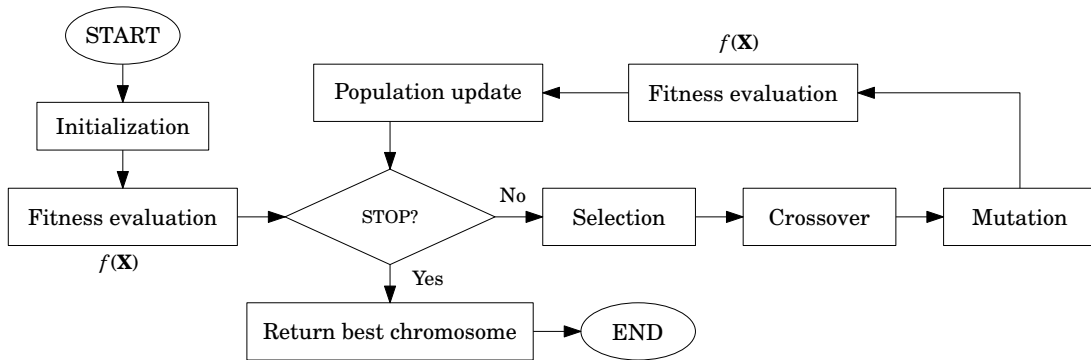
Figure 2.4: Generic flow diagram of a genetic algorithm.

For non-binary implementations of algorithms, the crossover and selection operators can be kept as defined for the standard algorithm, whereas only the mutation operator would change, which should suit the implemented encoding selected for the specific problem. For a complete and comprehensive outlook on genetic algorithms, the reader is referred to the bibliography on this matter available in [72, 63, 83, 84].

At this point it is also noteworthy to mention the potentiality of evolutionary algorithms to efficiently solve multi-objective optimization problems, which was originally pinpointed by Rosenberg in [85] and thereafter unchained a flurry of mostly genetically inspired multi-objective solvers such as the Vector Evaluation Genetic Algorithm (VEGA, [86]), Weight-based Genetic Algorithm (WBGA) [87], Multi-Objective Genetic Algorithm (MOGA, [88]), Niched Pareto Genetic Algorithm (NPGA) [89], Non-Dominated Sorting Strategy (NSGA, [90]), Pareto Archived Evolution Strategy (PAES, [91]) and Multi-Objective Evolutionary Algorithm (MOEA, [92]), among others. By virtue of their population-based search strategy, evolutionary algorithms are able to produce an entire set of solutions at a single iteration of their working procedure which, by intelligently modifying their solution archiving criteria, renders an estimated Pareto set in a single run of the algorithm.

This is indeed the rationale of the fast non-dominated sorting approach followed by the improved version of the NSGA algorithm previously cited, coined as NSGA-II [93]: at each iteration each solution k within the Ψ-sized population is assigned two different measures of its Pareto quality: 1) the number of solutions that dominate the solution ψ at hand; and 2) the set of solutions which the ψ-th solution dominates. If no other vector results to dominate the ψ-th solution, it is declared to belong to the first non-dominated front, ranking 1 for the first parameter. The solutions belonging to the first front are set apart and the procedure iterates on the remaining solutions by assigning increasing rank values for subsequently non-dominated fronts, and so forth. This imposes the ordering criteria for assessing the Pareto optimality of the archived solutions

through the iterations: candidate vectors with rank equal to 1 will be kept in the population preferably than those with higher rank or equivalently, less relevant in the context of Pareto dominance.

However, there is still a need for establishing a sorting strategy for those solutions sharing the same Pareto dominance rank. To this end, NSGA-II establishes the so-called *crowding distance* as a measure of the diversity and span of a front, which is defined as the average distance of the two neighboring solutions of a particular solution $k \in \{1, \dots, \Psi\}$. Intuitively this parameter provides an estimation of the density of solutions surrounding a point of the front at hand. This being said, solutions with large crowding distance are preferred to solutions with small crowding distance. Consequently, the population is filled iteratively by considering first the rank order criteria among the fronts (lower rank values are preferred), followed by the ordering among the solutions driven by their crowding distance values.

2.3.4.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based meta-heuristic technique developed by Kennedy and Eberhart in [94], inspired by social behavior of bird flocking and fish schooling. A PSO system is initialized with a population of random solutions, and searches for the optimal one by updating the population over several generations. PSO has no evolution operators, such as crossover and mutation as genetic algorithms do, but potential solutions instead, called *particles*, which fly through the problem search space to look for promising regions on the basis of their own experiences and those of the whole group. Thus, social information is shared, and also individuals profit from the discoveries and previous experiences of other particles in the search.

Mathematically, given a swarm of Ψ particles, each particle $\psi \in \{1, \dots, \Psi\}$ is associated with a position vector $\mathbf{X}_\psi = \{X_1^\psi, X_2^\psi, \cdots, X_K^\psi)\}$, with K being the number of parameters to be optimized in the problem. Let $\mathbf{X}_\psi^*$ be the best previous position that particle ψ has ever found, i.e. $\mathbf{X}_\psi^* = \{X_1^{\psi,*}, X_2^{\psi,*}, \dots, X_K^{\psi,*}\}$, and $\mathbf{X}^\triangle$ be the group's best position ever found by the algorithm, i.e $\mathbf{X}^\triangle = \{X_1^\triangle, X_2^\triangle, \dots, X_K^\triangle\}$. At each iteration step $i+1$, the position vector of the ψ-th particle is updated by adding an increment vector $\Delta\mathbf{X}_\psi(i+1)$, called velocity $\mathbf{V}_\psi(i+1)$, as

$$V_k^\psi(i+1) = V_k^\psi(i) + c_1 r_1 (X_k^{\psi,*} - X_k^\psi(i)) + c_2 r_2 (X_k^\triangle - X_k^\psi(i)), \tag{2.6}$$

$$V_k^\psi(i+1) = \frac{V_k^\psi(i+1) \cdot V_k^{max}}{|V_k^\psi(i+1)|} \qquad \text{if } |V_k^\psi(i+1)| > V_k^{max}, \tag{2.7}$$

$$X_k^\psi(i+1) = X_k^\psi(i) + V_k^\psi(i+1), \tag{2.8}$$

where $k \in \{1, \dots, K\}$, c_1 and c_2 are two positive constants, r_1 and r_2 are two random parameters which are found uniformly within the interval $[0, 1]$, and V_k^{max} is a parameter that limits the velocity of the particle in the k-th coordinate direction. This iterative process will continue until a stop criterion is fulfilled, this forming the basic iterative process of the standard PSO algorithm first formulated in [94], subsequently extended in [95, 96] by including concepts such as the inertia weight and the constriction factor for a better balance between the intensification and diversification capabilities of the algorithm.

2.3.4.3   Simulated Annealing

Proposed by Kirkpatrick in [97], Simulated Annealing (SA) is essentially a stochastic optimization algorithm inspired by the physical process of annealing in metallurgy. As opposed to gradient-based search methods, which employ the idea of steepest descent at each iteration, SA allows random uphill perturbations, thus preventing the search process from getting stuck in local minima by accepting worse candidate solutions based on probabilistic parameters. SA can be seen as a single-point evolutionary algorithm in which crossovers are disabled and only mutations are used. This is also a global search strategy and can work in very high-dimensional searches given enough computational resources.

The search procedure of this solver is based on the analogy with the physical process of annealing: a lattice structure of a solid is achieved by heating up the solid to its melting point, and then slowly cooling until it solidifies to a low-energy state characterized by a robust molecular structure. To this end SA simulates this heating process by establishing a temperature variable that is initially set at a high value and progressively decreased as the algorithm runs to recreate the cooling stage of annealing. A high value of the temperature variable will allow the algorithm to accept frequently solutions worse than that proposed as the best candidate solution up to the given iteration, which contributes to the capability of the solver to escape from any local optima found in early stages of its execution. As the temperature variable goes down, so does the probability of accepting worse solutions, which makes the algorithm gradually focus on local areas of the search space. In other words, intensification is progressively favored in the simulated cooling process of SA. Traveling salesman problems are known to be efficiently solvable by this heuristic.

2.3.4.4   Other Meta-heuristic Algorithms

Many other algorithms are actually inspired by natural phenomena and have been developed by mimicking the intelligence characteristics of biological and physical agents. Noteworthy is to briefly mention Ant Colony Optimization (ACO, [98]), which mimics the behavior of ants when laying down pheromone trails once food has been found after wandering randomly. Artificial Immune algorithms [99], on the other hand, focus on imitating the behavior of the immune system in vertebrates when detecting the presence of strange elements in the body in order to eliminate or neutralize the foreign invaders. In this same line of research, Artificial Bee Colony [100] imitates the behavior of bees when locating and bringing food to the hive, whereas other recently proposed techniques inspire from Physics such as the Gravitational Search Algorithm [101], which hinges on the notion of mass interactions and the theory of Newtonian physics. Other meta-heuristic algorithms grounding on the observation of biological behaviors include the Monkey Algorithm [102], which imitates the behavior of a monkey climbing trees in its search for food; the Intelligent Water Drops algorithm [103], which emulates the dynamics and interactions of natural water drops moving in riverbeds, lakes and seas; the Invasive Weed Optimization Algorithm [104], based on the growth pattern and invasive properties of weed colonies; the Hunting Search [105], which simulates how groups of animals behave when hunting; the Biogeography-Based Optimization algorithm [106], based on the geographical distribution of living organisms; optimization based on virus infection [107], on colonies of bacteria [108, 109]; the so-called Cuckoo search approach [110], built upon the reproduction and breeding of the cuckoo bird; and the recently published Coral Reefs Optimization (CRO, [111]), based on the algorithmic simulation of the coral reproduction and reef formation processes.

In this context, this dissertation gravitates around one of the meta-heuristic algorithms that can be classified within the above general class of bio-inspired random solvers: Harmony Search (HS, [112]), for which a separate section within this chapter is allocated.

2.4   The Harmony Search Algorithm

The algorithmic core of the resource allocation algorithms for wildfire proposed in this Thesis will gravitate on the Harmony Search (HS) algorithm, which is a meta-heuristic solver first proposed by Geem et al. in [112], and thenceforth applied to a wide spectrum of optimization problems in very diverse fields such as road routing [113, 114], Sudoku puzzle solving [115], water network design [116], dam operation [117], vehicle routing [118], multicast routing [119], multiuser detection [120, 121], design of Telecommunication networks [122, 123], indoor localization [124, 125] and radar code design [126], among many other application scenarios thoroughly surveyed in [127]. HS is inspired by the improvisation process of an orchestra in their attempt to compose the most harmonious melody under an aesthetic point of view. During this process musicians improvise different pitches of their instruments to produce a melody whose aesthetic quality is expected to improve progressively as the improvisation process evolves. Following the fundamentals of music composition it is known that the aesthetic quality of a certain melody relies mainly on the frequency ratios between the played pitches (which, as a matter of fact, keep an interesting, succinct connection to the Theory of numbers and the Golden mean [128]): as such, two notes playing one octave apart have been proven to sound pleasantly, similarly to other simple ratios such as 3:4 or 2:3. By contrast, pitch gaps of 7 semitones (e.g. "DO" and "SI") are dissonant.
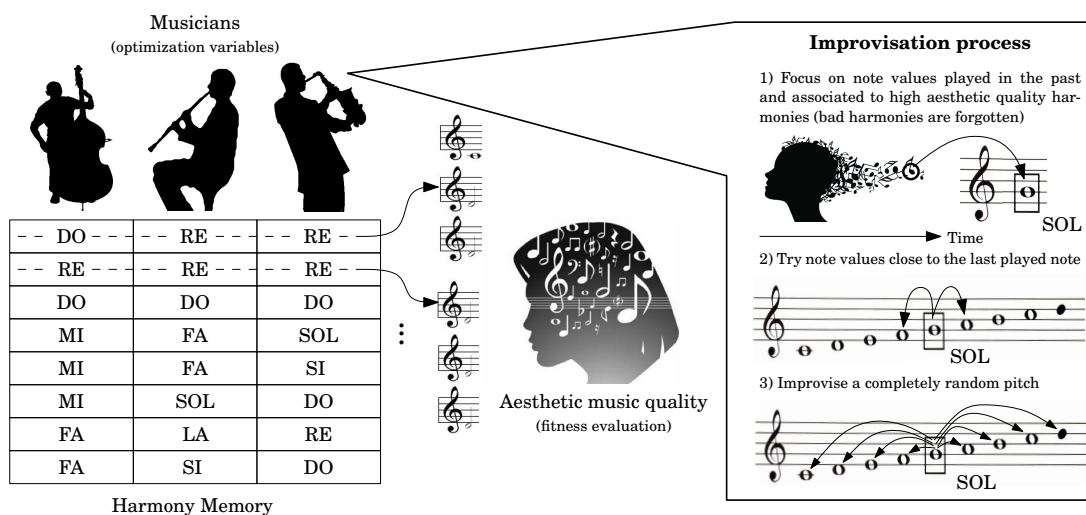
Figure 2.5: General overview of the improvisation process of a music band composed by $K = 3$ musicians and a harmony memory of size $\Psi = 8$.

If the aesthetic quality of music is used to measure the *fitness* of a certain produced harmony, the mapping between the process of music composition of an orchestra or band results straightforward if one notices that each musician denotes a decision variable X_k, being K their total number. On the other hand, the pitch range of the instrument played by a musician represents the alphabet $\mathcal{X}$ of the decision variable X_k; the harmony or melody improvised at a certain time stands for a solution vector **X** at a given iteration; and the aesthetic impression of the audience is indeed

the fitness function of the optimization problem at hand. Since musicians improve progressively the melody through time by varying the pitch of their instruments and checking whether an aesthetic enhancement has been achieved, the HS algorithm improves the fitness of the solution vector iteratively by applying a set of intelligent stochastically-driven operators, similar to other meta-heuristic algorithms described previously (e.g. genetically inspired approaches). The definition and design of these operators is based again on the behavior of musicians when improvising new melodies, as shown in Figure 2.5 and explained in what follows.

HS is a population-based algorithm where the Ψ-sized archive of candidate solutions is referred to as Harmony Memory (HM), which can be thought of as resembling the archive of harmonies that the musicians of the orchestra remember as aesthetically good during the composition process. Similarly to the manner in which the population of chromosomes is handled in genetic algorithms, at every iteration a set of operators is applied to each of the candidate vectors or *harmonies* of the HM, each generating a newly improvised vector every time. A reader experienced in the essentials of meta-heuristic optimization would at this point unveil clear connections between HS and classical evolutionary optimization, in the sense that the former incorporates key ingredients from the latter such as polygamy (each offspring may become from several parents) or incremental evolution. However, there is a subtle, yet paramount difference with respect to naïve genetic optimizers: HS applies such operators to each of their compounding elements or *notes* separately based on independent probability distributions. This *per note* application and the definition of the operators permit to easily balance the trade-off between the explorative and exploitative behavior of the HS heuristics in a generally[3] more efficient fashion than other solvers.
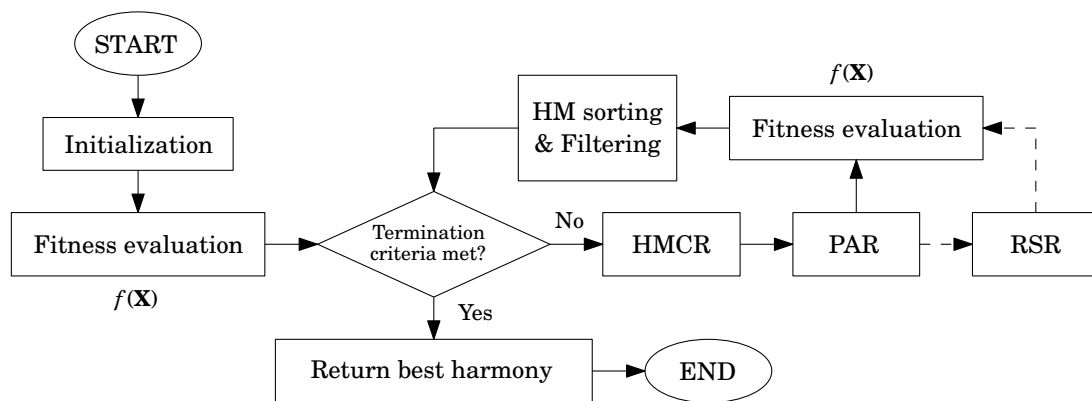
Figure 2.6: Generic flow diagram of the HS algorithm. Dashed arrows correspond to optional stages aimed at controlling the level of randomization of the search process independently from the nominal operator of the algorithm.

The above being said, the flow diagram of the HS algorithm comprises four steps as depicted in Figure 2.6: 1) initialization of the Harmony Memory; 2) improvisation of a new harmony vector; 3) update of the memory with those newly generated harmonies better – as dictated by the fitness function – than any of the currently solutions in the HM; and 4) return to step 2 until a termination criteria is met. A maximum of three probabilistic operators drive the search behavior of this algorithm:

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[3]It is known that no algorithm rendering the best performance in all optimization problems exists [129], but the HS algorithm has certainly in practice to outperform other meta-heuristic methods in a diversity of scenarios. This empirical fact buttresses the general statement on the claimed supremacy of HS made at this point.

- The Harmony Memory Considering Rate emulates the exploitation – or consideration – of the archive of *good* harmonies by the musician: when improvising a new pitch in the played instrument, each musician should recall which pitches led to a aesthetically pleasant melody. To emulate this in the search process, this operator establishes a probabilistic parameter HMCR $\in [0,1]$ that sets when the new value for a certain note is drawn uniformly from the values of this same note in all the remaining melodies. Otherwise (i.e. with a probability $1-$HMCR), the new value is randomly chosen from their alphabet $\mathcal{X}$, which increases the diversity of the solutions towards optimality. Following the notation introduced in this chapter, if the HM is denoted as $\{\mathbf{X}(\psi)\}_{\psi=1}^{\Psi}$ with $\mathbf{X}(\psi) \triangleq \{X_1(\psi), X_2(\psi), \dots, X_K(\psi)\}$ representing the ψ-th archived harmony, and K the number of notes, then

$$\text{HMCR} \triangleq Pr\left\{X_k(\psi) \rightsquigarrow \omega_{\text{HMCR}}\right\}, \tag{2.9}$$

  where ω_{HMCR} is a discrete random variable uniformly distributed in

$$\left\{X_k(1), \dots, X_k(\psi-1), X_k(\psi+1), \dots, X_k(\Psi)\right\}.$$

  This operator operates in a per note basis through the different harmonies of the HM, i.e. the above operation is repeated for every $k \in \{1, \dots, K\}$ and $\psi \in \{1, \dots, \Psi\}$ by properly varying the support of ω_{HMCR}. It should be also remarked at this point that some contributions consider the random consideration as a separated operator (RSR, Random Selection Rate) with its own probabilistic parameter, rather than statistically driven by the complementary of the HMCR probability. Disregarding its implementation, randomization would reflect the creativity of the musician to improvise new notes in a more radical and explorative manner than through the pitch adjustment next explained.

- The Pitch Adjusting Rate imitates the way a composer varies subtly the pitch of the played instruments when detecting that the improvised melody is close to a good aesthetic quality. To this end, the PAR operator poses a probability PAR $\in [0,1]$ that the new value $\widehat{X}_k(\psi)$ for a given note value $X_k(\psi)$ is given by a random perturbation centered on $X_k(\psi)$, namely

$$\text{PAR} \triangleq Pr\left\{X_k(\psi) \rightsquigarrow \widehat{X}_k(\psi)\right\}, \tag{2.10}$$

  where

$$\widehat{X}_k(\psi) = \begin{cases} \omega_{\text{PAR}} & \text{if } |\mathcal{X}| < \infty, \\ X_k(\psi) + \beta \cdot z & \text{otherwise,} \end{cases} \tag{2.11}$$

  with $\beta \in \mathbb{R}^+$ representing the pitch bandwidth, and z denoting a continuous random variable following an uniform distribution with support $[-1,1]$. As for the case of discrete alphabets, ω_{PAR} is a random binary variable with equal probability of taking the neighboring values on $X_k(\psi)$ in $\mathcal{X}$. When handling discrete alphabets for the compounding notes of the harmony, ω_{PAR} denotes a random binary variable with equal probability of taking the neighboring values on $X_k(\psi)$ in $\mathcal{X}$: when this is the case, the best search strategy is to define a vicinity relationship criterion between the components of $\mathcal{X}$, which is usually driven by the implications of such alphabet values on the fitness function $f(\cdot)$ to be optimized.

As mentioned earlier, these parameters balances the diversification and intensification capabilities of the HS solver. For instance, the combination of a high PAR value and a narrow bandwidth β may hinder the exploratory behavior of the algorithm in favor of a deeper intensification

around intermediately discovered solutions. Contrarily, a low pitch adjusting rate and/or high values of β may push the algorithm away from local areas featuring solutions of potential optimality. On the other hand, the consideration of the information contained in the harmony memory can be regarded as a probabilistically driven exploitative search method embedded within the overall thread of the solver: high values of the HMCR parameter will force the algorithm to draw new note values from the already improvised ones at the risk of trapping the algorithm into local optima, whereas configurations with low HMCR values will delegate most of the randomized search capability of the algorithm to the RSR operator, through which regions of the search space far apart from each other are examined. Interestingly, a recent contribution has proposed a simple yet insightful mathematical framework that unveils the exploratory principles of HS [130].

Several differences between Harmony Search and other evolutionary meta-heuristics can be found beyond the pure interpretation and *simile* of HS to the process of music composition in groups. Clearly similarities arise in what relates to its population-based nature and e.g. genetic algorithms, but HS combines polygamy in a probabilistic basis that make any newly improvised harmony potentially inherit characteristics of the entire memory. Besides, the note-wise application of the improvisation operator unchains a search process of finer granularity, allowing for a more flexible randomized refinement of the produced solutions. Finally, its simplicity and flexibility to accommodate hybrid meta-heuristic approaches in combination with other heuristics has ignited a flurry of modified versions of the original HS algorithm in [112] with no specific application scenario, as has been recently reviewed in [131]. Such modifications include hybridizations with Hill Climbing and a global-best Particle Swarm Optimization [132], as well as stochastic derivatives supporting HS when tackling combinatorial optimization problems [133].

2.5 Meta-heuristics for Resource Management in Disaster Scenarios

The optimization of operations in disaster events have grasped the interest of the research community with special intensity during the last couple of decades. The classification of the produced literature can be driven by several non-overlapping criteria. If the classification is made at first based on the type of resource involved in the operations, it should be first emphasized that the provision and distribution of material goods in disaster scenarios (also referred to as *logistics*) has been often modeled as variants of the vehicle routing problem (VRP). This optimization model essentially consists of the discovery of optimal routes for vehicles starting and finishing at a given depot so as to deliver goods to a set of scattered nodes under different criteria (e.g. distance, time or cost minimization). This seminal definition of the vehicle routing problem has evolved to a wide spectrum of alternative formulations and extensions such as the Capacitated VRP (CVRP), the Vehicle Routing Problem with Pick-up and Deliveries (VRPPD), the Multiple Depot VRP (MD-VRP), the Periodic VRP (PVRP) and the Split Delivery VRP (SDVRP), as well as hybridizations of these extensions with soft and hard time constraints.

In particular, the SDVRP, first defined in [134] as an instance of the VRP where the demand can be satisfied by more than one-time delivery or by two or more vehicles, has been mainly tackled via Tabu Search (TS, [135, 136]), which is a meta-heuristic solver that hinges on the construction of memory structures that describe the visited solutions during the search process. A new logistics model encompassing soft time windows, multi-period routing, and split delivery strategies has been recently proposed in [137] and solved via genetic heuristics. This model builds upon previous work in [138], where the delivery of relief supplies in disaster areas was approached

via a similar model, but subject to hard timing constraints (i.e. the demand of supplies must be served immediately after the occurrence of the disaster). As for the rest of VRP variants there are myriads of contributions dealing with the application of evolution strategies [139, 140], Ant Colony Optimization [141, 142], Greedy Randomized Adaptive Search Procedure (GRASP, [143, 144, 145]), Simulated Annealing [146, 147, 148] and Variable Neighbor Search (VNS, [149, 150]), among others. For the sake of space, the reader is referred to the comprehensive survey in [151] for further details on the state of the art around meta-heuristics for vehicle routing problems.

One of the most profusely addressed problems in operational research capitalizing on the above literature focuses on the dispatching and routing of emergency vehicles after the occurrence of the disaster at hand. For instance, a line of research related to the allocation and routing of emergency vehicles aims at finding the optimal assignment between casualties of a certain disaster and the set of available transport vehicles, and qualified physicians, such that all casualties can be medicated as good and quickly as possible with respect to the severity and triage categories of their individual injuries. To efficiently solve this combinatorial assignment paradigm, a meta-heuristic approach combining a local greedy method with a modified version of the Simulated Annealing algorithm is proposed in [152], which is proven to outperform current casualty assignment policies (D'Hondt). In this same context, Yi and Odamar in [153] considered a optimization model combining two different yet related objectives: the minimization of the delay in the arrival of commodities and health-care for injuries, and a second criterion based on the assignment of loading and unloading schedules to each itinerary of the deployed vehicles. A similar formulation was undertaken in [154] to include the evacuation of injuries to medical centers as an objective criterion. In both references the formulated problem is tackled by means of a decomposition of the model in two sub-models, which are solved in an iterative fashion via Ant Colony Optimization. Recent contributions resorting to meta-heuristics to solve VRPs in the context of emergency operations include [155, 156, 157] and references therein.

Another paradigm considers the road network itself as the central variable of the optimization problem at hand: as such, the allocation task reduces to the elaboration of the optimal repair plan for a devastated road network after the occurrence of a natural disaster, which can be regarded as a combinatorial network design problem driven by distinct fitness criteria. For instance, the maximization of the accessibility to the road infrastructure has been considered in [158, 159, 160], the latter two focusing on rural areas for developing countries for which GRASP and VNS heuristics are utilized. Road reconstruction is also addressed via genetic algorithms in [161] by formulating a fuzzy triple-objective problem: 1) minimization of the travel time over the road during its reconstruction; 2) minimization of the time taken by any individual work team in their reconstruction duties; and 3) the minimization of the idle time between team shifts. Similarly, genetic optimizers have been used for the cost-constrained reconstruction of bridges after natural disasters with real test data from Athens, Greece [162]. Alternative multi-objective formulations incorporating real simulation cases (the Chi-Chi earthquake in Taiwan, Asia, in 1999) were also reported in [163, 164], the latter interestingly considering the minimization of the risk for rescuers as one of the optimization criteria. More recently, logistical support scheduling for emergency repair works has been studied in [165], which is modeled as the minimization of the short-term operating cost of the support planning subject to time constraints and other related operating conditions. Ad-hoc heuristics are designed for a decomposed formulation of the optimization problem, and subsequently validated for the Chi-chi Taiwanese earthquake mentioned above.

When the optimization scope targets the deployment of supply depots, field hospitals and in general, infrastructure supporting emergency operations, the corresponding problem falls within

the broad category of facility location problems. In this class of optimization paradigms the objective is to determine the position – and eventually, number – of service nodes in a certain geographical area so as to either maximize the demand covered by such nodes or minimize the time taken to satisfy such demands [166]. The literature around this paradigm contextualized in emergency services abounds since the early 80s, specially in regards to problem extensions imposing multiplicity in the service from the deployed nodes to the demanding locations [167, 168], probabilistic models to account for busy call centers [169, 170] or several service types [171]. Meta-heuristics have been extensively utilized for their resolution, such as Tabu Search [168, 172], Genetic Algorithms [173, 174], Simulated Annealing [175, 176], Particle Swarm Optimization [177, 178] and Ant Colony Optimization [179, 180]. Scenarios where the facility location problem has been shown to overlap and interact with vehicle routing aspects have been also handled via heuristic methods [181].

Historically the activity in regards to the specific application of meta-heuristics to resource allocation problems in wildfire disasters has mainly gravitated on the problem of sitting fire stations in urban areas, which has been put to practice in several geographical locations such as Bristol, UK [182], Denver, USA [183], Rotterdam, Netherlands [184] and Dubai, UAE [185]. However, despite the noted suitability of meta-heuristic algorithms for the management and preservation of forest landscapes [186], research around this particular disaster has lately tilted towards the allocation of emergency management systems and ground vehicles [187, 188], thus leaving aside other resources of relevance for the operations in such scenarios. An exception within the scarce contributions found beyond facility location and ground vehicle routing is the work by Barbarosoglu et al. in [189], where a mathematical framework is presented for the scheduling of helicopters tasks for disaster relief operations. Specifically the assignment problem was divided in two sub-problems: the tactical allocation of helicopters from the air force facilities to the command center, and operational routing and loading decisions, both of which are solved by means of an interactive bi-objective heuristic procedure. On the other hand, optimal route planning of unmanned aerial vehicles for wildfire detection and surveillance has been recently tackled in [190] by considering distance and coverage criteria and collision avoidance constraints, being solved via multi-objective genetic optimizers.

OPTIMAL DEPLOYMENT OF WIRELESS RELAY COMMUNICATIONS OVER LARGE-SCALE WILDFIRES

"The single biggest problem in communication is the illusion that it has taken place."

- George Bernard Shaw

When a wide-area disaster such as a big forest fire occurs, it is likely that wired communication infrastructures in the affected area – if any – become severely damaged or even destroyed [191]. To effectively deal with this problem there exist different technological solutions incorporating emergency contingency mechanisms in the development of diverse communication services, such as standard mobile telephony networks [192]. From the operational point of view different location problems can be formulated towards minimizing the impact of the affected communication service in an area devastated by a given disaster, as exemplified by the optimization of the location of fire stations [187] or other paradigms related to the deployment and routing of vehicles for emergency services [193, 188]. Non-technological approaches have been also exploited to alleviate the effect of damages in the communications infrastructure [194, 195]. In forest fires, however, none of such existing solutions are useful due to the peculiarities of the affected wild zones which are, in the majority of cases, far away from inhabited zones with developed services.

In such cases it is crucial to deploy alternative ad-hoc wireless communication networks as quickly and efficiently as possible in order to guarantee the communication and security of the emergency teams (correspondingly, firefighters). In this way, emergency teams will be informed of their location with respect to any other teams, as well as of the progress of the disaster (fire front, for example). Historically there is a plethora of cases that exemplify the fatal consequences of team isolation and lack of coordination in emergency situations (especially fire events), e.g. the death of eleven firefighters occurred in a 130 km^2 forest wildfire in Guadalajara (Spain) in 2005, or the 74.18 km^2 fire on the Lüneburg Heath in Lower Saxony (Germany) in 1975, killing five firefighters [196].

Generally speaking the main characteristics of this emergency telecommunications network should be the ease of deployment, its independence with respect to fixed wired infrastructures and its capacity to be rapidly reconfigured. In this context, dynamic wireless relay networks are gaining momentum in such catastrophic scenarios: as schematically shown in Figure 3.1, relays

offering satellite communication capabilities are usually carried by mobile nodes (e.g. airplanes, helicopters or unmanned aerial vehicles), allowing them to rapidly move from one position to another and hence, adapting the wireless network coverage to the mobility of emergency teams. Technologically speaking, nowadays there is an upsurge of dynamic relaying commercial equipment based on VSAT (Very Small Aperture Terminal) relays: as to mention, specialized products within the portfolio of companies such as SELEX, TRIAGNOSYS, TELTRONIK and AGIOSAT provide interoperability for high-speed voice, image and video communications between local, infrastructure-less networks based on conventional wireless protocols (e.g. 2G/3G/4G, Private Mobile Radio - PMR and WLAN) and satellite links. As a matter of fact, the earthquake occurred in Haiti in 2010 hit massively the telecommunication network of the whole country, whose eventual collapse affected the Haitian population, the operations and planning activities of emergency teams and essential services like radio stations and airport communications. In this large-scale disaster scenario relay devices such as those exemplified above excelled at providing hybrid satellite-wireless coverage thanks to the initiative of telecommunications companies and non-governmental organizations.
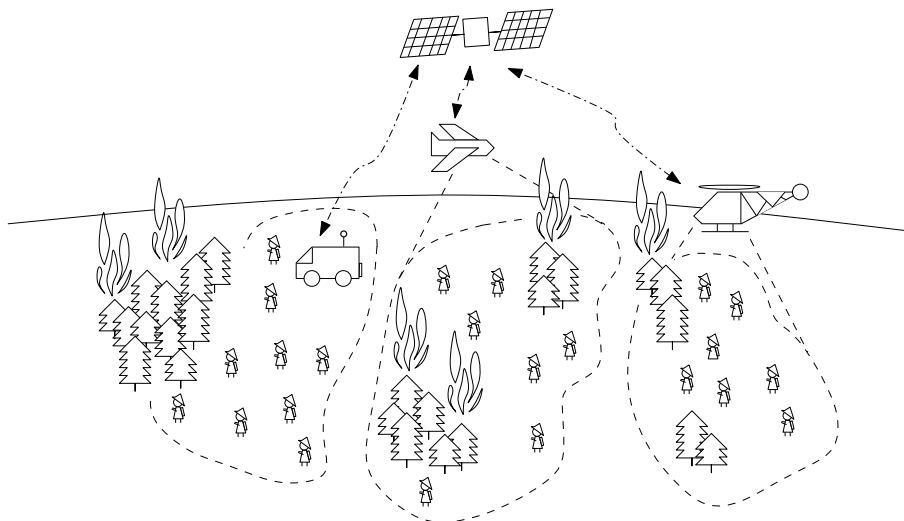
Figure 3.1: Schematic example of a dynamic relay deployment scenario.

This chapter focuses on the deployment of *any* kind of relaying equipment by withdrawing from any specific relay technology in favor of a general formulation of the underlying optimization problem. This being said, the paradigm of optimally deploying relays in a disaster area is closely related to the so-called Dynamic Relay Deployment Problem (DRDP), which consists of establishing the number and optimal position of an indeterminate set of relays, to ensure communication between the emergency teams deployed over the area at hand and the backbone network. This initial formulation of the problem can be regarded as a modification of the well-known disk cover problem, which was first formulated by Zahn in [197]. The objective of the problem is, given a unit disk, to find the smallest radius required for a given set of equal disks to completely cover the unit disk. Johnson in [198] showed that the disk cover problem is a NP-hard problem. Later, Houchbaum and Maass in [199] presented a set of approximated local semi-exhaustive schemes for solving a modification of the disk cover and packing problem that focused on *points* to be covered rather than *areas*. Houchbaum inspired from the observation that in order to maximize the number of points covered by a disk of a certain radius, at least two points must be on its border, concluding that the number of non-covered points can be bounded by applying a divide-

and-conquer approach, iteratively selecting the best solution at each iteration. More recently, and focusing on disaster wireless networks, Guo et al. in [200] adapt three different algorithms to deal with the aforementioned modified disk cover problem: the two-vertex square covering (TVSC), the circle covering algorithm [201] and the binary integer programming algorithm (BIP [202]). All these algorithms are based on greedy strategies: from a given initialization, and following a local semi-exhaustive search procedure, these schemes provide the best deployment of a given set of disks in order to maximize the number of covered points distributed over a plane. It is important to remark that in these references a set of possible relay locations is a priori assumed, and thus the search space is significantly reduced with respect to the case when the relay locations are unconstrained. Another related contribution addresses the specific problem of covering points on a single-dimensional straight line with a set of sensors [203].

Alternatively, the DRDP can also be considered as a clustering problem, where a set of mobile users must be associated to a given set of relays, under geometrical and cost constraints. Therefore, this clustering problem may be solved by resorting to e.g. the K-means algorithm [204]. The K-means algorithm has been applied to a wide variety of clustering problems [205]. This algorithm follows a search strategy rather different than the previous algorithms, but both share essentially the same shortcomings when dealing with this optimization problem: 1) both strategies have to be adapted in order to deal with spatial restrictions (coverage radius); 2) their results strongly depend on the initialization; and 3) the number of clusters must be a priori assumed (or at least, estimated), and kept fixed while the algorithm is working.

This chapter extends further the set of assumptions taken in the formulation of the DRDP in [200], aimed not only at optimizing the location of the relays to ensure maximum communication coverage, but also at properly estimating their number and model (radius, cost), based on the number and position of emergency teams working on the area at a given time. We have coined this new paradigm as the Modified Dynamic Relay Deployment Problem (MDRDP). Note that in the MDRDP the number of relays to be deployed is not assumed to be known a priori, but will be adapted – jointly with the model of relay deployed – to the scenario at hand. To this end, relays will be assumed to have a circular coverage area of variable radius, which are associated to different costs due to e.g. power consumption or price of the equipment itself. In light of these assumptions, an optimal relay network deployment reduces to determining the number, locations (geographical coordinates over the area affected by the disaster) and models of the relays, in order to set a balance between the number of covered emergency teams (depending not only on the number of relays but also on their respective models) and the corresponding overall cost of the deployment. Since 100 % coverage may not be pursued, this single-objective formulation of the problem represents the case when an initial emergency deployment must be set, being conservative with respect to the use of the available communication resources (and ultimately, the overall cost). Once the dimension of the disaster has been assessed on site, a wider relay deployment with enhanced coverage (at a relaxed cost limit) could be done or discarded, e.g. if the emergency was solved by the initial exploring teams or a false alarm was triggered. On this purpose a second formulation of the MDRDP regards coverage and cost as two interrelated yet conflicting, separated criteria, which jointly describe a Pareto set of available network deployments. This permits to perform a cost-efficient, scalable emergency deployment once their occurrence has been verified.

To efficiently deal with the above defined hard optimization problem, a novel meta-heuristic hybrid approach is herein proposed, which combines the global search capabilities of the HS algorithm with an adapted version of the K-means algorithm acting as a local search procedure. The proposed scheme is able to provide a good balance between the explorative and exploitative

searching strategy, not only on the relays' coordinates but also on their respective models. Specifically, HS is the responsible for determining the coordinates (x, y) at which the relays have to be deployed, its number and their correct radius or model. On the other hand, K-means greedily exploits a certain fraction of the potential solutions (i.e. number of relays, radii and locations) produced by Harmony Search to perform a fine-grained adjustment of the relays' positions, in order to maximize the whole network coverage. Besides the lack of previous schemes tackling this specific optimization problem, the reasons for specifically selecting the K-means clustering algorithm are threefold: 1) it is widely used for any general-purpose application; 2) its results are usually efficient and accurate when dealing with unsupervised clustering problems; and 3) its lightweight implementation. In line with the dual-stage deployment strategy outlined previously, single- and bi-objective versions of the algorithm are described and discussed. In order to assess the performance of the proposed algorithms, simulations are carried out on a synthetic tool example and an emulated scenario based on real statistical data of the fire events in the *Castilla La Mancha* region (center of Spain). The obtained results verify that the proposed scheme is able to outperform naive K-means based strategies by jointly optimizing the number of relays and their models towards better cost-coverage ratios at a reduced computational cost.

The rest of the chapter is structured as follows: the novel extension of the dynamic relay deployment (MDRDP) is posed in Section 3.1, whereas Section 3.2 delves into the main characteristics of the proposed meta-heuristic hybrid algorithm. Finally, Section 3.3 discusses a comparison study between the proposed approach and a standard K-means algorithm.

3.1   Problem Formulation

In reference to Figure 3.2, the MDRDP can be defined as follows: let N be the number of emergency teams deployed over a disaster area $A \subset \mathbb{R}^2$, and $\{\mathbf{p}_i\}_{i=1}^N \triangleq \{(x_i, y_i)\}_{i=1}^N$ their respective locations. The goal is to find the optimal relay deployment in order to ensure cost-effective communications among the emergency teams deployed over the disaster scenario. In this chapter each relay deployment $\mathcal{D}$ can be specified by using three variables, which gives rise to a three-fold optimization problem:

- The number M of relays to be deployed. This parameter is assumed not to be known a priori, but its value is limited to a certain set $M \in [M_{min}, M_{max}]$, which may represent the range of available relay resources in the emergency management facilities.

- The relay locations $\{(x_m^R, y_m^R)\}_{m=1}^M$ over the affected zone A.

- Their corresponding models $\{\phi(m)\}_{m=1}^M = \{(R(m), C(m))\}_{m=1}^M$, selected from a set $\{\Phi_t\}_{t=1}^\tau = \{(R_t, C_t)\}_{t=1}^\tau$ of possible models, where τ stands for the total number of relay models, R_t the radius and C_t the cost for model t. Clearly, $\phi(m) \in \{\Phi_t\}_{t=1}^\tau \ \forall m \in \{1, \ldots, M\}$. Intuitively, the larger the coverage radius R_t is for a given model, the higher its associated cost C_t will be. The model alphabet $\{\Phi_t\}_{t=1}^\tau$ is sorted in ascending order of radius and cost, i.e. $R_{t'} > R_t$ and $C_{t'} > C_t$ if $t' > t$.

A binary $N \times M$ coverage matrix $\mathbf{X}$ is further defined with entries $x_{i,m}$ given by

$$x_{i,m} = \mathbb{1}\left(\sqrt{(x_i - x_m^R)^2 + (y_i - y_m^R)^2} \leq R(m)\right), \tag{3.1}$$

where $\mathbb{I}(\cdot)$ is an indicator function taking value 1 if its argument is true. This matrix $\mathbf{X}$ can be computed straightforward from $\{(x_i, y_i)\}_{i=1}^N$, $\{(x_m^R, y_m^R)\}_{m=1}^M$ and the coverage radii implicitly expressed by $\{\phi(m)\}_{m=1}^M$. Having this notation in mind, the single-objective formulation of the MDRDP aims at finding the optimum deployment

$$\mathcal{D}^* = \left\{ M^*, \{(x_m^{R,*}, y_m^{R,*})\}_{m=1}^{M^*}, \{\phi^*(m)\}_{m=1}^{M^*} \right\} \tag{3.2}$$

that satisfies

$$\mathcal{D}^* = \underset{\substack{M \\ \{(x_m^R, y_m^R)\}_{m=1}^M \\ \{\phi(m)\}_{m=1}^M}}{\arg\min} \left[\sum_{i=1}^N \mathbb{I}\left(\sum_{m=1}^M x_{i,m} = 0 \right) + \sum_{m=1}^M C(m) \right]. \tag{3.3}$$

In words, this metric quantifies the fitness of each deployment: the first term represents the total number of emergency teams not covered by any of the relays deployed, and the second term takes into account the overall cost associated to the relay deployment.
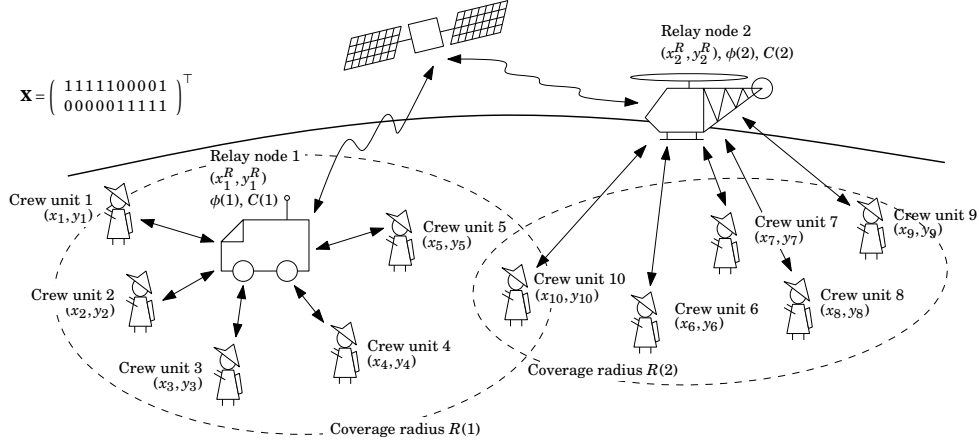
Figure 3.2: Example of an MDRDP instance with $M = 2$ relays and $N = 2$ nodes to be covered.

It is important to point out that the above metric targets the connection of every team to a deployed relay rather than inter-team communications; in practice this simplified approach guarantees that communication links are established between the relay and the covered teams in a star-like topology, as tree-like network layouts might bring about error interdependencies between mutually connected links that would made the network deployment significantly more involved. Nevertheless, from the algorithmic point of view this observation and the link redundancy that several commercial relay equipment incorporates nowadays suggest an interesting line of future research aimed at extending the MDRDP problem here tackled with routing aspects in multi-hop emergency communications, which could eventually help extending the coverage area of single relay nodes far beyond their nominal radio coverage. This research line and its implications in the design of the optimization solver will be further developed in Chapter 5.

The bi-objective formulation of the problem at hand is straightforward by decoupling both terms in the metric of Expression (3.3), i.e.

$$\{\mathcal{D}_1^*, \mathcal{D}_2^*, \dots, \mathcal{D}_\Psi^*\} = \underset{\substack{M \\ \{(x_m^R, y_m^R)\}_{m=1}^M \\ \{\phi(m)\}_{m=1}^M}}{\arg\min} \left\{ \sum_{i=1}^N \mathbb{I}\left(\sum_{m=1}^M x_{i,m} = 0 \right), \sum_{m=1}^M C(m) \right\}, \tag{3.4}$$

where the output is a family of Ψ network deployments differently balancing coverage and cost. This family will serve as a decision substrate for the operations commander to *a posteriori* span or reduce the initially deployed network in light of the severity of the disaster.

3.2   Description of the Proposed Hybrid Heuristic Algorithm

As previously introduced in Chapter 1, the MDRDP formulated above will be efficiently tackled by means of a novel hybrid heuristic scheme based on the combination of two algorithms: the Harmony Search algorithm on which the algorithmic core of the overall Thesis is rooted; and a modified approach of the K-means clustering algorithm. On the one hand HS is the responsible, as a global search scheme, for determining the optimum number of relays to be deployed by resorting to a variable-length solution encoding strategy, as well as their respective types $\{\phi(m)\}_{m=1}^{M}$ and coordinates $\{(x_m^R, y_m^R)\}_{m=1}^{M}$. Due to the complexity of the three-dimensional problem defined in Section 3.1, the HS global search (explorative) strategy is hybridized with a modified version of the K-means algorithm, which takes as inputs the potential solutions produced by the HS, and refines only the set of coordinates contained therein.

3.2.1   Proposed Global Search Algorithm

As mentioned before, the HS algorithm will be adopted as the global search approach that iteratively estimates the number, type and position of the set of relays to be deployed. Chapter 2 has previously introduced the foundations of this meta-heuristic solver, which deals with a set of Ψ candidate solutions or harmonies (Harmony Memory or HM) that are processed through a set of stochastically-driven operators. The resulting refined harmonies or solutions are evaluated at each iteration by means of the fitness function defining the optimization problem at hand.

In the proposed scheme, two different harmony memories are kept during the iterative process: the first contains the iteratively refined coordinates of the relays, whereas the second represents their respective models. Both memories are of the same size $\Psi \times M(\psi)$ (i.e. $M(\psi)$ varies from harmony to harmony) and their harmonies are associated note by note, i.e. each note of one memory is linked to the note located at the same position in the other memory. It is important to notice that the solution space associated to coordinates and models are both of different cardinality (continuous alphabet for the locations, and discrete alphabet for the relay model). Therefore, the improvisation operators applied to each HM are different, and will be remarked by subscripts ^{M} (models) and ^{C} (coordinates).

At the first iteration, both memories are initialized with 1) random number of relays $M(\psi)$ uniformly from the set $\{M_{min}, \ldots, M_{max}\}$; and 2) values picked uniformly at random from their respective alphabets. Based on the description of HS detailed in Chapter 2, the HS improvisation operators are ruled by three probabilistic parameters:

- *Harmony Memory Considering Rate*: $\mathrm{HMCR}^M, \mathrm{HMCR}^C \in \mathbb{R}[0,1]$, which sets the probability that the newly improvised value for a given note is taken from the values of this same note in all the other $\Psi - 1$ harmonies existing in the considered Harmony Memory. Since the number of notes $M(\psi)$ for a given $\psi \in \{1, \ldots, \Psi\}$ depends on ψ, this operator may involve,

besides the refinement of the coordinates/models, the deletion or addition of relays in the corresponding memories (hence, $M(\psi)$ is affected).

- *Pitch Adjusting Rate*: $\text{PAR}^M, \text{PAR}^C \in \mathbb{R}[0, 1]$ establish the probability that, for a given note, a fine adjustment of its value is applied based on the neighboring values of its corresponding alphabet. Due to the aforementioned differences between alphabets of the two constituent harmony memories, different neighborhood definitions are considered. In the case of coordinates (continuous alphabet), and by denoting the new improvised coordinate for relay m in harmony ψ as $\left(x_m^{R,\diamond}(\psi), y_m^{R,\diamond}(\psi)\right)$, the operational procedure of PAR^C is given by

$$\left(x_m^{R,\diamond}(\psi), y_m^{R,\diamond}(\psi)\right) = \begin{cases} \left(x_m^R(\psi), y_m^R(\psi)\right) + \mathbf{z}_\beta & \text{with probability } \text{PAR}^C, \\ \left(x_m^R(\psi), y_m^R(\psi)\right) & \text{with probability } 1 - \text{PAR}^C, \end{cases}$$

where $\mathbf{z}_\beta$ is the vector realization of a two-dimensional uniform random variable Z_β with continuous support in the range $[-\beta, \beta] \times [-\beta, \beta]$, with $\beta \in \mathbb{R}^+$ standing for the pitch adjustment bandwidth. On the other hand, considering the discrete alphabet for the harmony memory containing the estimated models, PAR^M defines the probability that the new value is taken from its closest neighbor discrete value in the model alphabet $\{1, \ldots, \tau\}$, where τ stands for the number of relay models considered.

- *Random Selection Rate*: $\text{RSR}^M, \text{RSR}^C \in \mathbb{R}[0, 1]$ pose the probability that a new value for a note will be selected uniformly at random from its corresponding alphabet. As opposed to PAR, no alphabet neighborhood considerations are taken in this operator.

These operators are sequentially applied to each note of every harmony included in both harmony memories. Once they have been applied over the entire set of notes, the newly produced harmonies are then passed to the local search procedure explained in the next subsection.

3.2.2 Proposed Local Search Algorithm

The local search procedure is applied once a new set of Ψ harmonies have been generated by applying the above set of operators, and aims at further refining the set of relay *position* estimates produced by the HS solver. This algorithm is basically a modification of the K-means algorithm, which is a widely-known clustering algorithm that minimizes the inter-cluster sum of squared distances between each point and its associated centroid.

Let $\{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$ denote the set of points[1] to be disclosed into $S \leq n$ sets. K-means works sequentially by assigning, one by one, each point $\mathbf{x}_i$ to one of the iteratively defined centroids with associated points $\{\mathbf{x}_s^C\}_{s=1}^S$. First, a user-specific value for the number of clusters S is set, and then their associated points $\{\mathbf{x}_s^C\}_{s=1}^S$ are randomly distributed over the considered region. At each iteration, one point $\mathbf{x}_i$ is added to each cluster. The cluster to which each point is assigned is the one with the closest mean of its constituent points. Once the point has been assigned, the mean value (centroid) of the augmented cluster is updated. The iterative process is repeated until all points $(\mathbf{x}_1, \ldots, \mathbf{x}_n)$ have been assigned to a cluster. The K-means algorithm can be regarded as a greedy strategy, and implies a semi-exhaustive search not considering any coverage constraints. For these reasons its nominal form is adapted to the problem at hand by modifying its iterative working procedure as follows:

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[1]Any dimensionality of the points holds.

- Initialize the number of centroids S and locations $\{\mathbf{x}_s^C\}_{s=1}^S$ with the information $M(\psi)$ and $\{(x_m^R(\psi), y_m^R(\psi))\}_{m=1}^{M(\psi)}$ coming from harmony $\psi \in \{1, \dots, \Psi\}$.

- Assign each of the set of points to be clustered $\{(x_i, y_i)\}_{i=1}^N$ (i.e. the coordinates of the emergency teams) to the closest point in the coordinate set $\{(x_m^R(\psi), y_m^R(\psi))\}_{m=1}^{M(\psi)}$, and recalculate the position of every relay once a new point has been assigned to it. The assignment and recalculation is done point by point, similarly to the original K-means algorithm. No coverage constraints are imposed at this step, since the global HS algorithm adjusts the best model (and hence, radius) for every relay in the solution at hand.

- Repeat this process until all points are assigned to a given centroid or until the distance between two relays falls below than the sum of their respective radius (i.e. their coverage radii start to overlap with each other).

By repeatedly applying the above modified K-means procedure to the whole set of newly produced harmonies, the exploitative behavior of the algorithm is favored with respect to its explorative nature, and thus the proposed hybrid scheme might prematurely converge to local optimal points. To avoid this, the proposed K-means local search approach is applied to a user-defined percent of the new Ψ harmonies included in the harmony memory. Besides, it is applied not at each iteration of the global iterative process, but only at some given iterations $\mathcal{I}_{\wp} \in \{1, \dots, I\}$, where I denotes the overall number of iterations of the proposed hybrid algorithm.

3.2.3 Extension to Bi-objective Optimization

As sketched in the introduction of this chapter, the single-objective formulation and the hybrid heuristic designed towards its efficient solving can be extended to a bi-objective approach where cost and coverage are considered as conflicting, separated optimization criteria. As a result and following Expression (3.4), the commander is supplied with a family of possible network deployments, each featuring a different balance between coverage and cost, on which to make subsequent decisions about the size, spread and resource allocation of the network deployment. Algorithmically speaking, this is accomplished by replacing the selection method of the hybrid technique – i.e. survival of those Ψ harmonies with lowest value of the sum metric in Expression (3.3) – with the ordered dual selection based on rank and crowding distance exposed in Chapter 2. As such, each current and improvised harmony is associated with a numerical rank equal to its non-dominance level (namely, 1 for the best non-dominated level, 2 for the next best level, and so forth). Once all fronts have been identified and ranked, a measure representing the sum of distances to the closest harmony along each metric establishes an ordering among the solutions belonging to a certain rank: harmonies with large crowding distance are preferred to solutions with small distance so as to span the overall metric space. Thus, the harmony memory is filled by selecting the best Ψ harmonies (considering first the ordering among the fronts and then the one among the harmonies).

3.3   Experiments and Results

In order to evaluate the performance of the proposed algorithms, several simulations have been run over a synthetic toy example and an emulated relay deployment based on statistical data

of the *Castilla La Mancha* region (center of Spain). First, it is important to remark that to the knowledge of the authors, no previous work in the related literature has addressed a similar problem formulation to the one posed in Expressions (3.3) and (3.4). Therefore, we compare the performance of the proposed method with that of:

A. Two different wrapping techniques operating around the K-means algorithm aimed at estimating the number of relays M (namely, X-means [206] and G-means [207]), along with a random selection of their models. Both of these wrappers resort to different distance-based scores of successively partitioned clustering models. On one hand, X-means relies on the Bayesian Information Criterion BIC($\cdot$) as a score to choose the best among a set of models $\{\Delta_1, \ldots, \Delta_J\}$ corresponding to clustering solutions with different values of M (i.e. $\{M_j\}_{j=1}^J$). This index approximates the posterior probabilities of the models given the positions of the nodes to be covered (namely, firefighting crew) by assuming that they are spherically Gaussian distributed, yielding

$$\text{BIC}(\Delta_j) \triangleq \text{LL}\left(\{\mathbf{p}_i\}_{i=1}^N\right) - \frac{p_j}{2} \cdot \log N, \tag{3.5}$$

where $\text{LL}\left(\{\mathbf{p}_i\}_{i=1}^N\right)$ denotes the log-likelihood of the data subject to the j-th clustering model Δ_j. In this formula, also known as the Schwarz criterion [208], p_j is the number of parameters in Δ_j computed as $p_j = 3 \cdot M_j$, which results from the sum of $M_j - 1$ class probabilities, $2M_j$ centroids coordinates and one variance estimate required for the computation of the aforementioned log-likelihood. Leaving aside further mathematical foundations of the BIC score (a thorough explanation can be found in [206]), the X-means algorithm starts with the lower bound of the range $[M_{min}, M_{max}]$, and adds up centroids in those regions where the aforementioned BIC criterion results to be minimum; in words, clusters whose distribution fits worst to spherical Gaussians are selected to split in two children clusters. This procedure is repeated until the effective number of clusters reaches M_{max}: the estimated number of clusters is then given by the value of M_j for the model Δ_j featuring the globally highest value of the BIC score.

On the other hand, G-means resorts to a similar constructive procedure where the Anderson-Darling statistic [209] is utilized to estimate the number of clusters based on the best scoring model. The main difference between both scores is that the BIC score used by X-means is formulated to maximize the likelihood for spherically-distributed data, which makes the overall clustering algorithm overestimate the number of true clusters in non-spherical data spaces. In both cases these schemes produce single network deployments to be compared to the single-objective approach of the proposed hybrid algorithm.

B. An exhaustive search over the τ^M possible relay-model combinations of the topology produced by the K-means algorithm for a given value of M. The coverage-cost value pair featured by each of such combinations can be compared to the proposed single-objective approach.

C. An exhaustive search over all possible relay-model combinations and values of M, i.e. with no a priori setting of the number of clusters. As for the previous scheme, comparisons with this method can be established with the bi-objective formulation of the proposed hybrid solver.

It is important to observe that for a given M, the overall complexity (measured in terms of the number of relay-model combinations) of the MDRDP grows exponentially with the number

of models τ; this dependence makes the problem particularly complex as the number of relays M increases. Also interesting is to remark that since the performance of K-means is strongly biased by its initialization, simulation results must be understood statistically. Therefore, all the compared algorithms will be run several independent times (*realizations*, hereafter denoted by ϖ) over a given scenario. The comparative study aims at demonstrating that the adoption of a heuristic procedure as a global search method, hybridized with the local greedy modified version of K-means algorithm, entails a suitable combination for dealing efficiently with the MDRDP.
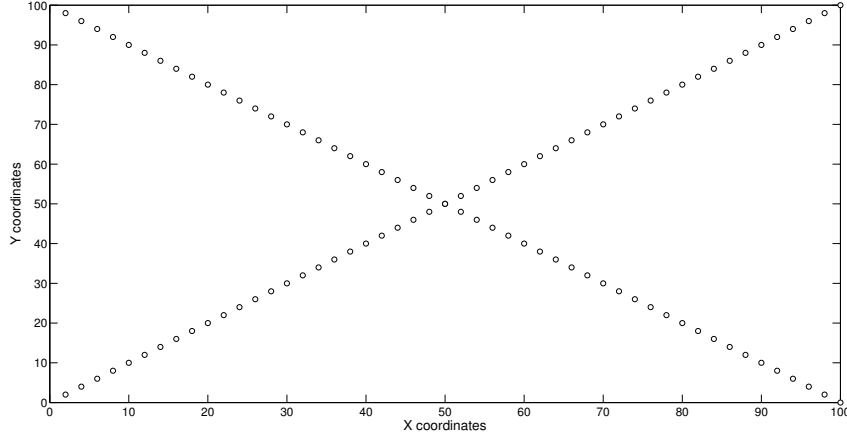
Figure 3.3: Synthetic scenario used to evaluate the performance of the proposed schemes. Circles represent the points to be covered.

In the first set of simulations, the synthetic tool scenario in Figure 3.3 is used. Although the setup is very simple, at the same time it becomes very easy to check visually the quality of the proposed solutions. In this scenario, $N = 100$ points representing emergency teams are distributed along the two diagonals of a 100×100 square area. Three ($\tau = 3$) different relay models $\{\Phi_t\}_{t=1}^{3}$ are considered with radii $\{R_t\}_{t=1}^{3} = \{7, 9, 11\}$ and costs $\{C_t\}_{t=1}^{3} = \{5, 8, 12\}$ (quantified in monetary units). The number of relays of the proposed scheme is initialized uniformly at random between $M_{min} = 10$ and $M_{max} = 50$. In the case of the approaches under category A, the models for the relays are selected randomly (again, uniformly) among the three different defined options. A harmony memory of $\Psi = 20$ harmonies is considered with the set of parameters specified in Table 3.1 obtained from a previous optimization study. During the iterative process (consisting of $I = 200$ iterations), the modified version of the K-means algorithm, described in subsection 3.2.2, is applied twice over the first 5 harmonies included in the harmony memory, at iterations $\mathcal{J}_{\wp} = \{20, 100\}$.

Table 3.1: Values of the HMCR, PAR, RSR and bandwidth β for relay models and coordinates, denoted with superscripts ^{M} and ^{C}, respectively.

$HMCR^{M}$	PAR^{M}	β^{M}	RSR^{M}
0.5	0.2	1	0.01
$HMCR^{C}$	PAR^{C}	β^{C}	RSR^{C}
0.7	0.1	10	0.01

The metric values averaged over $\varpi = 20$ different realizations of Algorithms A and the herein proposed solver are presented in Figure 3.4 and Table 3.2. Focusing first on the figure, the points

with circle ($\bigcirc$, $\bullet$) and square ($\square$) markers represent the metric value – Expression (3.3) – split in cost (horizontal axis) and coverage (vertical axis) obtained for each experiment. Note that the coverage provided by the X-means algorithm ($\square$) is, on average, higher than the one provided by the proposed hybrid heuristic scheme, but at a higher deployment cost. On the other hand, the [cost, coverage] pairs obtained by G-means ($\bigcirc$) concentrate on the low coverage region, as the Anderson-Darling normality test utilized therein for estimating the number of relays does not take into account any cost or coverage criteria. Neither does the Bayesian information criterion used in X-means, but the overestimated number of clusters by this approach allows attaining higher coverage values at a significant cost penalty. This can be also noticed by taking a closer look at the statistics of this Figure in Table 3.2, where the extreme values obtained with the three schemes in coverage (maximum) and cost (minimum) are reflected. In the coverage extreme point (maximum coverage of 98%) X-means requires a minimum total deployment cost of 153 monetary units, whereas for the cost extreme point (minimum cost of 94 monetary units) 78% of the emergency teams deployed is covered by the relays. On the other hand, the proposed hybrid algorithm balances between deployed resources and coverage, producing a maximum coverage of 88% at a considerably smaller cost (82 monetary units). Correspondingly, a minimum cost of 60 units corresponds to 65% of coverage. As anticipated earlier, G-means produces poor [coverage, cost] statistics.

Table 3.2: Statistical results provided by the proposed single-objective hybrid scheme and Algorithm A (X-means and G-means) in terms of coverage and cost (mean $\pm$ standard deviation) and extreme values for the synthetic scenario of Figure 3.3, assuming relay costs $\{C_t\}_{t=1}^3 = \{5, 8, 12\}$.

Method		Coverage (%)	Cost (m.u.)	Extreme values
Proposed Single-Objective		77 ± 6	82 ± 13	Max. cover.=88% (cost=91) Min. cost=60 (cover.=65%)
A	X-means	89 ± 6	120 ± 16	Max. cover.=98% (cost=153) Min. cost=94 (cover.=78%)
	G-means	13 ± 1	25 ± 6	Max. cover.=14% (cost=36) Min. cost=15 (cover.=10%)

When assessing the performance of Algorithm B in this synthetic scenario, one obtains $\varpi \cdot \tau^M$ pairs of [cost, coverage] values corresponding to each model combination, whose scatter plot for a given M is simplified by each of the convex hulls represented in Figure 3.4. The output of Algorithm C can be realized by merging all convex hulls for $M = 1, \ldots, M_{max}$. Notice that for this simple setting ($\tau = 3$, $M_{max} = 50$) the number of model combinations to be computed and evaluated by Algorithm C is $\varpi \sum_{m=1}^{50} \tau^m = 2.1537 \cdot 10^{25}$, which evinces the need for the bi-objective solver proposed in this chapter. The dominant Pareto front estimation produced by the proposed bi-objective approach is given in the same figure with triangular markers ($\triangle$), computed by using $I = 500$ iterations, $\varpi = 20$ realizations and a $\Psi = 50$-sized harmony memory. This amounts up to $I \times \Psi \times \varpi = 500 \cdot 10^3$ evaluations of model combinations, which are significantly less than those of algorithm C. As shown in the plot, the bi-objective approach of the proposed algorithm is able to produce a wide Pareto front estimation that can be utilized a posteriori to refine the network deployment once the disaster area has been explored. Relevantly, this estimated front dominates all solutions produced by its single-objective counterpart and Algorithms B and C, which adds to the reduced number of model combinations mentioned previously. As for Algorithm B (exhaustive search for a given M) the number of evaluated model combinations for the range $M \in \{10, 11, 12\}$ where the results of the proposed single-objective approach are located are $\varpi\tau^M = 1.181 \cdot 10^6$ ($M =$

10), $3.543 \cdot 10^6$ ($M = 11$) and $10.628 \cdot 10^6$ ($M = 12$), which are significantly higher than that of the single-objective algorithm ($\varpi \Psi I = 80 \cdot 10^3$), and are even dominated in some realizations by the proposed approach.

Figure 3.4: Scatter plot of the [cost,coverage] value pairs obtained by the algorithms under consideration over the synthetic scenario in Figure 3.4. Every convex hull determines the geometric space in the plane containing the [cost,coverage] points computed by Algorithm B for a given M (i.e. conventional K-means followed by exhaustive search over all possible model combinations). In the plot □, ○, ● and △ markers correspond to Algorithms A (X-means, G-means), and the proposed single- and bi-objective approaches, respectively.

In order to make the considered algorithms comparable in the extreme values of the coverage metric, the previous study is replicated by changing costs to $\{C_t\}_{t=1}^3 = \{2, 3, 4\}$ (the radii is kept unchanged). This relaxes the overall cost in the considered fitness, and enables the compared algorithms to achieve 100% coverage. Figure 3.5 shows that in this cost-relaxed case, the proposed single-objective hybrid scheme attains coverage levels close to 100%. Expectedly, when cost constraints are relaxed the coverage values achieved by X-means get closer to (but still lower than) those of the proposed scheme at similar cost values. As it is not driven by any cost criteria, G-means again underestimates the number of relays M and therefore, yields very low [cost, coverage] pairs in this second study.

The conclusions drawn in this cost-relaxed scenario and their joint interpretation with those from the first study demonstrate that the proposed single-objective algorithm is very useful if a trade-off between coverage and the number of relays is sought. This is an important aspect when an emergency network should be deployed in a scalable fashion, because if there exists a limited number of relays, an initial overestimation of resources in the early stages of the deployment may affect dramatically subsequent distributions. Thus, in the proposed scheme the relays' cost can be regarded as a trade-off factor which conservatively avoids the overestimation of the number and relay model to be deployed at early stages of the disaster. In other words: if the costs are kept higher then a smaller number of relays will be deployed, hence saving resources for a posterior deployment. Likewise, if the costs are reduced then potentially full coverage would be attained at the expense of incrementing the number of deployed relays. This is the rationale for proceeding,
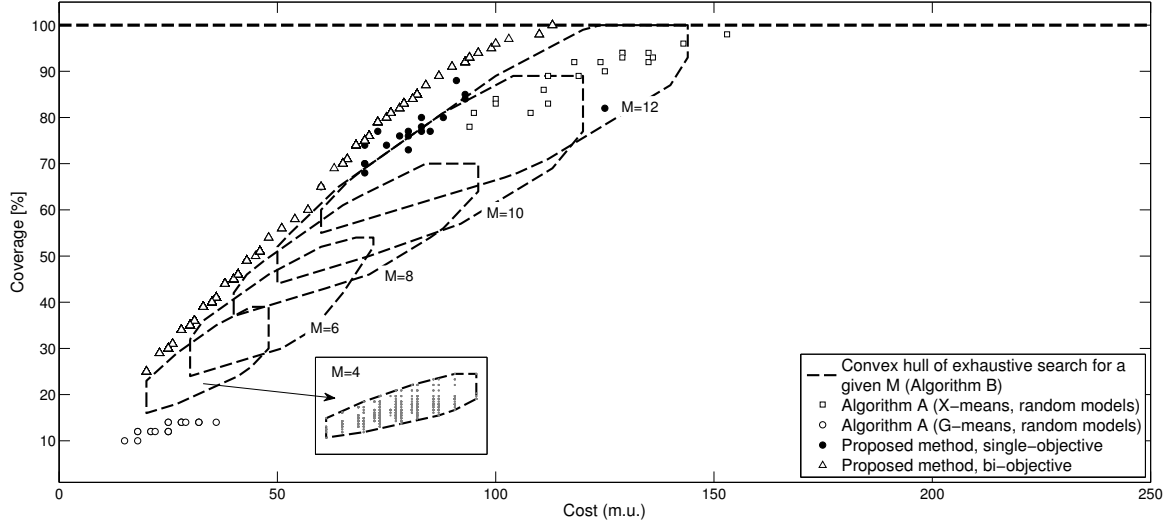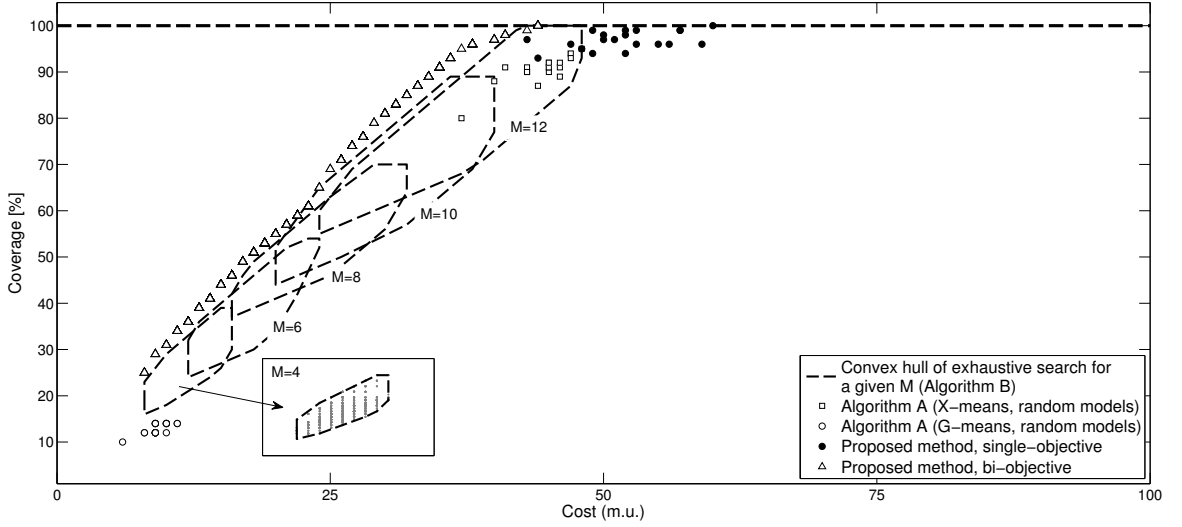
Figure 3.5: Scatter plot of the [cost,coverage] value pairs obtained by the algorithms under consideration over the same synthetic scenario in Figure 3.4, but at a reduced cost for the relay models.

once the disaster has been inspected, with a second network planning stage where the bi-objective version of the proposed hybrid scheme unfolds a whole portfolio of deployments featuring different cost-coverage trade-offs. As for the derived bi-objective solver similar conclusions hold in this cost-reduced setup: strict Pareto dominance over Algorithm C at a reduced number of model evaluations.

Table 3.3: Statistical results provided by the proposed single-objective hybrid scheme and Algorithms A (X-means and G-means) in terms of coverage and cost (mean ± standard deviation) and extreme values for the synthetic scenario of Figure 3.3, assuming relay costs $\{C_t\}_{t=1}^3 = \{2, 3, 4\}$.

Method		Coverage (%)	Cost (m.u.)	Extreme values
Proposed Single-Objective		97 ± 2	52 ± 5	Max. cover.=100% (cost=60)
				Min. cost=43 (cover.=97%)
A	X-means	90 ± 4	45 ± 3	Max. cover.=95% (cost=48)
				Min. cost=37 (cover.=80%)
	G-means	13 ± 1	9 ± 1	Max. cover.=14% (cost=12)
				Min. cost=6 (cover.=10%)

In the second set of simulations, an emulated, yet realistically-modeled massive forest wildfire scenario has been generated based on the fire risk data from the "Plan Especial de Emergencias de Incendios Forestales de Castilla La Mancha" [210] published by the regional Spanish Government of Castilla La Mancha (center of Spain). In this case $N = 200$ firefighter teams are deployed over the entire region based on this forest fire risk, imposing that more firefighters are located in regions where the forest fire risk is higher (red zones in Figure 3.6). Correspondingly, less firefighters will be assigned to (green) zones where the forest fire risk is lower. In this scenario, three different relay models have been considered with costs $\{C_t\}_{t=1}^3 = \{5, 8, 12\}$ monetary units, and radii $\{R_t\}_{t=1}^3 = \{8, 15, 21\}$ kilometers. As in the previous scenario, 20 different runs of the algorithm are carried out to obtain statistics on the obtained results based on the stochastic nature of the algorithms.

As first shown in Table 3.4, in this scenario the proposed single-objective hybrid scheme provides a mean coverage of $69 \pm 4\%$ with an associated cost of 97 ± 7 monetary units. On the other side, the mean coverage provided by X-means and G-means is clearly lower (30 ± 6 % and 15 ± 4 %, respectively), as a result of the fact that these schemes do not consider the limited coverage radii of relays when estimating M. As a result, a reduced number of relays is always deployed at a consequently low cost disregarding the available budget for the operations commander. The proposed hybrid schemes, however, are flexible enough to produce 1) well-balanced deployments for initial inspections of the disaster at hand (single-objective); and 2) a wide range of deployments that permit to find the maximum-covering deployment under cost constraints (bi-objective).
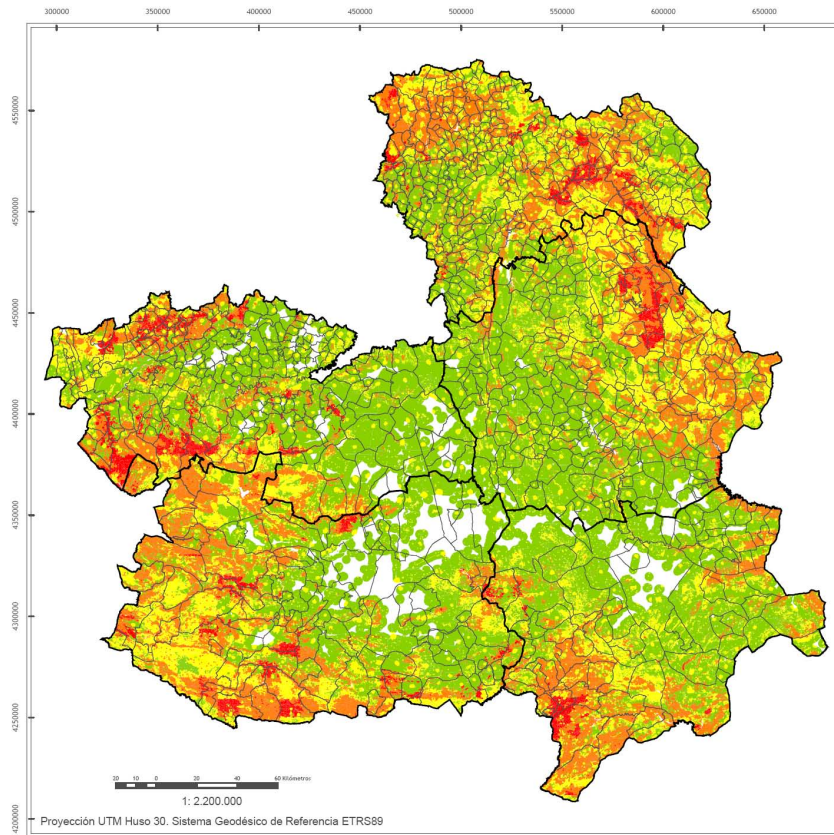
Figure 3.6: Fire risk map over the Castilla La Mancha region (center of Spain) extracted from [210].

Table 3.4: Statistical results provided by the proposed single-objective hybrid scheme and Algorithms A (X-means and G-means) in terms of coverage and cost (mean ± standard deviation) and extreme values for the emulated scenario of Figure 3.6, assuming relay costs $\{C_t\}_{t=1}^3 = \{5, 8, 12\}$.

Method		Coverage (%)	Cost (m.u.)	Extreme values
Proposed Single-Objective		69 ± 4	97 ± 7	Max. cover.=78% (cost=116) Min. cost=82 (cover.=61%)
A	X-means	30 ± 6	43 ± 6	Max. cover.=38% (cost=56) Min. cost=32 (cover.=20%)
	G-means	15 ± 4	33 ± 4	Max. cover.=20% (cost=40) Min. cost=23 (cover.=8%)

This remark is further complemented by Figures 3.7 and 3.8 (a) to (c), where a similar scatter plot to the ones analyzed for the synthetic case and realization examples of the network topologies produced by the proposed bi-objective solver are correspondingly depicted. For problems of higher dimensionality (i.e. higher M and/or τ) the performance of procedures based on the conventional K-means is expected to degrade further due to the fact that they can get trapped in local optima, fact that the hybrid schemes here proposed circumvent thanks to their incorporated HS-based global search procedure.
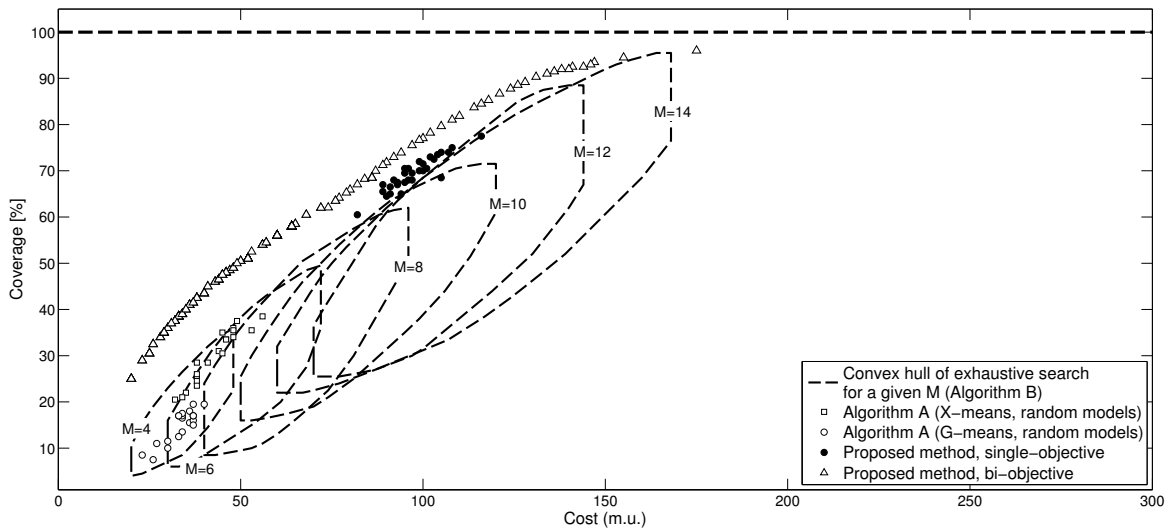
Figure 3.7: Scatter plot of the [cost,coverage] value pairs obtained by the algorithms under consideration over the emulated scenario in Figure 3.6.
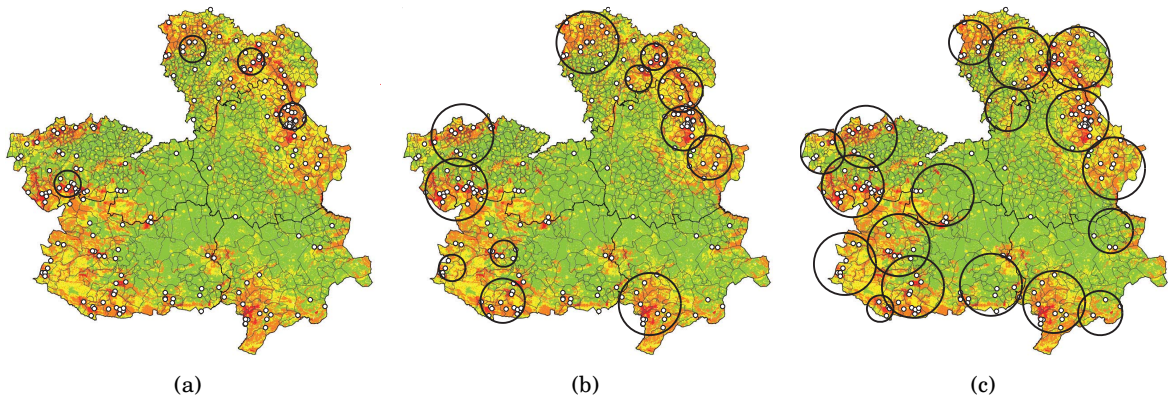
Figure 3.8: Examples of relay deployments featuring different [cost,coverage] ratios computed by the proposed bi-objective approach on the emulated scenario based on Figure 3.6. White circular markers denote firefighters, whereas black circles represent the coverage area of the deployed relays. These deployments correspond to (a) [coverage, cost]=[24.5%, 20 m.u.]; (b) [coverage, cost]=[74%, 96 m.u.]; (c) [coverage, cost]=[95%, 177 m.u.].

OPTIMAL PREDICTIVE DEPLOYMENT OF FIREFIGHTING AIRCRAFTS

"Human development is a form of chronological unfairness,
since late-comers are able to profit by the labors of their
predecessors without paying the same price."

- Alexander Herzen

So far the main motivational argument of this Thesis has been buttressed by many references and factual indicators evidencing that many regions around the world have undergone intensive and seasonally severe forest wildfire periods during the last years. Wildfires may occur on every continent (except Antarctica), but they have been notably frequent in the southern part of Europe where, unfortunately, the intensity and spread of such wildfires has occasionally lead to casualties and extensive damages to civil infrastructures [212]. In this context, intensive efforts are being taken in the research community on novel advances that enhance the speed and effectiveness of prevention, detection and suppression techniques, in a technological attempt at minimizing the severity and frequency of wildfires (as done, for instance, in the EFFMIS [213] and FIRESENSE [214] European initiatives).

One of the most widely adopted fire combating strategies relies on the direct human intervention in the form of firefighting brigades, which have traditionally shown to be effective in small-to-moderate wildfires over areas with scarce vegetation density. However, fighting to extinguish wildfires may become deadly dangerous due to life-threatening hazards including disorientation, heat stress, fatigue, smoke and dust, as well as the risk of other injuries such as burns, cuts and scrapes. Other side dangers in human intervened fire suppressing campaigns include faults in communication facilities and issues in the logistics and operational procedures, as exemplified by the Australian Victorian bushfires in 2009 (where 173 people died and over 2000 homes and 3500 structures were destroyed due to fire ambush [215, 216]). This motivates the use of fire retardants and water dropped onto wildfires by planes and helicopters, by virtue of which the risk for human casualties is dramatically decreased.

Similarly to the research presented in Chapter 3, of particular interest for the scope of this chapter is the natural wildfire happened in Guadalajara (Spain) in July 2005, where 11 fire-fighters died due to a confessed lack of effectiveness in the timing and deployment of the necessary aerial firefighting vehicles [217]. From the operational perspective, the preventive emergency deployment of fire combating fleets over aerodromes happens to be in general uncoordinated with

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respect to well-known and accurate predictive numerical methodologies for assessing the fire risk of a certain geographical area. Such quantitative forecasts may rely on different information sources that ultimately allow for diverse prediction horizons. For instance, the so-called Social and Infrastructure Flood Vulnerability Index (SIFVI, [218]) focuses on flood disasters at a county level in Germany to quantitatively assess the social vulnerability associated to this particular class of fatalities. This index has been developed by selecting and aggregating demographic statistical data; therefore, it can be regarded as a stable risk indicator based on which long-term strategic decisions on the geographical allocation of firefighting resources can be made. Many other indicators of similar stability can be found such as the Earthquake Disaster Risk Index (EDRI [219]), the social vulnerability index for hurricane-induced storm surges [220] or the index to evaluate socio-economic vulnerability to drought exposed in the Mediterranean Drought Preparedness and Mitigation Planning [221], among many others.

However, when the utility of any computed indicator is intended to aim at optimizing the effectiveness of preventive deployment strategies for firefighting resources, it becomes of utmost importance to capitalize any predictive method quantifying the fire risk in a shorter term. The spontaneous and particularly fast evolving characteristics of this class of disasters usually requires more dynamic resource allocation policies, far beyond strategic decisions guided by steady information such as demographic statistics, the location of urban areas and forest vegetation. To this end, this chapter proposes to exploit the short-term accurate predictability of atmospheric phenomena as a risk-based guiding criteria for the preventive deployment of firefighting vehicles. Indeed, weather information is known to play a central role in the probability of occurrence of wildfires: for instance, fire potential can be measured by the Keetch-Byram Drought Index (KBDI [222]), which is determined by daily maximum temperature and precipitation. Evapotranspiration – soil water transfer to the atmosphere – is determined by temperature and annual precipitation, which is used in this index as a surrogate model for estimating the vegetation cover (areas with higher annual rainfall are assumed to support more vegetation). Another index based exclusively in weather-related parameters is the FWI (Fire forest Weather Index [223]), which is exemplified in Figure 4.1 for the Spanish Peninsula and further detailed in Appendix A. In short, the FWI quantifies, in a user-defined scale, the fire risk of a certain geographical coordinate based on the temperature, relative humidity, wind speed, and 24-hour accumulated precipitation, whose influence in the fire ignition, intensity and durability of different forest soil layers is estimated and aggregated through a series of regressed models. The accurateness and fine granularity of current weather models yield an equally good predictability of the fire potential for a given area by virtue of the exclusively meteorological input information to indexes like the ones above.

Such weather indexes theoretically indicate solely the probability of fire ignition of a geographical point, but their computation also produces information about the virulence or severity of an eventual fire. Indeed the computation of the FWI system relies on the intermediate estimation of the Initial Spread Index (ISI) and the Build Up Index (BUI), which indicate the rate of fire spread immediately after ignition and the total amount of fuel available for consumption, respectively. This rationale supports the hypothesis that a tool capable of dynamically matching the deployment of aerial firefighting fleets (helicopters and air-tankers) with the risk predictions offered by national weather services would eventually entail an improved speed and effectiveness when dealing with massive wildfires, as well as reduce the number of casualties due to the minimum human intervention necessitated in land. This chapter addresses this need by elaborating on the formulation of an optimization problem with cost constraints that blends together predictive fire weather risk quantification and operational fleet deployment over available aerodromes.

In its simplest form, the derived formulation takes into account the amount of aerial vehicles, the number and position of existing aerodromes, available operational budget and the predicted fire weather risk metrics of the area under study, based on which a fitness function assessing the utility of a fleet deployment with respect to all the geographical coordinates with predicted risk is described and maximized. To the knowledge of the author of this Thesis, this operational logistics field has not been so far tackled from an analytical, formal standpoint, nor even under this simplistic approach.

In order to lessen the computational complexity incurred when solving the aforementioned problem in a nation-wide scale, the HS meta-heuristic solver will be utilized to trade optimality of the produced solutions for a lessened complexity required for the resolution of the formulated problem. Specifically, the designed evolutionary approach incorporates a solution encoding strategy representing the airport to which each aerial firefighting vehicle is assigned. Besides, an iterative greedy local method is designed to repair those solutions not fulfilling with imposed capacity constraints at every aerodrome, which model practical situations where the dimensions of hangars, the use of the airport facilities for other duties (e.g. commercial flights) or budgetary limitations restrict the number of firefighting aircrafts deployable therein.
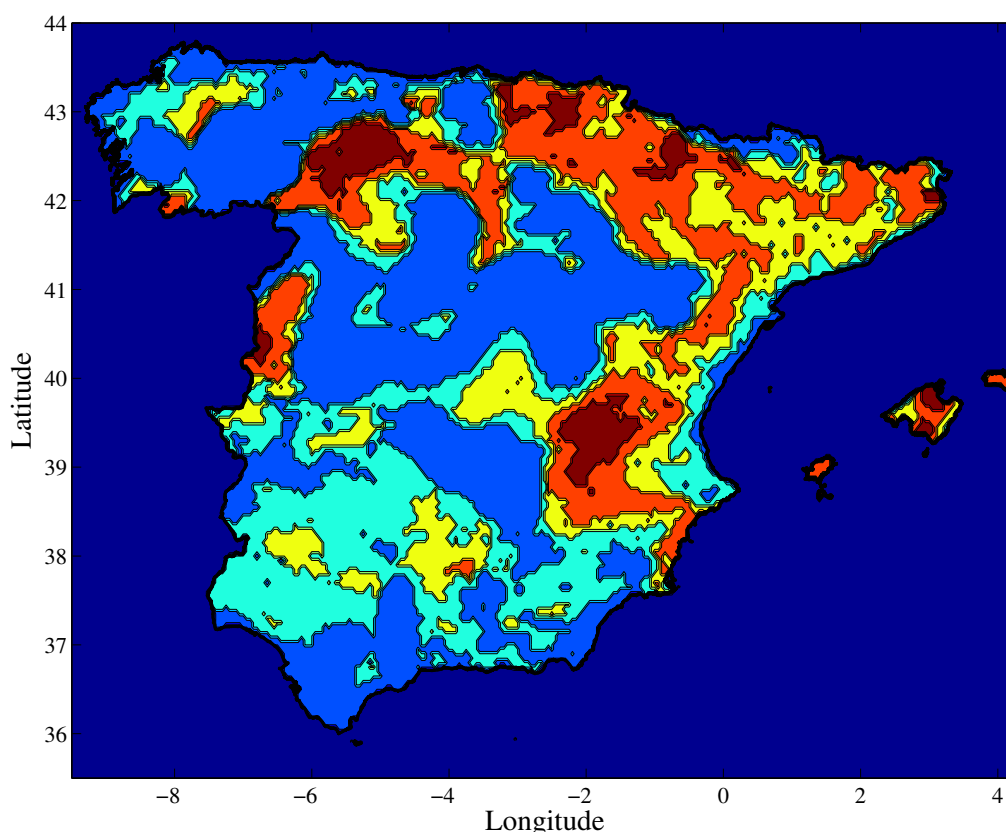
Figure 4.1: FWI for the Spanish mainland and Balearic Islands, corresponding to July 26th, 2012. Dark red colored regions delimit those areas featuring a higher wildfire risk, whereas dark blue denotes null probability of fire ignition (France and Portugal are not taken into account in the computation).

Once the satisfactory performance and scalability of the proposed optimizer have been verified over a number of synthetic scenarios, the chapter proceeds by extending this first simplistic pro-

blem formulation by incorporating realistic factors impacting on the firefighting potential of the deployment strategy: heterogeneous aircraft models and airports, the relative position of water resources with respect to any given wildfire, and cost implications derived from the consumption of fuel in the reallocation of aircrafts from one aerodrome to another and utilization fees imposed by commercial airports and regional authorities. The resulting extended problem models are approached via multi-objective heuristics grounding on an HS algorithmic core, which produces a set of different reallocation strategies differently balancing fire combating potentiality and the economical cost associated to the preventive reassignment of aircrafts to aerodromes. Numerical experiments will be performed using real FWI estimations computed over the Spanish mainland and the Balearic Islands, as well as technical specifications of the aircraft fleet operated by the Ministry of Agriculture, Nutrition and Environment (*Ministerio de Agricultura, Alimentación y Medio Ambiente*). The Pareto trade-off between cost and fire combating potentiality traced by the deployments produced by the algorithm evinces the practical applicability of the proposed suite of algorithms to real strategic decision making in the region- and nation-wide management of firefighting vehicles and aircrafts.

The chapter is structured as follows: first the reader is introduced to the system model and its corresponding notation in Section 4.1, which is done in the context of the simplistic approach to the problem mentioned above. Next, Sections 4.2 delves into the description of the proposed HS heuristic, addressing the solution encoding, searching operators and the greedy repair procedure for handling the capacity constraints. After validating the performance of the meta-heuristic solver in a set of synthetic scenarios, Sections 4.3 and 4.4 elaborate on two incremental extensions of the simplistic problem formulation and their algorithmic implications in the design of the designed reallocation method.

4.1   A Simplistic Problem Formulation

The system model under consideration is depicted in Figure 4.2, where M airport facilities are deployed over a certain area $A \subset \mathbb{R}^2$, with locations $\{\mathbf{p}_m\}_{m=1}^M$ assumed to be known a priori for the operations commander. The same assumption holds for the number N of firefighting aircrafts, where a function $\lambda : \{1,\ldots,N\} \mapsto \{1,\ldots,M\}$ denotes the assignment of every aircraft $n \in \{1,\ldots,N\}$ to an airport $m \in \{1,\ldots,M\}$. However, the location of the aircrafts is not fixed and can hence be selected according to a criteria which, as anticipated in the introduction of this Chapter, depends on predictive indicators of the fire risk associated to the area at hand. Without loss of generality the FWI index is hereafter adopted, which is computed over a number Z of points arranged on a square lattice grid over A. Therefore, FWI_z will stand for the FWI value associated to point z belonging to the aforementioned grid. The aircraft capacity $B(m)$ will be measured in terms of allocatable aircraft slots – a total of $B(m)$ aircrafts can be assigned to airport m – and may vary between different aerodromes, but for any given aerodrome $B(m)$ falls within the integer range $[0,N]$. This capacity per airport reflects the maximum operational budget assigned to each aerodrome to cover maintenance, fuel distribution and facilities for the pilots in charge for the firefighting fleet. For the sake of feasibility of the problem, it is assumed that $\sum_{m=1}^M B(m) \leq N$, i.e. there are enough aircraft slots to accommodate the N aircrafts to be allotted. Besides, each aircraft is characterized by an coverage radius $R(n)$ equal to half its range with maximum fuel, which reflects its finite fuel autonomy and restricts the number of grid points it could eventually support if an eventual wildfire initiated therein.

In this first formulation of the problem the utility function of each aircraft with respect to every single point z of the risk grid is assumed to depend exclusively on the Euclidean distance $d_{m,z}$ from the assigned aerodrome m to the point itself. This being said, it is important to point out that the fire risk FWI_z should be considered pivotal when quantifying the potential fitness of the position assigned to a certain aircraft with respect to the grid point at hand. Intuitively, the higher the fire risk at z is, the closer the aircraft should be to z, with more emphasis if a higher risk comes along with an expectedly increased severity of the wildfire upon its occurrence. Consequently, a crucial conclusion stems from this reasoning: the fitness criterion to be optimized should be an increasing function of the fire risk in range for every aircraft, as well as a decreasing function of the distance $d_{m,z}$ from the airport where the aircraft is deployed to the point z at hand. Operationally speaking, setting this relative dependence on distance and risk ensures that aircrafts are assigned to those airport sites where they could eventually contribute *better* (faster, as the distance is minimized) to extinction duties of fire events of potentially higher severity.

This being said, the combinatorial optimization problem under study can be summarized as to maximize the aggregate fire risk covered by the allocated aircrafts subject to resource and budget constraints, which can be mathematically cast as follows:

$$\underset{\lambda(1),\ldots,\lambda(N)}{\text{Maximize}} \quad \sum_{n=1}^{N}\left(\sum_{z=1}^{Z}\text{FWI}_z \cdot J(d_{\lambda(n),z})\right), \tag{4.1}$$

$$\text{subject to} \quad \sum_{m=1}^{M}\left|\lambda^{-1}(m)\right| = N, \tag{4.2}$$

$$\left|\lambda^{-1}(m)\right| \leq B(m) \quad \forall m = 1,\ldots,M, \tag{4.3}$$

where $\lambda(n)$ denotes the airport to which aircraft n is assigned; $\lambda^{-1}: \{1,\ldots,M\} \mapsto \mathcal{N} \subseteq \{1,\ldots,N\}$ denotes its inverse function indicating the subset of aircrafts assigned to a given aerodrome; $|\cdot|$ returns cardinality of the argument set; and $J(d_{m,z})$ stands for a strictly decreasing function accounting for the utility of an aircraft deployed on airdrome m with respect to a given point z at a distance $d_{m,z}$ ($J(d_{m,z}) = 0 \ \forall d_{m,z} > R(n)$, where $R(n)$ denotes the coverage radius of aircraft n that fulfills $\lambda(n) = m$).

The optimization variable of this problem is the assignment function $\lambda(\cdot)$ that maps aircrafts to aerodromes. However, in this initial formulation all such aircrafts will be assumed to be equal to each other, which entails $R(n) = R$ and enables the chance to reformulate the problem by using the *number* of aircrafts θ_m assigned to aerodrome m as the decision variable. This results in

$$\underset{\theta_1,\ldots,\theta_M}{\text{Maximize}} \quad \sum_{z=1}^{Z}\text{FWI}_z \cdot \left(\sum_{m=1}^{M}\theta_m \cdot J(d_{m,z})\right), \tag{4.4}$$

$$\text{subject to} \quad \sum_{m=1}^{M}\theta_m = N, \tag{4.5}$$

$$\theta_m \leq B(m) \quad \forall m = 1,\ldots,M. \tag{4.6}$$

which can be regarded as an equivalent – yet more restricted – problem formulation featuring a better readability of the constraints than the above formulation. Nevertheless, as shown throughout the following sections the consideration of the aircraft-to-aerodrome assignment vector $\{\lambda(1),\ldots,\lambda(N)\}$ as the solution encoding approach allows generalizing the proposed metaheuristic to extensions of this scenarios in a more straightforward manner.
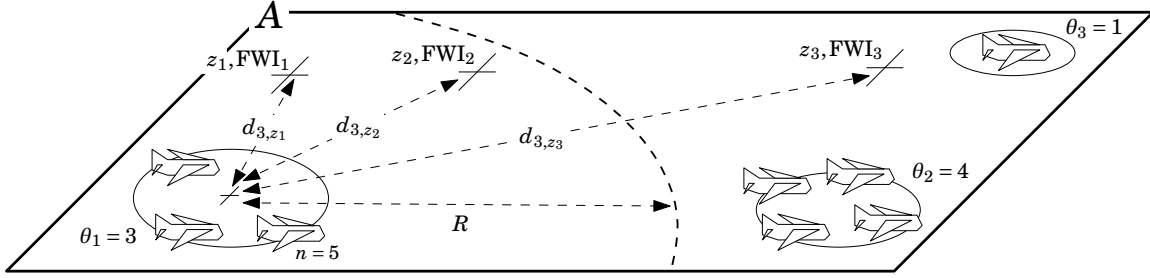
Figure 4.2: Example of the considered scenario for $M = 3$ airport facilities and $N = 8$ aircrafts. In the plot three different grid points are highlighted: z_1 and z_2, which are in range of the aircrafts deployed in aerodrome $m = 1$ and which may contribute to the fitness depending on the values of their FWI indicators; and z_3, which is beyond the coverage radius of such aircrafts and does not contribute to the fitness at all disregarding its FWI value.

4.2 Proposed Meta-heuristic Allocation Algorithm

The heuristic utilized for efficiently solving this optimization problem grounds on the HS algorithm [14], which is combined with a greedy method to account for the capacity/budgetary constraints in Expression (4.6) and equivalently, (4.3). As detailed previously in Section 2.4 of Chapter 2, the algorithm operates on a set of Ψ candidate vectors or harmonies representing candidate solutions or harmonies, which are iteratively refined by successive applications of HS and the aforementioned greedy procedure, and evaluated so as to select and filter the *worst* harmonies out from the Ψ-sized population according to the metric in Expression (4.4). The solution encoding for the evolutionary process is set to be $\{\lambda(1), \ldots, \lambda(N)\}$, i.e. the vector of N integer variables corresponding to each aircraft, whose value indicates the aerodrome to which the aircraft at hand is assigned. A slight notation abuse permits to denote the ψ-th solution within the memory of harmonies as $\{\lambda(\psi, 1), \ldots, \lambda(\psi, N)\}$. It is important to note that this encoding implicitly makes the iteratively produced solutions meet the resource constraint in Expressions (4.5) and (4.2). Therefore, the greedy algorithm is used to repair the solutions that do not comply with the capacity/budget constraints, whereas the HS plays the role of a *global* search procedure driven by its constituent improvisation operators, namely:

- The Harmony Memory Considering Rate operates as in its nominal definition, i.e. by setting the probability HMCR $\in [0, 1]$ that the new value for a certain note $\lambda(\psi, n)$ is drawn uniformly from the values of this same note in all the remaining melodies. Formally,

$$\text{HMCR} \triangleq Pr\left\{\lambda(\psi, n) \rightsquigarrow \omega_{\text{HMCR}}\right\}, \tag{4.7}$$

where ω_{HMCR} is a discrete random variable uniformly distributed in

$$\left\{\lambda(1, n), \ldots, \lambda(\psi - 1, n), \lambda(\psi + 1, n), \ldots, \lambda(\Psi, n)\right\}.$$

This operator works in a per note basis through $k \in \{1, \ldots, K\}$ and $\psi \in \{1, \ldots, \Psi\}$ by properly varying the alphabet over which the values of ω_{HMCR} are drawn.

- The Pitch Adjusting Rate is identical to its naïve form in regards to its basic working procedure: it sets the probability PAR $\in [0, 1]$ that the new value for $\lambda(\psi, n)$ is given by a random perturbation centered on its value. Since the support of the constituent decision variables

is discrete, the random perturbation reduces to the change of the note at hand by any of its neighboring values with equal probability. However, a subtle, yet relevant change is done at this point: the vicinity relationship criterion for a given value of $\lambda(\psi, n)$ (namely, the airport to which aircraft n is assigned within the ψ-th solution produced by HS) is given by the indexes of the rest of airports sorted in increasing order of their distance to the $\lambda(\psi, n)$-th aerodrome. Furthermore it is permitted that the PAR operates over a wider (> 2) range of neighboring airports in order to attain higher levels of explorative randomization and dismiss the need for any further diversifying operators (e.g. RSR).

During the evolutionary process, aircrafts are assigned to aerodromes in a directed yet random fashion, which may go against the imposed maximum budget constraints $\{B(m)\}_{m=1}^{M}$. Assuming that all aircraft models and their associated operational costs are equal, it does not matter which aircraft is assigned to which aerodrome, but it all depends on the amount of aircrafts assigned to each aerodrome. Based on this rationale, budget constraint $B(m)$ establishes how many aircrafts could eventually be assigned to aerodrome m. If any airport happens to be over its capacity, the first aircraft assigned to this aerodrome is swapped to the nearest airport whose occupancy (i.e. number of assigned aircrafts) falls below its capacity.
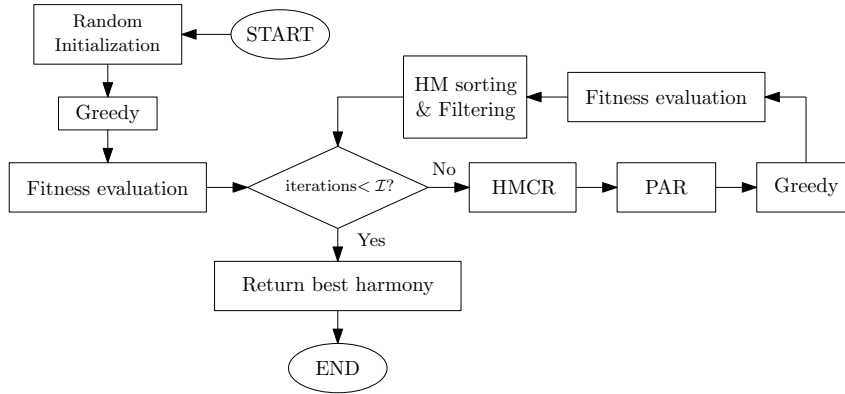
Figure 4.3: Diagram flow of the proposed meta-heuristic allocation process for the simplistic scenario.

The overall flow diagram of the algorithm is depicted in Figure 4.3: first the whole harmony memory is randomly filled with values drawn from $\{1, \ldots, M\}$ without considering, at this moment, any capacity constraints. Next the greedy repair method is executed by going through the airport indexes $m \in \{1, \ldots, M\}$ and checking whether the inequality constraint in Expression (4.3) is met. If positive, the verification process proceeds with the next value of m. If negative, the rest of airports $\{1, \ldots, m-1, m+1, \ldots, M\}$ are ordered increasingly with respect to their distance to airport m, and the aircrafts in excess assigned to airport m are reallocated to those airports with enough space subject to the distance-based ordering criterion previously performed. Once this has been made, the search procedure iterates similarly to the nominal HS algorithm in Section 2.4, except for the inclusion of the greedy method right after the improvisation stage.

4.2.1   Numerical Experiments for the Simplistic Scenario

In order to assess the performance of the proposed heuristic solver, different synthetically generated scenarios have been arranged over a 500×500 rectangular area A, built on combinations

of the number of aircrafts (N) and aerodromes (M) jointly with 5 different risk estimation maps composed by distinct values for $\{FWI_z\}_{z=1}^{Z}$. The objective is to lay a sufficiently diverse simulation benchmark from where to extract well-reasoned generalized conclusions on the performance and scalability of the proposed algorithm. To this end, simulation scenarios will be denoted by $[N, M, R]$, where R indexes the risk estimation grid under consideration: namely, $\{[4, 9, r]\}_{r=1}^{5}$, $\{[7, 16, r]\}_{r=1}^{5}$, $\{[10, 25, r]\}_{r=1}^{5}$, $\{[13, 36, r]\}_{r=1}^{5}$ and $\{[16, 49, r]\}_{r=1}^{5}$. Statistics (minimum, maximum, standard deviation, mean) of the value of the best fitness after 150 iterations of the solver are computed over 20 independent runs over each of such scenarios. In particular, the value obtained for the fitness standard deviation will shed light on the stability of the algorithm as the scales of the underlying optimization problem increase. Regarding the budget constraint $B(m)$ per airport, all have been assigned the same budget without loss of generality. Considering that the cost per aircraft is also assumed to be constant, the maximum number of aircrafts per airport is $B(m) = 3$ for all the scenarios. Based on a previous simulative optimization stage, the parameters controlling the HS solver are set to HMCR = 0.5, PAR = 0.05 and $\Psi = 25$ for all the simulated scenarios. As for function $J(d_{m,z})$, it is assumed to decrease linearly from the center to the boundary of a circular coverage area with radius $R = 100$.

$[N, M, R]$	Minimum	Maximum	Standard Deviation	Mean
$[4, 9, 1]$	2613.60	2613.60	$4.6656 \cdot 10^{-13}$	2613.60
$[4, 9, 2]$	3112.10	3112.10	$9.3312 \cdot 10^{-13}$	3112.10
$[4, 9, 3]$	3928.40	3928.40	$1.8662 \cdot 10^{-12}$	3928.40
$[4, 9, 4]$	3615.20	3615.20	$1.3997 \cdot 10^{-12}$	3615.20
$[4, 9, 5]$	4220.50	4220.50	0.00	4220.50
$[7, 16, 1]$	4535.90	4535.90	$1.8662 \cdot 10^{-12}$	4535.90
$[7, 16, 2]$	6401.90	6642.30	53.75	6630.30
$[7, 16, 3]$	7663.20	7748.50	19.07	7744.20
$[7, 16, 4]$	7166.90	7185.20	5.36	7182.00
$[7, 16, 5]$	7688.50	7709.20	4.62	7708.20
$[10, 25, 1]$	6970.60	7042.50	22.41	7.027.40
$[10, 25, 2]$	8006.70	8059.70	23.18	8.041.20
$[10, 25, 3]$	9639.50	9668.60	6.52	9.667.20
$[10, 25, 4]$	9356.50	9400.00	15.37	9.391.00
$[10, 25, 5]$	11447.00	11447.00	$3.7325 \cdot 10^{-12}$	11447.00
$[13, 36, 1]$	9731.50	9736.50	1.47	9734.90
$[13, 36, 2]$	10461.00	10506.00	15.62	10493.00
$[13, 36, 3]$	13255.00	13646,00	116.79	13559.00
$[13, 36, 4]$	13171,00	13360,00	49.25	13329.00
$[13, 36, 5]$	14974,00	14987,00	3.73	14985.00
$[16, 49, 1]$	11762.00	11967.00	46.28	11943.00
$[16, 49, 2]$	14173.00	14306.00	50.14	14250.00
$[16, 49, 3]$	17370.00	17460.00	25.08	17431.00
$[16, 49, 4]$	15772.00	16022.00	65.73	15972.00
$[16, 49, 5]$	17778.00	17953.00	64.24	17927.00

Table 4.1: Results' statistics computed over 20 runs of the algorithm for each scenario.

Having said this, the obtained statistics are summarized in Table 4.1. It can be observed that the proposed algorithm renders a very stable performance behaviour for the simulated scenarios of lowest dimensionality, showing a negligible (even null, in some instances) standard deviation

of the fitness over the executed 20 runs of the algorithm. Noteworthy is to mention that for the scenarios with highest dimensionality, the scale order of the resulting standard deviation is well below that of the average metric value, which further buttresses the conclusion that the HS-based solver results to be quite stable. Not shown for the sake of clarity in the explanation, it has been noted that in the easiest scenarios the results converge very quickly. The convergence speed slows down for the complex scenarios, but as mentioned before, the variance between the results in each run is negligible with respect to the obtained mean.
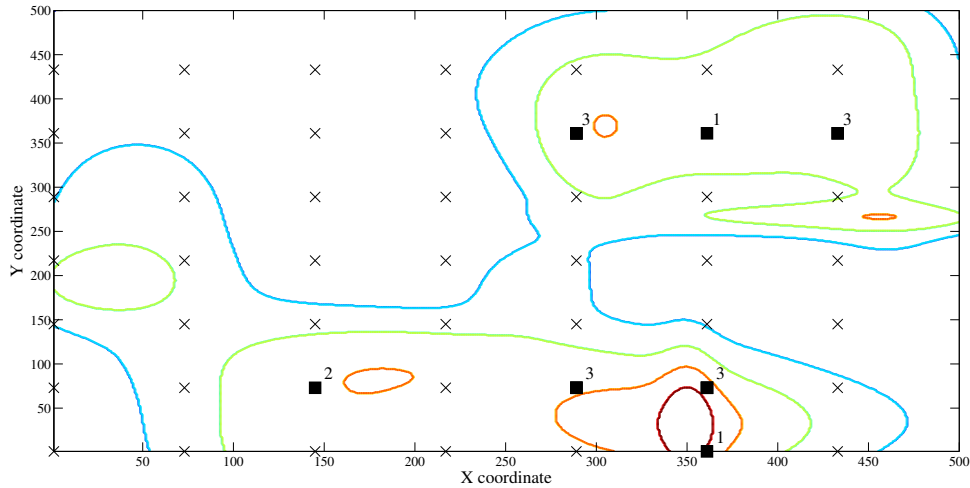
Figure 4.4: Assignment of aircrafts to aerodromes for a $[16, 49]$ risk estimation map.

Figure 4.4 exemplifies one of the produced solutions for the $[16, 49, 1]$ scenario, that is, the scenario consisting of $N = 16$ aircrafts and $M = 49$ aerodromes. The risk map is plotted as a two-dimensional contour map, where coloured lines indicate the boundaries between regions with different risk level, from red (boundary between $FWI_z = 5$ and $FWI_z = 4$) to orange ($FWI_z = 4$ and $FWI_z = 3$), green ($FWI_z = 3$ and $FWI_z = 2$) and blue ($FWI_z = 2$ and $FWI_z = 1$). Black crosses identify those points where aerodromes are located in the area, whereas airdromes with aircrafts assigned are surrounded with a circle along with a number denoting their number. As can be seen from the plot, the assignment is correctly realized: airports close to risk *peaks* are assigned more aircrafts, always respecting their budget-driven capacity constraints.

4.3   A Problem Extension: Reallocation and Cost

An explicit assumption within the formulation of the firstly studied problem is the consideration of a unique aircraft model. In practice, however, firefighting fleets are extremely heterogeneous, not only in regards to the type of apparatus (ranging from airtankers to single- or dual-turbine helicopters), but also between aircrafts of the same type. For instance, the AT-802 model manufactured by Air Tractor spans a whole family of variants of similar capacity specifications. As such, those versions specially designed for fire extinguishing assistance (namely, AT-802F/AF and the AT-802 "Fire Boss") can drop a similar amount of retardant (around 820 US Gallons or equivalently, 3104 litres [224]) over a given wildfire. However, the "Fire Boss" variant is equipped with amphibious floats and a computerized fire gate that allows recharging water in lakes and wide rivers. Further differences also arise between models in what relates to their autonomy (fuel tank

capacity and fuel consumption), as well as on the economical costs incurred by their operation and maintenance.

Following this reasoning, an interesting extension can be made by considering a portfolio of different aircraft models, each characterized by distinct values for their coverage radius and cost. This change reflects a more realistic scenario where aircrafts of different sizes and firefighting capabilities eventually coincide in the extinction of the same wildfire. Mathematically this extension requires the definition of a τ-sized coverage vector $\{R_1, R_2, \ldots, R_\tau\}$ and an equally dimensioned cost vector $\{C_1, C_2, \ldots, C_\tau\}$, where τ denotes the number of different models. By defining the mapping $\vartheta : \{1, \ldots, N\} \mapsto \{1, \ldots, \tau\}$, the model for aircraft n will be given by $\vartheta(n)$, being correspondingly its coverage radius and cost given by $R(n)$ and $C(n)$.

However, it is on the airport budget where this first extension of the problem becomes even more relevant: if different budgets $\{B(m)\}_{m=1}^{M}$ are assigned to the available airports, one could straightforwardly model the scenario where the ownership/management of the airport is not necessarily the same over all the existing facilities. For instance, civil airports can be thought of as incurring significant economical losses if part of their resources are redirected towards managing and assisting firefighting aircrafts, hence the value of their budgets $B(m)$ should be set low to reflect these losses. On the contrary, military aerodromes do not necessarily suffer from these high costs, as firefighting is among the duties for their troops and vehicles; therefore, the budget for firefighting operations should be made high enough to accommodate preventive logistics as the ones studied in this Chapter. By inserting different airport models the problem gets even more involved due to a solution space of finer granularity. In summary: the fleet of heterogeneous aircrafts should be deployed over the set of available airports by considering their budget as *hard* constraints to be met by their aggregated costs.

Before reformulating the problem, another interesting aspect arises when reallocating the aircrafts rather than assigning them to airports without any a priori consideration of their initial position (i.e. what has been assumed so far). When this is the case, the cost of reassigning a given aircraft must also include the fuel price paid by the operator to move a given aircraft from one airport to another. In other words, under this approach the reassignment between physically distant airports could be avoided by an eventual optimization solver due to the high associated costs of this operation. If one increases the admissible budget, the overall cost of the reassignment and in general, of the operation itself would be relaxed and hence permit long aircraft movements provided that the effectiveness of this preemptive logistic operation is high enough. Algorithmically this problem can be tackled by means of a bi-objective solver capable of estimating the dominant [cost,effectiveness] Pareto front, as this trade-off results to be crucial for a good, timely decision making by commanders.

Based on the above extensions, the reformulation of the problem must start by redefining the wildfire combating potential of a certain resource allocation strategy so as to accommodate the newly introduced aircraft model heterogeneity, which yields the distance and risk-dependent fitness function

$$\Upsilon(\lambda(1), \ldots, \lambda(N)) \triangleq \sum_{n=1}^{N} \left(\sum_{z=1}^{Z} \text{FWI}_z \cdot J(d_{\lambda(n),z}, \vartheta(n)) \right), \tag{4.8}$$

where it should be remarked that $\{\vartheta(1), \ldots, \vartheta(N)\}$ are fixed parameters that participate in the utility function but are not to be subsequently optimized. In other words, aircraft models are given as a priori static parameters for the optimization algorithm, similarly to the vector **S** of static variables used in Expression (1.1) of Chapter 1. On the other hand, $J(d_{\lambda(n),z}, \vartheta(n))$ abuses

notationally the former definition of $J(d_{\lambda(n),z})$ to stress on the aircraft dependency of the coverage radius $R(n)$, i.e. $J(d_{m,z}, t) = 0 \ \forall d_{m,z} > R_t$, where R_t denotes the coverage radius for model $t \in \{1, \dots, \tau\}$ and aircraft n fulfills $\lambda(n) = m$ and $\vartheta(n) = t$.

Different cost concepts are considered in the second objective function of the reformulated problem. To begin with, each aircraft model will be assumed to feature a distinct fuel consumption rate Q_t [litres per kilometer]. By denoting as $d^{ra}_{m,m'}$ the distance traveled by an aircraft that is reallocated from airport m to m', the cost of a given reallocation strategy due to fuel expenditure is given by

$$W_F(\lambda(1), \dots, \lambda(N), \vartheta(1), \dots, \vartheta(N)) \triangleq \sum_{n=1}^{N} Q_{\vartheta(n)} \cdot p_c \cdot d^{ra}_{\lambda_0(n), \lambda(n)}, \tag{4.9}$$

where $\lambda_0(n)$ stands for the initially assigned airport of aircraft n and p_c is the unitary price of a fuel litre. At this point it is important to point out that when the reallocation distance for aircraft n results to be higher than their maximum autonomy, i.e. when $d^{ra}_{\lambda_0(n), \lambda(n)} > 2R(n)$, a constant cost penalty ΔW_F is further added to the overall cost so as to emulate the costs associated to intermediate refueling stops. Other operational cost sources considered in this new problem formulation refer to 1) usage fees imposed by airport authorities when allocating aircrafts coming from other administrative regions; 2) economical compensations to the operators of commercial airports for the maintenance of the firefighting airplanes deployed in their facilities. Such other costs are given by

$$W_R(\lambda_0(1), \lambda(1), \dots, \lambda_0(N), \lambda(N)) \quad \text{and} \quad W_C(\lambda_0(1), \lambda(1), \dots, \lambda_0(N), \lambda(N)),$$

respectively; the former depends on the regional belonging of the geographical location of $\lambda_0(n)$ and $\lambda(n)$, whereas the latter will be nonzero whenever the aircraft n under consideration is reallocated from a military to a commercial airport.

With these definitions in mind, the optimization problem considering operational costs, potential firefighting utility and reallocation aspects is given by

$$\underset{\lambda(1), \dots, \lambda(n)}{\text{Maximize}} \quad \Upsilon(\lambda(1), \dots, \lambda(N)), \tag{4.10}$$

$$\underset{\lambda(1), \dots, \lambda(n)}{\text{Minimize}} \quad W_F(\lambda(1), \dots, \lambda(N)) + W_C(\lambda(1), \dots, \lambda(N)) + W_R(\lambda(1), \dots, \lambda(N)), \tag{4.11}$$

$$\text{subject to} \quad \sum_{m=1}^{M} |\lambda^{-1}(m)| = N, \tag{4.12}$$

$$\sum_{\substack{n=1 \\ \lambda(n)=m}}^{N} C(n) \leq B(m), \quad \forall m \in \{1, \dots, M\}, \tag{4.13}$$

i.e. as a bi-objective problem formulation whose Pareto set is built by cost-constrained aircraft deployments optimally balancing fire combating potentiality and operational cost based on the models of the aircrafts and their previous locations $\{\lambda_0(n)\}_{n=1}^{N}$.

Such Pareto front will be estimated by means of a similar HS meta-heuristic solver to the one proposed for the simplistic problem statement. However, the greedy algorithm must be modified so as to account for aircraft models rather than units. To this end, let m denote the index of a saturated airport in terms of budget, i.e. $\sum C(n) \ \forall n : \lambda(n) = m$ is higher than $B(m)$. In such a case, not any of such aircrafts is selected at random and reallocated to other nearby airport within its coverage radius, but the choice is driven by the cost $C(n)$ associated to them and its similarity to

the excess budget $\sum C(n) - B(m)$. Thereby, the aircraft n' whose associated cost $C(n')$ is closer to – yet higher than – the excess budget is chosen and reallocated to the closest airport with enough budgetary capacity to host it. If no such aircraft n exists due to all costs $C(n)$ falling below the excess budget $\sum C(n) - B(m)$, the procedure is repeated to reallocate as many aircrafts as required to fulfill the budgetary constraint. The same assumption hold in regards to the cost penalty ΔW_F for reallocation in an beyond the autonomy of the selected aircraft.

The bi-objective solver also differs from its single-objective counterpart in terms of the selection of the fittest candidate harmonies between iterations, which must be now done under Pareto optimality criteria. Therefore, the single-objective fitness sorting and harmony memory filtering method is replaced with the ordered dual selection based on rank and crowding distance exposed in Chapter 2 and used in the bi-objective algorithm in Chapter 3. Each newly improvised harmony $\{\lambda(\psi, 1), \ldots, \lambda(\psi, N)\}$ is assigned a numerical rank representing its Pareto dominance level (namely, 1 for the best non-dominated level, 2 for the next best level, and so forth). After identifying and scoring all fronts, the computation of the crowding distance establishes an ordering among solutions belonging to a given rank. The memory is then filled with the best Ψ harmonies considering dominance rank as the primary criteria and crowding distance as the secondary one.

4.3.1 Numerical Experiments for the Problem Extension

In order to shed light on the performance of the designed bi-objective solver when tackling the above extension of the aircraft reallocation problem, numerical experiments have been carried out over the synthetic scenario [16, 49, 5] generated previously, from which the risk values $\{\text{FWI}_z\}_{z=1}^{Z}$, the number of aircrafts ($N = 16$) and the positions of the $M = 49$ airports are utilized. The initial positions $\{\lambda_0(n)\}_{n=1}^{N}$ of the aircrafts are generated at random from the alphabet $\{1, \ldots, M\}$, whereas their types are set to

$$\{\vartheta(n)\}_{n=1}^{16} = \{1, 1, 2, 2, 3, 3, 1, 1, 1, 1, 3, 2, 2, 2, 1, 1\}, \tag{4.14}$$

i.e. $\tau = 3$ aircraft models are considered with coverage radii $\{R_t\}_{t=1}^{3} = \{250, 500, 750\}$, costs $\{C_t\}_{t=1}^{3} = \{0.5, 0.75, 1.0\}$ and fuel consumption rates $\{Q_t\}_{t=1}^{3} = \{1, 1.3, 1.5\}$. The price per litre of fuel is set to $p_c = 0.499$ Euros per litre, which is a realistic value given the U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price averaged over the first semester of 2013 (approximately 2.14 US dollars per gallon [225]). The military/ commercial character of each airport and its regional belonging are drawn at random by considering 16 administrative regions in which the deployment area is divided, along with associated cost penalties $\Delta W_F = 3000$, $W_R = 600$ and $W_C = 400$ Euros per penalized airplane. The budget imposed to the airports are taken randomly from the set $\{1, 2, 3\}$, e.g. if $B_m = 3$, airport m may host 3 aircrafts of type $t = 3$ ($C_3 = 1.0$), 6 aircrafts of type $t = 1$ ($C_1 = 0.5$) or any other combination provided that the budget constraint is satisfied.

A total of 20 runs of the reallocation algorithm are performed keeping the above set of parameters fixed. Each of such experiments produced an estimation of the Pareto front between the operational cost and firefighting potentiality fitness metrics given in Expressions (4.11) and (4.10), respectively. The underlying HS meta-heuristic features a memory size of $\Psi = 50$ harmonies, which are iteratively refined by the constituent HS operators with parameters equal to HMCR = 0.5 and PAR = 0.1. The maximum number of iterations is set to $I = 150$.

The discussion starts by analyzing the produced estimation of the overall Pareto front depicted in Figure 4.5, where the horizontal axis denotes the increase in firefighting potentiality

metric (normalized with respect to its value when no reallocation is performed) and the vertical axis reflects the cost associated to each of the produced solutions. Here, ∇ markers are used to represent the obtained Pareto front approximation, whereas ● markers stand for the Pareto front dominating the produced solutions of all Monte Carlo realizations. Points in this dominant set have been linked with a dashed line for clarity. The overall Pareto front approximation provides a wide range of solutions (i.e. 243 points belonging to the overall estimated front), differently trading cost for the firefighting contribution increase of the deployment. By using the information provided in this plot an operations commander would be able to e.g. find the allocation strategy rendering the best responsiveness against wildfires for a given cost or, alternatively, infer the minimum funds required to achieve a certain figure of the firefighting potentiality increase.
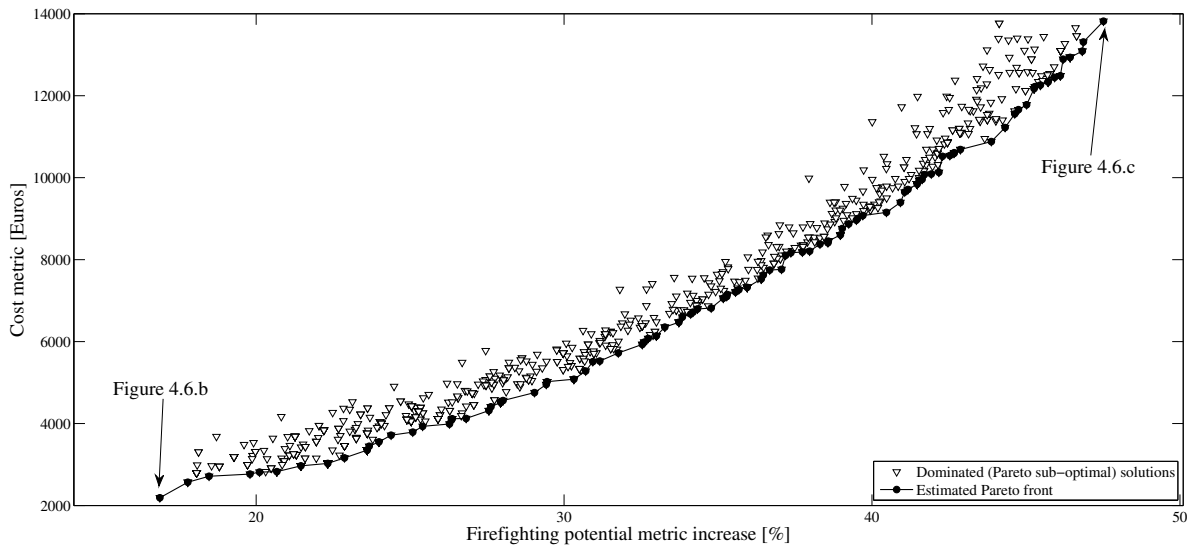
Figure 4.5: Estimated Pareto front for the extended problem formulation using the risk grid and airport positions of the [16, 49, 5] scenario.

Two extreme points of the estimated Pareto front are highlighted and marked with arrows: the allocation strategy featuring the minimum non-null cost (leftmost point of the Pareto set), and the solution yielding the highest value of the firefighting potentiality metric (rightmost point, correspondingly). The specific solutions of these two extremal Pareto points are depicted in Figures 4.6.b and 4.6.c, jointly with the initial allocation of aircrafts to airports (Figure 4.6.a). It can be verified in these plots that the minimum cost solution in Figures 4.6.b features less reallocated aircrafts that the maximum potentiality solution in Figure 4.6.c (5 versus 12, respectively). Besides, the average distance taken by such reallocations result to be shorter for the minimum cost deployment (159.613 versus 243.743), which evinces the capability of the proposed metaheuristic solver to adaptively vary the reallocation distances and consequently, the value of the fuel consumption cost $W_F(\cdot)$ defined in Expression (4.9). Finally, it is important to note that in the solution with higher firefighting potentiality (Figure 4.6.c), almost all available aircrafts are located around areas of high wildfire risk value FWI_z, yielding a firefighting potentiality increase close to 47% at the overall cost of approximately 13800 Euros for the deployment.

(a)

(b)

(c)
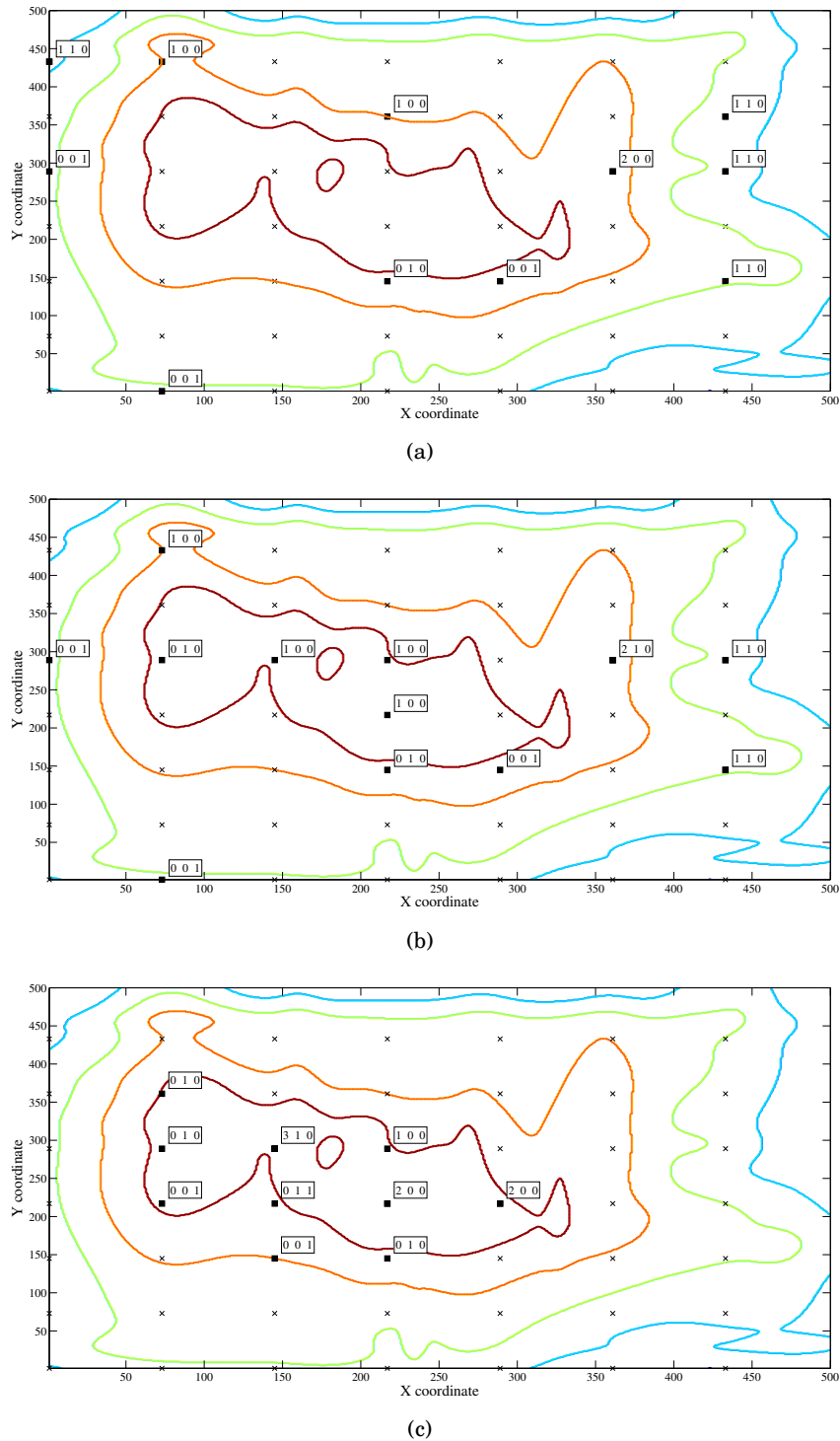
Figure 4.6: Solutions obtained by the proposed meta-heuristic allocation algorithm: (a) initial deployment (or equivalently, zero-cost solution); (b) cost-minimizing Pareto extreme solution; (c) firefighting potential maximizing Pareto extreme solution. Airport locations are indicated with × markers, whereas aerodromes hosting at least one aircraft are marked with ■ and a boxed string indicating the number of aircrafts with model $t = 1$, $t = 2$ and $t = 3$ (in this order).

4.4 A Realistic Fitness Metric Definition: Water Resources

The above extended model for large-scale aircraft reallocation based on predictive fire risk estimations can be further enhanced if the firefighting potentiality metric in Expression (4.8) incorporates analytic means to consider the effect of the relative location of water resources with respect to any eventual wildfire. Many aircraft models used in practice for fire extinction (also referred to as air tankers or water bombers) are fixed-wing aircraft equipped with tanks that can be filled on the ground at an air tanker base or by skimming water from lakes and reservoirs. The same holds for some helicopter models resorting to refillable buckets for delivering water in aerial firefighting campaigns. For these classes of aircrafts the proximity from the wildfire location to water resources should play a central role in its firefighting potentiality assessment: the shorter this relative distance is, the more times these aircrafts are able to replenish their water tankers without refueling, and the more effective their operations are with respect to the wildfire at hand.

Based on this argument, a more realistic definition for the aircraft model should incorporate the capacity of its water tanks, which will be hereafter denoted as V_t [litres], with $t \in \{1, \ldots, \tau\}$. Likewise, let $d_{z,t}^{wr}$ denote the distance from grid point z to the closest water resource compatible with aircraft type t; intuitively an air tanker might not be able to restock water from as many resources as an helicopter due to the distance requirements of landing and take-off maneuvers. Therefore, the amount of water $V(n,z)$ eventually dropped by an aircraft n with type $\vartheta(n)$ and assigned airport $\lambda(n)$ in point z is given by

$$V(n,z) = \left(N_r\left(\vartheta(n), \lambda(n), d_{z,\vartheta(n)}^{wr} \right) + 1 \right) \cdot V(n), \tag{4.15}$$

where $V(n)$ is the capacity of the water tank of aircraft n. It should be clear that $V(n) = V_t$ if $\vartheta(n) = t$. The newly introduced function $N_r(t,m,d)$ denotes the number of water reloads that an aircraft model t could attain when departing from airport m to z bearing in mind that the closest *compliant* water resource is at distance d from the grid point under consideration. It is assumed that the aircraft departs from its assigned aerodrome with their tanks filled, being this the reason for the +1 term in the above expression.
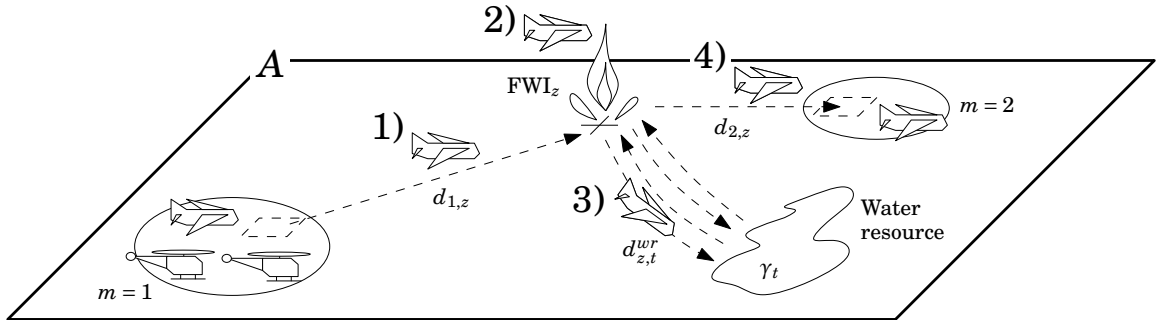
Figure 4.7: Diagram of the steps considered in the firefighting operations of an aircraft.

The computation of $N_r(\cdot)$ can be done based on the coverage radius already utilized in the definition of the aircraft models and Figure 4.7, where a schematic diagram of the distances involved in this metric is provided. As shown, the steps involved in the firefighting service of a type-t aircraft n include 1) traveling to the area where the fire has originated; 2) inspect the area and drop the initial water charge on critically affected zones; 3) repeatedly recharge water from the

nearest water reservoir, lake or river compatible with their restocking specifications; and 4) travel to the closer airport to point z for refueling. All such steps are subject to the fuel autonomy of the aircraft at hand, which is given by twice[1] its coverage radius R_t. Besides the relevance of the relative distances in this setup, the number of water recharges is further restricted by an additional penalizing factor $\gamma_t \geq 1$ that accounts for the higher fuel consumption due to the increased weight of the aircraft when transporting water and refilling landing and take-off maneuvers.

Based on the above observations one obtains, for aircraft n, the inequality

$$2R_{\vartheta(n)} \geq \gamma_{\vartheta(n)} \cdot d_{\lambda(n),z} + \gamma_{\vartheta(n)} \cdot d^{wr}_{z,\vartheta(n)} \cdot N_r\left(\vartheta(n), \lambda(n), d^{wr}_{z,\vartheta(n)}\right) + \min\left[\{d_{m,z}\}^M_{m=1}\right], \qquad (4.16)$$

where the first term is the distance from the assigned airport to the grid point z, the second term collects the aggregated distance of all penalized water recharges that the aircraft can perform, and the third term denotes the distance from the last water drop to the airport nearest to z. By isolating and casting the sought function one obtains

$$N_r\left(\vartheta(n), \lambda(n), d^{wr}_{z,\vartheta(n)}\right) = \left\lfloor \frac{2R_{\vartheta(n)} - \gamma_{\vartheta(n)} \cdot d_{\lambda(n),z} - \min\left[\{d_{m,z}\}^M_{m=1}\right]}{\gamma_{\vartheta(n)} \cdot d^{wr}_{z,\vartheta(n)}} \right\rfloor, \qquad (4.17)$$

where $\lfloor \cdot \rfloor$ returns the largest positive integer less than or equal to its argument. By inserting this computed function and the capacity of the water tank $V(n)$ in Expression (4.10), a more realistic firefighting potentiality metric results as

$$\Upsilon(\lambda(1), \ldots, \lambda(N)) \doteq \sum_{n=1}^N \left(\sum_{z=1}^Z \mathrm{FWI}_z V(n,z) \right) = \sum_{n=1}^N \left(\sum_{z=1}^Z \mathrm{FWI}_z \left(N_r\left(\vartheta(n), \lambda(n), d^{wr}_{z,\vartheta(n)}\right) + 1 \right) V(n) \right), \quad (4.18)$$

which can directly replace the former definition of $\Upsilon(\cdot)$, giving rise to a third reformulation of the problem under study. Since the cost metric in Expression (4.11) and the budget constraints remain untouched, the meta-heuristic solver and the greedy repair method capable of efficiently solving this new problem formulation are kept the same as the one used for the first extension.

4.4.1   Numerical Experiments for the Realistic Model

In this last set of Monte Carlo experiments real information of the aircrafts and aerodromes operated by the Ministry of Agriculture, Nutrition and Environment (*Ministerio de Agricultura, Alimentación y Medio Ambiente*) has been collected from [226], which contains up-to-date information on the characteristics, models and allocation policies of the Spanish national aerial firefighting fleet. A total of $\tau = 5$ aircraft models are currently used by this authority for fire risk suppression task, whose characteristics of relevance for the problem are summarized in Table 4.2. The fleet is composed by $N = 55$ aircrafts which, during the summer fire campaign, are statistically deployed over a subset of $M = 58$ available airports ranging from small-sized aerodromes (with low capacity B_m) to large airports such as Barajas (*Madrid*) or El Prat (*Barcelona*). Table 4.3 lists all such facilities along with their budget and the number of assigned aircrafts per model type t. Regional belonging of each airport is also inferred from its location and the current Spanish administrative map. The rest of parameters for the scenario are left unchanged with respect to the simulations in Subsection 4.3.1, except for the distribution of models

$$\{\vartheta(n)\}^{55}_{n=1} = \{\mathrm{rep}(16,1), \mathrm{rep}(6,2), \mathrm{rep}(9,3), \mathrm{rep}(7,4), \mathrm{rep}(17,5)\}, \qquad (4.19)$$

---

[1]As defined previously, the coverage radius is defined as half the maximum travel distance permitted by the fuel tank capacity of the aircraft due to the implicitly assumed need for refueling at the airport to which it is assigned.

with rep(x, t) returning a set with x repetitions of value t. Again, $I = 150$ iterations of the meta-heuristic allocator are run for 20 independent Monte Carlo experiments aimed at providing a wide and diversely populated estimation of the Pareto front.

Table 4.2: Aircraft types based on the information from [226].

t	Aircraft description	γ_t	R_t [km]	V_t [l]	Q_t [l/km]	C_t [ud]
1	CL-215T/CL-415	4	1130	5500	1.5	1.3
2	Air Tractor 802 "Fire Boss"	4	644	3100	1.3	1
3	Air Tractor 802	3.3	644	3100	1.3	1
4	Kamov K32A 11 BC	2.8	490	4500	0.9	0.6
5	SOKOL/BELL 412	2.2	244	1500	0.5	0.4

Table 4.3: Summertime deployment for aerodromes based on the information in [226]. Fields indicating the aircrafts assigned to every airport denote the number of allocated units per type.

m	Location	Aircrafts	B_m	m	Location	Aircrafts	Q_m
1	Labacolla (A Coruña)	2,0,0,0,0	2.5	30	San Javier (Murcia)	0,0,0,0,0	2.5
2	Albacete	2,0,0,0,0	2.5	31	Palma de Mallorca	0,0,0,0,0	2.5
3	Alicante	0,0,0,0,0	2.5	32	Pamplona	0,0,1,0,0	2.5
4	Almería	0,0,0,0,0	2.5	33	Reus (Tarragona)	0,2,0,0,0	2.5
5	Gijón	0,0,0,0,0	2.5	34	Sabadell	0,0,0,0,0	2.5
6	Talavera la Real (Badajoz)	2,0,0,0,0	2.5	35	Salamanca	2,0,0,0,0	2.5
7	Barcelona	0,0,0,0,0	2.5	36	Donostia-San Sebastian	0,0,0,0,0	2.5
8	Bilbao	0,0,0,0,0	2.5	37	Santander	0,0,0,0,0	2.5
9	Burgos	0,0,0,0,0	2.5	38	Santiago	0,0,0,0,0	2.5
10	Rota (Cádiz)	0,0,0,0,0	2.5	39	Sevilla	0,0,1,0,0	2.5
11	Córdoba	0,0,0,0,0	2.5	40	Moron (Sevilla)	0,0,0,0,0	2.5
12	Ampuriabrava (Girona)	0,0,2,0,0	2.5	41	Manises (Valencia)	0,2,0,0,0	2.5
13	Armilla (Granada)	0,0,0,0,0	2.5	42	Valladolid	0,0,0,0,0	2.5
14	Jaén	0,0,0,0,0	2.5	43	Vigo	0,0,0,0,2	2.5
15	Huesca	0,0,0,1,0	2.5	44	Vitoria	0,0,0,0,0	2.5
16	Ibiza	0,0,0,0,0	2.5	45	Zaragoza	2,0,0,0,2	2.5
17	Jerez	0,0,0,0,0	2.5	46	Rosinos (Zamora)	0,2,0,0,0	1.5
18	León	0,0,0,0,2	2.5	47	Xinzo de Limia (Orense)	0,0,2,0,0	1.5
19	Alguaire (Lleida)	0,0,0,0,0	2.5	48	Huelma (Jaen)	0,0,0,1,0	0.6
20	Logroño	0,0,2,0,0	2.5	49	La Almoraina (Cadiz)	0,0,0,1,0	0.6
21	Barajas (Madrid)	0,0,0,0,0	2.5	50	Plasencia (Caceres)	0,0,0,1,0	0.6
22	Cuatro Vientos (Madrid)	0,0,0,0,0	2.5	51	Ibias (Asturias)	0,0,0,1,0	0.6
23	Getafe (Madrid)	0,0,0,0,0	2.5	52	Villares (Guadalajara)	0,0,0,1,0	0.6
24	Torrejón (Madrid)	2,0,0,0,0	2.5	53	Tabuyo del Monte (Leon)	0,0,0,0,2	0.8
25	Málaga	2,0,0,0,0	2.5	54	Pinofranqueado (Caceres)	0,0,0,0,2	0.8
26	Pollensa (Mallorca)	2,0,0,0,0	2.5	55	La Iglesuela (Toledo)	0,0,0,0,2	0.8
27	Son Bonet (Mallorca)	0,0,1,0,0	2.5	56	Cuenca	0,0,0,0,2	0.8
28	Menorca	0,0,0,0,0	2.5	57	Puerto del Pico (Avila)	0,0,0,0,1	0.8
29	Alcantarilla (Murcia)	0,0,0,1,0	2.5	58	Lubia (Soria)	0,0,0,0,2	0.8

As for the location of water resources, geographical information about the position of rivers, ponds, lakes and the coast of the Spanish peninsula is added to the simulation setup, each being assumed to be compliant with specific aircraft models. As such, rivers, lakes and the sea are supposed to be compliant with helicopters ($t \in \{4, 5\}$), whereas model $t = 3$ (namely, the Air Tractor

802) reloads water exclusively on the ground, thus imposing that the only compliant water resource is the closest airport facility to the grid point z being attended. Likewise, relatively large airplane models ($t \in \{1, 2\}$) may skim water from ponds, lakes and the sea, but not from rivers.
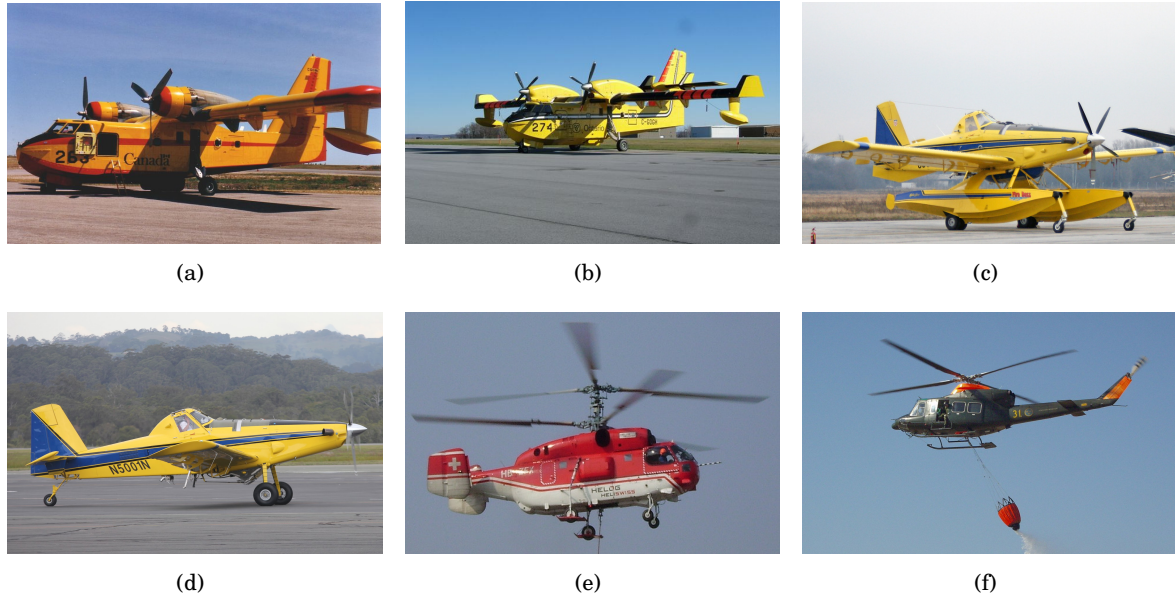

| (a) | (b) | (c) |
| (d) | (e) | (f) |

Figure 4.8: Pictures of the real aircrafts used in the simulations: (a) CL-215; (b) CL-415; (c) Air Tractor 802 "Fire Boss"; (d) Air Tractor 802; (e) Kamov K32A 11 BC; (f) SOKOL/BELL 412.

Before proceeding to the discussion on the obtained simulation results, it is important to notice that given the aggregation over n done in the definition of the firefighting potentiality metric $\Upsilon(\cdot)$, the reallocation priority contributed by high fire risk points located close to the coast could be masked by the null fire risk characterizing such surrounding points falling on the sea. Consequently, $\Upsilon(\cdot)$ is normalized by the number of grid points with nonzero fire risk FWI_z, yielding a measure of the firefighting potentiality averaged over all grid points that could eventually benefit from the proposed deployment strategy.

Having said this, Figure 4.10 depicts the overall estimated Pareto front after running the proposed algorithm over the risk grid $\{FWI_z\}$ of Figure 4.1, which comprises $Z = 47367$ points arranged in a regular lattice within the longitude and latitude ranges $[-10, 5]$ and $[35, 44]$ [decimal degrees], respectively. It is important to a priori pinpoint the fact that the risk distribution depicted in this figure falls within the typical set of risk predictions for the Spanish summertime, lacking of any meteorological incident that could drive the predicted grid towards atypical distributions. If current aerial resource allocation strategies have so far hinged on the long-term observation and study of typical weather conditions during summertime, it is expected that low firefighting potentiality increases are provided by the developed meta-heuristic allocator. This is indeed what can be observed in the obtained Pareto front (firefighting potentiality improvements between 0 and 7%). This can be regarded as a technical proof of the suitability of current resource allocation strategies under typical weather conditions, but definitely puts to question the effectiveness of such static procedures when non-typical weather forecasts (e.g. lightning storms in combination with severe droughts or heat waves) come into play. There lies the contribution of the proposed tool, which can dynamically compute and provide decision makers with the most
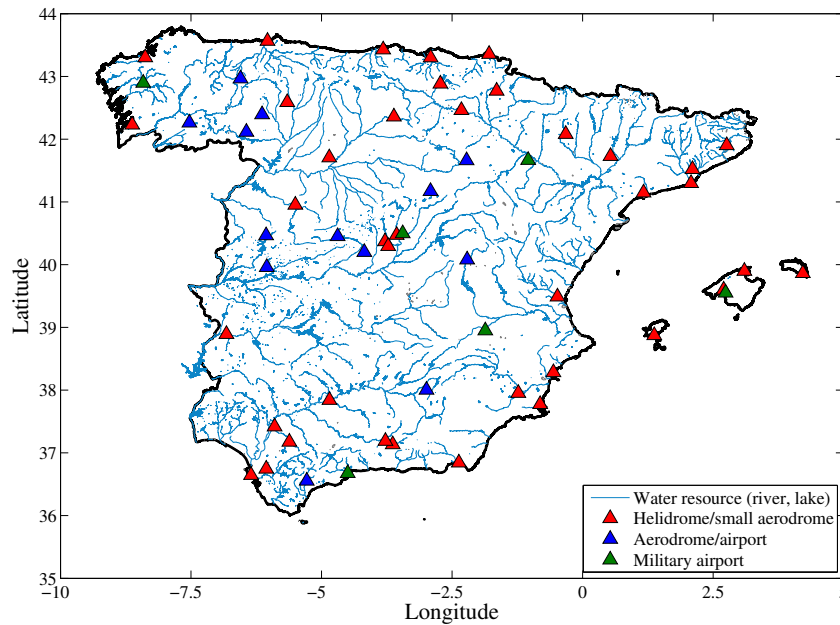
Figure 4.9: Map of the Spanish peninsula with real data on the location and type of water resources (ponds, lakes and rivers) and the geographical position of airports (circle colored markers discriminating between civil or military owned facilities). This information, jointly with the FWI index represented in Figure 4.1, lay the basis for a realistic assessment of the derived meta-heuristic solver.

cost-effective reallocation strategies subject to the characteristics of the operated airports and the specifications of the available aircrafts. For the sake of coherence with previously discussed simulations, Figure 4.11.a to 4.11.c show the solutions of the algorithm corresponding to those points featuring null cost, minimum non-zero cost and maximum firefighting potentiality increase.
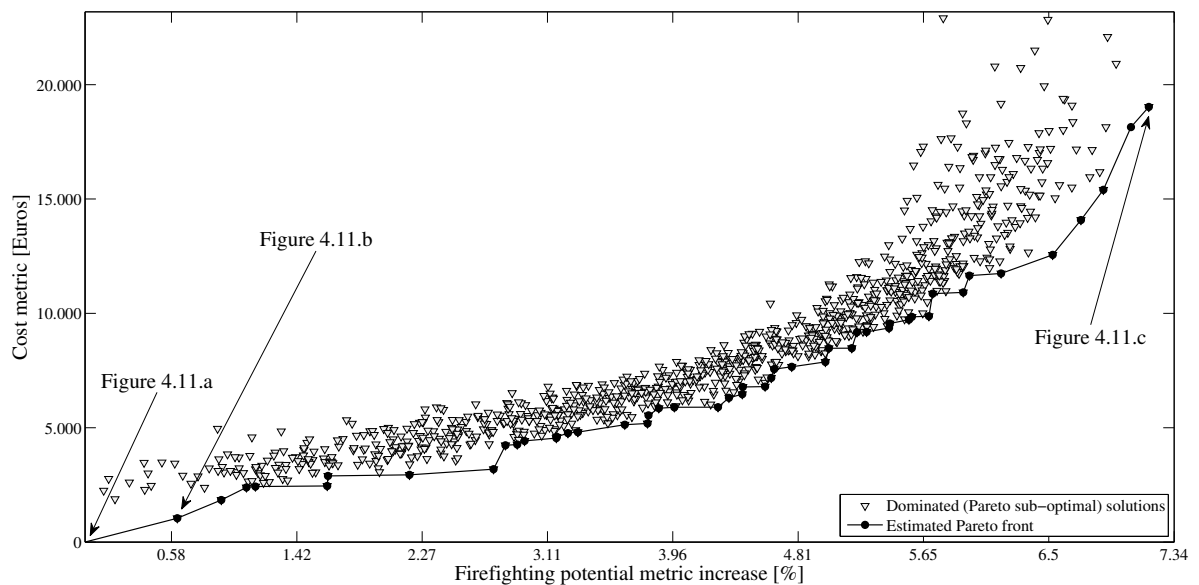
Figure 4.10: Estimated Pareto front for the realistic problem formulation using real data for the Spanish aerial firefighting fleet.
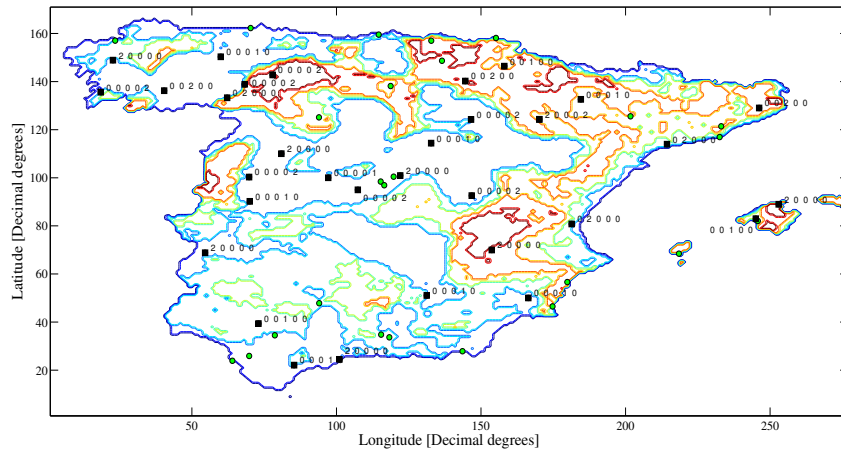
(a)
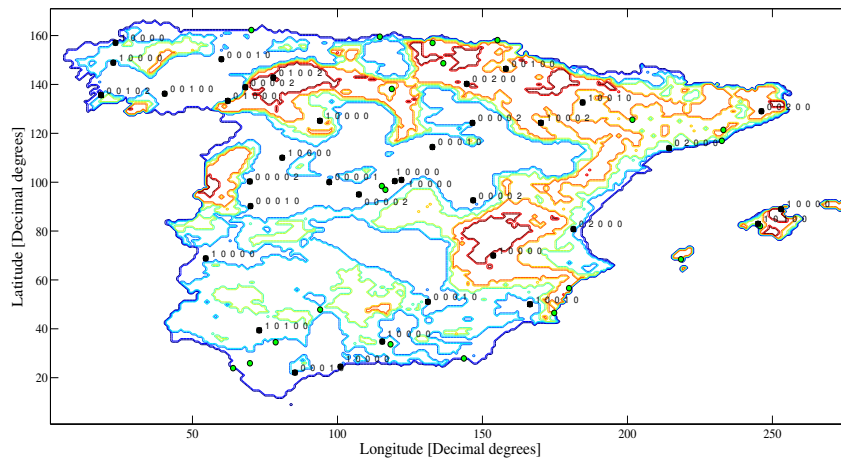
(b)
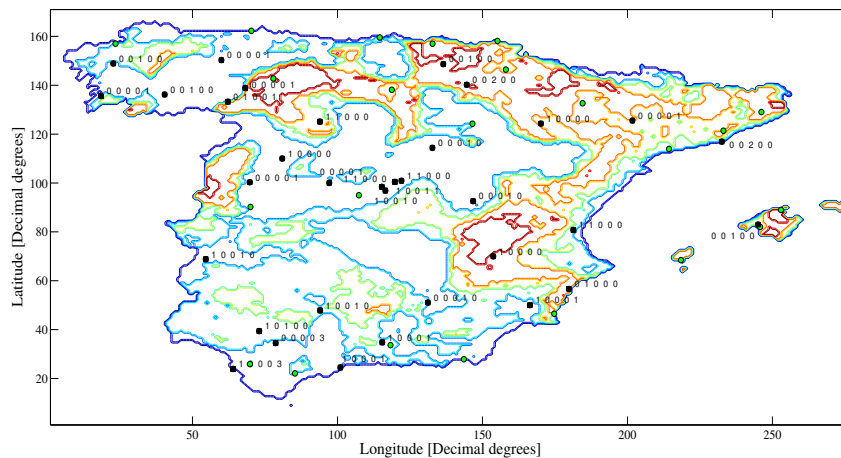
(c)

Figure 4.11: Solutions obtained by the proposed meta-heuristic allocation algorithm in the realistic simulation scenario over the Spanish peninsula: (a) initial deployment (or equivalently, zero-cost solution); (b) cost-minimizing Pareto extreme solution; (c) firefighting potential maximizing Pareto extreme solution. Airport locations hosting at least one aircraft are marked with ■, along with string indicating the number of aircrafts with models $t = 1$ to $t = 5$ (in this order).

CONCLUDING REMARKS AND FUTURE RESEARCH LINES

"Enough research will tend to support your conclusions."

- Arthur Bloch

From a general standpoint, the motivation for the research work carried out within this Thesis can be recapitulated in the appreciation of the increased complexity of the management of large-scale disasters when several criteria are involved in decision making processes. This complexity increase is not only a matter of the limited reasoning capabilities of the human being when encountering decisional scenarios of high dimensionality (as argued by the cross-national scales of lately occurred disasters), but is also a consequence of the confluence of diverse, yet conflicting criteria in the decision processes. In particular, cost implications are indeed severely restricting the amount of resources available for preventive campaigns and reactive procedures against wildfire, which eventually impacts on the coordination in the allocation and management of resources and ultimately, on the effectiveness of the prompted initiatives.

The above motivation being noticed, this dissertation has conjectured on the design of modern meta-heuristic algorithms to efficiently deal with optimization problems that model the allocation of resources in wildfire disasters. The selection of this class of stochastically-driven optimization approaches is founded on their well-known capabilities to explore continuous and discrete multivariable search spaces at a reduced computational cost when compared to analytical approximations. However, the contributions of this Thesis are not uniquely restricted to the formulation and naive application of such meta-heuristics to practical scenarios springing from the management of firefighting resources. The derived solvers also incorporate novel, distinctive algorithmic ingredients aimed at addressing particularities and constraints in the problem formulations at hand, as exemplified by the greedy repair procedure designed in Chapter 4 to fulfill the capacity constraints of the airports under consideration. It is indeed in these ad-hoc procedures where the main technical added value of the proposed research resides, further shielded by the innovative, more realistic problem models tackled via the developed optimization tools.

More specifically, several interesting conclusions can be drawn from the two application scenarios where Harmony Search heuristics have been proven to yield an efficient optimization solver for strategic and operational resource allocation against wildfire events:

- In Chapter 3 a novel hybrid meta-heuristic algorithm specially tailored for dealing with an extension of the dynamic relay deployment problem for large-scale wildfire disasters. The

scenario consists of the dynamic deployment of heterogeneous wireless communication relays (each featuring distinct coverage radius and cost) in such a way that the connectivity between the firefighting resources deployed on site and the command center is maximized while, at the same time, yielding a minimum cost of the deployment. From a mathematical perspective this resource allocation paradigm has been shown to ground on a modification of the so-called disk covering problem where, in its seminal form, the locations of a number of relays over a certain area so that the surface covered on such an area is maximized. This classical optimization problem is extended by also optimizing the number and model (namely, coverage radius and cost) of the deployed relays. The heuristic solution proposed to efficiently tackle this novel problem statement resorts to Harmony Search as a global searching strategy, which is hybridized with a modified version of the K-means clustering algorithm so as to refine the location of the relays. By deriving both single- and bi-objective versions of the heuristic solver, its applicability has been extended beyond emergency relay deployments towards tactical communications planning, where a wide spectrum of different optional network topologies is required by the operations commander. Two different simulation scenarios have been analyzed for assessing the efficiency of the proposed scheme when compared to two different extensions of the K-means approach – X-means and G-means – where the number of clusters (i.e. relays) is estimated based on different model scoring criteria. In all the performed experiments, the proposed algorithmic solutions have obtained a better balanced trade-off between coverage and cost (number, model) of the deployed relays with respect to its aforementioned counterparts, results that pave the way towards their applicability to scalable communication deployments over wide-area disasters.

• The scenario addressed in Chapter 4 capitalizes on the availability of localized predictive fire risk rating indicators to drive the optimal deployment of firefighting aircrafts (i.e. airplanes and helicopters) over airports and aerodromes. The hypothesis buttressing this research line hinges on the fact that if a priori information on the probability of fire ignition of large-scale areas is supplied in the form of an quantifiable index to the decision maker, this stakeholder in the fire logistics chain should adopt this index as a leverage for subsequent allocation procedures of firefighting resources based on effectiveness and cost criteria. To algorithmically support this decision making procedure, several single- and bi-objective problem formulations have been derived so as to realistically model the allocation of resources in this envisaged scenario. The resulting series of combinatorial optimization problems has been efficiently solved by means of a combination of the HS meta-heuristic algorithm and a greedy repair procedure to account for airport capacity constraints, both of which constitute the algorithmic core of the derived single- and bi-objective optimization tools. Numerical experiments have been first carried out in a set of synthetically-generated scenarios to validate the performance of the proposed hybrid optimizer in a controlled scenario. The obtained results confirm that the performance of the meta-heuristic solver scales up nicely. A second set of simulations has considered real fire risk estimations based on the Forest Weather Index system over the Spanish peninsula, as well as real positions of aerodromes, airports and water resources in this geographical area. The range of deployments efficiently furnished by the application of the proposed bi-objective solver to this realistic experiment serves as a scalable, near-optimal decisional basis for commanders and decision makers in preventive operations planning against large-scale wildfires.

Despite the fact that the two addressed application setups detailed above have gravitated on the management of firefighting resources, the derived algorithms might be directly extrapolated

to the allocation of resources in disasters of different nature and characteristics. The flexibility of the Harmony Search heuristic solver lying at the heart of the derived methods to efficiently deal with continuous and discrete-variable (i.e. combinatorial) optimization paradigms makes it suitable for alternative problem formulations involving e.g. emergency health logistics, field hospitals or supply chains, among many others. As has been overseen in Chapter 4, this becomes even more relevant when one notices that the risk ascribed to other classes of disasters (especially those strongly affected by weather conditions such as tropical cyclones, tornadoes, droughts, severe thunderstorms and lightening) can be predictively quantified in the form of geolocalized indicators similar to the FWI utilized in this dissertation. This two-fold appreciation unchains a promising line of future research aimed at predictively optimizing the effectiveness of deployed resources for the management of disasters by means of hybrid Harmony Search heuristics and other approximative solvers alike.

5.1 Publications and Merits

The scientific contributions and merits achieved by the author of this Thesis during her academic track include 1 book chapter and 4 articles in journals with JCR index related to the application of Harmony Search to different scenarios (among which those tackled in Chapters 3 and 4 can be found), 5 contributions to international and national conferences and 1 edited lecture notebook. Theses. A list of these publications and merits is next provided:

- Books and book chapters:

  1. M. N. Bilbao, D. Gallo-Marazuela, S. Salcedo-Sanz, J. Del Ser, C. Casanova-Mateo, "A Meta-Heuristic Approach for the Optimal Deployment of Firefighting Aircrafts based on Fire Risk Predictions", chapter accepted for its inclusion in *New Perspectives on Stochastic Modeling and Data Analysis*, edited by C. H. Skiadas, V. Girardin and J. Bozeman, pp. 300-360, November 2013.

- Articles in refereed international journals:

  1. M. N. Bilbao, S. Salcedo-Sanz, J. Del Ser, C. Casanova-Mateo, "Design and Application of Single and Multi-objective Harmony Search to the Predictive Deployment of Firefighting Aircrafts: a Realistic Case Study", invited paper for its inclusion in *International Journal of Bio-Inspired Computation*, special issue on "Theory and Applications of the Harmony Search Method" by X.-Z. Gao and Z. W. Geem, 2014 (JCR: 1.351).

  2. M. N. Bilbao, S. Gil-López, J. Del Ser, S. Salcedo-Sanz, M. Sánchez-Ponte, A. Arana-Castro, "Novel Hybrid Heuristics for an Extension of the Dynamic Relay Deployment Problem over Disaster Areas", *TOP*, accepted (published on line), November 2013 (JCR: 0.765).

  3. D. Manjarrés, I. Landa-Torres, S. Gil-López, J. Del Ser, M. N. Bilbao, S. Salcedo-Sanz, Z. W. Geem, "A Survey on Applications of the Harmony Search Algorithm", *Engineering Applications of Artificial Intelligence*, Vol. 26, N. 8, pp. 1818-1831, September 2013 (JCR: 1.625).

  4. J. Del Ser, M. N. Bilbao, S. Gil-López, M. Matinmikko, S. Salcedo-Sanz, "Iterative Power and Subcarrier Allocation in Rate-Constrained OFDMA Downlink Systems based on Harmony Search Heuristics", *Engineering Applications of Artificial Intelligence*, Vol. 24, N. 5, pp. 748-756, August 2011 (JCR: 1.665).

- International and national conference proceedings:

  1. M. N. Bilbao, D. Gallo-Marazuela, S. Salcedo-Sanz, J. Del Ser, C. Casanova-Mateo, "A Meta-Heuristic Approach for the Optimal Deployment of Aerial Firefighting Fleets based on Predictive Fire Risk Estimations", *International Conference on Applied Stochastic Models and Data Analysis*, Mataró, Spain, June 2013.

  2. J. Del Ser, M. N. Bilbao, S. Gil-López, M. Matinmikko, S. Salcedo-Sanz, "Resource Allocation in Rate-limited OFDMA Systems: A Hybrid Heuristic Approach", *IEEE/ITG Workshop on Smart Antennas*, pp. 1–5, Aachen, Germany, February 2011.

  3. M. N. Bilbao, L. Aginako, O. Lazaro, T. Hof, C. Bonnet, F. Filali, P. Vaquero, S. De la Maza, R. Atkinson, B. Molina, J. O'Flaherty, R. Mazza, "MULTINET: Enabler for Next Generation Enterprise Wireless services", *eChallenges2007*, published in *Expanding the Knowledge Economy: Issues, Applications and Case Studies*, The Hague, Netherlands, October 2007.

  4. I. Echave, J. I. Goirizelaia, M. Huarte, M. Madarieta, M. N. Bilbao, "Implementation of a Sure and Auditable System of Vote through Internet", VOTOBIT II, León, Spain, October 2004.

  5. M. Madarieta, M. Huarte, I. Echave, M. N. Bilbao, J. I. Goirizelaia, "Using Virtual Learning Asynchronous Tools as an Efficient Help to Traditional Learning Environments", IADAT-e2004 (International Conference on Education), Bilbao, July 2004.

- Educational material:

  1. M. N. Bilbao, C. Perfecto, G. Abaroa, "Programazioaren Oinarriak: C-ko eta Java-ko Praktikak" (in Basque), edited by the publishing services of the University of the Basque Country, ISBN 978-84-694-1991-5, 2011.

5.2 Future Research Lines

The promising results obtained in this work pave the way towards future research lines of interest within the overall scope of the Thesis: the cost-efficient management of resources in wildfires and, in general, large-area disaster events. Such research directions are hereafter broken down in specific aspects applicable to each of the scenarios tackled through the Thesis – namely, the allocation of communication and aerial firefighting resources –, followed by a research topic that could hold for both considered setups. Here is a brief sketch of such lines:

- As for the system model formulated in Chapter 3, it has been implicitly assumed that communications between the firefighting crew – the deployed communicating nodes – and the relays are established under a star-like topology, i.e. a direct link between each of such nodes and the serving relay is imposed so as to guarantee that no crew happens to be in radio isolation while undertaking field operations. While this may yield a relatively straightforward approach to set direct error-free communication links between nodes and relays, in practice radio paths are subject to failures as a result of 1) the mobility of nodes; 2) the orographic characteristics of the area; and 3) the low received power at the relay due to the limited transmit power on the node side and the wide distances at which the crew operate.

This observation motivates conducting further research aimed at cost-efficient radio resource allocation in large-area disasters with faulty communications. In this context, multi-hop networking is envisaged as an effective alternative since:

– Setting multiple communication paths between source and destination decreases the link failure probability exponentially with the number of redundant links.

– When the link failure probability is sufficiently low, multi-hop networking may serve as an energy-efficient coverage extension scheme, as the effective radii of the areas covered by the deployed relay are increased by virtue of several nodes acting themselves as *local* relays.
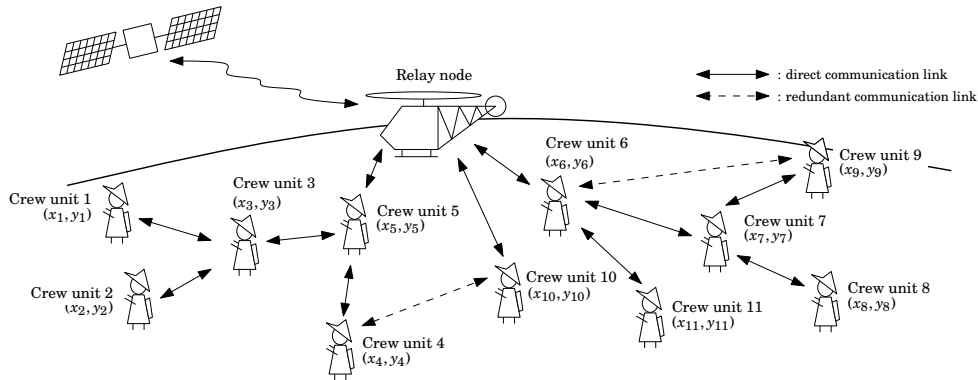

Figure 5.1: Extension of the system model in Chapter 3 considering multi-hop communications.

In regards to the system model, the adoption of multi-hop links would modify substantially the star-like topology to yield a multiple-tree-like network as shown in Figure 5.1, where cost and coverage considerations would be imposed on the root and the intermediate nodes (*global* and *local* relays). It is important to note that link redundancy between a certain node and different root nodes could be established by simply defining interconnections between the corresponding trees and/or parallel trees sharing the same root node. The underlying optimization problem would address the estimation of the position, number and model of relay nodes and the tree topology interconnecting the covered mobile nodes under cost and coverage criteria for which the application of meta-heuristic algorithms as the one used in this Thesis along with encoding strategies well suited for tree network topology (e.g. Dandelion encoding [227]) would unchain a new operations research area gravitating on resource allocation paradigms modeled by tree-like data structures (from the here exposed communications network deployment to vehicle routing in ground logistics).

• Again in connection to Chapter 3, the criteria driving the optimization problems defined in Expressions (3.3) and (3.4) focus strictly on coverage and cost, the latter finding its rationale in the need for including cost aspects in the optimization of resources that motivates the whole Thesis. In this context, it would be interesting to explore, from an optimization point of view, how the battery lifetime of mobile nodes becomes affected in long-term disaster events. In these situations it results impractical to replace or recharge batteries on site, whose eventual depletion could lead to a risky radio isolation of the deployed firefighters. To avoid this potential danger, the deployment of relays should take into account the unequally lasting battery lifetime of relay (higher and more easily rechargeable) and mobile nodes (lower), in such a way that the effective radii of the coverage ranges would vary in time depending on the relative position and battery left of the covered mobile nodes. Studying

how the problem could be reformulated to consider the maximization of the average battery lifetime as another (if not the main) optimization criterion – along with the algorithmic consequences of its efficient resolution – is definitely a research line to be pursued.

- The successive problem formulations in Chapter 4 have been kept restricted to the allocation of aerial firefighting resources. Consequently, the metric involved therein considers effectiveness against wildfires as directly dependent on the effective amount of water dropped by the aircraft at hand during the time taken by its fuel deposit to deplete. A immediate research line arising from this problem would aim at the inclusion of ground vehicles in the ecosystem of firefighting resources being optimally allocated by the derived optimization tool. A redefinition of the metric in Expression (4.18) would be required to reflect the fact that 1) ground vehicles can be allocated, in general, to developed city areas; 2) they can refill their water tanks in fire hydrants, whose number happens to be much higher that lakes and rivers; 3) the time taken by a ground vehicle to reach a certain area affected by a wildfire is longer than that of any aircraft model and subject to geographical constraints, implying the need for including in the metric the time of arrival as a key factor in the effectiveness against a fire; and 4) the potential risk for firefighting crews operating ground vehicles are several orders of magnitude higher than those driving firefighting aircrafts, which would come along with an interesting algorithmic synergy of this problem with the allocation of communication resources in Chapter 3. Regarding the latter, communications relays would embody another resource model to be preventively allocated through the optimization solver in Chapter 4.

- As shown in Appendix A, the FWI utilized as an indicator of the probability of occurrence and potential severity of a given wildfire is computed exclusively by resorting to the fire behavioral characteristics of generic soil layers against different weather characteristics. This computation is made under a geographically agnostic fashion, i.e. the specific soil properties of a certain area are not taken into account, but the method assumes instead that all areas under study are made of the three soil layers specified in Figure A.1. In other words: the FWI only reflects the climatological fire risk of a given zone disregarding its particular soil characteristics. To circumvent this issue, alternative fire risk scores could be certainly developed by exploiting already available geolocalized information about soil type and characteristics. However, a first approach to leverage the already developed algorithms towards a more realistic model of fire risk and severity would be to include, in the defined metric of Expression (4.18), information about the position of cities, villages and in general, human settlements whose proximity to an eventual wildfire should increase dramatically its firefighting resource requirements.

Finally, a line of future research applying to both scenarios considered in this dissertation lies at the algorithmic heart of the proposed resource allocation methods: it has been argued through the Thesis that since its invention [14], Harmony Search has excelled in the literature related to meta-heuristic optimization as one of the most utilized schemes in a wide portfolio of application fields surveyed in [127]. However, recently a number of novel meta-heuristic approaches have been proposed by combining innovative perspectives based on the observation of different phenomena in the literature. In this context, future research will be devoted to the consideration of Coral Reefs Optimization (CRO, [111]), which is based on the simulation of the reproduction, colonization and depredation processes of coral reefs thanks to which it has been recently proven to outperform Harmony Search in the optimal deployment of mobile networks under electromagnetic pollution criteria [228].

PRINCIPLES AND COMPUTATION OF THE FIRE WEATHER INDEX (FWI) SYSTEM

"Humor starts like a wildfire, but then continues on, smoldering, smoldering for years."

- Robert Orben

The relevance of forests for the whole Earth has been highlighted frequently throughout this Thesis, due to their essential role in 1) the carbon dioxide cycle; 2) the soil conservation and 3) the survival of animal and plant species. This utmost importance of preserving forest areas motivates the need for quantitatively estimating the likelihood of fires starting in forests, as well as the velocity at which they spread geographically.

On this purpose, one of the most utilized risk assessing systems for forest fires is the so-called Forest Weather Index (FWI), which was originally developed by the Canadian Forest Service (CFS) [223] after years of forestry research [229]. In essence the FWI comprises a series of estimates for the moisture content of three different fuel classes using daily weather observations, including temperature, relative humidity, wind speed, and 24-hour accumulated precipitation measured at noon Local Standard Time (LST). The reason for selecting these specific weather data for the computation of the FWI lies on their impact on the fire ignition potentiality, intensity, and fuel consumption of a fire event located in the area where such indicators are recorded. As such, it is well known that air temperature affects the drying rate of fuels and therefore determines the heating of fuels to ignition temperature. Likewise, a higher value of the relative humidity involves a slower drying of fuels since in this case, more moisture will be contained in the air and hence available to the fire for its absorption. Fire spread, however, gets strongly biased by the wind speed as it also contributes to the oxygen supply to the burning fuel, and drives flames towards unburned areas [230]. Finally, precipitation rules the wetting dynamics of fuels. The moisture content estimates resulting from the processing of weather data are then elaborated to quantify the potential, intensity and fuel consumption of a location at 4:00 pm LST.

As shown in Figure A.1, the FWI System builds upon three fuel codes representing the moisture content of the organic soil layers of forest floor, and three fire indexes that model the fire behavior. In general, the forest soil can be stratified in five different layers, each featuring distinct types of fuels for forest fires which are in turn reflected in the FWI System. This fuel categorization hinges on the drying rate or *time lag* at which the fuel loses moisture as a result of combustion, and on the fuel loading metric, which describes the average density (in tons per hectare) of the fuel at hand over a certain area. Three codes result from the processing of these weather indicators within the FWI system, which are described as follows:

- Fine Fuel Moisture Code (FFMC): this numeric rating reflects the moisture content of litter and fine fuels of around 2 cm deep, a typical fuel density of 5 tons per hectare and 16-hour time lag. Due to these characteristics, the FFMC code is a quantitative indicator of the probability (ease) of ignition.
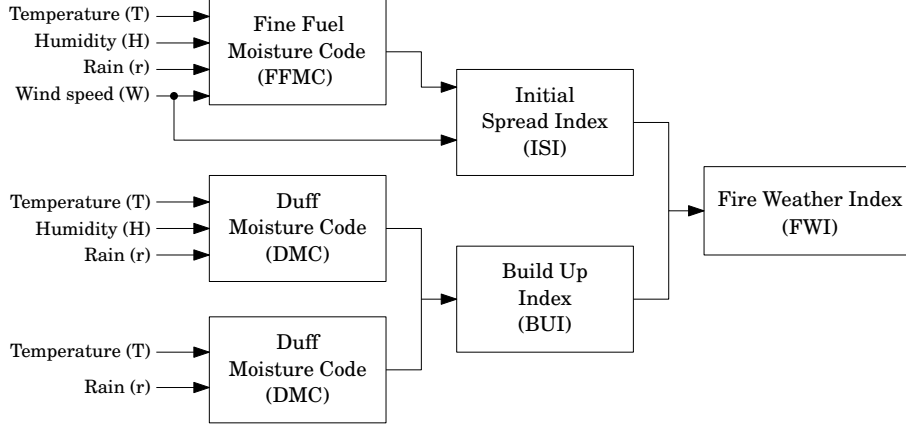

Figure A.1: Computation flow of the FWI index system.

Mathematically speaking and following the notation from [231], the computation of this code and those considered within the FWI system requires the definition of several weather parameters: temperature, relative humidity and wind speed measured at noon will be denoted as T [ºC], H [%] and W [km per hour], respectively. Likewise, rainfall measured in an open environment at the same time of the day will be given by r_0 [mm]. With this notation in mind, the fine fuel moisture content m_0 from the previous 24 hours is estimated for the FFMC code as

$$m_0 = 147.2 \cdot (101 - F_0)/(59.5 + F_0), \tag{A.1}$$

where F_0 is the value of the FFMC index corresponding to the day before the computation is made. If the effective rainfall r_f [mm] is given by $r_0 - 0.5$, then the fine fuel moisture content after rain m_r is defined as

$$m_r = \begin{cases} m_0 + 42.5 r_f (e^{-100/(251-m_0)})(1 - e^{-6.93/r_f}) & \text{if } m_0 \leq 150, \\ m_0 + 42.5 r_f (e^{-100/(251-m_0)})(1 - e^{-6.93/r_f}) + \frac{3(m_0-150)^2}{2000} r_f^{0.5} & \text{if } m_0 > 150, \end{cases} \tag{A.2}$$

whereas the equilibrium moisture content (EMC) for drying (E_d) and wetting (E_w) relate to temperature and humidity as

$$E_d = 0.942 H^{0.679} + 11 e^{(H-100)/10} + 0.18(21.1 - T)(1 - e^{-0.115H}), \tag{A.3}$$

$$E_w = 0.618 H^{0.753} + 10 e^{(H-100)/10} + 0.18(21.1 - T)(1 - e^{-0.115H}). \tag{A.4}$$

By defining intermediate variables κ_o and κ_1 required to compute the log drying and wetting rates κ_d and κ_w [$\log_{10}$ m per day] as

$$\kappa_o \triangleq 0.424(1 - (H/100)^{1.7}) + 0.0694 W^{0.5}(1 - (H/100)^8), \tag{A.5}$$

$$\kappa_d = \kappa_o 0.581 e^{0.0365T}, \tag{A.6}$$

$$\kappa_1 \triangleq 0.424 \left(1 - \left(\frac{100-H}{100}\right)^{1.7}\right) + 0.0694 W^{0.5} \left(1 - \left(\frac{100-H}{100}\right)^8\right), \tag{A.7}$$

$$\kappa_w = \kappa_1 0.581 e^{0.0365T}, \tag{A.8}$$

the fine fuel moisture content after drying m_{ad} and the value of the FFMC code result in

$$m_{ad} = \begin{cases} E_d + (m_r - E_d)10^{-\kappa_d} & \text{if } m_r > E_d, \\ E_w - (E_w - m_r)10^{-\kappa_w} & \text{if } m_r < E_w, \\ m_r & \text{if } E_w \leq m_r \leq E_d, \end{cases} \tag{A.9}$$

$$\text{FFMC} = 59.5\frac{250 - m_{ad}}{147.2 + m_{ad}}, \tag{A.10}$$

which rates, in a 0-99 scale [%], the likelihood of fire ignition in a geographical location.

- Duff Moisture Code (DMC): this code attempts at quantifying the combustion properties of moisture contained in loosely compacted organic matter subject to decomposition, which usually lies in substrates 5–10 cm deep, at a density of approximately 50 tons per hectare. Although rainfall, temperature and humidity are still relevant factors for the behavioral features of this moisture under fire, its constituent fuels lie below the floor surface (particularly for forest terrains) and is kept isolated from wind bursts. Hence DMC fuels yield a slower drying rate than their FFMC counterparts, with a typical time lag of 12 days. Given this deeper location of the involved substrates, the DMC code can be interpreted as the probability of fire ignition due to lightning, as well as the fuel consumption rate for moderately deep organic layers and medium sized woody material.

The formulae required for the computation of the DMC index relies on the definition of the effective rainfall for this type of moisture, which will be hereafter referred to as r_e [mm] and relates to the total amount of rain r_0 as

$$r_e = 0.92r_0 - 1.27. \tag{A.11}$$

On the other hand, the duff moisture content M_0 from the day prior to the computation is given by

$$M_0 = 20 + e^{(5.6348 - P_0/43.43)}, \tag{A.12}$$

where P_0 denotes the DMC corresponding to the previous day. The moisture content after rain M_r results from

$$M_r = M_0 + \frac{1000r_e}{48.77 + b \cdot r_e}, \tag{A.13}$$

with b denoting the so-called slope variable that establishes the relation between these two variables (M_r and r_e) through the initial value of the DMC code P_0. This slope is determined by a set of empirical equations for different ranges of P_0, namely

$$b = \begin{cases} 100/(0.5 + 0.3P_0) & \text{if } P_0 \leq 33, \\ 14 - 1.3\ln P_0 & \text{if } 33 < P_0 \leq 65, \\ 6.2\ln P_0 - 17.2 & \text{if } P_0 > 65, \end{cases} \tag{A.14}$$

which give rise to the value of the DMC after rain (DMC$_r$) and the value of the DMC index itself as

$$\text{DMC}_r = 244.72 - 43.43\ln(M_r - 20), \tag{A.15}$$

$$\text{DMC} = \text{DMC}_r + 1.894 \cdot 10^{-4}(T + 1.1)(100 - H)L_e, \tag{A.16}$$

where L_e is the effective length of the day for which the DMC is computed, which is tabulated in the FWI system as shown in Table A.1. It should be noted that the practical value range of the DMC code is upper bounded by 40, i.e. a DMC beyond 30 is dry, whereas intensive, complexly extinguishable burning will occur in the duff and medium fuels if the DMC value falls above 40.

- Drought Code (DC): this last fuel code quantifies the moisture content of deep layers of compacted organic matter lying 10–20 cm deep and containing a fuel density of approximately 440 tons per hectare. This depth is enough to isolate the layer from wind speed and relative humidity, but temperature and precipitation do still impact on their combustion properties. Consequently, fuels with significant DC render a very slow drying rate (time lag of 52 days), which sheds light on the resistance to extinguishing of a given fire.

Table A.1: Values of L_e and L_f for the computation of DMC and DC.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
L_e	6.5	7.5	9.0	12.8	13.9	13.9	12.4	10.9	9.4	8.0	7.0	6.0
L_f	-1.6	-1.6	-1.6	0.9	3.8	5.8	6.4	5.0	2.4	0.4	-1.6	-1.6

The computation of this last fuel rating index grounds on the determination of the potential evapotranspiration of the layer, denoted as V and measured in units of 0.254 mm water per day, as well as on the definition of a day length factor L_f to reflect seasonal effects on the noon temperature that leads to the aforementioned evapotranspiration (Table A.1). Rainfall r_0 is first reduced to an effective rainfall r_d as $r_d = 0.83r_0 - 1.27$, which is added to the existing moisture equivalent Q_0 to provide the effective Q_r as

$$Q_0 = 800e^{-D_0/400}, \tag{A.17}$$

$$Q_r = Q_o + 3.937r_d, \tag{A.18}$$

where D_0 is the value of the DC index of the day prior to the computation. The evotranspiration of the layer is then given by

$$V = 0.36(T + 2.8) + L_f \tag{A.19}$$

which leads to the actual value of the DC code through the intermediate estimation of this parameter after rain (DC$_r$), i.e.

$$\text{DC} = \text{DC}_r + 0.5V = 400\ln(800/Q_r) + 0.5V. \tag{A.20}$$

The typical range of values for the DC rating is [0,350]; a value above 300 is deemed extreme indicating that fire will involve deep sub-surface and heavy fuels. In this situation no burning-off initiatives should be triggered nor permitted due to their lack of effectiveness.

Once the above codes have been computed, the computation flow proceeds by computing the intermediate Initial Spread Index (ISI) and Build Up Index (BUI), which indicate the rate of fire spread immediately after ignition and the total amount of fuel available for consumption, respectively. Intuitively the ISI index is strongly biased by the wind speed and the FFMC, whereas the BUI index is affected by the DMC and DC codes differently depending on the relative values of these codes with respect to each other: the DMC code features the most influence on the BUI value, but DC dominates the BUI value at high DMC values. Such indexes are computed as

$$\text{ISI} = 0.208 \cdot e^{0.05039W} \cdot 91.9e^{-0.1386m_{ad}}\left(1 + m_{ad}^{5.31}/(4.39 \cdot 10^7)\right), \tag{A.21}$$

$$\text{BUI} = \begin{cases} \frac{0.8 \cdot \text{DMC} \cdot \text{DC}}{\text{DMC}+0.4\text{DC}} & \text{if DMC} \leq 0.4\text{DC}, \\ \text{DMC} - \left(\frac{1-0.8\text{DC}}{\text{DMC}+0.4\text{DC}}\right)\left(0.92 + (0.0114\text{DMC})^{1.7}\right) & \text{if DMC} > 0.4\text{DC}, \end{cases} \tag{A.22}$$

Table A.2: Summary of features of the FWI moisture code system [232].

	FFMC	DMC	DC
Fuel type	Litter, cured fine fuels	Loosely-compacted organic layers of moderate depth	Deep, compact organic layers
Interpretation	Ease of ignition and flammability of fine fuels	Probability of lightning fires; fuel consumption in moderate duff	Resistance to extinguishing; fuel consumption of deep organic material
Depth	1-2 cm	5-10 cm	10-20 cm
Fuel density	5 tons per hectare	50 tons per hectare	440 tons per hectare
Time lag	16 hours	12 days	52 days
Parameters	T, H, W, r	T, H, r	T, r
Value range	0-99	0-350	0-1200

where m_{ad}, DMC and DC are given by Expressions (A.9), (A.16) and (A.20), respectively. The Fire Weather Index (FWI) is calculated from the above expressions to yield an estimate of the intensity of a spreading fire, for which it combines the rate of fire spread and the amount of fuel being actively consumed by the fire itself. Specifically,

$$\text{FWI} = \begin{cases} e^{2.72(0.434\ln\text{FWI}_i)^{0.647}} & \text{if FWI}_i < 1, \\ \text{FWI}_i & \text{if FWI}_i \geq 1, \end{cases} \tag{A.23}$$

where FWI_i denotes an intermediate FWI index that depends on ISI and DC as

$$\text{FWI}_i = \begin{cases} 0.1\text{DC}\left(0.626 \cdot \text{BUI}^{0.809} + 2\right) & \text{if BUI} \leq 80, \\ 1000/(25 + 108.64e^{-0.023\text{BUI}}) & \text{if BUI} > 80, \end{cases} \tag{A.24}$$

which renders a risk index whose range value can be discretized and classified as shown in Table A.3. This classification rules out the FWI indexes used in the realistic simulations of Chapter 4.

Table A.3: Categorization of the Fire Danger based on the FWI index [223].

FWI class	Value range	Type of fire	Potential danger
Low	0-5	Creeping surface fire	Fire will be self extinguishing
Moderate	5-10	Low vigor surface fire	Easily suppressed with hand tools
High	10-20	Vigorous surface fire	Power pumps and hoses are needed
Very high	20-30	Very intense surface fire	Difficult to control
Extreme	>30	Developing active fire	Immediate, strong action required

In general the FWI index can be exploited to assess fire suppression requirements and to drive early resource allocation procedures (as done in Chapter 4 of this Thesis), but also provides a easily understandable indicator of the fire risk that can be utilized for awareness rising campaigns. Last but not least, it should be noted that the FWI index is not directly calculated from weather data, but rather depend on such data indirectly through the ISI and BUI indicators.

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