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Subject

Optimizing Health Care Delivery System for Resource-Constrained Environment using Genetic Algorithm

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DEDICATION

To our dear parents and friends, and to all those we cherish, this thesis comes to you with gratitude and appreciation for all the support and love you have shown us throughout this academic journey. Thanks to you and your encouragement, we have achieved this accomplishment, and we will never forget how valuable your support and guidance have been to us. We hope you find value and significance in this work, and may our appreciation and gratitude be an expression of the deep love we hold for all of you. With all our love and gratitude, and with hope for a bright future that we strive to build together.

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General Introduction

A healthcare system constitutes an integrated set of essential health services provided by healthcare centers. Improving these systems in resource-limited environments requires meticulous strategic planning and efficient utilization of available resources to ensure maximum benefit. This entails addressing the issue of resource allocation to achieve the lowest possible cost by determining the optimal method of distributing resources across different time periods. Our study of this topic was driven by several key motivations, including enhancing healthcare delivery, addressing rising costs, ensuring equitable access, and preparing for health crises. Accordingly, we have outlined our objectives for this work, which include improving patient outcomes, enhancing access to healthcare services, optimizing resource allocation efficiency, increasing overall healthcare efficiency, reducing healthcare costs, and improving the quality of healthcare services.

By applying the genetic algorithm, healthcare providers can not only improve the efficiency of resource distribution but also enhance service delivery, ensuring that all services are adequately supported even in the face of financial and logistical constraints.

Our brief will be divided into four chapters:

1 In the first chapter, we provide a definition of the healthcare delivery system and its various types.

2 In the second chapter, titled "State of the Art," we explore and present the current advancements related to our topic. Here, we summarize the contributions of other researchers and practitioners through brief abstracts of their work.

3 In Chapter Three, we explore applying the genetic algorithm to enhance healthcare delivery systems in resource-constrained environments. We delve into how this algorithm, inspired by nature, effectively manages and allocates resources to minimize costs, thereby improving the efficiency and responsiveness of healthcare services.

4 The final chapter, we present our application and detail the methodology used to implement our solutions. This includes a discussion on how we applied the concepts outlined in earlier chapters to optimize healthcare delivery in resource-constrained environments.

Chapter 1

Health care delivery system

1.1 Introduction

A health system is typically defined as an organized network encompassing all organizations, institutions, and resources focused on promoting, restoring, or maintaining health. This system is dedicated to providing health care services tailored to meet the health requirements of a specific population, highlighting the collaborative and comprehensive efforts involved in managing public health. [1]

The health system in any country is the framework through which the population's needs for health services and systems are recognized and provided, and one of the most important of these services and systems is the health care delivery system, which is one of the biggest priorities around the world, and its importance is increasing day by day.

At its core, the healthcare delivery system aims to improve health outcomes and support community well-being.

1.2 Health system

A health system is the set of organizations, institutions, and resources dedicated to health interventions.

While improving health is the primary goal of the health care system, it is not the only goal. This goal is divided into two parts: Achieving the best possible level of health (quality), and minimizing disparities between individuals and groups in managing their access to health care (equity).

In addition, a health system is characterized as the structure through which the healthcare needs of the population are recognized and met. This involves the creation and proper management of essential resources. The ultimate goal is to preserve and promote the well-being of individuals and ensure that health services are delivered in a comprehensive, integrated, affordable and accessible manner [2].

1.3 Key components of a health system

1.3.1 Health information systems

Effective governance depends on accurate and up-to-date information about health challenges and the health system's broader environment and performance. Key information includes the following:

- Tracking progress in addressing health challenges and achieving social goals, particularly equity, through household surveys, civil registration and epidemiologic surveillance.

- Insights on health financing from national health accounts, analyzing financial hardships and barriers to accessing health services for economically disadvantaged and vulnerable groups.

- Trends and imperatives in human resources for health, access to and consumption of medicines, cost and appropriateness of technology, and adequacy and distribution of infrastructure.

- Information on access to health care and the quality of services provided see the figure(1.1) below.

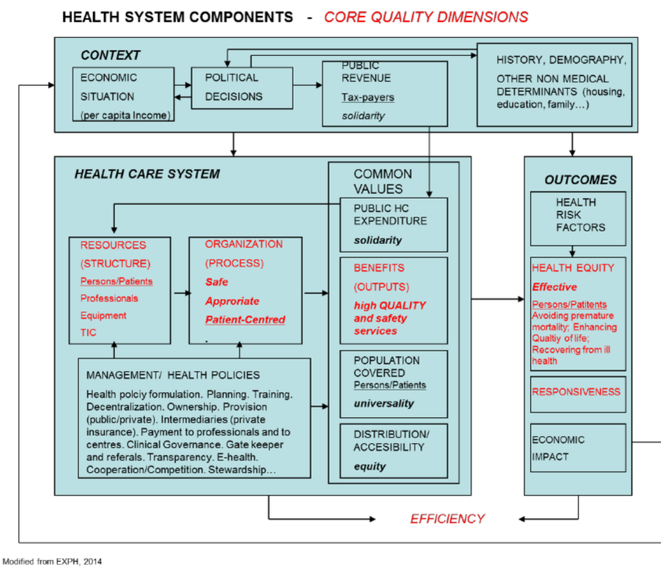


Figure 1.1: Health system components

1.3.2 Health financing

Health financing can significantly improve health outcomes and reduce health disparities when it prioritizes universal coverage, with the goal of removing financial barriers and avoiding financial stress and catastrophic expenditures. To achieve these goals, several measures are necessary:
- Implement a system to equitably generate adequate financing for health.
- Establish a mechanism for pooling funds among different population groups and distributing financial risks.
- Develop a governance structure for financing, supported by relevant laws, financial audits, public expenditure reviews, and transparent operational guidelines to ensure efficient resource allocation.

1.3.3 Human resources for health

The health workforce plays a critical role in achieving health goals. An effective workforce is responsive, equitable and efficient, maximizing results within the limits of resources and circumstances. Although at different stages of development, common challenges include improving recruitment, education, training and deployment, enhancing productivity and performance, and strengthening workforce retention. Addressing these challenges requires:

- Strategies to ensure sufficient numbers of health workers with the right mix of skills, diversity, and competencies.
- Payment systems designed to incentivize desired behaviors.
- Organizational frameworks to ensure system-wide deployment and equitable distribution based on needs.
- Work standards, support systems, and work environments that enable productivity.
- Mechanisms to ensure collaboration among all stakeholders, including advisory groups, donor coordination entities, the private sector, professional associations, and consumer groups.

1.3.4 Essential medical products and technologies

Universal access to UHC is critically dependent on the availability of essential medicines, vaccines, diagnostics and health technologies of assured quality and their use in a scientifically sound and cost-effective manner. In economic terms, medical products represent the second largest expenditure in health budgets - after salaries - and make up the bulk of private health spending in low- and middle-income countries. Key elements of an effective system include the following:

- A regulatory framework for licensing and safety monitoring of medicinal products, supported by appropriate legislation, enforcement mechanisms, an inspection body, and access to a laboratory for quality control of medicinal products.

- National lists of essential medical products, diagnostic and treatment protocols and standardized equipment for different levels of care, guiding procurement, reimbursement and training.

- A supply and distribution system that ensures universal access to essential medical products and health technologies, including the poor and disadvantaged, through both public and private channels.

- A system to monitor the availability and prices of medical products at the national level.

- A national program to promote good prescribing practices.

1.3.5 Service delivery

The effectiveness of health systems is directly related to the quality and accessibility of the services they provide, which critically depends on:
- Accessible primary care networks, organized in health districts or local networks with specialized services and hospital services supported by specialized services and hospital services, serving specific populations.
- Provide a package of benefits that includes a comprehensive and integrated range of clinical and public health interventions that address the full range of health issues faced by the population, including those highlighted by the Millennium Development Goals.
- Standards, norms and guidelines to ensure access and key quality dimensions such as safety, effectiveness, integration, continuity, continuity and people-centeredness.
- Mechanisms to hold health service providers accountable for both access and quality, and to ensure that consumer perspectives and voices are heard and considered [3].

1.4 The importance of a health system

The importance of the health system lies in its critical role in promoting, restoring, and maintaining the health of populations. A health system includes all organizations, individuals, and activities aimed at improving health, encompassing efforts to influence health determinants and conduct health-enhancing activities. Health systems are essential for disease prevention through education, managing chronic diseases, and restoring health in acute care settings. They play a crucial role in ensuring access to healthcare services, promoting public health initiatives, and addressing health determinants. Moreover, health systems are vital for providing universal health coverage, ensuring equitable access to care, and maintaining health as a human right. The efficiency, quality, acceptability, and equity of health systems are key dimensions for evaluating their performance. Overall, health systems are fundamental in enhancing the well-being and quality of life of individuals and communities by delivering essential healthcare services and promoting overall health outcomes [4].

1.5 Health care delivery system

A healthcare delivery system is a framework designed to optimally serve a country's population by ensuring that resources and funds are allocated in an effective, efficient and equitable manner through a well-organized infrastructure see the figure(1.2) below. [5]

Figure 1.2: Healthcare system [6]

It represents an organized, community-based approach to addressing the health challenges of its population. It includes individuals, organizations, and services that contribute to the coordination of care, patient pathways, diagnosis, disease management, and the promotion of health maintenance programs. It encompasses diverse service areas such as emergency and primary care, public health, rehabilitation, hospital care, mental health services, and specialty care, and can be categorized as either a single provider service or an evolving health framework tailored to meet the unique care needs of a particular population [7].

1.6 Types of healthcare delivery systems

There are three main types of healthcare delivery systems: primary care, secondary care, and tertiary care [7].

1.6.1 Primary care

Primary care serves as the initial point of contact between a patient and the healthcare system, delivered by professionals such as family doctors, nurse practitioners, or community health workers. Its significance lies in its preventative role, mitigating the progression of health issues.

1.6.2 Secondary care

conversely, is typically provided by specialists who attend to patients referred by primary care providers. This level of care can also be dispensed in hospitals or specialized clinics.

1.6.3 Tertiary care

represents the pinnacle of healthcare services and is generally offered in hospitals by specialists with specific medical expertise. This level of care is indispensable for addressing intricate conditions that demand more intensive and specialized treatments.

1.7 Frameworks health care delivery systems

The healthcare delivery system is a complex network designed to provide medical services to individuals and communities. It is structured to ensure that patients receive high-quality care through a coordinated approach involving multiple components. The following sections outline the key elements that constitute this system, highlighting how organizational structure, patient experiences, financial mechanisms, capacity, service culture, and care infrastructure collectively contribute to effective healthcare delivery [7].

1.7.1 Organizational structure

Operations follow a hierarchical and leadership-based structure, with all components adhering to established governance and procedural rules.

1.7.2 Patients

Patients' experiences are influenced by the nature of the care they need and the decision-making procedures of healthcare organizations as they provide their services.

1.7.3 Finances

The delivery system orchestrates payments through programs, such as provider payment systems, to fund operations and allocate resources.

1.7.4 Capacity

This encompasses all organizational assets – personnel, infrastructure conditions, and medical supplies – influencing service quality and the ability to execute care routines.

1.7.5 Service culture

Delivery systems operate based on shared values impacting fundamental service competencies, patient health benefits, and community guidelines.

1.7.6 Care Infrastructure

Healthcare services undergo evaluation and maintenance through health information systems, standardized practices, performance indicators, quality management, and clinical decision platforms.

The conceptual framework of continuity of care and its three components can be seen in the Figure(1.3) below.

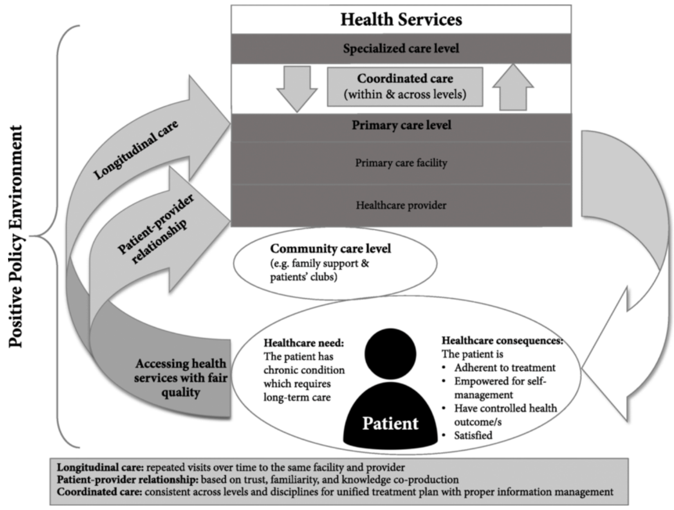


Figure 1.3: Conceptual framework for continuity of care and its three components [8]

1.8 Components of the healthcare delivery system

1.8.1 Payers

This group consists of both public and private entities that offer financial support for healthcare services and distribute funds to healthcare organizations. This encompasses insurance firms as well as government-supported schemes like Medicare and Medicaid.

1.8.2 Service providers

These are individuals and organizations dedicated to offering healthcare services to the public. Included among healthcare providers are physicians, nurses, nurse practitioners, therapists, specialists, and pharmacists.

1.8.3 Facilities

These are the tangible venues that facilitate the provision of healthcare services, allowing healthcare providers to administer medical treatment. The infrastructure of a healthcare system includes hospitals, clinics, rehabilitation facilities, and nursing homes.

1.8.4 Patients

These are individuals who turn to physicians or healthcare establishments for medical treatment [9].

1.9 Quality of health care

A quality health care delivery system is characterized by the provision of effective, safe, people-centered, timely, equitable, integrated, and efficient care. This approach is essential for achieving universal health coverage and improving health outcomes for all populations. The World Health Organization (WHO) and other organizations have emphasized the importance of quality health services, which include. See the figure (1.4) below:

Figure 1.4: Quality of health care [10]

1. **Effective:** Delivering healthcare services based on solid evidence to those in need.
2. **Save:** Minimizing any potential harm to the individuals receiving care.
3. **Person-centered:** Tailoring care to meet the unique preferences, requirements, and values of individuals.
4. **Timely:** Decreasing wait times and harmful delays in receiving care.
5. **Equitable:** Ensuring the quality of care remains consistent regardless of an individual's gender, ethnicity, geographic location, or socio-economic background.
6. **Integrated:** Offering a complete spectrum of health services across an individual's lifespan.
7. **Resource-efficient:** Optimizing the use of available resources and minimizing waste [11].

1.10 Four-level model of the health care system

This model, refined from the works of Ferlie and Shortell (2001), organizes the healthcare system into four integrated levels see the figure(1.5) below:

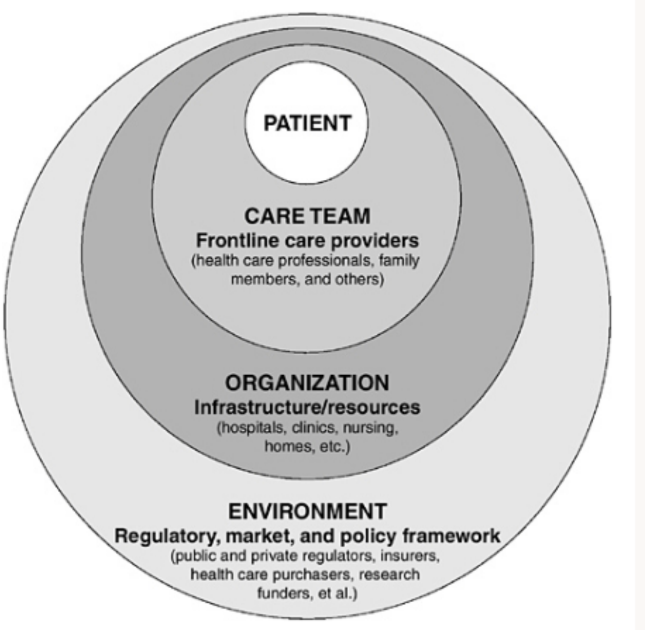


Figure 1.5: Conceptual drawing of a four-level health care system

1. **The individual patient**
2. **The care giving team:** encompassing healthcare professionals (such as doctors, pharmacists, etc.), the patient, and their family members.
3. **The supporting organization:** (for instance, hospitals, clinics, nursing homes, etc.) that facilitates the functioning and development of care giving teams through the provision of essential infrastructure and resources.
4. **The political and economic environment:** (e.g., regulatory, financial, payment regimes, and markets), within which organizations, caregiving teams, individual patients, and healthcare providers operate. [12]

1.11 Challenges in Health Care Systems

- Lack of interoperability
  - Optimizing clinical workflows
  - Personnel shortages and burnout

- Keeping up with advances in medical science and information
- Advancing health equity
- Patient safety [13]

1.12 How does a health system enhance healthcare provision?

How does a health system enhance healthcare provision? Health systems facilitate uniform and integrated patient care experiences across various organizations and medical professionals.

1. Resource generation

2. Provision of healthcare services

3. Steardship

4. Financing

By executing these functions, health systems ensure that patients have fair access to healthcare services, in addition to fostering overall health improvement for the community [14].

1.13 Conclusion

In conclusion, the healthcare delivery system is of great importance in maintaining individual and community health, improving the quality of life, and providing early preventive and curative services. This system plays a crucial role in limiting the spread of diseases and providing appropriate care to minimize complications. Effective communication between patients and healthcare providers is emphasized, contributing to the accurate identification of individual needs. The benefits of this system include improving patients' quality of life and reducing healthcare costs by focusing on preventive measures. In addition, it promotes social solidarity by providing care for vulnerable groups, contributing to the creation of a healthy and sustainable society.

Chapter 2

State of the art

2.1 Introduction

In this chapter, we present studies conducted by researchers within the scope of our topic. Each article is then summarized in a brief summary for clarity and understanding.

2.2 Related work

Morteza Assadi (2008)

The research focuses on modeling and optimizing a healthcare system, particularly in managing patient flow through different phases of care. Closed queuing systems are used to represent the limited capacity of the system, where patients are admitted and discharged according to various phases of care. Unlike previous models, this study considers generally distributed service times in each phase, aiming to determine the optimal number of nurses based on admission and discharge rates. The research aims to enhance efficiency and productivity in healthcare systems amidst increasing patient numbers and rising costs. [15]

Singh Amarjeet others (2011)

The article explores the use of Information and Communication Technology (ICT) to enhance healthcare delivery, particularly in rural areas where access to basic and quality healthcare is limited. It discusses leveraging technology for diagnosing patients and providing appropriate treatments based on known symptoms, thereby reducing severe cases and improving efficiency in directing patients to appropriate medical services. The article also highlights improving healthcare distribution through early screenings in rural areas and utilizing models and algorithms to enhance diagnosis and predict disease outbreaks. Case studies on using ICT for cardiovascular disease risk detection in Punjab, India, and diagnosing leptospirosis in Gujarat are presented, demonstrating the potential benefits of technology in healthcare delivery and the importance of customizing solutions to local environments and conditions [16].

Tsai Chun-Wei others (2016)

The article explores how metaheuristics can revolutionize healthcare by addressing challenges posed by advances in medical technology and an aging population. It outlines the evolution of healthcare towards integrating smart devices and data analytics to improve efficiency and reduce costs. Key contributions include a review of metaheuristics in healthcare and the introduction of a data analytics framework. Technologies like smart devices and wireless sensor networks enable extensive data collection, while metaheuristics like genetic algorithms and particle swarm optimization aid in data mining tasks. The proposed framework, LBDAF, integrates compression processes and parallel computing to handle big data complexity effectively. Future directions include addressing challenges in information fusion, data analytics, and security/privacy, with metaheuristics playing a vital role in these areas. Overall, integrating metaheuristics with emerging technologies promises to drive innovation and improve healthcare systems. [17]

William Crown others (2017)

The article explores the vital role of constrained optimization techniques in healthcare decision-making, stressing the necessity of mathematically-driven optimal solutions that account for system complexities and constraints. These methodologies find application across various healthcare studies, tackling issues such as capacity management, resource allocation, and patient scheduling, thereby enhancing efficiency and outcomes in healthcare delivery. Constrained optimization entails systematically identifying the most optimal solution to a problem while respecting imposed limitations, employing mathematical tools to either maximize or minimize an objective function subject to specified constraints. The process encompasses multiple stages, including problem structuring, mathematical formulation, model resolution, sensitivity analysis, interpretation, and implementation, highlighting the importance of collaboration and continual assessment. The article presents a hypothetical scenario involving a healthcare center manager striving to maximize patient health benefits within predefined time and budget constraints, illustrating the problem formulation and its graphical depiction. Diverse optimization frameworks, including combinatorial, nonlinear, stochastic, and dynamic methods, may be employed depending on the problem's nature.

Moreover, the article explores the application of constrained optimization techniques in healthcare services, enumerating various domains where these approaches have been utilized. It underscores the significance of reporting both optimal solution outcomes and sensitivity analysis results, along with involving decision-makers in potential policy or service adjustments. Furthermore, the article juxtaposes constrained optimization methods with traditional health economic modeling and Dynamic Simulation Models (DSMS), emphasizing their complementary roles and potential for enhancing health technology assessment processes. In summary, the article acquaints readers with the terminology, methodology, and practical applications of constrained optimization techniques in healthcare, laying the groundwork for further exploration through case studies and recommendations aimed at fostering emerging best practices in future endeavors. [18]

Mourine Achieng, Ephias Ruhode (2019)

The paper delves into the challenges surrounding the implementation of Health Information Systems (HIS) in public healthcare, particularly in resource-limited settings. Despite technological advancements, effective HIS implementation remains elusive. The study investigates this issue by employing qualitative research grounded in critical realism and utilizing the Activity Analysis and Development (ActAD) framework.

Through an empirical case study in OR Tambo Municipality, South Africa, the paper uncovers a complex landscape where both electronic and paper-based systems coexist. It emphasizes the critical role of user skills and competencies in maximizing the potential of HIS. Furthermore, the study sheds light on the significance of reliable system functionality and the importance of achieving full utilization of healthcare systems. Despite challenges such as limited network capacity and functionality issues, users generally maintain positive attitudes towards HIS. In conclusion, the paper underscores the need for a regulatory framework to guide HIS implementation, especially in resource-constrained environments, aiming to address disparities in healthcare service delivery. [19]

AMH Pardede, Herman Mawengkang, Muhammad Zarlis, T Tulus (2019)

The introduction addresses the hurdles encountered in delivering healthcare services efficiently and underscores the necessity for optimal resource allocation. It underscores the significance of dynamic scheduling strategies and instantaneous communication in mitigating queue management challenges.
In the methodology section, the focus is on the integration of smart health solutions to surmount resource constraints and elevate the quality of patient care. Techniques for data collection and modeling are delineated to streamline healthcare procedures.
Results and discussions center on the reduction of costs and delays alongside the enhancement of patient service quality via the proposed optimization framework.
Lastly, the conclusions highlight the pivotal role of the smart health service model in augmenting healthcare efficacy and fostering patient contentment. [20]

Rebecca Jessup, Polina Putrik, Rachelle Buchbinder, Janet Nezon,Kobi Rischin, Sheila Cyril, Sasha Shepperd, Denise A O'Connor (2020)

A study published in BMJ Open explores alternative healthcare delivery methods in high-income countries over the past five years. The article aims to review recent evidence on these methods and identify areas needing further research, focusing on effectiveness and economic impact.
Transparent methodology was used, including English systematic reviews published in the last five years focusing on various aspects of healthcare delivery. Databases like Cochrane and MEDLINE were searched, emphasizing high-income country-related procedures.
Results revealed 531 systematic reviews covering a wide range of care delivery categories. Telehealth applications received significant attention, especially in mental healthcare and lifestyle changes. However, economic evaluations were scarce, indicating a gap in understanding the economic impact of alternative care models. The article underscores the importance of further research, particularly in evaluating economic outcomes and understanding the impact of care delivery models on healthcare outcomes, to enhance decision-making and identify future research priorities. [21]

Zahraa Abdalkareem, Amiza Amir, Mohammed Azmi Al-Betar, Phaklen Ekhan, Abdelaziz Hammouri (2021)

The article discusses the critical role of healthcare optimization, particularly in scheduling, to improve service quality while reducing costs. It reviews existing literature on healthcare scheduling, emphasizing the use of metaheuristic approaches for optimization. The focus areas include patient admission scheduling, nurse rostering, and operating room scheduling, highlighting the effectiveness of optimization methods in addressing constraints and enhancing resource utilization.

Patient Admission Scheduling Problem (PASP) and its uncertainty extension (PASU) are examined, considering factors like emergency admissions and uncertain stay lengths. The Dynamic Patient Admission Scheduling with Operating Room Constraints, Flexible Horizons, and Patient Delay (version 3) introduces customizable cost functions based on constraint importance to optimize patient admission processes.

Nurse rostering, a challenging optimization problem, aims to balance workload and preferences while meeting constraints. Various optimization methods, including metaheuristic algorithms and integer programming techniques, are employed to tackle nurse scheduling challenges.

Operating room scheduling, vital for hospital performance, involves complex resource allocation strategies such as block scheduling and advanced scheduling. The article discusses mathematical formulations and optimization methodologies, emphasizing efficient resource utilization and minimizing idle time in operating rooms.

In conclusion, the article underscores the significance of optimization methods in healthcare scheduling and suggests future research directions to enhance outcomes, including exploring alternative metaheuristic algorithms, analyzing algorithm robustness, and integrating scheduling systems across various healthcare domains. [22]

Ahmeed Yinusa and Misagh Faezipour (2023)

The article introduces an MILP model designed to optimize resource allocation and scheduling in healthcare organizations, aiming to enhance patient care and operational efficiency. It addresses challenges such as staff shortages and scheduling complexities, emphasizing the importance of effective scheduling for overall performance. Key points include the detailed description of the MILP model, which outlines variables, parameters, objectives, and constraints to ensure operational feasibility. Simulated data is utilized to customize the model, and the Gurobi Optimizer is employed for efficient solving. Results demonstrate the model's effectiveness in optimizing resource allocation and scheduling. The article concludes by highlighting the model's contributions to academic discourse and managerial decision-making, with future research focusing on enhancing its performance and adaptability through real-world data integration and addressing uncertainties. Overall, it presents a comprehensive framework for improving healthcare resource management and operational efficiency through optimized scheduling and resource allocation. [23]

2.3 Conclusion

In conclusion, this chapter has provided a succinct overview of pertinent research within our thematic scope. By summarizing each article, we aim to enhance the clarity and understanding of these complex studies.

Chapter 3

Optimizing Health Care Delivery System for Resource-Constrained Environment Using genetic algorithm

3.1 Introduction

In this chapter, we explore the concept of Optimizing Health Care Delivery Systems in resource-constrained **(OHCDS)**environments using the Genetic Algorithm.

3.2 Problematic

In a healthcare delivery improvement system in resource-limited environments, the system faces significant challenges in allocating resources effectively and sustainably due to the increasing demand for healthcare services and fluctuations in economic and social conditions. The main objective is to minimize the overall cost of healthcare by optimizing the distribution of available resources. To achieve this goal, the objective function can be formulated to represent the cost related to resource allocation, with a focus on achieving optimal allocation. The proposed objective function aims to minimize the total cost of resource allocation across all resources and time periods. The constraints must ensure that each resource is allocated to only one time period, and include budget constraints that ensure the total cost of resource allocation does not exceed the specified budget. Additionally, the decision variables must be binary to ensure the model's effectiveness. This approach contributes to creating a more efficient and sustainable healthcare system, enhancing the quality of services, ensuring timely access to healthcare, and ultimately leading to a comprehensive and sustainable improvement in healthcare delivery.

3.3 Context

In the face of the diverse challenges confronting healthcare delivery systems in environments with financial constraints and limited resources, improving resource allocation efficiently and effectively requires comprehensive and multifaceted strategies. Despite the increasing demand for healthcare services and escalating financial challenges, healthcare systems must be capable of meeting the growing needs of patients and providing high-quality healthcare while maintaining financial sustainability.

Therefore, it necessitates the use of innovative technologies such as genetic algorithms, quantitative analysis, and artificial intelligence to analyze big data and optimize resource allocation. This approach contributes to enhancing the efficiency, effectiveness, and quality of healthcare.

By focusing on improving resource allocation processes and developing appropriate policies and procedures, patient experience can be enhanced, treatment outcomes improved, and sustainable savings in healthcare achieved. Consequently, this approach can contribute to achieving defined health objectives and ensuring the sustainability of healthcare service delivery in the long term.

3.4 Motivation

The motivations that prompted us to study this topic are:

Firstly, Improving healthcare delivery

Secondly, the rising costs of healthcare, which puts pressure on the financial resources of individuals and governments.

Third, Ensuring equitable access to healthcare

Fourth, responding to epidemics and health crises, such as recent events such as the COVID-19 pandemic.

3.5 Objectives

To achieve this work, we have set the following objectives.

1. Enhancing patient outcomes

2. Improving access to healthcare
3. Enhancing resource allocation efficiency
4. Increasing the efficiency of health systems
5. Reducing the overall healthcare costs
6. Improving the quality of healthcare services

3.6 OHCDS statment

In a healthcare delivery optimisation system in resource-constrained environments, the main objective of focusing on resource allocation is to achieve optimal performance by allocating resources in a way that minimises the total cost of healthcare delivery, taking into account the availability of resources and budget. To achieve this, we use binary decision variables z_{rt} to represent resource allocation decisions, where a value of 1 indicates the allocation of resource r for time period t and a value of 0 indicates otherwise.

Resource allocation constraints must be adhered to, including ensuring that each resource is allocated to only one time period. In addition, if necessary, a specific budget constraint must be set to guide the overall resource allocation and ensure the sustainability of the healthcare system's budget.

To ensure the effectiveness of the proposed solutions, these constraints must be addressed through planning and analytical strategies aimed at balancing the growing demand for healthcare with the limited resources available.

Using these goals and rules, we try to find the best way to allocate health resources at a lower cost, achieve the desired goals, and thus enhance the overall efficiency of the health system.

3.7 Mathematical formulation

Improving healthcare delivery systems in resource-limited environments (OHCDS) requires the creation of mathematical models designed to minimize the overall cost of healthcare by optimizing the distribution of available resources.

Here is a general mathematical formula, for creating these optimization plans:

3.7.1 Decision Variables

In optimization mathematical models, decision variables play a pivotal role in constructing a model that aims to find the best possible solutions within a set of defined constraints and criteria. In this context, we use binary variables to determine whether a resource is allocated to a specific time slot or not, as well as to specify the costs associated with using this resource during that time period.

Our decision variables include:

z_{rt} : Binary decision variable indicating whether resource r is allocated at time slot t

D_{rt} : The cost associated with allocating resource r at time slot t.

This could represent the cost of using this resource at this time.

3.7.2 Input data

To effectively execute the mathematical model, we need a set of input data that defines the criteria and constraints within which the model will operate. These input data include:

- R: Number of available resources.
- T: Number of available time slots.
- B: Specified budget, if budget constraint is used.

3.7.3 Objective Function

We aim to minimize the total cost of resource allocation across all time periods and resources. This is achieved through the following objective function:

$\sum_{r=1}^{R} \sum_{t=1}^{T} D_{rt} z_{rt}$

3.7.4 Constraints

We need to establish some basic constraints to ensure effective resource allocation. In this model, we require two types of constraints:

3.7.4.1 Resource Allocation:

$$\sum_{t=1}^{T} z_{rt} = 1 \quad \forall r = 1, \ldots, R$$

Ensuring that each resource is allocated to only one time slot.

3.7.4.2 Budget Constraint:

$$\sum_{r=1}^{R}\sum_{t=1}^{T} D_{rt} z_{rt} \leq B$$

The total costs associated with resource allocation across all time periods and over all resources must not exceed the specified budget B.

3.7.5 Mathematical formulation of the OHCDS

$$\text{Minimize } Z = \sum_{r=1}^{R}\sum_{t=1}^{T} D_{rt} z_{rt}$$

Subject to:

$$\sum_{t=1}^{T} z_{rt} = 1 \quad \forall r = 1, \ldots, R \tag{3.1}$$

$$\sum_{r=1}^{R}\sum_{t=1}^{T} D_{rt} z_{rt} \leq B \tag{3.2}$$

3.7.6 Example

- We have a small hospital that needs to allocate 3 doctors (resources) during 3 different time periods.
- The cost of allocating each doctor in each time period is given in the following table:

	Period 1	Period 2	Period 3
Doctor 1	100	120	150
Doctor 2	200	80	100
Doctor 3	140	110	130

- We have a total budget of 320.

3.8 Used method

We used the genetic algorithm due to its effectiveness in solving optimization problems and its simplicity in implementation. It has the ability to handle large search spaces, ensuring the generation of a diverse set of solutions. The versatility of the algorithm across various domains and applications makes it an effective and valuable tool.

3.8.1 Overview of Genetic Algorithm

3.8.1.1 genetic algorithm (GA)

Genetic Algorithms(GAs) are adaptive heuristic search algorithms that belong to the larger part of evolutionary algorithms. Genetic algorithms are based on the ideas of natural selection and genetics. These are intelligent exploitation of random searches provided with historical data to direct the search into the region of better performance in solution space. They are commonly used to generate high-quality solutions for optimization problems and search problems [24].

Genetic algorithms simulate the process of natural selection which means those species that can adapt to changes in their environment can survive and reproduce and go to the next generation. In simple words, they simulate "survival of the fittest" among individuals of consecutive generations to solve a problem. Each generation consists of a population of individuals and each individual represents a point in search space and possible solution. Each individual is represented as a string of character/integer/float/bits. This string is analogous to the Chromosome [24].

3.8.1.2 Principles of genetic algorithms

Genetic algorithms use Darwin's theory of species evolution and rely on three core principles: variation, adaptation, and heredity. These principles align with genetic terminology, where the population represents all potential solutions, individuals represent specific solutions, chromosomes are components of these solutions, and genes represent specific traits or characteristics.

1 Principle of Variation: Individuals within the population are characterized by their distinctiveness, as this variation is crucial for the selection process, driving evolutionary progress.

2 Principle of Adaptation: Individuals that adapt better to their environment are more likely to thrive and reproduce, enhancing the overall adaptation of the population.

3 Principle of Heredity: Traits must be heritable to be passed down to offspring, allowing species to develop beneficial characteristics over time.

Essentially, genetic algorithms emulate the process of natural selection, mimicking these principles to iteratively improve solutions to complex problems [25].

3.8.1.3 Genetic algorithm operators

There are three evolution operators in genetic algorithms:

1. Selection: Choosing the fittest individuals.

2. **Crossover**: Mixing the traits of selected individuals through reproduction.
3. **Mutation**: Random alteration of an individual's traits.

1 Selection

Selection involves choosing the most well-adapted individuals to achieve a population of solutions that is closest to converging towards the global optimum. This operator applies the principle of adaptation from Darwin's theory [26].

There are several selection techniques. Here are the main ones used:

1 Roulette Wheel Selection This method is often utilized due to its simplicity and effectiveness for moderately sized problems [25].

2 Rank-Based Selection This method is frequently employed for problems exhibiting significant variability in the fitness scores of individuals [25] .

3 Tournament Selection This method proves useful for problems where individuals have very close fitness scores [25].

Here's an example with individuals represented in binary format after the selection process. See Figure 3.1 [26]

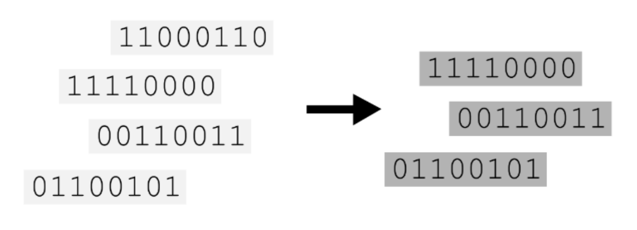


Figure 3.1: Individuals in binary format after the selection process

2 Crossover

Crossover, also known as crossing-over, occurs when two chromosomes exchange their traits. This process facilitates genetic recombination within the population, in line with Darwin's principle of inheritance. [26]

There are two types of crossover methods:

1 single-point or double-point crossover. See Figure 3.2

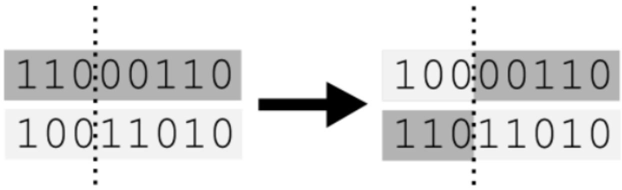


Figure 3.2: Single-point crossover

2 Double crossover operates on the same principle as simple crossover, but with two pivot points. See Figure 3.3

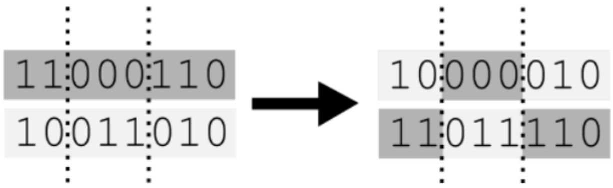


Figure 3.3: two points crossover

3 Mutation

A mutation involves a small modification of a gene within a chromosome based on a mutation factor. This factor represents the probability of an individual undergoing a mutation [26].

This factor adheres to Darwin's principle of variation, while preventing premature convergence of the algorithm towards a local maximum.

The illustration in Figure 3.4 below depicts a mutation that occurs in an individual with a single chromosome.

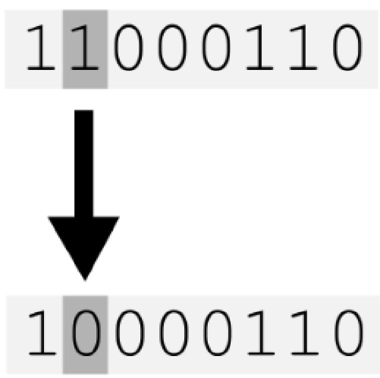


Figure 3.4: mutation Operator representation

3.8.1.4 General Algorithm

After explaining the basic principles, here's how genetic algorithms work, as shown in Figure 3.5 Genetic algorithms begin with a population of potential solutions, represented by chromosomes. These undergo selection based on a fitness function, with the best individuals chosen for reproduction. Through crossover and mutation, new offspring are created, introducing variability. This process repeats over multiple generations until a satisfactory solution is found or a set number of iterations is reached [26].

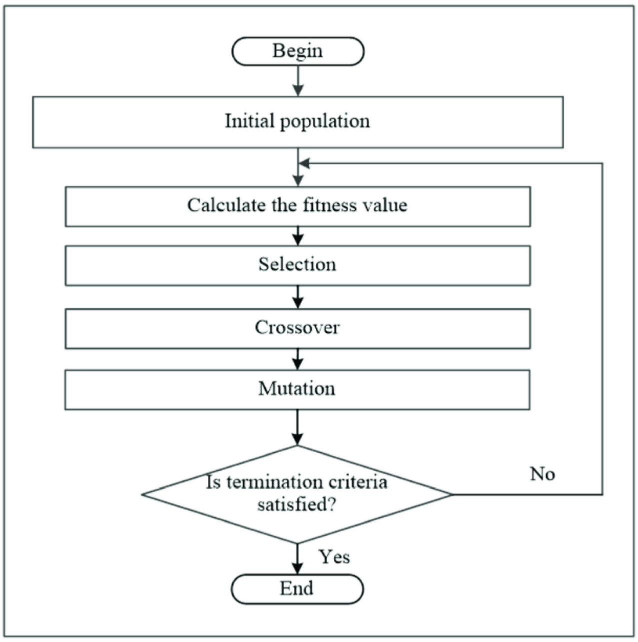


Figure 3.5: How genetic algorithms work in general [27]

3.8.2 Application of Genetic Algorithms on OHCDS

To apply genetic algorithm in the OHCDS, we start first:

3.8.2.1 Solution Coding

The solution can be encoded using a binary matrix. For each resource, a binary matrix (a bit or an integer taking values 0 or 1) is allocated to represent the allocation of the resource for each time period. For example, if we have 3 doctors and 3 time periods, the solution encoding can be as follows:

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

Assume that each resource is represented by a bit or an integer, where the value 1 means the resource is allocated to the time period, and the value 0 means it is not allocated. This representation means that Doctor 1 is allocated to the first period, Doctor 2 is allocated to the second period, and Doctor 3 is allocated to the third period.

3.8.2.2 The fitness function

In the context of healthcare delivery optimization, the primary objective of focusing on resource allocation is to achieve optimal performance by allocating resources in a manner that minimizes the total cost of healthcare delivery. To attain this objective, we can define a fitness function based on the total cost of resource allocation across all resources and time periods.

Mathematical Expression of the Fitness Function

The fitness function can be defined as follows:

$$\text{fitness}(Z) = \sum_{r=1}^{R} \sum_{t=1}^{T} D_{rt} z_{rt}$$

where:

D_{rt} : The cost associated with allocating resource r at time slot t.

z_{rt} : Binary decision variable indicating whether resource r is allocated at time slot t.

3.8.2.3 Initialisation

In the initial stage, a set of potential solutions, known as the initial population, is generated. Each individual in this population represents a potential solution to a particular problem. In this case, each individual represents a potential allocation of resources over different time periods.

Example:

$$\text{population} = \begin{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} & \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix} & \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \end{bmatrix} \end{bmatrix}$$

Algorithm 1 Initialization Algorithm

Inputs:
  pop_ size: Population size
  R: Number of resource allocations
  T: Number time slots
Outputs:
  population: Initial population of solutions
Initialize an empty list *population*.
for k ***in*** *range pop_ size* **do**
  {
Initialize an empty list *individual*.
for i ***in*** *range* (R) (T) **do**
  {
Append a random binary value (0 or 1) to *individual*. }
Append *individual* to the *population* list. }
return *population*.

3.8.2.4 Evaluation of the population

Population Evaluation

Population evaluation is the process of evaluating the quality and efficiency of each individual (potential solution) in a population using a fitness function to identify the best solutions and perpetuate them in subsequent generations in evolutionary algorithms. This process directs optimisation towards optimal solutions for a given problem.

Steps

1. Initialise the initial fitness value for each individual.
2. Calculate the fitness score for each individual in the population.
3. Check the constraints.
4. Calculate the fitness function.

Fitness Evaluation Algorithm
Inputs:

- R: Number of resources.
- T: Number of time slots.
- D_{rt}: Cost associated with allocating resource r at time slot t.

- z_{rt}: Binary decision variable indicating whether resource r is allocated at time slot t (1 if allocated, 0 otherwise).

Output:

- *fitness*(Z): Fitness value, representing the total cost of resource allocation across the time slots.

Algorithm 2 Fitness Evaluation Algorithm

Input: R: Number of resources
Input: T: Number of time slots
Input: D_{rt}: Cost associated with allocating resource r at time slot t
Input: z_{rt}: Binary decision variable indicating whether resource r is allocated at time slot t
Output: *fitness*(Z): Fitness value

Initialize fitness value: $fitness \leftarrow 0$ **Loop through resources and time slots:**
for $r \leftarrow 1$ **to** R **do**
  for $t \leftarrow 1$ **to** T **do**
    if $z_{rt} = 1$ **then**
      Update the fitness value: $fitness \leftarrow fitness + D_{rt}$
    end
  end
end
Return the final fitness value: return $fitness$

3.8.2.5 Example

For example, let's assume we have a resource allocation matrix as follows:

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

And we have the following cost matrix:

$$\begin{bmatrix} 5 & 8 & 6 \\ 7 & 6 & 9 \\ 8 & 7 & 4 \end{bmatrix}$$

The adaptation function will be:

$$Z = (5 \times 1) + (8 \times 0) + (6 \times 0) + (7 \times 0) + (6 \times 1) + (9 \times 1) + (8 \times 0) + (7 \times 0) + (4 \times 1)$$

So,

$$Z = 5 + 0 + 0 + 0 + 6 + 9 + 0 + 0 + 4 = 24$$

Thus, the value of the adaptation function for this solution is 24. The lower the value of the adaptation function, the better the solution.

3.8.2.6 Selection

The tournament selection method is considered one of the common and effective approaches in selection operations in genetic algorithms. This method is characterized by several technical and practical advantages that make it a good choice for selecting individuals participating in the evolution process. Firstly, the tournament selection method enhances diversity in the genetic population and prevents dominance by providing equal opportunities for every individual regardless of their genetic fitness level. By forming small tournaments where a limited number of individuals compete, individuals with lower fitness levels have a chance to win and participate in the evolution process. Secondly, the tournament selection method increases the exploration of the search space and the discovery of new solutions, as individuals from different levels can participate in the selection process and compete for victory. Lastly, the implementation of the tournament selection method is easy and flexible, as selection criteria and tournament size can be easily adjusted to meet the specific problem requirements. Based on these advantages, it can be said that the tournament selection method is a useful and efficient choice in selection operations in genetic algorithms.

Selection by Tournament

In tournament selection, a random group of individuals (called a tournament) is chosen, and the individual with the lowest fitness value from this group is selected. Repeating this process multiple times ensures that a group of individuals with lower fitness values is chosen to generate the next generation.

Steps

1. **Select a Random Group of Individuals (Tournament):** A certain number of individuals are randomly chosen from the current population.

2. **Competition Among Individuals in the Tournament:** The fitness values of the selected individuals are compared.

3. **Select the Winner:** The individual with the lowest fitness value in the tournament is selected.

4. **Repeat the Process:** Steps 1 to 3 are repeated until the required number of individuals is selected for the next generation.

Algorithm 3 Selection by tournament

```
procedure SELECTION(population, tournament_size)
    selected_population ← empty list while size of selected_population < required_population size do
    tournament ← RandomSelection(population, tournament_size)
    winner ← individual with the lowest fitness in the tournament
    Add winner to selected_population
    return selected_population
end procedure
```

Example

Suppose we have a population of candidate individuals with their corresponding fitness scores:

- Individual 1: Fitness score = 90
- Individual 2: Fitness score = 75
- Individual 3: Fitness score = 80
- Individual 4: Fitness score = 85
- Individual 5: Fitness score = 70

If the tournament size is 3, the selection process may be as follows:

1. Randomly select individuals 1, 3, and 5.

2. Compare their fitness scores:

    - Individual 1: Fitness score = 90
    - Individual 3: Fitness score = 80
    - Individual 5: Fitness score = 70

3. The winner of this tournament is individual 5 because they have the lowest fitness score.

3.8.2.7 Crossover

Crossover is one of the main operations in genetic algorithms used to produce a new generation of individuals by exchanging genetic information between current individuals. The goal of this process is to combine the genetic traits of the selected individuals to produce new individuals that exhibit a mix of traits from the original individuals, thereby increasing the diversity of the new generation and potentially improving solutions.

Basic Steps of the Crossover Process

1. **Selection of Individuals for Reproduction:**
   - Two individuals from the current generation are selected for the crossover operation. Typically, individuals are chosen based on the quality of their solutions (fitness values) using methods such as roulette wheel selection or tournament selection.

2. **Determining the Crossover Point:**
   - In a one-point crossover process, a single random point is selected along the genetic sequences of each individual. For example, if an individual's genetic sequence is a string of numbers or characters, the crossover point is a specific location on this sequence.

3. **Exchanging Genetic Segments:**
   - After determining the crossover point, the genetic sequence of each individual is divided into two parts: a part before the crossover point and a part after it.
   - The segments after the crossover point are exchanged between the selected individuals. This means the first part of the genetic sequence remains unchanged, while the second part is swapped between the individuals.

4. **Producing New Individuals:**
   - After exchanging the genetic segments, two new individuals are formed. These new individuals carry a combination of the genetic traits from the original individuals.

By following these steps, the crossover process effectively combines the genetic material from two parent individuals to create offspring with potentially better and more diverse genetic characteristics.

Algorithm 4 Single Point Crossover

```
procedure SinglePointCrossover(parent1, parent2, crossover_point)
    child1 ← empty list
    child2 ← empty list
    if random.random() > crossover_probability then
        return parent1, parent2
    for i ← 1 to crossover_point do
        Append parent1[i] to child1
    for i ← crossover_point + 1 to length of parent2 do
        Append parent2[i] to child1
    for i ← 1 to crossover_point do
        Append parent2[i] to child2
    for i ← crossover_point + 1 to length of parent1 do
        Append parent1[i] to child2
    return child1, child2
end procedure
```

Example

$$\text{Parent 1:} \begin{bmatrix} 1 & \mathbf{0} & \mathbf{0} \\ 0 & \mathbf{1} & \mathbf{0} \\ 0 & 0 & 1 \end{bmatrix} \quad \text{Parent 2:} \begin{bmatrix} 1 & \mathbf{1} & \mathbf{0} \\ 0 & \mathbf{1} & \mathbf{0} \\ 1 & 0 & 0 \end{bmatrix}$$

$$\text{Child 1:} \begin{bmatrix} 1 & \mathbf{1} & \mathbf{0} \\ 0 & \mathbf{1} & \mathbf{0} \\ 0 & 0 & 1 \end{bmatrix} \quad \text{Child 2:} \begin{bmatrix} 1 & \mathbf{0} & \mathbf{0} \\ 0 & \mathbf{1} & \mathbf{0} \\ 1 & 0 & 0 \end{bmatrix}$$

In this example, genetic material from parent1 up to the crossover point (index 3) is combined with genetic material from parent2 after the crossover point to generate child1. Similarly, genetic material from parent2 up to the crossover point is combined with genetic material from parent1 after the crossover point to generate child2.

Repeating these steps generates the required number of offspring for the next generation. The crossbreeding process allows combining the characteristics of both parents, enabling new solutions to be explored to discover more optimal sequences.

3.8.2.8 Mutation

After the process of crossover, through which new individuals are produced, the next stage is mutation.

Mutation aims to introduce random changes to some individuals in the new generation to ensure genetic diversity and prevent the convergence of solutions towards local minimum or maximum values. This process mimics the natural mutations that occur in the DNA of living organisms.

Steps to carry out mutagenesis: Determine the mutation rate: This rate determines the percentage of genes that will undergo change in each generation.

The mutation rate is usually low (1% to 5%).

Selecting individuals: Individuals are randomly selected from the new generation based on the selected mutation rate.

Applying the changes: The values of specific genes are changed in the randomly selected individuals. These changes can be small or large depending on the nature of the issue.

Algorithm 5 Mutation Algorithm

Inputs : *Chromosome*: The chromosome containing the genetic information to be mutated *MutationRate*: The mutation rate (default is 0.01)
Outputs: *Chromosome*: The chromosome after mutation

```
for i ← 1 to length of Chromosome do
    if random number() < Mutation Rate then
        Chromosome[i] ← 1 − Chromosome[i]
return Chromosome
```

Example

Suppose we have a chromosome: Chromosome:

$$\begin{bmatrix} 1 & \mathbf{1} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Let's apply the mutation algorithm with a mutation rate of 0.1.

After mutation, the chromosome might become: Chromosome:

$$\begin{bmatrix} 1 & \mathbf{0} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

In this example, the mutation algorithm randomly selects certain positions in the chromosome and flips the values with a probability determined by the mutation rate. We repeat these steps for all individuals who need to undergo a mutation.

This leads to a random exploration of the solution space, which helps in the search for possible better solutions. It is important to choose an appropriate mutation threshold to control the frequency of mutations.

Stopping criteria

Define stopping criteria for terminating the genetic algorithm, such as the maximum number of cycles, achieving acceptable convergence, or reaching an optimal solution.

Repetition

The steps of selection, crossover, mutation, and replacement are repeated until the termination criteria are met.

3.9 Conclusion

In conclusion, the widespread use of genetic algorithms in solving optimisation problems is a testament to their effectiveness and power in finding optimal solutions. By effectively mimicking genetic processes and natural evolution, genetic algorithms are a valuable tool for researchers and engineers in various fields. They excel at solving a variety of optimisation problems including patient scheduling and over time medical resource allocation (OHCDS).

Chapter 4

Implementation and results

4.1 Introduction

Implementation and results are vital components of any research study. In this chapter, we will elucidate how to implement the proposed solution to the resource allocation problem and analyze the obtained results. We will begin by describing the physical and software environments used in the implementation process, then move on to explaining how to utilize the data and execute the algorithms. Subsequently, we will present the results and provide a comprehensive analysis, aiding in understanding the effectiveness of the proposed solution and its applicability in practical contexts.

4.2 Physical Environment

We have used as a hardware environment lenovo pc having the following characteristics:

- Processor: Intel(R)Core(TM) i5-6200U CPU @ 2.30GHz
- RAM: 8.00 Go

4.3 Software Environment

Platform used is Windows 10 with the help of the following program:

4.3.1 used programming language Python

Python is an open-source, object-oriented programming language that is compatible with multiple platforms. With its specialized libraries, Python can be utilized in various contexts such as software development, data analysis, and infrastructure management [25].

Python was created by Guido van Rossum and was first released in 1991 [28].

Figure 4.1: Python logo

4.3.2 The Visual Studio Code environment

Visual Studio Code, commonly known as VS Code, is an open-source code editor developed by Microsoft. Renowned for its speed, lightness, and versatility, it features an intuitive interface, smart code completion, debugging tools, Git integration, live editing capabilities, and access to a vast library of extensions, among other functionalities. See Figure 4.2 [29].

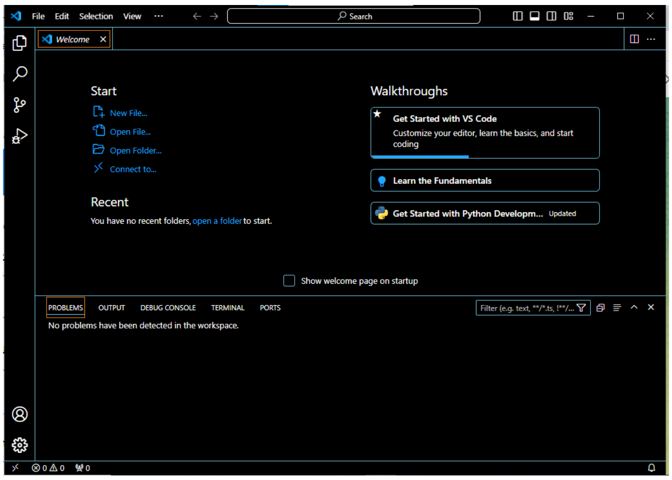


Figure 4.2: The Interface VS Code

4.4 Implementation

The code was written and executed using an integrated programming environment to ensure smooth and accurate performance in data analysis and the implementation of genetic algorithms. Visual Studio Code was used as the development environment, providing the necessary tools for code editing, debugging, and project management. The details are as follows:

- **Operating System**: Windows 10
- **Programming Language**: Python 3.8
- **Development Environment**: Visual Studio Code
- **Libraries Used**:
  - **random**: For generating random numbers.
  - **numpy**: For numerical operations and array processing.
  - **matplotlib.pyplot**: For creating plots and visualizations.
  - **seaborn**: For creating more interactive and aesthetic plots.
  - **time**: For calculating time intervals and controlling execution time.

4.5 Used data

In this study, we used randomised data to simulate an experimental environment and evaluate the performance of genetic algorithms. The data was randomly generated to ensure a variety of scenarios and to test the algorithm under different conditions. The details of the random data used are detailed below:

- Number of rows: The number of rows was based on the number of resources used in the experiments. Random numbers were generated for each experiment in the range of 1 to 20.

- Number of columns: The number of columns was determined based on the number of available time slots. Random numbers were generated for each trial in the range of 1 to 20.

- Matrix Drt: This matrix represents the costs associated with each resource for each time period. The values in the matrix were generated using a uniform random distribution within the range [1, 10].

The random data was generated using the random library in the Python programming language, leveraging the np.random.randint function to generate random numbers within a specific range. Below is an example of the code used to generate the random data:

```python
import random
min_size = 1
max_size = 10
rows = random.randint(min_size, max_size)
cols = random.randint(min_size, max_size)
matrix = [[random.randint(0, 10) for _ in range(cols)] for _ in range(rows)]
print(f"Number of rows (resources): {rows}")
print(f"Number of columns (time periods): {cols}")
print("Generated Matrix:")
for row in matrix:
    print(row)
```

Below is an example of a randomly generated dataset that was used:

Instance 1:

- Number of resources: 10
- Number of time periods: 10
- Generated Matrix Drt:

$$\begin{bmatrix} 6 & 8 & 3 & 5 & 2 & 4 & 9 & 4 & 4 & 6 \\ 5 & 5 & 4 & 4 & 2 & 4 & 2 & 1 & 9 & 2 \\ 7 & 2 & 8 & 1 & 5 & 7 & 9 & 9 & 8 & 2 \\ 4 & 9 & 3 & 3 & 1 & 6 & 1 & 6 & 6 & 4 \\ 7 & 7 & 8 & 1 & 7 & 5 & 9 & 3 & 4 & 9 \\ 9 & 2 & 5 & 5 & 9 & 4 & 4 & 6 & 1 & 3 \\ 5 & 7 & 6 & 1 & 2 & 9 & 9 & 5 & 6 & 3 \\ 2 & 7 & 7 & 4 & 5 & 4 & 7 & 2 & 2 & 1 \\ 7 & 6 & 6 & 2 & 7 & 9 & 4 & 9 & 7 & 6 \\ 2 & 2 & 9 & 8 & 4 & 8 & 3 & 8 & 7 & 8 \end{bmatrix}$$

Instance 2:

- Number of resources: 5
- Number of time periods: 14
- Generated Matrix Drt:

$$\begin{bmatrix} 7 & 8 & 6 & 8 & 5 \\ 1 & 2 & 3 & 9 & 4 \\ 1 & 8 & 3 & 5 & 8 \\ 6 & 2 & 3 & 3 & 5 \\ 2 & 9 & 4 & 9 & 3 \\ 9 & 3 & 5 & 5 & 5 \\ 8 & 3 & 1 & 4 & 8 \\ 9 & 9 & 7 & 7 & 1 \\ 4 & 2 & 8 & 1 & 5 \\ 2 & 8 & 5 & 9 & 6 \\ 9 & 5 & 7 & 3 & 5 \\ 3 & 8 & 5 & 3 & 9 \\ 2 & 1 & 8 & 7 & 2 \\ 5 & 2 & 4 & 9 & 8 \end{bmatrix}$$

4.6 Results and Discussions

The results illustrate that the achieved objective values during the two optimization processes were of good quality, reaching 13 in the first process and 26 in the second process. The number of discovered solutions, which amounted to 1 in the first process and 1 in the second process, indicates that the best solutions were achieved with optimal values for the objective functions. Based on the best achieved values, it can be noted that there are no significant differences between the objective values and the theoretical lower bounds. This indicates that the optimal solutions were able to achieve good performance. Additionally, the execution time was 2.11661 seconds for the first process and 8.97485 seconds for the second process, reflecting the efficiency of the optimization procedures

Output for instance 1		**Output for instance 2**	
Term	**Value**	**Term**	**Value**
Objective value	13	Objective value	28
Solution count	1	Solution count	1
Best objective	13	Best objective	28
Best bound	13	Best bound	28
Execution time	2.11661 s	Execution time	8.974857 s

Table 4.1: Optimization results for the two model procedures

Table 4.2 describes the terms developed during the optimization procedures .

Term	Instance 1	Instance 2	Description
Objective Value	13.0	28	Optimized value of the objective function. Represents key measures like total cost or profit.
Solution Count	1	1	Number of feasible solutions satisfying all constraints.
Best Objective, Bound	13.0	28	Best value and lowest value found for the function during optimization.
Resource Allocations	10	14	Allocation of resources to specific time slots for effective resource management.
Execution Time	5.3904356 s	7.3015432 s	Time taken to execute the optimization process.

Table 4.2: Optimization results for the two model procedures

Table 4.3 illustrates the resource allocations (from 1 to 10) for the first procedure and (from 1 to 14) for the second procedure. These resources, such as buildings, medical equipment, staff (doctors, nurses), and others, are allocated to specific time slots. This process allows for effective management and coordination of resources to maximize their utilization.

Table 4.3: Resource allocations for first and second outputs.

Resource	Time Slot for instance 1	Resource	Time Slot for instance 2
1	5	1	5
2	8	2	1
3	4	3	1
4	5	4	2
5	4	5	1
6	9	6	2
7	4	7	3
8	10	8	5
9	4	9	4
10	2	10	1
		11	4
		12	1
		13	2
		14	2

Refer to Figures 4.3 and 4.4 for a clearer view of the table where:

1. The horizontal axis (Time Period): Represents different time periods.

2.The vertical axis (Resource): Represents various resources.

Heatmap Interpretation:

- Cells with the value 1:Indicate the activities allocated to each resource in each time period. If a cell contains the number 1, it means that the resource is allocated to a specific activity during that time period.

- Cells with the value 0: Mean that the resource is not allocated to any activity during that time period

We observe that the distribution is fairly balanced across the different time periods, indicating good planning to avoid the accumulation of activities in a single time period. Resources are also allocated efficiently, ensuring that each resource is utilized in a specific time period, which helps in achieving the maximum benefit from the available resources.

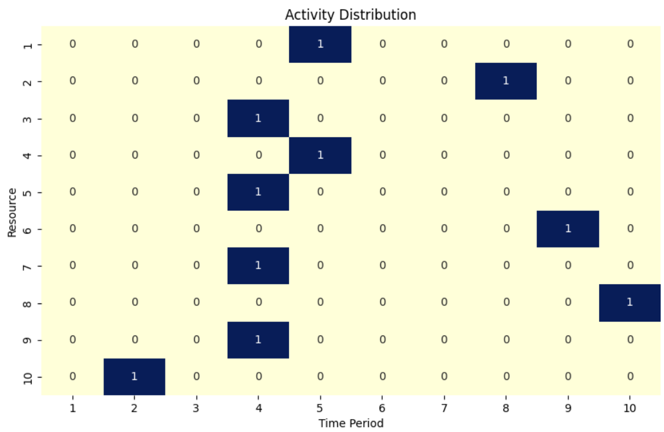


Figure 4.3: Resource allocation heatmap for the first model procedure.

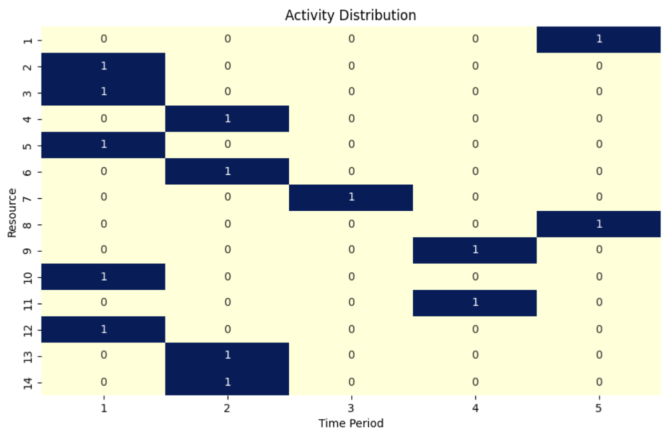


Figure 4.4: Resource allocation heatmap for the second model procedure.

The curves in Figure 4.5 and Figure 4.6 represent the relationship between cost and generation in the optimization process. The graphs illustrate how the cost changes over time across different generations of the genetic algorithm.

where the horizontal axis represents the generations and the vertical axis represents the cost.

The curves show how the cost decreases as generations progress, indicating the gradual improvement in solutions discovered by the genetic algorithm.

These charts help understand how genetic algorithms perform in improving resource allocation and reducing costs across successive generations.

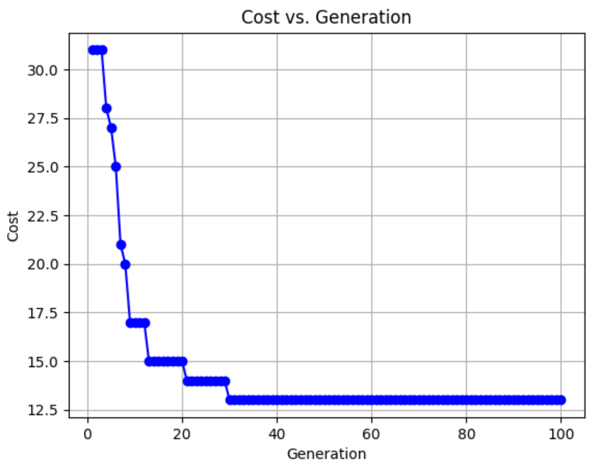


Figure 4.5: Cost vs. Generation for the first model procedurer .

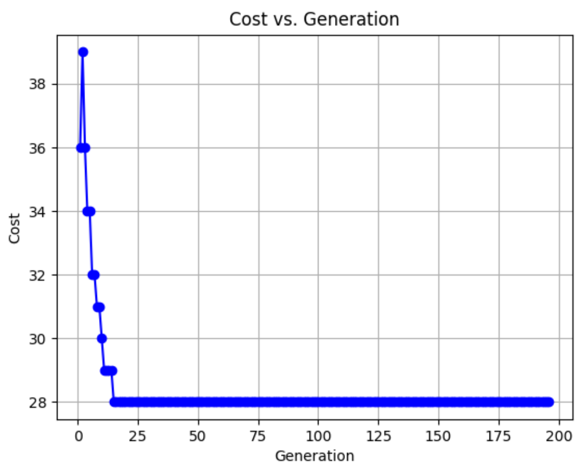


Figure 4.6: Cost vs. Generation for the second model procedure.

4.7 Effect of Mutation Rate, Number of Iterations, and Population Size on Healthcare Delivery System Performance: An Analytical Study

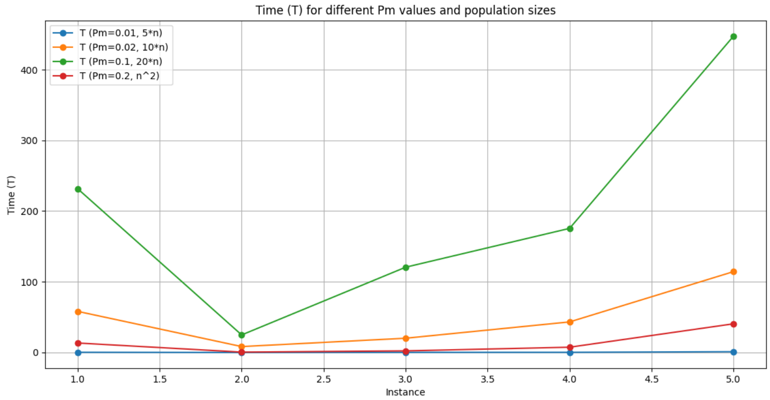
This table shows a summary of results for different experimental instances. It analyzes the impact of three different variables on the best obtained result and the time taken to reach it. The variables are:

- Mutation rate (Pm)
- Number of iterations (Nb iterations)
- Population size (Pop size)

Experiments were conducted for five different instances, and the best solutions along with the time taken for each were recorded.

Instance	Pm	Nb iterations	Pop size	Best S	Time (s)
1	0.01	n	$5n$	32	0.31003
	0.02	$100n$	$10n$	30	58.15040
	0.1	$200n$	$20n$	30	231.54388
	0.2	n^2	n^2	30	13.39032
2	0.01	n	$5n$	14	0.04698
	0.02	$100n$	$10n$	14	8.36201
	0.1	$200n$	$20n$	14	24.83827
	0.2	n^2	n^2	14	0.54179
3	0.01	n	$5n$	14	0.23578
	0.02	$100n$	$10n$	12	20.15688
	0.1	$200n$	$20n$	12	120.60084
	0.2	n^2	n^2	12	2.28003
4	0.01	n	$5n$	29	0.26765
	0.02	$100n$	$10n$	20	43.22933
	0.1	$200n$	$20n$	20	175.52219
	0.2	n^2	n^2	20	7.45209
5	0.01	n	$5n$	27	1.12066
	0.02	$100n$	$10n$	25	114.37523
	0.1	$200n$	$20n$	25	447.47937
	0.2	n^2	n^2	25	40.56605

Table 4.4: Summary of Results for Different Instances



Analysis of Time Curves

From the analysis of the time curves, we find that the configuration (Pm=0.01, 5*n) provides optimal performance in terms of stability and time consumption across different instances, making it the best choice for balancing performance and time efficiency. Configurations with higher mutation rates and population sizes, such as (Pm=0.1, 20*n) and (Pm=0.2, n^2), show significant increases in time consumption, indicating greater complexity and higher time costs despite offering greater diversity in solutions. Therefore, to achieve a balance between solution quality and time cost, it is preferable to use moderate mutation rates and population sizes, considering the available resources and desired objectives. This way, healthcare delivery systems in resource-limited environments can be effectively optimized, ensuring a balance between quality and time efficiency, leading to an overall improvement in the performance of the healthcare system.

4.8 Conclusion

In conclusion, the application of genetic algorithms for resource allocation in the adopted models demonstrates promising results that highlight the effectiveness of these algorithms in achieving optimal performance. Obtaining solutions close to theoretical lower bounds indicates the efficient capability of these algorithms to achieve desired improvements. Additionally, the execution times were acceptable, demonstrating the efficiency of the algorithms used in the process. Through meticulous resource allocation management, a balanced distribution of resources across different time periods was ensured, effectively maximizing their utilization. Furthermore, visual representations such as heatmaps and cost-generation curves provided comprehensive insights into the distribution pattern and the improvement of solutions across successive generations.

General conclusion

In our study, we explored the use of genetic algorithms to optimize healthcare delivery systems in resource-limited environments. Our primary goal was to improve the efficiency of these systems, especially in areas facing resource shortages, by optimizing the distribution and allocation of resources over different time periods. The objective was to minimize the overall cost of these allocations and distributions while maintaining effective and feasible scheduling under various constraints. The binary variables in this model represent different allocations and distributions.

By applying genetic algorithms, we developed mathematical models to increase efficiency and improve the allocation and utilization of available resources. We provided a general mathematical formulation to design these optimal plans, outlining the decision variables, criteria, and constraints necessary to achieve the desired objectives.

During our research, we encountered several challenges in studying this subject. Among the difficulties we faced were:

1. Data Collection: Obtaining accurate and comprehensive data to feed the mathematical models.

2. Problem Complexity: The complexities associated with modeling a multi-dimensional problem involving different variables and criteria.

3. Finding Optimal Parameters: Determining the optimal values for parameters to ensure the effective performance of the genetic algorithm.

4. Designing Practical Constraints: Developing effective constraints that reflect practical reality and ensure the achievement of desired objectives.

Despite these challenges, we were able to overcome them through a systematic approach, continuous iteration, and precise adjustments. The challenges we faced helped us enhance our understanding of the problem and identify opportunities for future performance improvements.

Through this work, healthcare delivery systems can be optimized to ensure high-quality healthcare even in difficult conditions. The developed models and applied genetic algorithms provide practical and effective solutions to improve resource allocation, achieving a balance between quality and cost, leading to overall improvement in the performance of the healthcare system in resource-limited environments.

During our research, we learned many important things that enhanced our capabilities and knowledge, including:

1. Mastering Python Programming: We learned how to use Python to develop mathematical models and efficiently implement genetic algorithms.

2. Mastering LaTeX: We acquired skills in using LaTeX to write and format research documents professionally.

3. Data Analysis: We delved into data analysis methods and extracting valuable information to feed our models.

4. Critical Thinking and Problem-Solving: We developed critical thinking and problem-solving skills by facing and overcoming research challenges.

In light of the results we have obtained, we see that there are vast prospects for further research in this field. Future researchers can explore:

1. Improving Algorithms: Developing new algorithms or enhancing current ones to make them more effective in facing different challenges.

2. New Applications: Studying other applications of these algorithms in various areas of healthcare systems.

3. Integrating Modern Technologies: Using modern technologies such as machine learning and artificial intelligence to improve the performance of genetic algorithms.

4. Expanding Scope: Applying the developed models to a broader range of data and geographical areas to improve the reliability of results and generalize the benefits.

Through this work, we hope to contribute to improving healthcare delivery systems in resource-limited environments, ensuring the provision of high-quality healthcare even in the most challenging conditions. The models and algorithms we developed offer practical and effective solutions to enhance resource allocation and achieve a balance between quality and cost, leading to overall improvement in the performance of the healthcare system.

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ملخص

في هذه الدراسة تناولنا مشكلة تحسين انظمة تقديم الرعاية الصحية في بيئات محدودة الموارد،باستخدام الخورزميات الجنية .
تم تطبيق هذه الخوارزميه لحل مشكلة تخصيص الموارد عبر فترات زمنية مختلفة باقل تكلفة ممكنة. اتاحت لنا الخوارزمية التي نفذناها تحقيق نتائج واعدة على رغم من ان الحل التي تم الحصول لم تصل الى الكمال في الامثلية الا انها كانت قريبة من المستوى الامثل في اطار زمني محدودة.

الكلمات المفتاحية: تحسين أنظمة تقديم الرعاية الصحية، الخوارزميات الجينية، تخصيص الموارد .

Abstract

In this study, we addressed the issue of optimising healthcare delivery systems in resource-constrained environments using genetic algorithms.
The algorithm was applied to solve the issue of resource allocation across different time periods at the lowest possible cost. The applied algorithm allowed us to achieve promising results. Although the obtained solution was not fully optimised, it was close to optimal within a limited time frame.

Keywords: Healthcare Delivery System optimization, Genetic Algorithms, Resource Allocation.

Résumé

Dans cette étude, nous avons abordé le problème de l'amélioration des systèmes de prestation de soins de santé dans des environnements aux ressources limitées en utilisant des algorithmes génétiques.
L'algorithme a été appliqué pour résoudre le problème de l'allocation des ressources sur différentes périodes de temps au coût le plus bas possible. L'algorithme mis en œuvre nous a permis d'obtenir des résultats prometteurs. Bien que la solution obtenue n'ait pas atteint une optimalité parfaite, elle était proche du niveau optimal dans un délai limité.

Mots Clé : Optimisation des systèmes de prestation de soins de santé, Algorithmes génétiques, Allocation des ressources .