Metaheuristic Optimization for Logistics in Natural Disasters

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Η ΜΕΤΑΠΤΥΧΙΑΚΗ ΕΡΓΑΣΙΑ ΕΞΕΙΔΙΚΕΥΣΗΣ

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ως μέρος των Υποχρεώσεων για τη λήψη του

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Abstract

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Humanitarian Logistics (HL) has attracted increasing interest over the last two decades due to the exponential surge in natural and man-made disasters. From earthquakes to tsunamis, natural disasters have produced startling devastation with major death tolls and economical consequences. Logistics during natural disasters or complex emergencies involve highly complicated optimization problems of various characteristics. The necessary effective planning is based on current information and includes many limiting factors such as supply constraints, transportation capabilities, and traffic conditions. Although optimal solutions may be attained by commercial solvers, the problems' NP-hard nature often prohibits their detection in reasonable time. This property violates the time-sensitivity requirement in decision making during emergencies, dictating the use of metaheuristics for the detection of (sub-)optimal solutions within reasonable time frames.

The contribution of the present thesis is twofold. First, it introduces a multi-period problem model for Humanitarian Logistics, aiming to minimize the shortages of different kinds of relief resources to a number of affected areas. The relief products are transported, via multiple modes of transportation, from dispatching centers to these areas. In addition, limitations in supply, transportation constraints and roadway capacity are considered. A test suite of benchmark problems with diverse characteristics is generated from the proposed model and all problems are solved with the commercial solver CPLEX.

Secondly, a number of modern metaheuristics are studied on the detection of (sub-) optimal solutions in prespecified time limits. Careful parameter tuning of the algorithms is conducted based on preliminary experimentation. Necessary modifications in their essential operations are made to fit the special requirements of the test problems.

The algorithms' performance is recorded and assessed in terms of solution accuracy with respect to the optimal solutions. Sensitivity analysis reveals the stability of each metaheuristic. Eventually, comparisons among the developed algorithms offer valuable information regarding their efficiency in solving Humanitarian Logistics problems.

Περιληψη

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Η Ανθρωπιστική Εφοδιαστική έχει προσελκύσει έντονα το ενδιαφέρον της επιστημονικής κοινότητας τις τελευταίες δύο δεκαετίες, εξαιτίας της ραγδαίας αύξησης των ανθρωπογενών και φυσικών καταστροφών. Οι τελευταίες, έχουν προκαλέσει αναπάντεχες απώλειες, βάζοντας σε κίνδυνο την ζωή εκατομμυρίων ανθρώπων και οδηγώντας σε ανυπολόγιστες οικονομικές επιπτώσεις. Η λογιστική διαχείριση κατά την διάρκεια φυσικών καταστροφών και γενικότερα σε καταστάσεις έκτακτης ανάγκης, περιλαμβάνει δύσκολα προβλήματα βελτιστοποίησης διαφόρων χαρακτηριστικών. Ο αναγκαίος και αποτελεσματικός σχεδιασμός δράσης σε τέτοιες καταστάσεις βασίζεται στην τρέχουσα πληροφορία και περιορίζεται από πολλούς παράγοντες. Παρόλο που βέλτιστες λύσεις μπορούν να επιτευχθούν χρησιμοποιώντας εμπορικά λογισμικά βελτιστοποίησης, η υψηλή υπολογιστική πολυπλοκότητα που εκ φύσεως διακρίνει τέτοιου είδους καταστάσεις συχνά εμποδίζει την επίλυσή τους σε εύλογα χρονικά πλαίσια.

Η συμβολή της παρούσας εργασίας στην Ανθρωπιστική Εφοδιαστική είναι πολλαπλή: Αρχικά προτείνεται ένα μοντέλο που στοχεύει στην ελαχιστοποίηση των ελλείψεων ενός συνόλου αγαθών πρώτης ανάγκης, τα οποία διανέμονται στις πληγείσες περιοχές. Τα προϊόντα μεταφέρονται με χρήση μέσων μεταφοράς διαφορετικών τύπων από τα κέντρα διανομής στις περιοχές που έχουν άμεση ανάγκη. Επιπρόσθετα, λαμβάνεται υπόψη ένας αριθμός περιορισμών που σχετίζεται με την αποθήκευση και την μεταφορά των αγαθών στις πληγείσες περιοχές, καθώς και την χωρητικότητα (σε οχήματα) του οδικού δικτύου. Δεδομένου ότι σε μία φυσική καταστροφή το οδικό δίκτυο έχει υποστεί σημαντικές (αν όχι ολικές) φθορές, η θεώρηση ενός μέγιστου αριθμού οχημάτων που επιτρέπεται να διασχίσει μία συγκεκριμένη διαδρομή που συνδέει το κάθε ένα κέντρο διανομής με τις περιοχές άμεσης ανάγκης, αποτελεί μία ρεαλιστικότερη προσέγγιση.

Από το παραπάνω μοντέλο, παράγουμε ένα σύνολο δοκιμαστικών προβλημάτων

βελτιστοποίησης με διαφορετικά χαρακτηριστικά. Όλα τα προβλήματα επιλύονται με το δημοφιλές πακέτο βελτιστοποίησης CPLEX και καταγράφεται η βέλτιστη λύση τους. Σε δεύτερη φάση, μελετάται ένας αριθμός σύγχρονων μεταευρετικών αλγορίθμων για την επίλυση των προβλημάτων αυτών σε περιορισμένο χρόνο. Η αναγκαία ρύθμιση των παραμέτρων των αλγορίθμων βασίζεται σε κατάλληλη προεπεξεργασία. Επιπλέον, γίνονται αναγκαίες τροποποιήσεις σε βασικούς τελεστές των αλγορίθμων, προκειμένου να προσαρμοστούν στις ιδιαίτερες απαιτήσεις του μοντέλου.

Η απόδοση των αλγορίθμων καταγράφεται και αξιολογείται ως προς την ακρίβεια σε σχέση με τις βέλτιστες λύσεις που ελήφθησαν από το CPLEX. Στατιστική ανάλυση των αποτελεσμάτων υποδεικνύει την σταθερότητα των προτεινόμενων μεταευρετικών αλγορίθμων. Τέλος, συγκρίσεις μεταξύ των αλγορίθμων προσφέρουν σημαντικές πληροφορίες σχετικά με την αποδοτικότητά τους στην επίλυση προβλημάτων Ανθρωπιστικής Εφοδιαστικής.

Chapter 1

Introduction

1.1 Natural Disasters

Disasters can be categorized according to their causes and speed of occurrence. Van Wassenhove [58] has defined four categories to explain the different types of disasters. More specifically, as illustrated in Fig. 1.1, Van Wassenhove distinguishes disasters between natural and man-made, as well as between sudden onset and slow onset. Apparently, natural disasters are caused by natural phenomena, while man-made disasters are caused by humans. Furthermore, in the case where a disaster occurs immediately with little or no forewarning, it is categorized as sudden-onset while slow-onset disasters are developed over time.

Thomas and Kopzack [56] state that both natural and man-made disasters are expected to increase another five-fold over the next fifty years due to environmental degradation, rapid urbanization, and the spread of HIV/AIDS in the developing world. Fig. 1.2 illustrates the global trends in disaster events and death toll from 1980 to 2013, recorded by the world database on disasters, namely the Emergency Database (EM-DAT) [68].

	Natural	Man-made
Sudden-onset	Earthquake Hurricane Tornadoes	Terrorist Attack Coup d'Etat Chemical leak
Slow-onset	Famine Drought Poverty	Political Crisis Refugee Crisis

Figure 1.1: Disaster Categories.

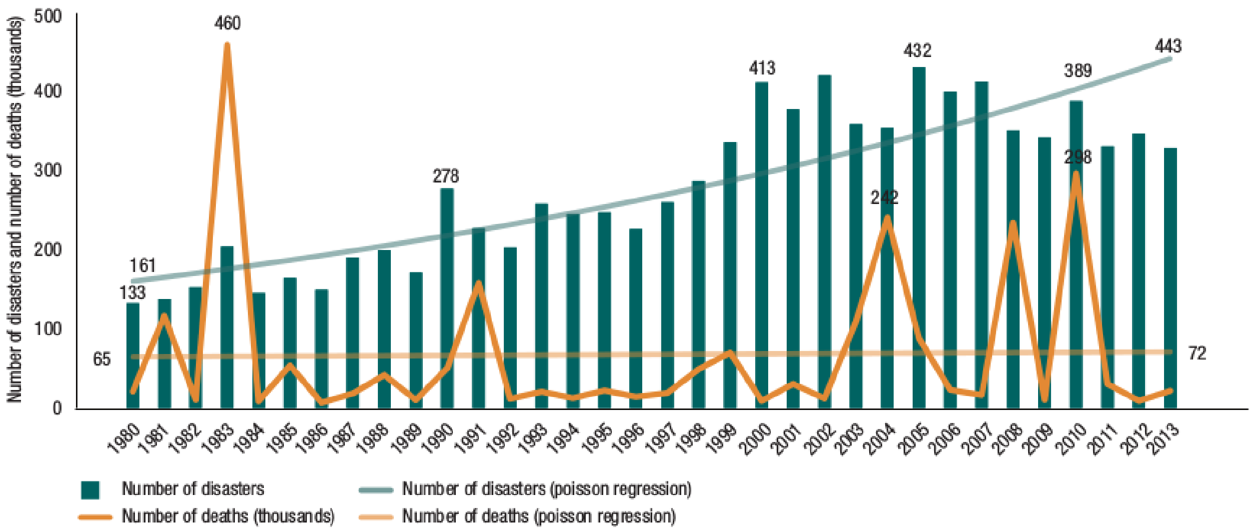

Figure 1.2: Global trends in disaster events and death tolls (1980-2013).

Recent concrete examples of severe natural disasters include the Chile earthquake in 2015, Nepal earthquake in 2015, Japan earthquake and tsunami in 2011, Haiti earthquake in 2010, Myanmar cyclone Nargis in 2008, and Pakistan earthquake in 2005. All these events caused thousands of deaths and left numerous people homeless and/or in need of emergency assistance. The long lasted, slowly progressing recovery efforts forced thousands of wounded people to continue living in refugee camps that were set up immediately after the disaster.

The importance of defining natural disasters lies not just because many of the definitions are descriptive but, furthermore, because they give an indication of impact issues for stricken areas with possible indicators relevant to Disaster Management process, as well as rapid response intervention. In general, the commonly accepted definitions incorporate the speed of onset of the event and the overwhelming nature or magnitude of the climatic surge in energy. Additionally, two other definition characteristics include the state of unpreparedness of the population and the unexpected nature of the event.

Furthermore, the lack of resilience of the affected population to endure the impact of the natural disaster constitutes another important characteristic. According to Smith [45] certain common features exist within natural disasters caused by environmental hazards. These features are:

- The origin of the damaging event is clear and produces characteristic threats to human life or well-being (e.g. a flood causes death by drowning).
- The warning time is normally short, i.e. the hazards are often known as rapid onset events. This means that they can be unexpected even though they occur within a known hazard zone.
- Most of the direct losses, whether to life or property, are suffered fairly soon after the event, i.e. within days or a week.
- The exposure to hazard or assumed risk is largely involuntary, normally due to the location of people in a hazardous area.
- The resulting disaster occurs with an intensity that justifies an emergency response, i.e. the provision of specialist aid to the victims. The scale of response can vary from local to international.

From the above features, Smith defines natural disasters as [45]: *"Extreme geophysical events, biological processes and major technological accidents characterized by concentrated releases of energy materials, which pose a largely unexpected threat to human life and can cause significant damage to goods and the environment"*.

As already mentioned, even though natural disasters definitions are helpful to a measure, the researchers adopt slightly different ways to define them. Consequently, no definition is universally accepted. According to the World Health Organization and the United Nations have adopted the following definition: *"The result of a vast ecological breakdown in the relationships between man and his environment, a serious and sudden (or slow, as in drought) disruption on such a scale the stricken community needs extraordinary efforts to cope with it, often with outside help or international aid"*.

Moreover, Perez and Thomson state [39]: *"The occurence of widespread, severe damage, injury, or loss of life or property, with which the community cannot cope, and during which the affected society undergoes severe disruption"*.

The United Nation's International Strategy for Disaster Reduction has confirmed that a natural disaster is to be regarded as: *"The consequences of the impact of a natural hazard on a socio-economic system with a given level of vulnerability which prevents the affected society from coping adequately with this impact"*.

Finally, Cheng defines the natural disasters as: *"A disaster is a sudden massive disproportion between hostile elements of any kind and the survival resources that are available to counterbalance these within shortest period of time"*.

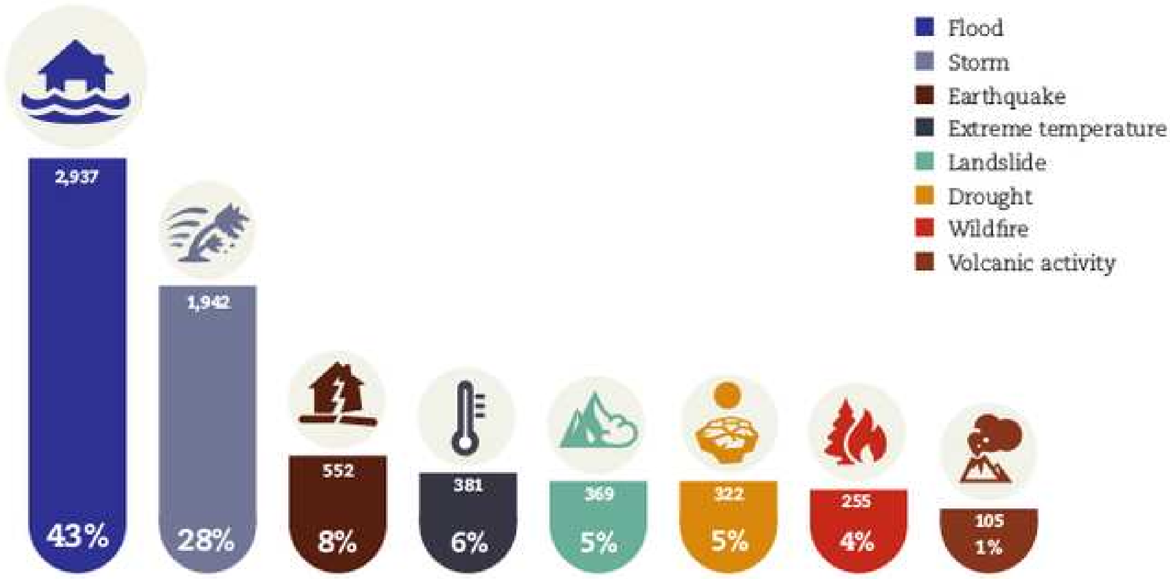

Figure 1.3: Share of occurrence of natural disasters by disaster type, (1994-2013).

1.2 Occurrence and Impact of Natural Disasters

1.2.1 Occurrence of Natural Disasters

The last two decades EM-DAT [68] has recorded around 6900 natural disasters on a world scale, which claimed 1.35 million lives. At the same time, the number of affected people through this period was 213 million on average per annum. According to EM-DAT, the frequency of geophysical disasters (earthquakes, tsunamis, volcanic eruptions, and mass movements) remained broadly constant during the latter period. However, a sustained rise in climate-related events (mainly floods and storms) has pushed the total occurrences to significantly higher rates. Since 2000 EM-DAT recorded an average of 341 climate-related disasters per annum, an increase of 44% from the 1994-2000 average and well over twice the level in 1980-1989.

From a disasters analysis point of view, population growth and patterns of economic development are generically considered as more important to explain this upward trend compared to climate change or cyclical variations in weather. At the present time, the number of people being in harm's way is significantly higher than that of 50 years ago. Also, the constant tend of building in flood plains, earthquakes zones, as well as other high-risk areas has increased the likelihood that a routine natural hazard will become a major catastrophe [68].

Figure 1.3 presents the share of occurrence of natural disasters by disaster type in

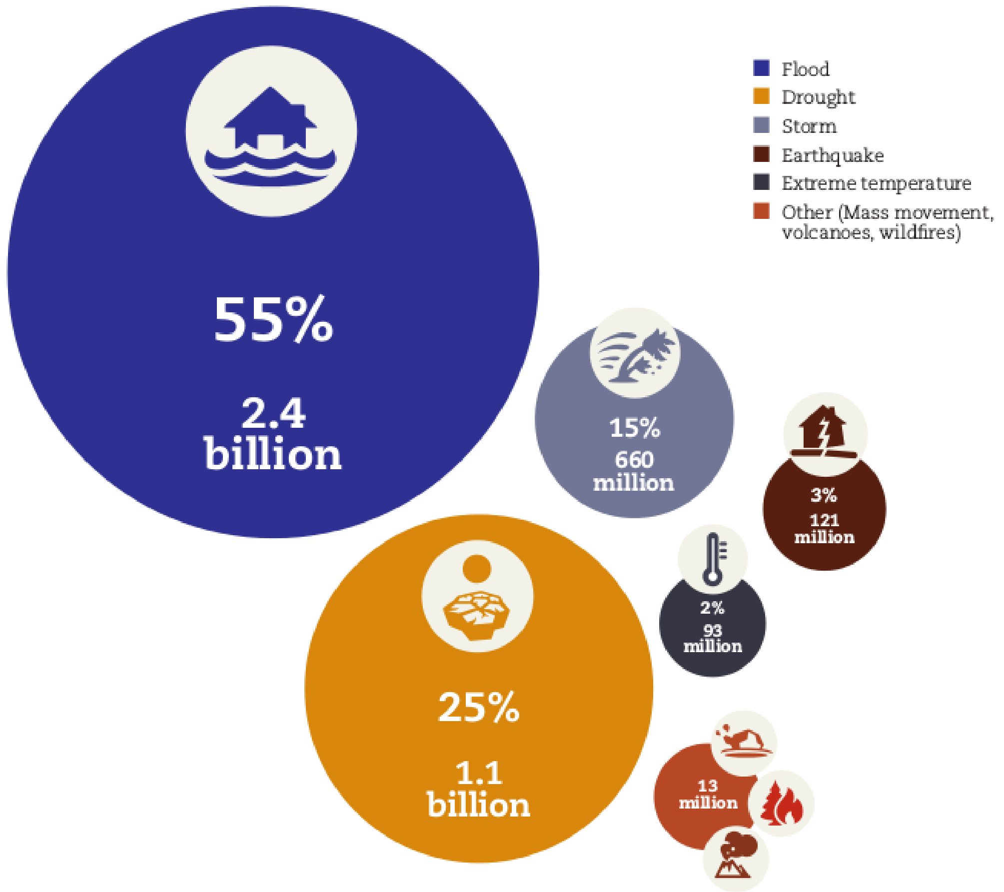

Figure 1.4: Number of affected people per disaster type (Deaths are excluded).

the period 1994-2013 [68]. It clearly demonstrates that the majority of disasters during the last 20 years have been caused by floods, accounting for 43% of all recorded events and affecting nearly 2.5 billion people. Storms constitute the second most frequent type of disaster, causing more than 240000 life-losses and raising a cost of US$940 billion in recorded damage. Interestingly earthquakes (including tsunamis) have killed more people than all other types of disasters put together, i.e. almost 750000 through this period. Another interesting point is that, even though droughts have accounted for just 5% of disaster events, they have affected more than one billion people or 25% of the global total as depicted in Fig. 1.4 [68].

Figure 1.5 presents the disaster occurrence in the last century (1900-2014) with respect to biological, climatological, geological, hydrological, and meteorological disasters [68]. The data indicate stable trends of occurrence until middle of the century. From 1950 to 1985 the number of registered hydrological and meteorological disasters rises. From 1985 to 2006 the number has doubled, while after 2006 it presented a gradual reduction. The occurrence of biological, climatological, and geophysical disasters are stable until 1975. Since then, one sees an increasing trend for all disaster types.

EM-DAT denotes that USA and China recorded the highest number of disasters

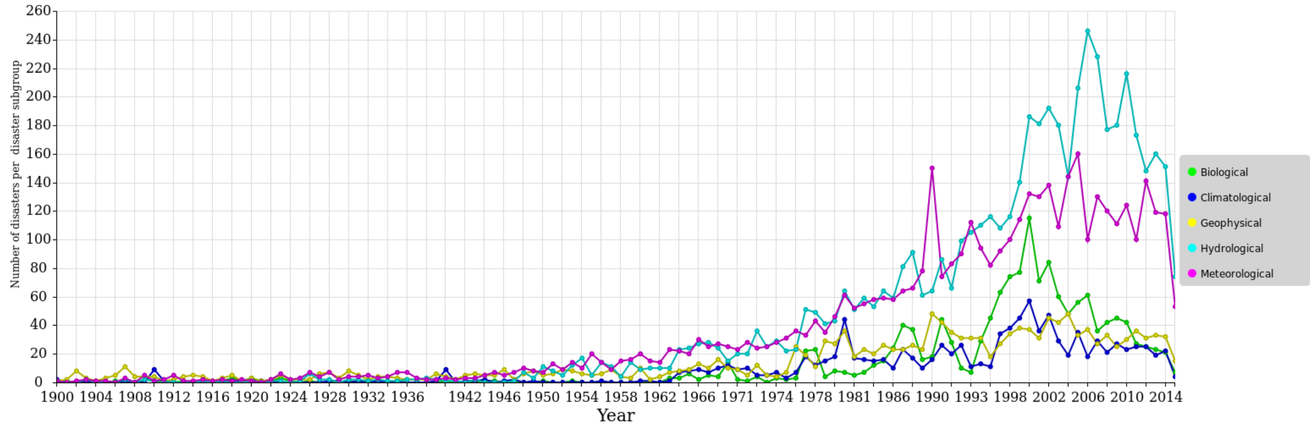

Figure 1.5: The trend of natural disaster occurrence in respect of biological, climatological, geological, hydrometeorological, and meteorological disasters.

between the latest twenty years, mainly as a consequence of their size and high population densities. In general, there may be several of reasons why the total numbers of registered disaster have increased. It is a matter of discussion whether the rapid growth of natural disasters is a result of increased frequency of disruption and fluctuation in nature, or a result of population growth and increased urbanization. The higher the growth and density of population is, the more interference will be between the human civilization and disruptions of nature.

1.2.2 Impact of Natural Disasters

As it can be deduced in the previous sections, the impact of natural disasters can be pernicious. From the destruction of buildings to the spread of disease, natural disasters can devastate entire countries overnight by causing major economic depression and disrupting people's lives. The major impacts of natural disasters are summarized in the following lines.

1. *Displaced Populations:* One of the most immediate effects of natural disasters is population displacement. When countries are ravaged by earthquakes and/or other powerful nature forces, a large number of human beings has to abandon their homes and seek shelter in other regions. A large influx of refugees can disrupt everything, from accessibility of health care and education to food supplies and basic hygiene. Large scale evacuations are common in the light of the power of natural disasters. Those fortunate enough to survive face a range of challenges following widespread destruction.

2. *Health Risks:* Aside from the obvious danger of the natural disasters itself, potential secondary effects can be significantly damaging as well. Natural disasters often

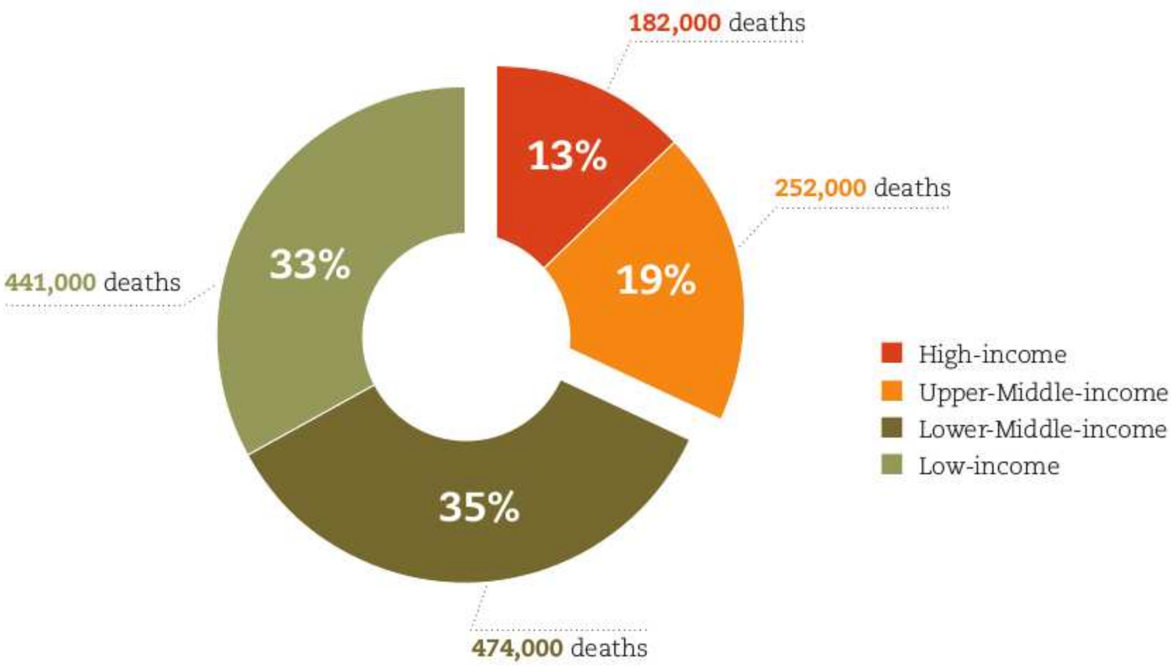

Figure 1.6: Number of deaths per income group between (1994-2013).

cause severe flooding, which can result in the spread of transmitted diseases. As a result, health complications can be prevalent among survivors and, without the help of emergency relief from aid organizations, death tolls can rise after the immediate danger has passed.

3. *Food and Water Scarcity:* After natural disasters food can become scarce. Thousands of people around the world go hungry as a result of destroyed crops and a loss of agricultural supplies.

4. *Economic and Financial Impacts:* Major natural disasters lead to severe negative short-run economic impacts. Disasters also appear to have adverse long-term consequences for economic growth, development, and poverty, causing inequalities. People in poverty suffer by income fluctuations and have limited access to financial services. In the aftermath of a disaster,they are more prone to reduce consumption and have a decreasing shock in other household indicators. In addition, there is a number of non poor (or close to be) who are not insured for those risks. These people may fall into poverty as a consequence of decapitalizing when coping with the shock. The impact of the initial shock and likelihood of falling into poverty is directly related to the available coping mechanisms [42].

It is worth mentioning that the income level affects the death tolls in natural disasters. In low income countries, more than three times as many people died per disaster in comparison to high income ones. Specifically, higher income countries experienced 56% of disasters but lost 32% of lives, whilst lower income countries experienced 44% of disasters but lost 68% of lives. This demonstrates that the levels of economic development rather than exposure to hazards constitute the major determinants of mortality. Figure 1.6 presents the number of deaths per income group for the last two decades [68].

1.3 Scope of the Thesis

Effective planning and scheduling of relief operations play a key role in saving lives and reducing damage in natural disasters. These emergency operations involve a variety of challenging optimization problems of various characteristics. The success or failure of a relief operation depends to a large extent on how the various logistics elements of the operation are handled.

Humanitarian Logistics models require efficient solvers that produce satisfactory solutions within strict time constraints. Metaheuristics have been recognized as valuable optimization tools for this purpose. Recently, metaheuristics have gained increasing popularity in academia and industry due to their successful application in solving complex real world problems. This can be attributed to their efficiency in decision making, simplicity, noise tolerance, and easy implementation [29].

In the present study, we consider a model where the objective is the minimization of losses caused by the mismatch between supply and demand of relief resources in the affected areas, taking into account the already existing quantities (if any) and the importance of the different resources. Furthermore, beyond constraints related to number, volume, and load capacity of vehicles, we consider also road capacity constraints imposed by authorities. The latter is the source of bottleneck in supply chain due to decrease in transportation capacity and unexpected increase of relief vehicles [6].

A test suite of benchmark problems is produced for the proposed model and they are solved to optimality with the commercial CPLEX solver. In addition, a number of modern metaheuristics, namely Differential Evolution (DE) [41] and Particle Swarm Optimization (PSO) [36], are considered and their efficiency is studied on the test suite. In order to fit the special requirements of the test problems, appropriate modifications are made in their basic operations. Moreover, we consider an enhanced DE (eDE) variant [31], which is characterized by significant improvement in solution performance. Finally, all the aforementioned algorithms are also utilized in a parallel Algorithm Portfolio (AP) framework [17, 18, 21, 37, 52], according to an efficient, recently proposed approach [46].

1.4 Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 offers the background in Emergency Management in Humanitarian Logistics, underlining the challenges in humanitarian sector. Also, it gives a literature review aiming to present the reader previously studied metaheuristic algorithms for Humanitarian Logistics done by researchers before. Chapter 3 presents the mathematical formulation of the proposed model and the employed algorithms are comprehensively discussed. Chapter 4 describes in detail the experimental setting and obtained results. Eventually, Chapter 5 concludes the thesis.

Chapter 2

Humanitarian Logistics

2.1 Emergency Management

Emergency Management or *Disaster Relief Operations* refers to the process of responding to a catastrophic situation, providing *humanitarian aid* to persons and communities who have suffered from some form of disaster. It involves dealing with and avoiding risks and preparing, supporting, and rebuilding society when natural or human-made disasters occur. In general, emergency management is the creation of plans through which communities reduce vulnerability to hazards and cope with disasters in an effort to avoid or limit the impact of disasters. Disaster management does not avert or eliminate the threats, instead it focuses on creating plans to decrease the impact of disasters. Actions taken depend in part on perceptions of risk of those exposed. Effective emergency management relies on thorough integration of emergency plans at all levels of government and non-government organizations. Activities at each level (individual, group, community) affect the other levels. Failure to create a plan has direct impact to assets, human mortality, and lost revenue.

2.1.1 Definitions of Emergency Management

According to the Disaster Management Center of the University of Winsconsin, emergency management is defined as:
"The range of activities designed to maintain control over disaster and emergency situations and to provide a framework for helping at-risk persons to avoid or recover from the impact of the disaster. Disaster management deals with situations before, during, and after a disaster".

The objective of disaster management can be described with respect to three key issues:

1. Reduce or avoid the human, physical, and economic losses suffered by individuals, the society, and the country.
2. Reduce personal suffering.
3. Speed recovery.

On the other hand Kovacs and Spens [24] states that the focus of emergency management is to:
"...design the transportation of first aid material, food, equipment, and rescue personnel from supply points to a large number of destination nodes geographically scattered over the disaster region and the evacuation and transfer of people affected by the disaster to the health care centers safely and very rapidly".

As it can be deduced, different researchers have different ways of defining what a disaster management is. However, the overall goal for all of them is to alleviate relief victims as soon as possible with the right supplies and services.

Figure 2.1: Disaster management cycle.

2.2 Disaster Management Cycle

Disaster management aims to reduce or avoid potential losses from hazards through prompt and appropriate assistance to victims, and achieve rapid and effective recovery. The Disaster Management Cycle (DMC) illustrated in Fig. 2.1 encompasses the ongoing process by which governments, businesses, and society plan for and reduce the impact of disasters, react during and immediately after a disaster, and take recovery steps [28]. Appropriate actions at all points in the cycle lead to greater preparedness, better warnings, and reduced vulnerability or prevention of disasters during the next iteration of the cycle. The complete DMC includes the shaping of public policies and plans that either modify the causes of disasters or mitigate their effects on people, property, and infrastructure. Related to time, disaster relief operations can be separated into four phases. Each phase requires different resources and skills. The first two phases mainly focus on strategic planning and preparation, while the other two require actual project management [24].

1. *Preparation Phase* (before a disaster strikes): The goal of emergency preparedness programs is to achieve a satisfactory level of readiness to respond to any emergency situation through programs that strengthen the technical and managerial capacity of governments, organizations, and communities. These measures can be described as logistical readiness to deal with disasters and can be enhanced by having response mechanisms and procedures, rehearsals, developing long-term and short-term strategies, public education and building early warning systems.

Preparedness can also take the form of ensuring that strategic reserves of food, equipment, water, medicines and other essentials are maintained in cases of national or local catastrophes.

During the preparedness phase, governments, organizations, and individuals develop plans to save lives, minimize disaster damage, and enhance disaster response operations. Preparedness measures include preparedness plans, emergency exercises/training, warning systems, emergency communications systems, evacuation plans and training, resource inventories, emergency personnel/contact lists, mutual aid agreements, and public information/education. As with mitigations efforts, preparedness actions depend on the incorporation of appropriate measures in national and regional development plans.

2. *Immediate Response Phase* (shortly after): The aim of emergency response is to provide immediate assistance to maintain life, improve health, and support the morale of the affected population. Such assistance may range from providing specific but limited aid. (e.g. assisting refugees with transport, temporary shelter and food) to establishing semi-permanent settlement in camps and other locations. It also may involve initial repairs to damaged infrastructure. The focus in the response phase is on meeting the basic needs of the people until more permanent and sustainable solutions can be found. Humanitarian organizations are often strongly present in this phase of the disaster management cycle.

3. *Reconstruction Phase* (in the aftermath): As the emergency is brought under control, the affected population is capable of undertaking a growing number of activities aimed at restoring their lives and the infrastructure that supports them. There is no distinct point at which immediate relief changes into recovery and then into long-term sustainable development. There will be many opportunities during the recovery period to enhance prevention and increase preparedness, thus reducing vulnerability. Ideally, there should be a smooth transition from recovery to on-going development.

   Recovery activities continue until all systems return to normal or better. Recovery short and long term measures include returning vital life-support systems to minimum operating standards, temporary housing, public information, health and safety education, reconstruction, counselling programs, as well as economic impact studies. Information resources and services include data collection related to rebuilding and documentation of lessons learned.

4. *Mitigation Phase* (afterwards): Mitigation activities actually eliminate or reduce the probability of disaster occurrence or reduce the effects of unavoidable disasters. Mitigation measures include building codes, vulnerability analyses updates, zoning and land use management, preventive health care, and public education.

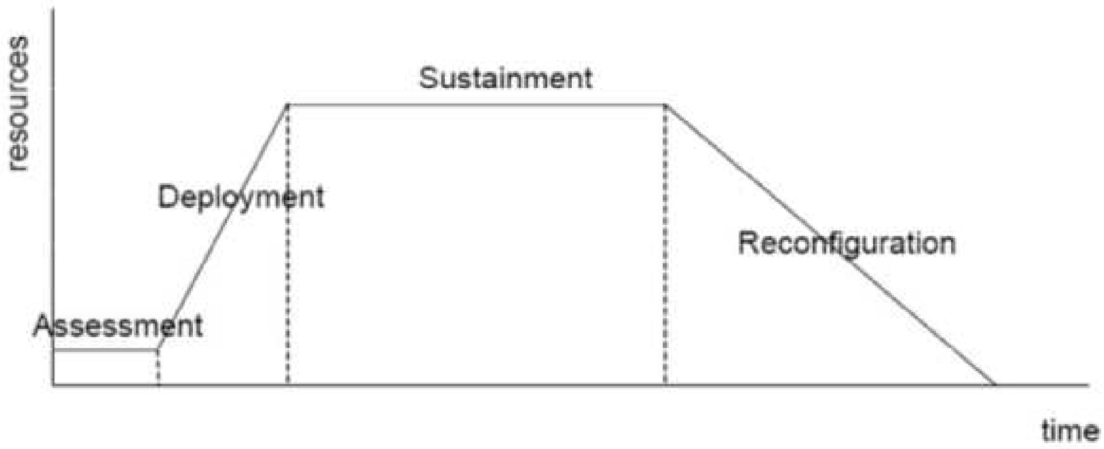

Figure 2.2: The Relief Mission Cycle.

> Mitigation depends on the incorporation of appropriate measures in national and regional development planning. Its effectiveness also depends on the availability of information on hazards, emergency risks, and the countermeasures to be taken. The mitigation phase, (as well as the whole DMC) includes the shaping of public policies and plans that either modify the causes of disasters or mitigate their effects on people, property, and infrastructure.

The general flow of resources to the affected areas, is described by the Relief Mission Cycle (RMC) identified by Thomas and Beamon [55, 4]. The RCM model consists of four phases:

1. *Assessment* of resources after disaster has occured.
2. *Deployment* of supplies in disaster areas to reach relief victims.
3. *Sustainment* of operations are for a time period.
4. *Reconfiguration* where operations are reduced and eventually terminated.

The length and importance of each phase varies, depending on the characteristics of disaster and affected areas. The RCM life cycle is depicted in Fig.2.2 [1].

The assessment phase involves the need of analysis. The information obtained at this phase is used to develop the disaster relief supply chain. The assessment determines the immediate needs of the affected people, the required resources and equipment, based on the severity and nature of the disaster. After assessing the needs, the resource mobilization process begins. Once the necessary resources and aid material has been obtained, it is strategically transferred to a location for easy access and deployment. During deployment, the resource requirements are ramped up to meet the identified demand. As more accurate information is obtained, the needs of the beneficiaries can be better matched, leading to more stable demand. This leads to the third phase (sustainment) where the relief effort is maintained at a particular level over a period of time. Lastly, at the reconfiguration phase, operations are ramped down and eventually terminated. It is important to note that the relief chain is modified across the phases. For instance, in the initial stage of a disaster, aid materials are pushed through the relief chain, while a pull strategy is in effect at the later phase, once demands have been well assessed. At the sustainment phase, focus shifts from speedy transportation of goods to accurately meeting the requirements of the beneficiaries at minimal cost. In this stage, an agile supply chain is required, while in the reconfiguration phase leanness is needed.

2.3 Actors and Parties Concerned

The surprise and devastating nature of natural catastrophes calls for a massive coordinated reaction on short notice. There is a need for all sectors to participate in the national platforms, from local, provincial, and national *stakeholders* to high-level political decision makers and the private sector. Any country can be a potential donor of humanitarian aid to another nation affected by a disaster or emergency. Bilateral assistance from government to government is probably the most significant overall source of foreign assistance, whether it involves human resources, humanitarian supplies, or both. The actors and stakeholders are divided in four groups [50]:

1. *Beneficiaries:* Those who receive some kind of aid from another part. The beneficiaries are separated into two groups, i.e. the local population of the affected area and the local government.

2. *Operational actors:* In the world of humanitarian aid logistics and relief operations, there are several actors that make contributions. Different actors have different roles but all are working towards the objectives of humanitarian relief. Operational actors serve as connection between donors and relief victims but work in different ways. Operational actors can be divided into four main groups: (i) multilateral, intergovernmental organizations (IGOs), (ii) Non-governmental organizations (NGOs), (iii) International coordination agencies and (iv) others (e.g., the Pan American Health Organization).

3. *Donors:* Donors are the source of funding for all kinds of humanitarian work. Most of the humanitarian organizations do not deal with commercial, profit making

activities and are dependent on donors to sustain their activities. Donors can be divided into three main groups [50]: (i) neighboring regions or governments, (ii) foreign governments, and (iii) the general public and private corporations.

4. *Media:* Has great power since it often provides direct information direct to potential donators. If a humanitarian crisis is covered by the press, it is easier for donors to relater their willingness to donate to the actual disaster.

2.4 Definitions and Characteristics of Commercial Logistics

Logistics embraces procedures for the management of materials flow between point of origin and point of consumption through supply chains, in order to meet requirements of customers or corporations. The materials can be tangible (such as raw materials, components, finished goods, and spare parts) or intangible (such as time, information, particles, energy). In practice the terms "logistics" and "supply chain management" are used interchangeably. However, as Misra [30] states, supply chain management originally refers (among other issues) to having a global vision of both production and logistics from point of origin to point of consumption. All these terms may suffer from semantic change as side effect of advertising.

The Council of Supply Chain Management Professionals defines: *"Logistics Management is that part of Supply Chain Management that plans, implements, and controls the efficient forward and reverse flow and storage of goods, services, and related information between the point of origin and point of consumption in order to meet customers' requirements."*

Christopher [9] states: *"The process of strategically managing the procurement, movement and storage of materials, parts and finished inventory (and the related in formation flows) through the organization and its marketing channels in such a way that current and future profitability are maximized through the cost effective fulfilment of orders."*

It is important to note that Logistics Management is vital not only to manufacturing and assembly industries, which are goods-oriented, but also to retailing, transport and other service-oriented industries. Logistics management involves numerous elements, including:

1. Selecting appropriate vendors with ability to provide transportation facilities.

2. Choosing the most effective routes for transportation.

3. Discovering the most competent delivery method.

4. Using software and IT resources to proficiently handle related processes.

Additionally, in logistics management multiple issues are created from unwise decisions. Specifically, a failure or a delay in the delivery process leads to buyer dissatisfaction. Another potential issue is a possible damage of goods due to careless transportation. To resolve such issues, companies shall implement efficient logistic management practises, focusing on collaboration rather than competition. The minimization of the use of resources is a common motivation in logistics for import and export.

2.5 History and Development of Logistics

Logistics is to be assumed far from being a new idea. Indeed, if one takes into consideration the procurement of raw materials and their conversion to become usable, it becomes evident that this concept was already discovered in areas all over the ancient world. This indicates that ancient civilizations developed techniques to cover their necessities.

During the two World Wars, logistics received special ettention by military forces especially in World War II, since the required transportation of troops and supplies surged than any other period in history. From that period, the term logistics was commonly refered to describe the support of military forces and their equipment. In addition, military forces made effective use of logistics models to ensure that materials were at the proper place and time.

In early '60s logistics was focused on engineering issues, calculating initial support requirements, and programming resources to keep a system operational. Eventually, a large number of firms realized that physical distribution and logistics were activities whose cost was neither well studied nor coordinated. The Persian Gulf War in 1991 contributed to the increased recognition of logistics, mainly due to the frequent mention by commentators of the logistical challenges to support the war effort in the Persian Gulf countries. The processes applied in the Persian Gulf War can be generalized to business, where planning and management of supplies, inventories, transportation, distribution networks, as well as supporting information are needed to meet customer requirements.

2.6 Humanitarian Logistics

2.6.1 Definition of Humanitarian Logistics

In the literature the terms “humanitarian logistics” and “disaster relief operations” are often used interchangeably. Kovacs and Spens [24] consider that logistics related to “disaster relief” and “continuous aid work” are subcategories of “humanitarian logistics”.

Many definitions have been proposed to describe humanitarian logistics (HL). Thomas's gives the following definition [56]:
“*HL is responsible for planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of alleviating the suffering of vulnerable people*”.

The latter emphasizes an end-to-end perspective as well as a beneficiary-oriented supply chain management approach, which is in line with the definitions for commercial logistics. Within the same framework Van Wassenhove [58] states:
“*Logistics is the process and systems involved in mobilizing people, resources, skills, and knowledge to help vulnerable people affected by disasters*”.
In general, according to many humanitarians, the definition of logistics is open to loose interpretation.

Jahre and Heigh [22] define three different types of humanitarian supply chains:

1. The *emergency supply chain*, which is characterized by unpredictable and a relatively unstable demand and nature.
2. The *project supply chain*, which is more predictable and stable due to its association with the reconstruction phase.
3. The *permanent supply chain*, which consists of all permanent or long-term facilities and equipment, staff, systems, and standardized processes that secure and prepare responsiveness to disaster relief operations. It also embraces ongoing projects related to emergency supply chains.

2.6.2 Characteristics of Humanitarian Logistics

Two utmost importance of supply chain principles in HL are *agility* and *leanness* [12]. The first one is defined as the ability to respond to unexpected changes when an unpredictable demand is combined with short lead times. The latter refers to achieving more and better with reduced resources, when demand is relatively stable and predictable.

Briefly, while agility focuses on effectiveness and speed, leanness focuses on efficiency and cost saving [58].

One of the tools utilized in HL is the development of warehouses to store all essential goods. Warehouses shall be properly designed for taking precautions for contamination or waste of materials and be organized a way that facilitates deliveries to desired areas at proper time and quantities. Another important issue for successful HL is the placement of distribution centers at strategically selected areas, that lie close to the region suspected or expected to be hit by a disaster. The latter can be predicted through software or mathematical models. The responsible authorities aim at maximization of response and minimization of distribution time, expenses, and number of distribution centers. Coordination of the delivery of goods, organization of teams, supplies and equipment movement are realized by mobilization centers, which are located near the affected region. A way of taking precautions before a disaster occurs, is to organize emergency response plans that will help preparation and, consequently, mobilization at the time of disaster.

Inventory pre-positioning is a logistical technique which can improve responsiveness. It is adopted for estimating item quantities required according to specific safety stock levels and order frequency, as well as for searching optimal locations for warehouses (facility location). Logistics is one of the major tools of disaster preparedness among surveillance, rehearsal, warning, and hazard analysis. Besides, success and performance in humanitarian relief chains are very difficult to be measured because of some distinct characteristics that humanitarian operations have. Such characteristics are unpredictable demand, difficulty to obtain data from operations, unpredictable working environment, lack of incentive for measurement (due to their non-profit character), short lead time, as well as other factors like geography, political situation, and weather.

2.7 Commercial Logistics versus Humanitarian Logistics

HL specialists face challenges that differ in various aspects (not only in terms of the price of failure) from the ones appearing in "for profit" cases. Yet, many approaches adopted in commercial context are also applicable in the HL setting. The main strategic goal of HL, which constitutes the source of most differences, is that alleviating suffering replaces the profit motive characteristic of commercial logistics. The distinct attributes required by HL as well as the differences and similarities to commercial logistics can be summarized as follows:

Differences

1. The demand requirements in HL are particularly complex due to the high uncertainty in location, time, type, and quantity. Demand is generated from random events, that render it unstable and unpredictable. Moreover, a key ingredient contributing to the aforementioned high complexity of demand arises from the fact that humanitarian supply chain needs to be designed and executed in shorter periods of time than commercial supply chain.

2. Inventory management in humanitarian supply chain is affected by unreliable, incomplete or non-existent information related to lead times and locations [4]. On the other hand, in commercial supply chain the inventory management has well established policies based on lead times and desired customer satisfaction levels.

3. The operational conditions in humanitarian supply chain are characterized by high rate of difficulties. As concrete examples we can mention difficulties associated with assessing the available resources due to the devastated nature during post-disaster periods, lack of resources (relief commodities, means of transport), unsolicited or unwanted donations, disruption in infrastructures (transportation and communication), and lack of professional human resources.

4. The complexity of disaster relied actions is increased due to the different ethical principles that humanitarian organizations follow.

Similarities

Even though HL appears to differ than commercial logistics, similarities still exist. Indeed, both areas aim to optimize efficiency and effectiveness on the basis of *"five rights"* (the right goods are available in the right place, at the right time, in the right quantity and quality, at the right cost). In principle, the main difference lies on the focus of optimization. In humanitarian sector the aim is the alleviation of suffering from vulnerable people, while in the commercial sector it is the maximization of profit.

2.8 Challenges in Humanitarian Logistics

In order to model a systems approach using analytical tools such as simulation, optimization, and forecasting, recognizing and addressing the specific challenges of HL is critical. Some of the major challenges identified are hereby highlighted:

1. *Professionalism*

   Employees in most humanitarian organizations are lacking of formal training but usually have only empirical knowledge [56]. The level of logistics expertise within these aid organizations is habitually low and the involved persons operate some way down the organizational structure. In addition, a high proportion of the employees in aid agencies barely has education in logistics and transportation management. Furthermore, the major of humanitarian organizations relies on volunteers who can only work for a limited period of time. Another critical point is that responding to disasters is a complex and high pressure job that requires long hours. This unstable nature of emergencies imposes real challenges to humanitarian organizations in terms of employee retention. The latter, ultimately leads to field workers quitting their job. The loss of such professional workers can be harmful to humanitarian agencies because experience is considered to be more valuable than relief operation plans.

2. *Collaboration*

   The lack of collaboration is another issue that should be addressed during disaster relief operations. The individual organizations have different interests, mission, capacity, and expertise [58]. The collaboration between the various actors is not satisfactory since humanitarian organizations do not cooperate in setting up their supply chains. This is a weak point in disaster response, because single humanitarian organizations have no capacity and required funds to adequately respond to an emergency situation. Moreover, effective collaboration is necessary for successful relief operations since lack of cooperation has negative impact to their performance and also leads to duplication of effort.

3. *Performance Management*

   Transparency, accountability, and evaluation of relief operations are critical issues in performance management. In the humanitarian sector there are no clear metrics for measuring performance, in contrast to the commercial sector where performance measurement is well defined [1]. The lack of performance measurement in HL, often prohibits access to relief operations in order to gain knowledge. Without clear metrics, relief workers cannot measure their success and improve their operations due to lack of reference point.

4. *Accessibility to Informations Technology Systems*

   The efficient and effective management of HL and specifically of supply chain, requires the existence of appropriate information systems that can take critical decisions in a time sensitive environment. Modern technologies have capability to extend the range of observation, improve operations, and increase the safety of employees. Nevertheless, there is need to extend the development and implementation of the aforementioned systems to tackle specific issues in HL problems. Unfortunately, only a small number of aid agencies have invested in modern information and logistics systems. As a result HL tasks are undertaken below the industrial standards. In addition, a related challenge is the effective communication systems between humanitarian organizations and donors. The fact that most humanitarian organizations have incompatible information systems leads to restriction of information flow.

5. *Funding*

   The “survival” of most humanitarian organizations is heavily dependent on donations, which may become a severe constraint when donations are inaccessible or even when pledged funds are either delayed or cancelled. Donors tend to have a substantial influence on where and how their donations are used, since the humanitarian organizations rely on funding.

2.9 Metaheuristic Optimization

2.9.1 Algorithms

The term *metaheuristics* mostly refers to nature-inspired algorithms that involve stochastic components. Nature by herself has evolved over millions of years and has found solutions to the arised problems. A number of optimization algorithms are based on Darwin's theory, thereby called *biology-inspired* or *bio-inspired* algorithms. Metaheuristics have been widely recognized as valuable optimization tools in producing optimal or near optimal solutions within strict time constraints. They are mostly applied on black box optimization problems, tackling a wide range of computationally intractable problems. They do not always guarantee solution optimality but in most cases they reach (sub-)optimal solutions within acceptable computational time.

There exist different definitions of metaheuristics in relevant literature. Some characteristic examples follow below:

“A metaheuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combing intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions” [33].

“A metaheuristic is an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions. It may manipulate a complete (or incomplete) single solution or a collection of solutions at each iteration.

The subordinate heuristics may be high (or low) level procedures, or a simple local search, or just a construction method" [60].

"A metaheuristic is a set of concepts that can be used to define heuristic methods that can be applied to a wide set of different problems. In other words, a metaheuristic can be seen as a general algorithmic framework which can be applied to different optimization problems with relatively few modifications to make them adapted to a specific problem" [67].

In summary, the properties that characterize most metaheuristics are the following:

1. Metaheuristics are strategies that guide the search process.
2. The goal is to efficiently explore the search space in order to find near-optimal solutions.
3. Metaheuristics consist of procedures that range from simple local search to complex learning processes.
4. Metaheuristics are approximation algorithms and usually non-deterministic.
5. Metaheuristics are not problem-specific.

Due to their efficiency and effectiveness in solving large-scale complex problems in various applications, metaheuristics have received increased popularity in the last decades. Today, they have been applied on different research areas including engineering design, system modelling and simulation in physical sciences (physics, chemistry etc.), image processing, supply chain management, logistics, and transportation. There are different ways to classify and describe metaheuristics depending on the specific perspective. Common classifications include:

1. Nature-inspired vs non-nature inspired.
2. Memory-intensive usage vs memoryless methods.
3. Deterministic vs stochastic approaches.
4. Population-based vs trajectory-based search.
5. Iterative vs greedy search.

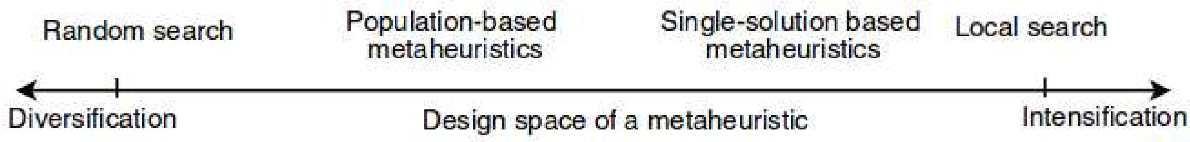

Figure 2.3: The two conflicting criteria in designing metaheuristics: exploration (diversification) vs exploitation (intensification).

2.9.2 Exploration vs Exploitation

Two major components of metaheuristic algorithms habitually are (i) the selection of best solutions, and (ii) randomization. The first one ensures that candidate solutions converge to the optimal ones. The latter prevents the search from being trapped in locally optimal solutions, while simultaneously promotes search diversity. The appropriate combination of these two components renders optimality of solutions achievable.

The dynamic of metaheuristics is governed by two major phases, namely *exploration* and *exploitation* [7]. Exploration is the ability to perform diverse search without neglecting regions of the search space, i.e., finding new points in areas of the search space that have not been investigated before. In other words exploration is a metaphor for procedures that allow search operators to find novel and/or better solution structures. Such operators (e.g., mutation in evolutionary algorithms) have high prospects of creating inferior solutions by destroying good building blocks, however they present a rather low probability of finding totally new and superior traits.

On the other hand, exploitation is the ability of performing refined search in the neighborhood of already detected candidate solutions by improving and combining the traits of the currently known solutions. For example this is done by the crossover operator in evolutionary algorithms. Exploitation-oriented operators often incorporate small changes into already tested individuals, leading to perturbed candidate solutions, or try to merge building blocks of different promising individuals. However, they usually have the disadvantage that other, possibly better, solutions located in distant areas of the problem space cannot be discovered.

In general, optimization algorithms shall employ at least one search operator of explorative character and one exploitation-oriented operator to improve promising candidate solutions. Global optimality of the solutions is highly related to appropriate balance of these two components. There exists a large number of research works on the trade-off between exploration and exploitation.

2.9.3 Premature Convergence

Premature convergence s an undesirable property of many optimization algorithms. The probability that a metaheuristic algorithm gets caught in a local optimum depends on the characteristics of the problem at hand, as well as on the parameter settings and features of the algorithm. An effective technique to prevent premature convergence is the restart of the optimization procedure at randomly selected time during execution. Intensifying exploration may also prevent from premature convergence. In order to diversify the search in evolutionary algorithms, a number of methods have been devised. Most of them steer the search away from areas that have been already frequently sampled. This can be achieved by integrating density metrics into the fitness assignment process.

Another approach for preventing premature convergence is to introduce self-adaptation, which allows the algorithm to change its strategies or modify its parameters based on its current state. However, such techniques are implemented not only to prevent premature convergence, but also to speed up the optimization process.

2.10 Metaheuristics in Humanitarian Logistics

From a mathematical point of view, HL involves highly complicated optimization problems of various characteristics. Computational optimization lies in the intersection of Computer Science and Operations Research (OR). An important concern is whether a computer scientist can encounter that a given problem can be solved in a reasonable time frame. In addition, even though optimal solutions can be attained by commercial solvers, the NP-hard nature of OR problems often prohibits their detection in acceptable time. This renders commercial solvers computationally expensive. Evolutionary computing techniques, which involve metaheuristic optimization algorithms, can handle effectively real-world problems involving nonlinearity, complexity, noise, imprecision, uncertainty, and vagueness. Consequently, these algorithms have attracted remarkable interest and been extensively used in OR the several decades.

Even though metaheuristics (specifically evolutionary algorithms) have been widely explored in various OR areas, the research in HL is presently limited. However a variety of algorithms, including Ant Colony Optimization, Genetic Algorithms and Particle Swarm Optimization have been applied in relief operations, exhibiting a growing number of applications. Previous relevant studies in the literature addressed (among others):

1. General transportation planning problems for delivering relief supplies from dispatch centers to demand points.

2. Facility location problems in order to the demand points served from appropriate locations.
3. Routing problems in order to plan appropriate routes for the vehicles, rescuers, and evacuees.
4. Roadway repair problems.

For the sake of completeness, we refer some relevant studies, where metaheuristic algorithms were employed to solve HL problems. Yan and Shih [61] developed an Ant Colony System algorithm, coupled with a threshold-accepting technique that is able to solve an emergency roadway repair time-space network flow problem. The objective of their work was to minimize the length of time needed for emergency repair of highway networks. Yi and Kumar [62] addressed a logistic plan for transporting commodities to distribution centers in the stricken areas, as well as evacuating the wounded people to medical centers. The problem was solved using Ant Colony Optimization. Zheng et al. [66] proposed a multi-objective particle swarm optimization technique for population classification in fire evacuation operations. Their method simultaneously optimizes the precision and recall measures of the classification rules. In addition, they reported an application of their method in a fire evacuation operation occurred in China. Yuan and Wang [64] designed two mathematical models for minimization of the arrival time and complexity of the chosen routes. The proposed model was solved using the Ant Colony Optimization algorithm. Balcik and Beamon [1] developed a model related to facility location decisions for humanitarian relief chain responding to quick-onset disasters. Their results show the effects of pre- and post-disaster relief funding on the system's performance, especially on response time and satisfied demand.

Chapter 3

Proposed Model and Employed Algorithms

3.1 Proposed Model

Liu and Ye [27] studied a multi-period problem taking into account limited supply and transportation capacity that aims to minimize losses caused by (i) the mismatch between supplies and demand, and (ii) the transportation time due to logistics processes. Based on this model we propose an extension that takes into account also transportation restrictions due to damaged infrastructures. In our model, we consider a set J of affected areas (AAs) and a set I of dispatch centers (DCs). Relief resources (commodities) are transported from DCs to AAs through a number of vehicles of different type and mode. In our case, ground and aerial vehicles of two sizes (big and small) are considered. We henceforth denote as C the set of commodities, M the set of transportation modes, and O_m the set of vehicles of mode $m \in M$. The planning horizon is finite and denoted as T. The complete notation used in our model is presented in Table 3.1.

Table 3.1: Notation used in the proposed model.

Model Variable	Description
T	Planning horizon
I	Set of Dispatch Centers (DCs)
J	Set of Affected Areas (AAs)
C	Set of commodities
M	Set of transportation modes
m	Index denoting the transportation mode (ground, air)
O_m	Set of vehicle types of transportation mode m
o	Index denoting the vehicle type (big vehicle, small vehicle)
b_{cj}	Importance weight of commodity c in AA j
w_c	Unit weight of commodity c
$volume_c$	Unit volume of commodity c
cap_{mo}	Capacity of type o, mode m vehicle
vol_{mo}	Volume capacity of type o, mode m vehicle
d^t_{cj}	Demand for commodity c in AA j at time period t
k^t_{ijm}	Traffic restriction for mode m vehicles travelling from DC i to AA j at time t
v^t_{imo}	Number of type o, mode m vehicles at DC i at time t
Decision Variable	**Description**
s^t_{cijm}	Delivered quantity of commodity c from DC i to AA j through transportation mode m at time t
v^t_{cijmo}	Number of type o, mode m vehicles used at period t to transport commodity c from DC i to AA j

Based on this notation, the optimization problem comprises the detection of optimal delivered quantities s^t_{cijm} per commodity $c \in C$ from DC i to AA j, using vehicles of transportation mode m, for each time period t. Moreover, we need to specify the optimal number v^t_{cijmo} of type o, mode m vehicles that are used to transport the commodities at each time period t. All decision variables assume integer values. The corresponding minimization problem is defined as follows:

$$\min \sum_{t\in T} \sum_{j\in J} \sum_{c\in C} b_{cj} \left(d^t_{cj} - \sum_{i\in I} \sum_{m\in M} s^t_{cijm} - I^{t-1}_{cj} \right)^2, \tag{3.1}$$

where b_{cj} is a scalar importance weight of commodity c at AA j. The model is subject to the following constraints:

$$I^0_{cj} = Y_{cj}, \qquad \forall\, c \in C,\ \forall\, j \in J, \tag{3.2}$$

$$I^t_{cj} = \sum_{i\in I} \sum_{m\in M} s^t_{cijm} - d^t_{cj} + I^{t-1}_{cj}, \qquad \forall\, t \in T,\ \forall\, c \in C,\ \forall\, j \in J, \tag{3.3}$$

$$\sum_{c\in C} \sum_{j\in J} s^t_{cijm}\, w_c \leqslant \sum_{o\in O_m} v^t_{imo}\, cap_{mo}, \qquad \forall\, t \in T,\ \forall\, i \in I,\ \forall\, m \in M, \tag{3.4}$$

$$\sum_{c\in C} \sum_{j\in J} s^t_{cijm}\, vol_c \leqslant \sum_{o\in O_m} v^t_{imo}\, vol_{mo}, \qquad \forall\, t \in T,\ \forall\, i \in I,\ \forall m \in M, \tag{3.5}$$

$$s^t_{cijm} \leqslant \min \left\{ \frac{\sum_{o\in O_m} v^t_{cijmo}\, cap_{mo}}{w_c},\ \frac{\sum_{o\in O_m} v^t_{cijmo}\, vol_{mo}}{volume_c} \right\}, \tag{3.6}$$

$$\sum_{c\in C} \sum_{o\in O_m} v^t_{cijmo} \leqslant k^t_{ijm}, \qquad \forall\, t \in T,\ \forall\, i \in I,\ \forall\, m \in M,\ \forall j \in J, \tag{3.7}$$

$$\sum_{c\in C} \sum_{j\in J} v^t_{cijmo} \leqslant v^t_{imo}, \qquad \forall\, t \in T,\ \forall\, i \in I,\ \forall\, m \in M,\ \forall\, o \in O, \tag{3.8}$$

$$s^t_{cijm}, v^t_{cijmo} \in \mathbb{N}^0, \quad \forall t \in T, \forall c \in C, \forall i \in I, \forall j \in J, \forall m \in M, \forall o \in O, \tag{3.9}$$

$$v^t_{imo}, d^t_{cj}, vol_{mo}, cap_{mo}, volume_c, w_c \in \mathbb{N}^+, \quad \forall t \in T, \forall c \in C, \forall i \in I, \forall j \in J, \forall m \in M, \forall o \in O, \tag{3.10}$$

$$k^t_{imo} = \{7, 8\}, \quad \forall t \in T, \forall i \in I, \forall m \in M, \forall o \in O, \tag{3.11}$$

$$b_{cj} = [0, 1], \quad \forall c \in C, \forall j \in J. \tag{3.12}$$

Equation (3.2) accounts for the initial inventory level of commodity c pre-existing at DC j. Equation (3.3) determines the inventory balance, which takes into account the demand of commodity c and replenishment quantity. Equations (3.4) and (3.5) refer to capacity and volume constraints, respectively. Equation (3.6) defines upper limit of the delivered quantity s^t_{cijm}, which is useful for bounding the decision variables. Equation (3.7) stands for traffic flow restrictions expected in natural disasters, e.g., roads that are partially damaged or destroyed thereby, reducing traffic capacity. Equation (3.8) ensures that the number of vehicles transporting the commodities in a particular AA does not exceed the total number of vehicles. Equations (3.9-3.12) define the appropriate domains for variables. The squared error in Eq. (3.1) can be replaced by absolute error if metaheuristics are the employed solvers. Nevertheless, the quadratic form is chosen in our work, in order to render the problem solvable by the state-of-the-art CPLEX [1] software.

3.2 Employed Algorithms

In the following paragraphs, we present the main features of the employed metaheuristics. For presentation purposes, we assume that the considered minimization problem is defined as,

$$\min_{\mathbf{x} \in X \subset \mathbb{R}^n} f(\mathbf{x}), \tag{3.13}$$

where X is the (real-valued) search space. The only requirement on the objective function is the availability of $f(\mathbf{x})$ at any $\mathbf{x} \in X$.

3.2.1 Differential Evolution

Differential Evolution (DE) was introduced in [49]. Being a population-based optimization algorithm, it proceeds by iteratively improving a population of candidate solutions,

$$S = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\},$$

consisting of N search points, called *individuals.* The population is randomly initialized, usually following a uniform distribution over the search space. DE applies biologically-inspired operators, namely *mutation*, *crossover*, and *selection* on each individual, in order

[1] http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/

to probe the search space by producing new candidate solutions through combinations of randomly selected individuals.

At each iteration g of the algorithm, a mutant vector $\mathbf{v}_i$ is generated for each individual $\mathbf{x}_i$, $i = 1, 2, \ldots, N$. This vector is produced by combining existing individuals from the population according to various *mutation operators*. The following are among the most popular ones:

$$\text{DE1}: \quad \mathbf{v}_i^{(g+1)} = \mathbf{x}_{\text{best}}^{(g)} + F\left(\mathbf{x}_{r_1}^{(g)} - \mathbf{x}_{r_2}^{(g)}\right), \tag{3.14}$$

$$\text{DE2}: \quad \mathbf{v}_i^{(g+1)} = \mathbf{x}_{r_1}^{(g)} + F\left(\mathbf{x}_{r_2}^{(g)} - \mathbf{x}_{r_3}^{(g)}\right), \tag{3.15}$$

$$\text{DE3}: \quad \mathbf{v}_i^{(g+1)} = \mathbf{x}_i^{(g)} + F\left(\mathbf{x}_{\text{best}}^{(g)} - \mathbf{x}_i^{(g)}\right) + F\left(\mathbf{x}_{r_1}^{(g)} - \mathbf{x}_{r_2}^{(g)}\right), \tag{3.16}$$

$$\text{DE4}: \quad \mathbf{v}_i^{(g+1)} = \mathbf{x}_{\text{best}}^{(g)} + F\left(\mathbf{x}_{r_1}^{(g)} - \mathbf{x}_{r_2}^{(g)}\right) + F\left(\mathbf{x}_{r_3}^{(g)} - \mathbf{x}_{r_4}^{(g)}\right), \tag{3.17}$$

$$\text{DE5}: \quad \mathbf{v}_i^{(g+1)} = \mathbf{x}_{r_1}^{(g)} + F\left(\mathbf{x}_{r_2}^{(g)} - \mathbf{x}_{r_3}^{(g)}\right) + F\left(\mathbf{x}_{r_4}^{(g)} - \mathbf{x}_{r_5}^{(g)}\right), \tag{3.18}$$

where $\mathbf{x}_{\text{best}}^{(g)}$ denotes the individual with the lowest objective value currently in the population. The indices $r_i \in \{1, 2, \ldots, N\}$, $i = 1, 2, \ldots, 5$, are randomly selected and they are different among them as well as from index i. The user-defined parameter $F \in [0, 2]$ is called the *scale factor*.

After generating the mutant vectors, crossover takes place. A *trial vector*, $\mathbf{u}_i = (u_{i1}, u_{i2}, ..., u_{in})^\top$, is generated for each individual as follows,

$$u_{ij}^{(g+1)} = \begin{cases} v_{ij}^{(g+1)}, & \text{if } \ R_j \leqslant CR \ \text{ or } \ j = RI(i), \\ x_{ij}^{(g)}, & \text{otherwise,} \end{cases} \tag{3.19}$$

where $j = 1, 2, \ldots, n$; R_j is the j-th evaluation of a uniform random number generator in the range $[0, 1]$; $CR \in [0, 1]$ is a user-defined *crossover rate*; and $RI(i)$ is a randomly selected index from $\{1, 2, \ldots, n\}$.

Eventually, the selection operator is applied, where the trial vectors compete against their original individuals. If the trial vector achieved a better objective value, it replaces the original individual in the population, as follows,

$$\mathbf{x}_i^{(g+1)} = \begin{cases} \mathbf{u}_i^{(g+1)}, & \text{if } f\left(\mathbf{u}_i^{(g+1)}\right) < f\left(\mathbf{x}_i^{(g)}\right), \\ \mathbf{x}_i^{(g)}, & \text{otherwise.} \end{cases} \tag{3.20}$$

The parameters F, CR, and N, must be carefully selected, due to their impact on DE's performance. A comprehensive presentation of DE-related research can be found in [41].

3.2.2 Enhanced Differential Evolution

Mohamed [31] proposed an enhanced DE (eDE) variant. It defines an alternative mutation scheme, while crossover is based on probabilistic selection between the new and the DE2 scheme of Eq. (3.15). Also, the algorithm is enhanced by using restart to alleviate local minima. More specifically, eDE introduces the mutation scheme,

$$\mathbf{w}_i^{(g+1)} = \mathbf{x}_{r_1}^{(g)} + F_1 \left(\mathbf{x}_{\text{best}}^{(g)} - \mathbf{x}_{r_1}^{(g)}\right) + F_2 \left(\mathbf{x}_{r_1}^{(g)} - \mathbf{x}_{\text{worst}}^{(g)}\right), \tag{3.21}$$

where $\mathbf{x}_{r_1}^{(g)}$ is a randomly selected individual; $F_1, F_2 \in [0, 2]$ are called the *differential weights*; and $\mathbf{x}_{\text{best}}^{(g)}$, $\mathbf{x}_{\text{worst}}^{(g)}$, denote the best and worst individuals at iteration g, respectively. The trial vector is given as follows,

$$u_{ij}^{(g+1)} = \begin{cases} w_{ij}^{(g+1)}, & \text{if } \left(R_j \leqslant CR \ \text{ or } \ j = RI(i)\right) \text{ and } R \geqslant \left(1 - \frac{g}{g_{\max}}\right), \\ v_{ij}^{(g+1)}, & \text{if } \left(R_j \leqslant CR \ \text{ or } \ j = RI(i)\right) \text{ and } R < \left(1 - \frac{g}{g_{\max}}\right), \\ x_{ij}^{(g)}, & \text{otherwise,} \end{cases} \tag{3.22}$$

where $g_{\max}$ is the total number of generations. The rest of the parameters are identical to the standard DE. Also, note that v_{ij} is the j-th component of the mutation vector $\mathbf{v}_i$ produced through Eq. (3.15).

A restart mechanism is also incorporated in eDE to avoid premature convergence. The restart mechanism is applied on each individual except for the best one, which is kept unaltered. In our case, we adopt restarts from mild perturbations $\mathbf{x}'_i$ of current individuals $\mathbf{x}_i$, as follows,

$$x'_{ij} = x_{ij} \pm 1. \tag{3.23}$$

According to this scheme, the local search capability is enhanced through the perturbation of individuals' position by ± 1. The sign "+" or "−" in Eq. (3.23) is randomly determined with probability 0.5 for each j. The perturbation bias is selected equal to 1 since it constitutes the smallest step size in integer search spaces as the considered ones.

3.2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was introduced in [23]. Similarly to DE, it is a population-based algorithm with special emphasis in cooperation. PSO does not have direct selection operator. Instead, a population (called a *swarm*) of candidate solutions (called the *particles*) probes the search space. Each particle retains in memory the best position it has ever visited. This position, along with information shared with the rest of the swarm, is used to bias the move of the particles.

Let $S = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$ be a swarm of N particles, each one being an n-dimensional vector in the search space, $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \in X$, $i = 1, 2, \ldots, N$. The particle moves by adding to its current position an adaptable bias vector, called the *velocity*,

$$\mathbf{v}_i = (v_{i1}, v_{i2}, ..., v_{in})^\top ,$$

while it has also a personal memory, called the *best position*,

$$\mathbf{p}_i = (p_{i1}, p_{i2}, ..., p_{in})^\top \in X.$$

Apart from its own best position, each particle assumes a *neighborhood* in the form of a set of particle indices. The particle exchanges information with its neighborhood by adopting the best findings of its constituent particles to bias its move. In the case where the particle's neighborhood is the entire swarm, the best position in the neighborhood is referred as *global best* particle, and the resulting algorithm is referred to as *gbest* PSO. On the other hand, when smaller neighborhoods are used, the algorithm is called *local best* PSO (*lbest* PSO) [36].

In literature, various neighborhood topologies have been proposed, e.g. star, Von Neumann, ring, and other hybrid ones. The most common topology is the ring, where all particles are assumed to lie on a ring with respect to their indices. Then, for a given particle, its neighborhood is defined by its immediate neighbors in the ring. Their number is called the neighborhood's *radius*. Thus, a ring neighborhood of radius r for a particular particle $\mathbf{x}_i$, is defined as follows,

$$NB_i^r = \{i - r, i - r + 1, \ldots, i, \ldots, i + r - 1, i + r\}. \tag{3.24}$$

Let best_i be the index of the best position found so far by any individual in the neighborhood NB_i of $\mathbf{x}_i$, i.e.,

$$\text{best}_i = \arg \min_{j \in NB_i^r} f(\mathbf{p}_j). \tag{3.25}$$

Also, let g denote the iteration counter. Then, the swarm is updated according to,

$$v_{ij}^{(g+1)} = \chi \left[v_{ij}^{(g)} + c_1 R_1 \left(p_{ij}^{(g)} - x_{ij}^{(g)} \right) + c_2 R_2 \left(p_{\text{best}_i j}^{(g)} - x_{ij}^{(g)} \right) \right], \tag{3.26}$$

$$x_{ij}^{(g+1)} = x_{ij}^{(g)} + v_{ij}^{(g+1)}, \tag{3.27}$$

where χ is the *constriction coefficient* parameter; c_1, c_2, are positive acceleration parameters; and R_1, R_2, are random variables uniformly distributed in the range $[0, 1]$. The constriction coefficient restricts the magnitude of the velocities and promotes convergence.

The best positions are updated at each iteration according to,

$$\mathbf{p}_i^{(g+1)} = \begin{cases} \mathbf{x}_i^{(g+1)}, & \text{if } f\left(\mathbf{x}_i^{(g+1)}\right) < f\left(\mathbf{p}_i^{(g)}\right), \\ \mathbf{p}_i^{(g)}, & \text{otherwise.} \end{cases} \tag{3.28}$$

For reader's convenience, we mention the typical values $\chi = 0.729$, $c_1 = c_2 = 2.05$, which are widely accepted as the default parameter set on the basis of PSO's stability analysis [11]. A compendium of PSO-related research can be found in [36].

3.2.4 Algorithm Portfolios

The term *Algorithm Portfolio* (AP) refers to a framework where different algorithms (*heterogeneous AP*) or different copies of the same algorithm (*homogeneous AP*) are combined in a single algorithmic scheme [21]. APs constitute a modern approach for solving challenging optimization problems. Their computational efficiency against common metaheuristics has lead to constantly increasing research production [17, 21, 37, 46, 47, 52].

The performance of APs depends on the selection of appropriate constituent algorithms. The constituent algorithms may either have some form of interaction or run independently. In the present work, the AP framework is used to define interactive algorithmic schemes consisting of the previously described metaheuristics [47]. The AP's algorithms interact with each other and employ a typical *master-slave* parallelization model. Each metaheuristic runs on one of M *slave nodes* for a pre-specified budget of total *running time*. The latter is divided into the *execution time* T_{exec}, i.e., the time that each algorithm uses for its own execution, and the *investment time* T_{inv}, i.e., the time that each algorithm has available to buy elite solutions from the other algorithms.

Slave nodes can communicate via the *master node*, which is responsible for two basic operations. Firstly, it maintains an archive of the M elite solutions detected by the algorithms. Secondly, it assigns *prices* to the elite solutions. For this purpose, the solutions are sorted in descending order with respect to their objective values. Then, the price of each one is defined in terms of its corresponding position ρ_i in the ranking, i.e.,

$$C_i = \frac{\rho_i \times BC}{M}, \tag{3.29}$$

where $BC = \beta\, T_{\text{inv}}$ is a base cost and β is a constant that takes values in $[0, 1]$, as suggested by [46].

When an algorithm (slave node) fails to improve its solution for some predefined amount of time, it requests from the master node to buy an elite solution from the archive. For the buyer algorithm, this comes at the cost of (a fraction of) its investment time, which is credited to the seller algorithm that offered the purchased solution. The master node proposes to the slave node its archived elite solutions that are better than the buyer algorithm's current best solution. Then, the buyer chooses the one that maximizes the *Return of Investment* (ROI) index, among the solutions it can afford. ROI comes from trading theory and, and in our case it is defined as follows,

$$ROI_j = \frac{f - f_j}{C_j}, \quad j \in \{1, 2, \ldots, M\}, \tag{3.30}$$

where f denotes the objective value of the buyer's best solution, f_j denotes the objective value of the seller's elite solution, and C_j is the assigned price [46]. The paid investment time from the buyer algorithm is then added to the total execution time of the seller algorithm. The purchased solution replaces the worst solution in the population of the buyer. In case of no affordable solution, the buyer algorithm simply restarts, retaining only its best solution.

Apparently, better-performing algorithms sell solutions more frequently and, consequently, gain additional execution time. It worths mentioning that the total execution time assigned to the AP remains constant, since time is dynamically transfered from inferior to the most promising constituent algorithms. This is a significant property in modern high-performance platforms where usage and execution time is expensive. Also, the distribution of execution time of the constituent algorithms offers useful insight regarding the best-performing one for the considered problem [46, 47].

3.2.5 Further Applicability Issues

Two main issues need to be addressed prior to the application of the presented metaheuristics on the problem under consideration. The first one is related to the discrete nature of the search space, while the second one refers to constraint handling. Regarding the first issue, simple rounding to the nearest integer is used. Specifically, the algorithms are applied on the corresponding real search space and, for the function evaluation, the vectors are rounded to the nearest integer ones. In DE and eDE, the rounded vectors are also retained in the population. In PSO, rounded vectors replace best positions. Rounding is a common approach, successfully applied in similar problems [40, 35].

The constraint handling problem is tackled with the widely used *penalty function* approach, combined with a set of preference rules between feasible and infeasible solutions:

1. Between two infeasible solutions, the one that violates fewer constraints is selected.

2. Between a feasible and an infeasible solution, the feasible one is preferred.

3. Between two feasible solutions, the one with the lowest objective value is preferred.

These rules have been successfully used with PSO and DE [35]. The employed penalty function has the form,

$$P(\mathbf{x}) = f(\mathbf{x}) + \sum_{i \in VC(\mathbf{x})} |V(i)|\,, \tag{3.31}$$

where $f(\mathbf{x})$ is the actual objective value of $\mathbf{x}$; $V(i)$ is the violation magnitude of the i-th constraint; and $VC(\mathbf{x})$ is the set of constraints violated by $\mathbf{x}$. Note that the penalty for a violated constraint depends on the magnitude of violation. Apparently, in absence of violated constraints, the penalty function is equal to the original objective function.

Chapter 4

Experimental Setting and Results

4.1 Experimental Setting

In this section we expose the experimental setting, as well as the obtained results from the application of the employed algorithms on the test suite produced for the proposed HL model. The main goal in our model is the minimization of losses caused by the mismatch between supply and demand, as well as the determination of the optimal number of vehicles for the transportation of relief resources to the stricken areas. In our experiments, we considered three life-essential commodities, namely:

1. *water*
2. *medicines*
3. *food*

Among them, the first two were assumed to have slightly higher importance weights than the third one.

Moreover, we assumed the existence of two DCs responsible to supply two AAs, and two modes of transportation, i.e., ground and aerial, using trucks and helicopters. For each transportation mode two vehicle types were considered, namely small and big

Table 4.1: Capacity and volume information for vehicles of Type I (small) and II (big).

	Transportation Mode			
	Ground		Air	
	I	II	I	II
Load Capacity (ton)	3	10	4	9
Load Volume (m^3)	20	44	35	75

Table 4.2: Commodities information.

	Water	Medicines	Food
Importance weight	0.35	0.35	0.30
Unit Weight (kg)	650	20	200
Unit Volume (m^3)	1.44	0.125	0.60

vehicles, henceforth denoted as Type I and II, respectively. Tables 4.1 and 4.2 report the relevant information for vehicles and commodities, respectively. Note that the reported data are based on real-world values (e.g., palettes of water bottles, typical transportation boxes for medication etc). Also, Table 4.3 reports the number of available vehicles per DC in our simulation scenario.

In the context of the proposed model, a test suite of 10 benchmark problems with diverse characteristics was initially generated and solved to optimality with the commercial CPLEX solver. The problems are henceforth denoted as $P1 - P10$. In a second phase, extensive experiments were conducted with the following algorithms: PSO, DE, eDE, AP with PSO+DE, AP with PSO+eDE, AP with DE+DE, AP with DE+eDE, AP with eDE+eDE, and AP with PSO+DE+eDE. The five basic DE and eDE mutation operators of Eqs. (3.14)-(3.18) were considered, along with all combinations of their parameters $F \in [0, 2]$ and $CR \in [0, 1]$, with step size 0.05.

Preliminary experiments provided clear evidence that DE2 with,

$$F = F_1 = F_2 = 0.4, \qquad CR = 0.05,$$

was the most promising setting. The PSO algorithm was considered in its lbest model with ring topology of radius $r = 1$, and the default parameter set,

$$\chi = 0.729, \qquad c_1 = c_2 = 2.05.$$

The population size for all algorithms was set to $N = 150$, since the corresponding optimization problem's dimension was $n = 144$. As boundaries for the decision variables were assumed the ones imposed by the given data (for vehicles) and the constraints of Section 4.1 (for delivered quantities).

Table 4.3: Number of vehicles per DC.

	Transportation Mode			
	Ground		Air	
	I	II	I	II
DC_1	4	5	1	1
DC_2	4	5	1	1

Table 4.4: Mean, standard deviation, minimum, and maximum solution error values for all algorithms, averaged over all problems. Best values are boldfaced. The "+" symbol denotes AP approach constituting of the corresponding algorithms.

Algorithm	Mean	St.D.	Min	Max
PSO	513.80	235.85	197.00	2442.20
DE	63.31	40.45	26.97	160.21
eDE	3.54	3.42	0.29	11.80
PSO+DE	52.28	31.11	27.01	129.42
PSO+eDE	4.14	3.99	0.16	13.77
DE+DE	59.65	55.36	21.15	193.81
DE+eDE	0.76	0.91	0.00	2.91
eDE+eDE	**0.75**	**0.85**	**0.00**	**2.27**
PSO+DE+eDE	0.84	1.18	0.00	3.74

In order to statistically validate each algorithm, 30 independent experiments were performed per problem instance. The experiments were conducted on Intel® i7 servers with 8GB RAM. The running time for each experiment was set to 10 minutes in order to be comparable with that of CPLEX. For each algorithm and experiment, the best solution $\mathbf{x}^*_{\text{alg}}$ and its objective value f^*_{alg} were recorded, along with the absolute solution error from the global minimum detected by CPLEX, i.e.,

$$solution \ \ error = \left| f^*_{\text{cplex}} - f^*_{\text{alg}} \right| .$$

Average values of solution error over the 30 experiments, along with standard deviation, minimum, and maximum values, were also recorded for performance comparison purpose.

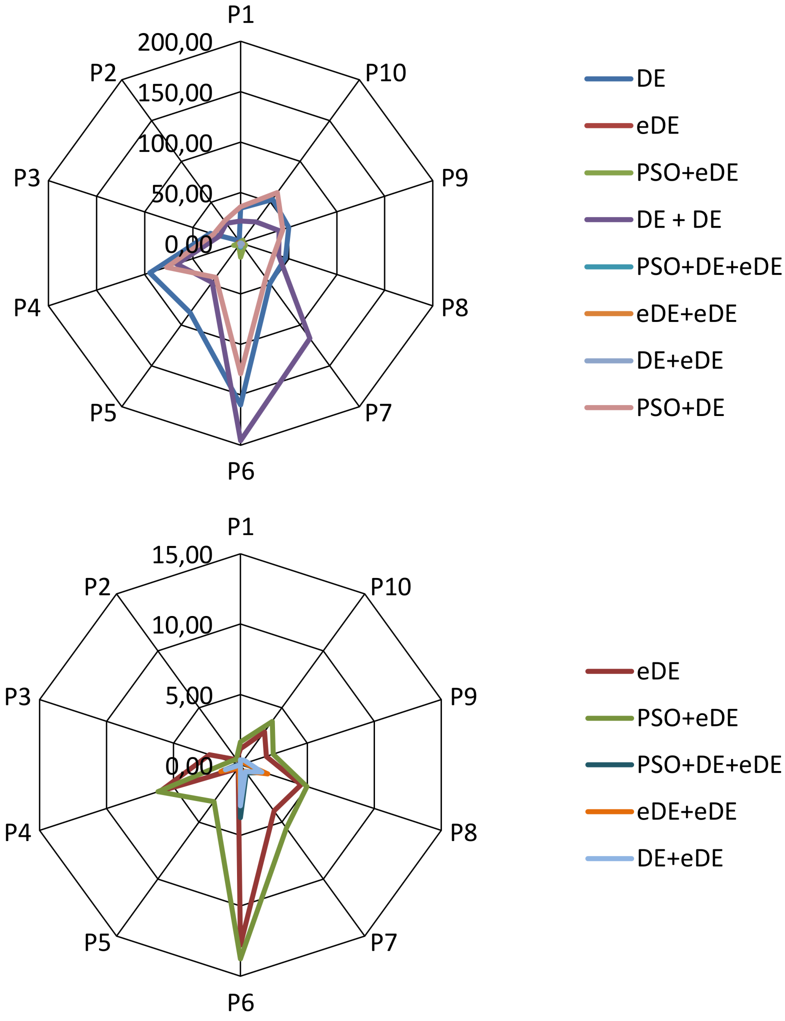

Figure 4.1: Averaged solution error per algorithm and problem (upper part) and zoom in center area (lower part).

4.2 Results and Discussion

A summary of all the recorded results is reported in Table 4.4, where the best-performing approach is boldfaced. Also, the results are graphically illustrated to facilitate visual comparisons. The average solution error from the global minimum per problem and algorithm is presented in the upper part of Fig. 4.1. In the lower part of Fig. 4.1, the central region around the origin is zoomed, exposing the corresponding curves of the most competitive algorithms. Similarly, in the upper and lower part of Fig. 4.2, we illustrate the averaged standard deviation per problem and algorithm. Note that in all figures we excluded the results of plain PSO due to scaling reasons.

Furthermore, we also recorded the success rate per algorithm, i.e., the percentage of experiments where it succeeded to reach the optimal solution within the available execution time. Figure 4.3 presents the resulted success rates per problem instance for

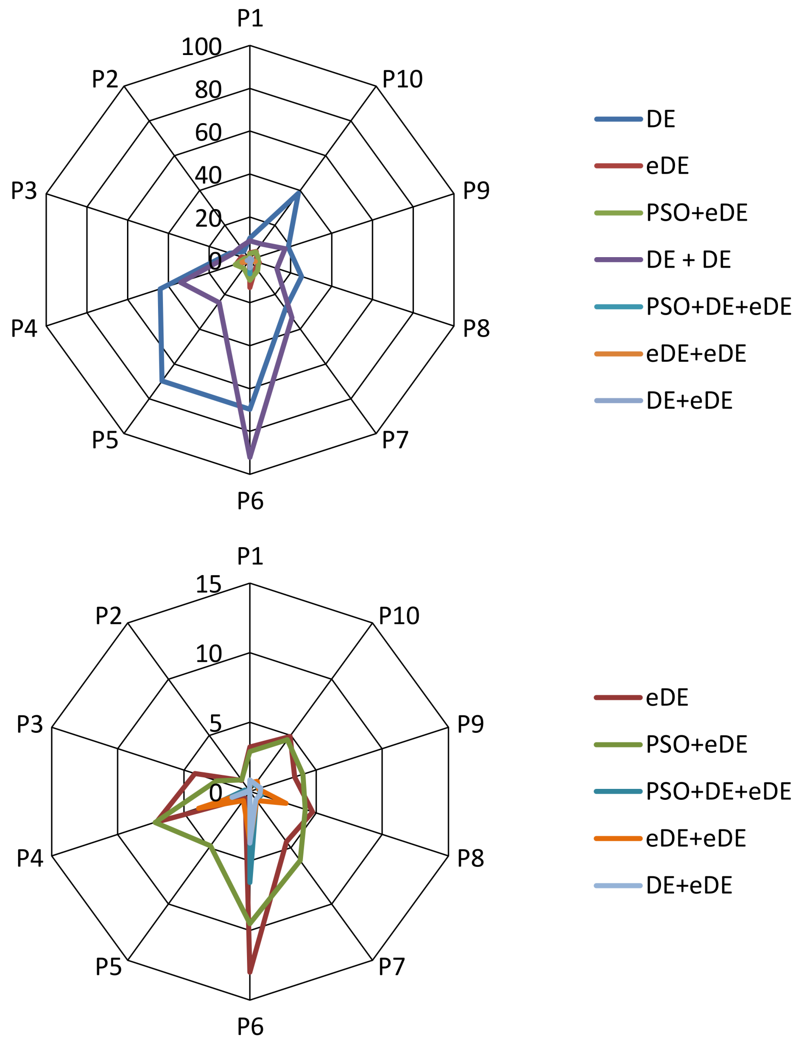

Figure 4.2: Standard deviation of the solution error per algorithm and problem (upper part) and zoom in center area (lower part).

the most promising algorithms. Finally, the boxplots of Fig. 4.4 illustrate the distribution of the obtained solution error values in all experiments.

The reported results offer interesting insight. Firstly, we can easily verify that the homogeneous AP approach eDE+eDE as well as the heterogeneous AP with PSO+DE+eDE, outperformed the rest of the algorithms, yielding higher success rates. Also, these two approaches exhibited almost equivalent performance. However, in problems P6-P8, which were proved to be the most difficult ones with respect to the success rates of the algorithms, the eDE+eDE approach dominated in terms of efficiency.

In order to quantitatively study this behavior, we further analyzed the solution purchases between the algorithms of the AP approaches. The analysis verified that, especially for these problems, the number of purchases between the algorithms was remarkably high. This leads to the conclusion that, due to the complexity of these problems, the constituent algorithms of the AP experienced severe difficulties in reaching the op-

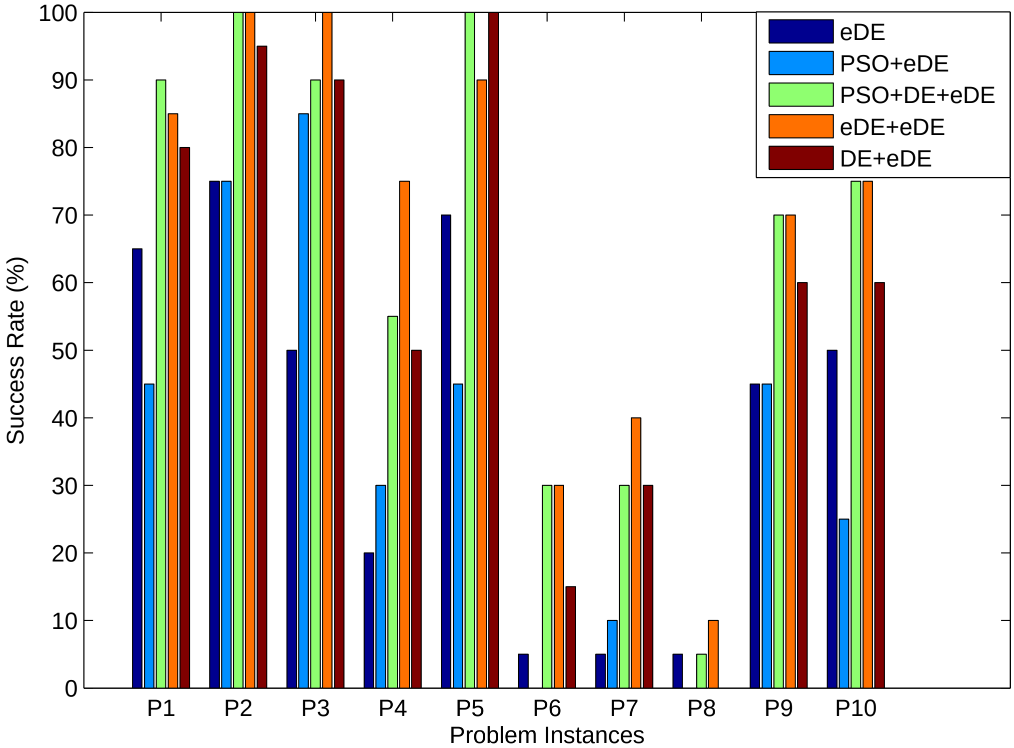

Figure 4.3: Success rates of the most promising algorithms per problem.

timal solution. Therefore, they were forced to exchange information in order to improve their performance. Also, in the case of PSO+DE+eDE, the assigned execution time per algorithm was shorter than that of each eDE instance in eDE+eDE, because in the first case the total time of the AP is divided by 3, while in the latter it is divided in 2 equal parts. Since PSO was proved to be less efficient than eDE, the assigned time in PSO+DE+eDE was proved to be insufficient.

Regarding the standalone algorithms, eDE was clearly the dominant one, exhibiting undoubtful advantages against the rest. This can also explain the superiority of the eDE-based AP approaches. Obviously, the special probabilistic operator of eDE as well as the restart mechanism with mild perturbations (see Section 3.2.2) were beneficial for the algorithm. Experimental evidence suggested that this can be attributed to the alleviation of search stagnation, caused by the rounding of the real-valued vectors to the nearest integers. Moreover, this can be related also to the domination of DE2 operator, which offers the necessary diversity to avoid stagnation. These properties were also identified in previous work [46].

Although there is clear advantage of some algorithms against the rest, there are marginal differences among the most promising approaches. In order to investigate whether these differences were the outcome of random fluctuations, we conducted statistical significance tests among the most competitive algorithms. Specifically, pairwise comparisons of the algorithms were conducted using the Wilcoxon ranksum tests at 95% confidence level, for all problems. Whenever an algorithm was statistically superior to

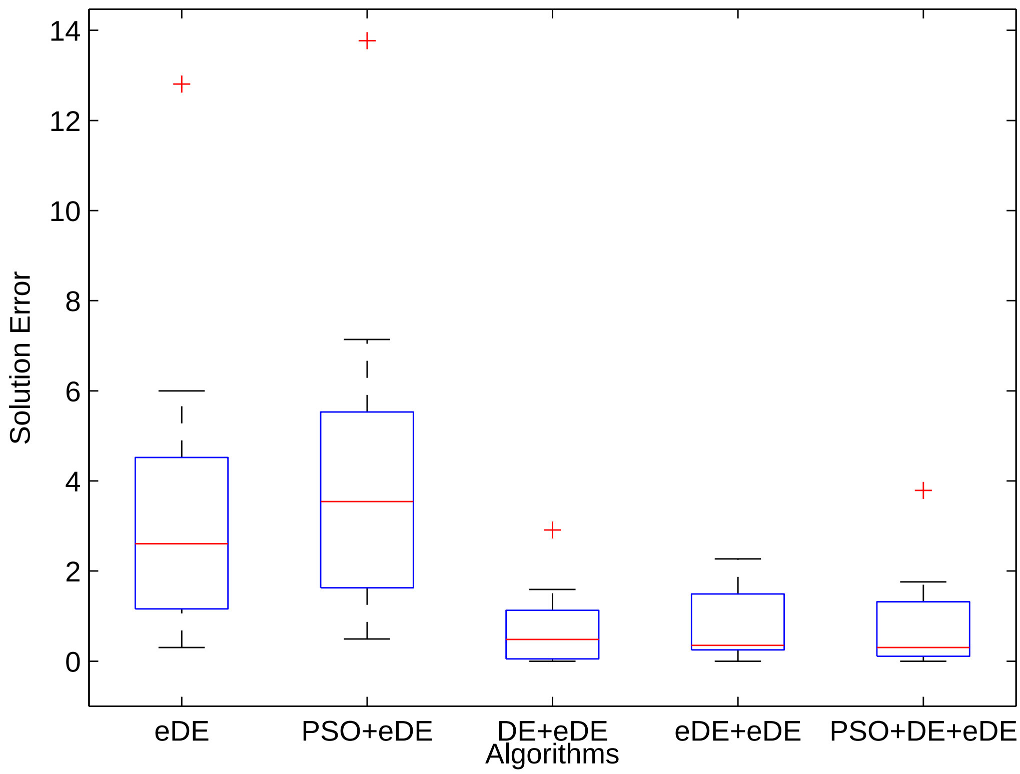

Figure 4.4: Solution error distribution of the most promising algorithms for all test problems.

another, we counted it as *win* of the algorithm. On the other hand, if it was statistically inferior, we counted it as *loss*. The lack of statistical significance was counted as a *draw* for both algorithms.

Table 4.5: Wins/losses/draws of row vs column algorithms for all problem instances.

	eDE	PSO+eDE	DE+eDE	eDE+eDE	PSO+DE+eDE
eDE	-	1 / 1 / 8	0 / 5 / 5	0 / 5 / 5	0 / 8 / 2
PSO+eDE		-	0 / 7 / 3	0 / 9 / 1	1 / 7 / 2
DE+eDE			-	0 / 0 / 10	0 / 0 / 10
eDE+eDE				-	0 / 0 / 10
PSO+DE+eDE					-

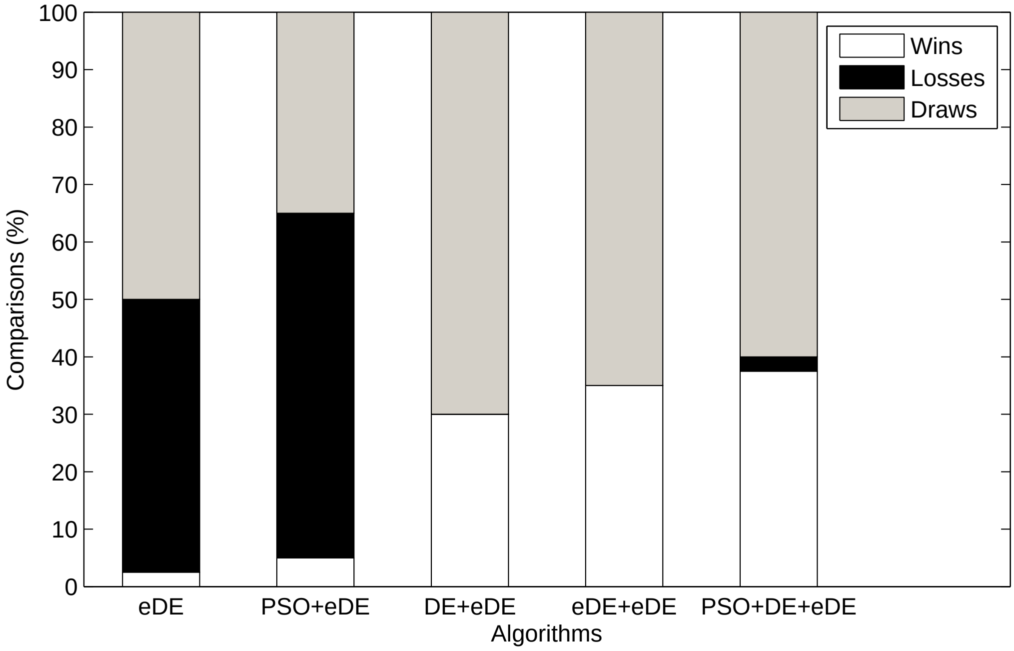

Figure 4.5: Results of the pairwise statistical comparisons among the most competitive algorithms for all test problems.

The results concerning wins/losses/draws are presented in Table 4.5 graphically illustrated in Fig. 4.5 for all problem instances. The superiority of DE+eDE, eDE+eDE, and PSO+DE+eDE was anew confirmed. In almost all comparisons, these approaches were prevalent against the rest. Yet, most of the comparisons among them resulted in draws, despite the marginal differences reported in Table 4.5. Especially for DE+eDE and eDE+eDE, no losses were reported. Thus, our initial assumption regarding the superiority of eDE-based approaches was corroborated by the statistical evidence, placing these AP approaches in a salient position among the most promising solvers.

Chapter 5

Synopsis

The contribution of the present work was twofold. On one hand, we introduced a model that aims at minimizing the losses caused by the mismatch between supply and demand, while concurrently determining the number of different types of vehicles used to transport relief commodities from dispatch centers to stricken areas. A number of test problems with diverse characteristics was generated for the proposed model and solved to optimality using CPLEX.

On the other hand, a number of prevalent modern metaheuristics was studied in solving Humanitarian Logistics problems. Our approach was based on DE, eDE, PSO, and parallel heterogeneous/homogeneous APs consisting of combinations of these algorithms. Proper modifications and refinements were introduced to tackle the special requirements of the test problems.

From the extracted results, we concluded that APs based on eDE offer remarkable performance efficiency and solution quality. Also, it became evident that APs can offer crucial insight in gathering information regarding the most appropriate metaheuristic for the problem at hand.

Future work will extend the test suite, aiming at an abundant set of test problems with a multitude of different characteristics and peculiarities. Also, the study of APs will be enriched by employing larger and diverse collections of metaheuristics, in order to efficiently deal with problems of higher complexity.

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Korkou, Th., Souravlias, D., Parsopoulos, K.E., Skouri, K.: Metaheuristic Optimization for Logistics in Natural Disasters, 2nd International Conference on Dynamics of Disasters, Kalamata, Greece, 2015 (to appear in Springer Proceedings in Mathematics & Statistics)

Short Vita

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