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Faculty of Technology
Department of Process Engineering

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THESIS

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الملخّص

تستكشف هذه الأطروحة تحسين جدولة العمليات الصناعية مع التركيز على تعزيز الكفاءة، السلامة والاستدامة في العمليات الصناعية المعاصرة. وفي مواجهة حدود الأساليب التقليدية في جدولة العمليات، تقوم الدراسة بفحص منهجيات وتقنيات متقدمة، ولا سيما الذكاء الاصطناعي وتعلم الآلة والخوارزميات الاستكشافية (الميتاهيورستية) لمعالجة التعقيدات الموجودة في بيئات الصناعات الديناميكية. وتوضح الدراسة الدور الحيوي لاستراتيجيات الجدولة الذكية في توزيع الموارد، والتخطيط للصيانة، وتيسير سير العمليات، مع تطبيق خاص في قطاع البتروكيماويات.

من بين المساهمات الرئيسية في هذه الأطروحة تطوير إطارات جدولة ذكية تستفيد من نماذج الصيانة التنبؤية لمنع الأعطال، وتقليص فترات التوقف، وتخفيف المخاطر، مما يضمن معدلات الموثوقية والتوافر للنظم الحيوية مثل النظم الآلية للسلامة)المعروفة بالاختصار .(SIS وتبرز الأطروحة كفاءة الخوارزميات الاستكشافية في معالجة مشاكل الجدولة المعقدة، والتوزين بين الأهداف المتنافسة، والتغلّب على القيود، مما يدلّ على مزاياها العملية في السيناريوهات الواقعية.

تؤكد النتائج على الإمكانات التحويلية لدمج التقنيات القائمة على الذكاء الاصطناعي في ممارسات الجدولة، مما يساهم في التميز التشغيلي والامتثال للسلامة. بينما يقدم البحث تطورات مهمة، إلا أنه يقر أيضاً بالقيود المتعلقة بالتحقق من الصحة في سياقات واقعية متنوعة وتحديات دمج التقنيات المتقدمة مع الأنظمة القديمة. تشمل اتجاهات البحث المستقبلية تحسين النماذج التنبؤية، واستكشاف التوائم الرقمية، ودمج مقاييس الاستدامة في أطر الجدولة، وتوسيع نطاق تطبيق هذه المنهجيات لتشمل قطاعات صناعية أخرى.

يؤسس هذا العمل أساسًا متينًا لتحسين الجدولة الصناعية، ويربط بين الرؤى النظرية والتطبيقات العملية. من خلال اعتماد منهجيات متقدمة، يمكن للصناعات تحقيق قدر أكبر من الكفاءة والمرونة والاستدامة، مما يمهد الطريق نحو ممارسات الإدارة الصناعية المبتكرة والتكيفية. لا تتصدى الرؤى المكتسبة للتحديات الحالية فحسب، بل توفر أيضًا خارطة طريق للتطورات المستقبلية في هذا المجال، وتوائم الممارسات الصناعية مع الضرورات التكنولوجية والبيئية المتطورة.

الكلمات المفتاحية: الجدولة الصناعية، التحسين الأمثل، خوارزميات ما وراء الطبيعة، أنظمة السلامة الآلية، صناعة البتروكيماويات، العمليات الصناعية المستدامة.

Abstract

This thesis investigates the optimization of industrial scheduling, focusing on enhancing efficiency, safety, and sustainability in modern industrial operations. Addressing the limitations of traditional scheduling methods, it explores advanced methodologies and technologies, particularly artificial intelligence (AI) and metaheuristic algorithms, to tackle the complexities of dynamic industrial environments. The research emphasizes the critical role of intelligent scheduling strategies in resource allocation, maintenance planning, and operational workflows, with a particular application in the petrochemical industry.

Key contributions include the development of smart scheduling frameworks that leverage predictive maintenance models to preempt failures, reduce downtime, and mitigate risks, thereby ensuring the reliability and availability of critical systems such as Safety Instrumented Systems (SIS). The thesis highlights the effectiveness of metaheuristic algorithms in solving complex scheduling problems, balancing competing objectives, and navigating constraints, demonstrating their practical benefits in real-world scenarios.

The findings underscore the transformative potential of integrating AI-driven technologies into scheduling practices, contributing to operational excellence and safety compliance. While the research presents significant advancements, it also acknowledges limitations related to validation in diverse real-world contexts and the challenges of integrating advanced technologies with legacy systems. Future research directions include refining predictive models, exploring digital twins, incorporating sustainability metrics into scheduling frameworks, and expanding the application of these methodologies to other industrial sectors.

This work establishes a robust foundation for optimizing industrial scheduling, bridging theoretical insights with practical applications. By adopting advanced methodologies, industries can achieve greater efficiency, resilience, and sustainability, setting a pathway toward innovative and adaptive industrial management practices. The insights gained not only address current challenges but also provide a roadmap for future developments in the field, aligning industrial practices with evolving technological and environmental imperatives.

Key words: Industrial scheduling, Optimization, Metaheuristic algorithms, Safety Instrumented Systems (SIS), Petrochemical industry, Sustainable industrial operations.

Résumé

Cette thèse explore l'optimisation de la planification industrielle, en se concentrant sur l'amélioration de l'efficacité, de la sécurité et de la durabilité dans les opérations industrielles modernes. En répondant aux limites des méthodes de planification traditionnelles, elle examine des méthodologies et technologies avancées, en particulier l'intelligence artificielle (IA), l'apprentissage automatique et les algorithmes métaheuristiques, pour relever les complexités des environnements industriels dynamiques. La recherche met en évidence le rôle crucial des stratégies de planification intelligente dans l'allocation des ressources, la planification de la maintenance et les flux de travail opérationnels, avec une application particulière dans l'industrie pétrochimique.

Parmi les contributions clés figurent le développement de cadres de planification intelligente exploitant des modèles de maintenance prédictive pour prévenir les pannes, réduire les temps d'arrêt et atténuer les risques, assurant ainsi la fiabilité et la disponibilité des systèmes critiques tels que les Systèmes Instrumentés de Sécurité (SIS). La thèse met en évidence l'efficacité des algorithmes métaheuristiques dans la résolution de problèmes complexes de planification, l'équilibrage d'objectifs concurrents et la navigation dans les contraintes, démontrant leurs avantages pratiques dans des scénarios réels.

Les résultats soulignent le potentiel transformateur de l'intégration des technologies pilotées par l'IA dans les pratiques de planification, contribuant à l'excellence opérationnelle et à la conformité en matière de sécurité. Bien que la recherche présente des avancées significatives, elle reconnaît également des limites liées à la validation dans divers contextes réels et aux défis de l'intégration des technologies avancées avec les systèmes existants. Les orientations futures de la recherche incluent le raffinement des modèles prédictifs, l'exploration des jumeaux numériques, l'intégration de métriques de durabilité dans les cadres de planification, et l'élargissement de l'application de ces méthodologies à d'autres secteurs industriels.

Ce travail établit une base solide pour l'optimisation de la planification industrielle, reliant des perspectives théoriques à des applications pratiques. En adoptant des méthodologies avancées, les industries peuvent atteindre une efficacité accrue, une résilience renforcée et une durabilité soutenue, traçant une voie vers des pratiques de gestion industrielle innovantes et adaptatives. Les enseignements tirés répondent non seulement aux défis actuels mais fournissent également une feuille de route pour les développements futurs dans ce domaine, alignant les pratiques industrielles sur les impératifs technologiques et environnementaux évolutifs.

Mots clés : Planification industrielle, optimisation, algorithmes métaheuristiques, systèmes instrumentés de sécurité (SIS), industrie pétrochimique, opérations industrielles durables.

Table of Contents

Table of Figures

Table of Tables

Abbreviation

$MTTR_S$ & MRT_s	Mean Time To Repair for safe failure.
β	Factor for quantification of common cause failure.
β_{SD}	Beta factor for safe detected failures.
β_{SU}	Beta factor for safe undetected failures.
λ_{SD}	Failure rate for safe detected failure mode.
λ_{SU}	Failure rate for safe undetected failure mode.
λ_{SUind}	Failure rate for safe undetected independent failure mode.
λ_{SDind}	Failure rate for safe detected independent failure mode.
N	number of identical elements forming the subsystem's redundancy
T_1	Time between periodic tests (test interval).
K	Number of elements out of N which their functionality ensure the subsystem's functionality
STR	Spurious Trip Rate
GA	Genetic algorithm
PSO	Particle swarm optimization
ACO	Ant colony optimization
SIS	Safety instrumented system

General Introduction

In today's fast-paced industrial landscape, characterized by increasing competition and heightened emphasis on sustainability, the effective optimization of industrial operations has become a cornerstone for achieving excellence. The rapid advancement of technology, coupled with global challenges such as resource scarcity and climate change, has placed unprecedented demands on industries to operate more efficiently, responsibly, and innovatively. Among the myriad challenges that modern industries face, the strategic scheduling of processes and resources stands out as a critical factor influencing efficiency, cost-effectiveness, and adaptability to dynamic demands. Beyond merely assigning tasks and resources, scheduling encompasses a strategic vision that aligns operational activities with long-term objectives, ensuring both productivity and resilience.

At the heart of industrial optimization lies the quest to harmonize operational schedules with organizational goals, ensuring the seamless utilization of resources while navigating complex constraints and uncertainties. Effective scheduling transforms organizational potential into actionable results by bridging the gap between theoretical efficiencies and real-world applications. This thesis embarks on a comprehensive exploration of the methodologies, technologies, and innovations that underpin the optimization of industrial schedules, delving into how these practices enhance safety, efficiency, and sustainability across diverse industrial sectors.

The evolution of industrial scheduling practices is deeply intertwined with the broader history of industrialization. In the early days of manufacturing, production schedules were often rigid, guided by predefined routines and simplistic resource allocation models. While such approaches were sufficient in less complex systems, they frequently resulted in inefficiencies, including resource underutilization and extended lead times. The advent of advanced technologies, from automation to artificial intelligence, has revolutionized the field, enabling industries to transition from static scheduling paradigms to dynamic, data-driven strategies. These strategies are not only responsive to real-time conditions but also predictive in nature, allowing industries to anticipate challenges and opportunities with unprecedented precision.

Industrial scheduling, as a discipline, is inherently multifaceted, encompassing diverse objectives such as maximizing productivity, minimizing operational costs, reducing downtime, and ensuring the optimal allocation of labor, machinery, and materials. The complexity of these objectives is further compounded by the need to balance competing priorities, adapt to unforeseen disruptions, and comply with stringent safety and environmental regulations. This complexity necessitates the adoption of sophisticated optimization techniques that can address the multifarious demands of modern industrial environments.

Central to the optimization of industrial schedules is the integration of emerging technologies, particularly artificial intelligence (AI) and machine learning. These technologies have introduced transformative capabilities, from predictive analytics that forecast equipment maintenance needs to optimization algorithms that dynamically adjust schedules based on real-time data. The incorporation of AI into scheduling systems has also facilitated the development of intelligent maintenance strategies, which not only enhance the reliability of critical systems but also contribute to the broader goals of safety and sustainability. For instance, predictive maintenance models leveraging AI can preempt equipment failures, thereby reducing unplanned downtime and mitigating safety risks.

The petrochemical industry, with its intricate processes and high-stakes operations, serves as an exemplary domain for examining the impact of optimized scheduling. Here, the interplay between safety, efficiency, and cost-effectiveness is particularly pronounced. Safety systems, such as Safety Instrumented Systems (SIS), play a pivotal role in mitigating risks and ensuring compliance with regulatory standards. The effective scheduling of maintenance activities for these systems is crucial for preserving their functionality and preventing catastrophic failures. This thesis delves into the nexus of maintenance scheduling and safety performance, proposing innovative approaches that leverage smart scheduling to enhance the reliability and availability of safety systems.

Beyond safety, the thesis addresses other critical dimensions of industrial scheduling optimization, including resource management, energy efficiency, and cost reduction. By systematically reviewing the literature and synthesizing insights from diverse fields, the research identifies gaps in existing methodologies and proposes actionable strategies to bridge them. The findings underscore the importance of adopting a holistic perspective that integrates technical, operational, and human factors in the design and implementation of scheduling systems.

As industries continue to evolve, the challenges associated with scheduling are likely to intensify. The increasing complexity of supply chains, the proliferation of interconnected systems, and the growing emphasis on sustainability will demand even more sophisticated solutions. This thesis not only contributes to the theoretical understanding of industrial scheduling optimization but also offers practical recommendations for navigating the challenges of the future. By highlighting the potential of technologies such as AI, the research provides a roadmap for industries aspiring to achieve resilience, agility, and excellence in their operations.

In conclusion, this thesis represents a comprehensive endeavor to advance the state of knowledge and practice in industrial scheduling optimization. By addressing critical issues, exploring cutting-edge technologies, and proposing innovative frameworks, the research aims to empower industries to overcome the challenges of the present and unlock new opportunities for the future. The subsequent chapters build on this foundation, delving into specific aspects of scheduling optimization, from maintenance strategies to the application of metaheuristic algorithms, thereby providing a robust and holistic framework for enhancing industrial performance. The insights and solutions presented aim to contribute to the broader discourse on industrial excellence, offering pathways for industries to navigate complexities and thrive in an era marked by rapid technological advancement and environmental imperatives.

Thesis organization

In order to overcome all the above-mentioned aspects our present work is subdivided into general introduction, general conclusion and four chapters.

Chapter 1: Literature Review

This chapter examines the existing body of knowledge surrounding industrial scheduling optimization. It explores traditional and modern approaches, emphasizing the limitations of static methods and the potential of advanced technologies like artificial intelligence (AI) and machine learning. The chapter also identifies research gaps and emerging trends, focusing on the need for adaptive, efficient, and sustainable scheduling strategies, particularly in the petrochemical industry.

Chapter 2: Maintenance Smart Scheduling in Enhancing Safety Systems Performance

This chapter delves into the critical role of smart maintenance scheduling in improving the reliability and performance of safety systems, such as Safety Instrumented Systems (SIS). It discusses traditional and smart scheduling approaches, highlighting the benefits of integrating predictive maintenance models and advanced algorithms to minimize downtime, mitigate risks, and ensure safety compliance in high-stakes industrial environments.

Chapter 3: Introduction to modern optimization

This chapter provides an in-depth analysis of optimization techniques, with a focus on metaheuristic algorithms like genetic algorithms, particle swarm optimization, and ant colony optimization. It outlines their application to complex scheduling problems, emphasizing their ability to balance competing objectives and navigate constraints. The chapter also discusses how these algorithms contribute to enhanced operational efficiency and cost-effectiveness in industrial settings.

Chapter 4: Case Studies and Practical Implementation

This chapter applies the proposed methodologies and technologies to real-world scenarios, using case studies from the petrochemical industry to validate the frameworks. It demonstrates the practical benefits of smart scheduling and optimization techniques, including improved resource allocation, enhanced safety measures, and reduced operational costs. Challenges related to scalability, integration, and implementation are also addressed.

Publications

The thesis is expanded from published papers, in journal and conferences, which are listed below:

Two papers published in international journals:

- Spurious Trip Rate Optimization Using Particle Swarm Optimization Algorithm International Journal of Safety and Security Engineering 2023 http://dx.doi.org/10.18280/ijsse.140106

- Multiobjective Optimization of the Performance of Safety Systems. Engineering Proceedings https://doi.org/10.3390/engproc2023029010

Two papers published in national journals:

- Assessing Fire and Explosion risks associated with gas turbine using the fire and explosion index. International Journal of Automation and Safety. **31-12-2024** https://asjp.cerist.dz/en/article/260883

- A Systematic Literature review on Industrial Scheduling Optimization Algerian Journal of Signals and Systems. **30-12-2024** https://doi.org/10.51485/ajss.v9i4.241

Paper published in international conferences:

- Assessing Fire and Explosion Risks Associated with Gas Turbines Using the Fire and Explosion Index. The first international conference on petrochemistry and energy transition (ICPET'23). 2023 University of 20 August 1955 of Skikda.
- Multi-objective optimising the performance of safety instrumented systems. The 3rd International conference on advanced engineering in petrochemical industry (ICAEPI 2021); In University of 20 August 1955 of Skikda.

Paper published in national conferences:

- Optimization of spurious activations using genetic algorithm. Conférence nationale sur le contrôle et la sécurité des systèmes industriels (**CNCSSI** 2021). In University of 20 August 1955 of Skikda.
- using neural network in industrial problems optimization. Conférence nationale sur le contrôle et la sécurité des systèmes industriels (**CNCSSI** 2022). In University of 20 August 1955 of Skikda.
- The importance of choosing the optimal maintenance strategy for the performance of industrial plant. 3émé conférence nationale sur le contrôle et la sécurité des systèmes industriels (**CNCSSI** 2024)

Chapter 1: Industrial Schedules Optimization

Part 1: Industrial Schedules Optimization literature Review

1.1 Introduction

In the dynamic landscape of modern industries, where efficiency and resource utilization are paramount, the optimization of industrial schedules emerges as a critical imperative. As organizations strive to enhance productivity, reduce costs, and meet ever-evolving demands, the scheduling of operational processes becomes a linchpin for success. This literature review undertakes a comprehensive exploration of the diverse strategies, methodologies, and technological advancements that contribute to the optimization of industrial schedules. By navigating through the existing body of knowledge, we aim to discern emerging trends, address gaps, and glean insights that can propel industries toward a new era of streamlined and agile operations.

The optimization of industrial schedules is a multifaceted and crucial aspect within the realm of modern industrial management. As industries continue to evolve and become increasingly complex, the effective coordination and utilization of resources have become essential for competitiveness, cost-effectiveness, and overall operational efficiency. Historically, industrial scheduling has been a fundamental component of manufacturing and production processes. Traditionally, schedules were created based on fixed routines and predetermined timelines, often resulting in suboptimal resource utilization and inefficient operations. However, with the growing complexity of industrial systems, industrial schedules now need to adapt to dynamic and unpredictable conditions, necessitating rigid scheduling approaches and advanced technologies and sophisticated scheduling methods to more adaptive and optimized strategies. The context of industrial scheduling optimization encompasses the need to balance conflicting objectives, including maximizing production output, minimizing costs, reducing lead times, and ensuring the efficient use of resources such as labor, machinery, and raw materials.

In this dynamic context, the literature on the optimization of industrial schedules becomes pivotal. Researchers seek to explore methodologies, algorithms, and technologies to develop scheduling approaches that are not only responsive to the current industrial exigencies but also anticipatory of future challenges. The literature review aims to dissect and synthesize these contributions, shedding light on the state of the art and identifying avenues for further research and application in the optimization of industrial schedules.

1.2 Literature review methodology

A systematic literature review is a comprehensive and transparent approach to gathering, critically evaluating, integrating, and presenting findings from multiple research studies on a specific research question or topic. It follows standardized methodologies and guidelines in searching, filtering, reviewing, critiquing, interpreting, synthesizing, and reporting findings from various publications on a particular topic and consists of four stages: planning, selection, evaluation and execution. The purpose of a systematic literature review is to provide a high-level understanding of existing evidence on a specific research question, offering a broader and more accurate level of understanding than a traditional literature review. **[1]**

a. Planning

The purpose of this study is to systematically review the existing literature, analyze the application status of optimization of industrial schedules.

b. Search for literature

Use academic databases (google scholar, IEEE Xplore; SCISPACE) to search for relevant articles, papers, books, and conference papers. With using key words related to the topic and the theme of the thesis.

c. Selection

In this stage, the literature was first explored and filtered, which provided a preliminary understanding of the literature. Based on the findings in the preliminary literature exploration, we established the practical screen criteria for the following literature retrieval activities.

d. Evaluation

Review for each article found in the previous process, the title, abstract, and introduction and conclusion sections to determine their relevance. Then we read the full text of selected sources to evaluate their quality, methodology and contribution to our research. Sources that are completely related optimization of industrial schedules were discarded. After this process, 53 sources were selected in this review for intensive reading.

e. Execution

Organize the gathered sources by categorizing them into categories based on their relevancy to the main objectives of the thesis and grouping sources into sections. The main sections by which we categorize resources are as follow:

- Built up of new strategies to control the resources and utilities used in the operation of a typical petrochemical plant.
- Improvement of the safety measures to protect the equipment, environment and health from any expected dangers.
- The use of artificial intelligence methods as tool to build new strategies to protect health and equipment and environment in industry.
- Improvement of maintenance strategies to minimize the cost of shutdowns and abnormal situations.
- Minimize the cost of execution time of any operation by developing intelligent schedules.

The literature review is organized into five sections to systematically address the multifaceted requirements of industrial scheduling optimization within complex environments like petrochemical plants. This division not only structures the extensive body of knowledge into targeted areas but also aligns with the overarching goals of improving operational efficiency, safety, and cost-effectiveness. Here is how each section contributes to these objectives:

1. **Built-up of New Strategies to Control Resources and Utilities**: Resource control and efficient utility management are foundational to optimizing industrial operations, particularly in energy-intensive sectors like petrochemicals. This section examines strategies that enhance resource utilization, reduce waste, and ensure sustainability—key factors in optimizing overall productivity and reducing operational costs. By focusing on these methods, the review establishes a baseline understanding of strategies for efficient resource management.
2. **Improvement of Safety Measures**: Safety is critical in industrial operations, where equipment and environmental risks are significant. This section addresses methodologies aimed at protecting equipment, personnel, and the environment from industrial hazards. Improved safety protocols are essential not only for regulatory compliance but also for minimizing downtime due to accidents or equipment failure, thus contributing to more stable and reliable scheduling practices.
3. **Use of Artificial Intelligence for Health, Equipment, and Environmental Protection**: Artificial intelligence (AI) has emerged as a powerful tool for developing intelligent safety and protection strategies. This section explores AI applications that enhance risk detection, safety monitoring, and real-time decision-making capabilities. Incorporating AI into industrial systems fosters proactive approaches that can prevent disruptions and streamline operations, thereby supporting more adaptive and resilient scheduling practices.
4. **Improvement of Maintenance Strategies**: Effective maintenance strategies are vital to prevent costly shutdowns and unexpected equipment malfunctions. This section reviews maintenance methodologies that reduce the likelihood and impact of abnormal situations. Optimized maintenance scheduling minimizes production interruptions and extends equipment lifespan, directly contributing to cost savings and operational efficiency.
5. **Minimization of Execution Time Costs through Intelligent Scheduling**: In industries with complex, interconnected processes, reducing the cost and time associated with task execution is essential. This section focuses on the development of intelligent scheduling techniques that leverage optimization algorithms to minimize delays and ensure timely resource allocation. By examining these scheduling innovations, the review highlights the role of smart scheduling in balancing production demands with resource availability, ultimately reducing execution costs.

1.3 Findings

1.3.1 Built up of new strategies to control the resources and utilities used in the operation of a typical petrochemical plant

The operation of a typical petrochemical plant can be optimized through various strategies to control resources and utilities. These strategies can include measures to reduce energy costs, increase energy efficiency, decrease emissions, and evaluate alternative processes. One approach is the implementation of digital transformation projects, which can provide custom reports for understanding optimization actions, real-time monetary savings, and monitoring of fuel usage and greenhouse gas emissions **[2]**. Additionally, advanced control strategies, such as model-predictive control and adaptive control, can play a vital role in the automation and process control of petrochemical plants, contributing to improved operational efficiency **[3]**. Furthermore, optimal operation of energy management systems in petrochemical plants can be achieved through utility optimization systems based on mixed integer linear programming, aiming to minimize the net cost of energy supplied to the plant **[4]**. These approaches can help in achieving cost savings, energy efficiency, and environmental sustainability in the operation of petrochemical plants. So many articles discussed this issue; the most relevant ones are discussed in this literature review.

In the maintenance unit of a petrochemical complex where the intervention of human is necessary a good strategy is mandatory that's what **Sharareh Mousavipour on (2016)** made when the unsafe actions of staff are investigated. Findings show that, there has been a rise in the number of unsafe actions in machinery and maintenance service units compared to other maintenance units. A new strategy has been implemented to control these actions, a strategy based on the safety behavior and its improvement by close monitoring of health safety environment (HSE) officials on the implementation of regulations **[5]**. The maintenance operation is mostly implemented by human intervention that is why this work focused on the unsafe actions of workers as a main reason of the accidents.

However, as a strategy based on the behavior of workers has a big limitation, which is the lack of workers commitment. To solve this problem an estimation is mandatory to estimate the results and the development of the new strategy, to find the gaps and improve it.

Modeling, Design, and Simulation is the first complete introduction to process control that fully integrates software tools helping you master critical techniques hands-on, using MATLAB-based computer simulations. Author **B. Wayne Bequette (2003)** includes process control diagrams, dynamic modeling, feedback control, frequency response, analysis techniques, control loop tuning, and start-to-finish chemical process control case studies. Gain practical experience with process control by using MATLAB(R) simulations and real-world applications. Through computer simulations based on the well-known MATLAB environment, professionals and students may learn essential skills firsthand with this comprehensive introduction to process control, which is the first to combine software tools. Process Control: Modeling, Design, and Simulation provides comprehensive exercises with thorough derivations, pertinent software files, and additional techniques available on a companion website. It teaches the most important techniques, behaviors, and control problems in the field through real-world examples **[6]**.

The digital plant is predicated on having a connection to the information space that links equipment suppliers and maintenance providers. Instantaneous information flow between the participants in this interaction environment directly affects the quality of decision-making, ensuring the absence of mishaps and downtime **[7]**. To find a solution for energy efficiency and resource conservation. The author suggests developing a novel plan to boost manufacturing efficiency, especially through process automation. It takes into account the fundamental instruments for petrochemical plants, process automation, and process enhancements.

This work focused on the management plans and how to use the automation in the development of an optimal plan. However, in fact the work only talked about some specific strategies and did not give a new one, or the optimal one among them. In addition, the technical field of petrochemical industry is absent in this work, in my opinion the most effective way to optimize a management plan for maintenance, is to optimize measurable variables in the system.

In other hand, **A. Vargas on 2000** worked on a time-optimal control strategy for a discontinuous aerobic bioreactor. The control strategy regulates the feed rate to maintain a constant optimal substrate concentration in the reactor, which in turn minimizes the reaction time. Peristaltic pumps, an electronic oxygen meter, and a personal computer equipped with real-time software tools and data gathering hardware made up the controller. Three tests were carried-out: one to determine the parameters and calibrate the observer; one to confirm the time-optimal plan; and one to assess how well a completely automated time-optimal operation performed. When the controller and observer were properly calibrated, the bioreactor's overall efficiency increased and reaction times were shortened. The observer also produced reasonable estimations **[8]**. In this study, they only used a simple mathematical model or simulator to optimize time of reaction in the reactors. However, in the real process the problem will be more complicated to be solved with such a simple simulation model. The study of the reality of the system, using a more efficient methods to overcoming the complexity of the real process.

Based on an analysis of the driving force for smart factory development, **Defang Li (2016)** proposes a lifecycle blueprint and consensus-based operating and technology roadmap **[9]**. In this study, the understanding of new technologies and their ability to be implemented is ignoring the old systems that already installed and operating in nowadays. We find that the technology changing is very expensive and hard to carry out for many factors, proposing the changing of technology in no applicable always due to its expensive charges. So the optimization objective is not achieved in this work because the cost of the implementation of the new technology in not taken into consideration.

Through the constant pursuit of meeting energy and transportation requirements, there are legitimate concerns about the environmental and safety issues associated with these industries, it is very difficult to imagine how industrialized societies could sustain a high standard of living without chemical products **[3]**. In this work, **Dale E Seborg (2009)** provides an overview of process control objectives and methodology in the chemical and petrochemical industries. This work is a good introduction to the petrochemical process control. In addition, we can talk about the use of the artificial intelligence to help in the decision-making in the process control.

In order to determine the role of automation of the main systems of petrochemical production. **A I Shinkevich1 (2020)** showed how industrial automation affects gross national product growth by optimizing production and logistics operations, labor efficiency, increasing equipment productivity, improving research and development and product development **[10]**. This work based on the improvement of the benefit of the petrochemical companies regarding the requirement of the market by the implementation of strategies of production cost and time optimization.

1.3.2 Improvement of the safety measures to protect the equipment, environment and health from any expected dangers.

To improve safety measures and prevent industrial accidents, several strategies can be implemented. Firstly, emphasizing the concept of "safety first, prevention first and comprehensive management" is crucial **Yu, Wang. (2022) [11]**. Regular investigation and analysis of safety accidents, along with continuous improvement, are necessary to prevent their reoccurrence Do, **Woo, Kim. (2022) [12].** Additionally, the use of deep learning and artificial intelligence can enhance safety production supervision, early warning, and intelligent operation in industrial enterprises **[13]**. Policy countermeasures, such as increasing the visibility of patrols and conducting on-site inspections, can also contribute to reducing death accidents **Heonseok, Kim (2021) [14]**. Furthermore, applying design thinking and other problem-solving techniques can help find innovative solutions to prevent industrial accidents **Hyeogsic, Kwon (2022) [15]**. Strengthening the execution capacity of safety management in the field and utilizing safety practice indexes can establish a mature safety culture and effectively prevent accidents. By implementing these measures, companies can create safer work environments and mitigate the risks of industrial accidents. Below is the discussion of most relevant articles.

For any firm, health, safety, environment, and ergonomics (HSEE) are critical components. To help organizations with this process, **Pourreza, Pooya (2018)** suggests a fuzzy cognitive map–Bayesian network (BN) model in this research. By using this, the authors determine which input component has the greatest influence on HSEE quantification, which can then be controlled to increase an organization's adherence to HSEE **[16]**. For limitation of this work we can talk about the data gathering method that has been choose in the work which is a survey, the questionnaire used and divided among the workers is a relative method which means that the data could be effected by social culture or belief that the workers in the company are believe. Lot of factors can affect the general opinion in the company.

Chalaris, Michail. (2022) highlighted in his book the importance of effectively managing occupational health and safety, and the environment during general industrial activities. Where they mentioned that an effective management of safety, health and environment in all workplaces has many benefits, the improved overall wellbeing of the workforce, increased productivity, reduced work-related accidents, injuries and fatalities **[17]**. This book discusses the impotency of flexible technologies in the HSE aspect to improve the effectiveness of management systems and the productivity. The author proposes to reach such an aim to integrate technologies of big data and internet of things and data analysis. For more improvement, we can also propose the using of artificial intelligence to help in decision-making. That is the aim of this work.

Mrozowska, Alicja and Mrozowski, Piotr. (2019) in their article describe how important Job Safety Analyses are for proper operations. The main aim of the article is to indicate steps and the best way of performing job safety analysis on board of the offshore installation to reduce the risk of emergency. The authors use the analysis of available international reports, the experience gained while working on different types of the offshore vessels and installations. In addition, focusing at the using of a job safety analysis JSA in the improvement of work condition **[18]**. In consequence, prevent environmental risks in oil and gas industry, specifically offshore installation. The use of technology to improve the implementation of the JSA is highly recommended in such situations where the major risks are taking place. As additional, the use of intelligent technology will improve the rapidity and the effectiveness of management system.

Operators of Major Hazard Facilities have found that the discipline of process safety management is a useful tool for helping them concentrate on the critically vital "few," giving them more attention than the "many" less crucial but nonetheless significant components of a process system **[19]**. Major Accident Risks can change during the course of an asset's life in terms of probability and severity. In this work, **Vandenberg, Erik (2023)** aims to reduce risks related to major hazard facilities by a good risk assessment procedure. The best and the most effective way to assess risks is the quantitative methods. The quantitative methods need the quantification of risks parameters. The simulation of events by mathematical equation will facilitate the minimization of the value of the targeted events, in other hand we know that the equations that express real events are not linear or simple. That is why the use of analytic methods will not help in the minimization of objective function due to the variety of its variables. To solve such issue, using the metaheuristic methods is more effective.

Bragatto, Paolo (2018) made a work aims to assess how the use of smart safety systems applied to critical equipment can improve the safety, reducing the likelihood of incidents occurrence or mitigating the consequences related to the loss of containment of hazardous substances. The author proposes a method, based on some primary criteria, useful for the stakeholders to address the choice of the smart safety systems and to assess the benefits for risk reduction. This work gives a bright idea to assess to effectiveness of a smart safety system. It passed on the calculation of the reliability of the system as criteria, and then after a good knowledge of the process, the way of risk management will be integrated to increase the reliability of the system **[20]**. Creating a standard communication protocol for smart safety systems is one of the goals of continuing research, as this will enable systems to communicate with one another and, crucially, with the safety management system, which should combine all the different features.

According to **DORMOHAMMADI, Ali (2021)**, Studies have concluded that the use of technical safety measures is not adequate to protect human, economic and environmental assets in industries. Therefore, developing Health, Safety and Environment (HSE culture), as an alternative method, is of considerable importance **[21]**. This study set out to assess and control the HSE culture among workers in the industrial sector. Data collected from the questionnaire was analyzed after the development of an HSE culture questionnaire. The study came to the conclusion that organizational and environmental elements should be looked into in addition to psychological and individual factors in order to promote safety culture in a workplace. In this manner, the real issues would be found, suitable approaches to solving them would be put into practice, and eventually the number of events would be decreased. This work present an important aspect in risk reduction, which is the safety culture. Nevertheless, we cannot consider it as an alternative to the technical solutions. Instead we should implement all the aspect together personal culture, organization and technical factors.

1.3.3 The use of artificial intelligence methods as tool to build new strategies to protect health and equipment and environment in industry.

Artificial intelligence (AI) can be used to protect health, equipment, and the environment in industry. AI technology for **Ghadimi, Mehdi (2023)** can help manage and improve environmental conditions by observing and analyzing data in real-time without getting tired as humans do **[22]**. Also **Pachot, Arnault (2023)** sees that AI can make reasonable plans in a much shorter time than humans can, by utilizing big data analysis and intelligent programs **[23]**. **Roumen, Trifonov (2022)** in their work show that AI can also be used for intrusion detection in industrial systems, helping to understand and counter the actions of malicious actors **[24]**. Furthermore, AI may be applied in a number of ways to enhance workplace health and safety, including risk prediction and prevention, ergonomics and worker well-being, real-time workplace monitoring to quickly identify safety hazards, and continuous improvement and optimization. Artificial intelligence (AI) can be used to reduce the risk of injuries to human workers by doing hazardous tasks like handling toxic substances or working in severe settings, as well as monitoring environments for possible hazards like gas leaks or broken equipment and alerting workers in real-time. We collect the most relevant articles where the authors and scientists tried to implement AI to improve the safety of human, equipment and environment.

Shaji, Harikrishnan (2022) automated methods for improving productivity, safety, and efficiency in modern industrial facilities using artificial intelligence (AI)-based techniques. It examines the difficulties and things to keep in mind when applying these methods to make sure there are no mistakes for real-world use. Depending on the application, both numerical input models and image processing models are covered under AI techniques. Safety observations made during maintenance tasks are recorded using image processing models, which also automate inspection data analysis. On the other hand, the numerical input models are mostly employed from the standpoint of process and planning optimization **[25]**. the limitation of using deep learning is the lack of data. In addition, the image processing models presented in the paper need to be trained on some particular situations where the training is putting systems in risk simulation, which is very expensive.

Deep learning can be used for the early warning, and intelligent operation **[26]**. In his paper **wang Yu (2022)**, studies the work safety in the supervision and early warning mechanism abides by the selection principle of the management system. The paper discusses how artificial intelligence can be used in industrial enterprise safety production supervision to provide technical assistance for effectively controlling safety accidents. Deep learning and artificial intelligence can be used for safety production supervision and early warning in industrial enterprises. Deep learning analysis ability is related to the range of sample data and the most significant issue in industrial studies is the lack of data so to make good training to the AI model we need time and lot of simulations.

According to **Petya Biolcheva's (2023)** perspective, the progressive introduction of autonomous technologies is necessary to ensure expert peace of mind and maximize accuracy in their capabilities. This study aims to present an artificial intelligence (AI) based approach to intelligent safety for the maritime sector **[27]**. In order to achieve the highest degree of safety in the maritime industry, the effort aims to combine the speed of artificial intelligence with human expertise.

Alonso, Ricardo (2021) aims in their study to protect workers in automated and robotized agile production environments from dangerous scenarios. To do this, artificial intelligence (AI) agents will collect data, audio, and video via arrays of cameras and microphones placed throughout the workspace. The new system will use Deep Reinforcement Learning (Double Deep Q Networks) and Deep Learning models to recognize abnormal patterns in behavior and workers' levels of attention, weariness, and distraction **[28]**. Due to emotion fluctuations and other factors that are incomprehensible to artificial intelligence, the prediction of human behavior based on ECG data and video recordings is ineffective. The deployment of such a technology, with its high expenses and unsatisfactory precision for human prediction is not recommended.

In his work, **Tang Kai (2019)** also focus on the improvement of workers behavior, using data value of big data mining and intelligently recognizes and processes images and voices to support innovative management models and applications, and provides safety technology support for smart factories and intelligent manufacturing **[29]**.

Also **Doherty, Mike and Esmaeili, Behzad (2020)**, propose algorithms scan images from jobsites for safety hazards. Such as workers not wearing protective equipment, and correlate the images with accident records; identify unsafe worker behavior and suggest training and education priorities; or track the real-time interactions of workers, machinery, and objects on the site and alert supervisors of potential safety issues **[30]**. This paper does not explore the limitations or challenges of implementing AI-based algorithms for scanning images from jobsites for safety hazards, in addition to the training and data issue there is other considerations such as false positives or false negatives in hazard detection.

based on **Rajesh Pillai (2020)** The ability of artificial intelligence (AI) systems to handle, process, and apply complicated algorithms to large amounts of data can increase aviation industry safety. The purpose of this study is to employ artificial intelligence responsibly in order to increase aircraft safety. The study focuses on how artificial intelligence can be used to lessen the effects of variables that affect aviation safety, such as pilot weariness, unfavorable weather, and misleading alerts [**31**]. This work does not discuss the specific AI algorithms or technologies that could be utilized to improve aviation safety. In addition, the paper does not discuss the potential costs or resource requirements associated with implementing AI solutions for aviation safety.

In this work **Ahmed, Salim (2021)**, identifies a few points that researchers need to consider for impactful research on process safety utilizing AI and suggests a systematic methodology to incorporate human knowledge and expertise in the development of a tool and during its use **[32]**.

Production control in petrochemical industry involves complex circumstances and a high demand for timeliness that's why smart controls are important components of intelligent manufacturing in the petrochemical industry **Min, Qingfei (2019)** uses digital twins, along with the internet of things (IoT), data mining, and machine learning technologies, as a potential in the transformation of nowadays manufacturing paradigm toward intelligent manufacturing. This work proposes a framework and approaches for constructing a digital twin based on the petrochemical industrial IoT, machine learning and a practice loop for information exchange between the physical factory and a virtual digital twin model to realize production control optimization **[33]**. It integrates machine learning and real-time industrial big data to train and optimize digital twin models.

1.3.4 Improvement of maintenance strategies to minimize the cost of shutdowns and abnormal situations.

According to **Yu, Zhao (2022)** Maintenance strategies can be improved to minimize the cost of shutdowns and abnormal situations by implementing optimized preventive maintenance (PM) cycles and planning horizons. This can be achieved by finding the optimal couple of PM cycle and planning horizon that minimizes the total maintenance cost **[34]**. Additionally, **Sofiene, Dellagi (2021)** sees that the impact of imperfect maintenance actions on equipment failure rate and the resulting number of failures should be considered. Performing PM actions more frequently can help reduce the expected number of corrective maintenance actions and the corresponding total cost **[35]**. Furthermore, the use of innovative maintenance strategies that take into account the system's reliability and the occurrence intensity of shocks can be effective. Based on **Raza, Naseem (2022)**, these strategies divide the system reliability into stages and implement maintenance activities accordingly, such as performing corrective maintenance or replacing the system **[36]**. By considering the effect of maintenance on structure performance and estimating reliability instead of assuming a reliability function, **Yanpei, Shi (2022)** established a general optimization model for preventive maintenance strategy **[37]**. Overall, optimizing maintenance strategies based on cost, reliability, and efficiency can help minimize shutdown costs and abnormal situations. We try to collect more articles, talking about this aspect, and discuss them.

The issue of planning routine maintenance tasks for oil and gas facilities is examined in this research. Every maintenance item has a different set of maintenance procedures and need for brief equipment shutdowns. Which are expensive and seriously impair productivity **[38]**. By combining maintenance items with similar shutdown requirements into campaigns short-term maintenance operations the aim is to reduce equipment shutdowns. Handling tens of thousands of maintenance items in real plants makes it extremely difficult to manually schedule the campaigns. In order to minimize the overall shutdown cost, **Seif, Zeinab (2020)** efficiently allocate maintenance items to campaigns using a mixed-integer linear programming model that they construct in this study.

By increasing productivity, proper equipment maintenance can drastically lower total operating expenses. Although maintenance is sometimes seen as an expense by management staff, seeing it as a profit center is a more constructive perspective. In light of this new understanding, the requirements for maintenance management have undergone a significant transition from the conventional "fix-it-when-broken" mentality to a more sophisticated strategy that calls for the adoption of a maintenance strategy for a more integrated approach and alignment **[39]**. **Behniaa, Foroogh (2023)** uses Goal Programming (GP) in their work to determine the most economical way to maintain a few essential pumps used in the paper industry. We can conclude from this work that the preventive maintenance approach is more cost effective then the corrective maintenance approach. but this is not always correct. Due to the specifications of some industrial systems, where the preventive maintenance will need a shutdown of the system and the use of special team, which make this option very expensive. That is why managers choose to take the corrective maintenance as the optimal strategy for those systems.

In order to assess the efficacy of the recommended maintenance method, **Mirsaeedi, Hamed (2023)** suggests a mixed-integer linear programming approach to maintenance budgeting that considers restoration time uncertainty. Case I of the analysis assumes that no maintenance actions are carried out in the system. In Case II, the maintenance expenditure is divided equally across all distribution feeders. In Case III, the recommended formulation allots the best maintenance budget based on restrictions **[40]**. The proposed method seeks to minimize total costs by determining the best budget for maintenance jobs in distribution network feeders. This covers the overall cost of the customer's interruption, the total cost of energy that is not supplied, the total cost of the materials and personnel needed for repairs, and the total cost of maintenance.

At some time, complete production lines will need to be shut down in order to do major maintenance or work that is too large to be completed while the facility is in operation. We call this closure a maintenance outage. Even if it would be feasible to only shut down the areas of the plant that require maintenance, it also makes the greatest financial sense to shut down the entire facility. When extensive maintenance needs to be performed on all plant equipment, it is far less expensive to shut down the entire plant at once than it is to shut down smaller sections of the plant more frequently **[41]**. **Kister, Timothy (2006)** sheds light on the financial losses resulting from the plant's complete shutdown because of the time lost from output and the associated maintenance expenses. The paper suggests planning maintenance as a solution to this problem, where the main requirements for successfully carrying out the plant shutdown for major maintenance are starting the outage with a workable schedule, complete work packages, and both material and personnel resources arranged for and available for contracted work as well as in-house efforts.

Another work of **Mirsaeedi, Hamed (2018)** proposes a practical method for reliability-centered maintenance budgeting. The proposed method determines the optimal maintenance actions and their execution times in electrical system. The objective is to minimize the total reliability cost. Including: the total customer interruption cost and total energy not supplied cost. Where the results show that maintenance budgeting with time allocation reduces total cost and improves reliability **[42]**.

We conclude our research on the topic of the impact of choosing the right maintenance strategies to minimize the cost of abnormal situations by presenting a handbook covering a wide range of topics related to maintenance management and engineering **[43]**. The book discuss the different aspect of maintenance (strategies tools and resources) to achieve a good management of maintenance activities to reduce likelihood and severity of risks.

1.3.5 Minimize the cost of execution time of any operation by developing intelligent schedules

Based on **Jiepin, Ding (2023)** intelligent scheduling in industry offers several benefits. It allows for the transformation of traditional production modes into intelligent factory modes, enabling green and sustainable development **[44]**. Moreover, for **D, Zhang (2022)** intelligent scheduling helps in meeting personalized customer needs by rational allocation of order size and resources, improving production efficiency **[45]**. In the process industry, optimal production schedules obtained through intelligent scheduling minimize delays, leading to robustness, economic advantages, and minimizing costs, improving production and safety. These challenges highlight the need for advanced techniques and algorithms to address the complexities and uncertainties involved in developing intelligent schedules.

N. Mirahmadi (2019) proposed stochastic mathematical model provides a scientific and helpful guideline for manufacturing system to plan production and maintenance simultaneously, with both economic and environmental benefits. The proposed stochastic model, combined with the Genetic Algorithm (GA), aims to minimize the expected makespan in the scheduling problem, with a focus on reducing CO_2 emissions in an actual workshop **[46]**.

Prostean, Gabriela (2007) proposes an operations scheduling intelligent system that deals with constraint handling decision in manufacturing operations, providing various optimization techniques and their application to production scheduling. The system is developed with a friendly graphical user interface that guides the user during the progress of the planner, providing warnings and suggestions for adjusting in real time the planner **[47]**.

Shrouf, Fadi (2014) proposed in his paper a mathematical model to minimize energy consumption costs for single machine production scheduling during production processes. Where genetic algorithm technology has been utilized. By making decisions at machine level to determine the launch times for job processing, idle time, when the machine must be shut down, "turning on" time, and "turning off" time, a comparison between the analytical solution and metaheuristic solutions is presented. This solution shows that the metaheuristic solution provides the optimal solutions in most test cases and nearly optimal solutions in others **[48]**. The results show that, when the computation time for longer schedules is relatively high, the metaheuristic solution is preferable.

Using metaheuristic (bio-inspired algorithm) in schedule optimization where a distributed job shop scheduling problem where the allocation of jobs to different factories needs to be done and additionally, the determination of good operation schedules for each factory is solved **[49]**. **Vivek, S (2022)** uses ant-colony optimization algorithm on each factory after the allocations, to get a solution that is close to the most optimal solution.

Klusáček, Dalibor (2015) proposes new complex and well-designed approaches that involve the use of metaheuristic, which periodically optimizes job-scheduling plan using several real life based optimization criteria **[50]**. **Broderick Crawford (2014)** used set of metaheuristics to solve Software Project scheduling problem as a combinatorial optimization problem, showing the resolution structure and its application **[51]**. Among these, we can find Simulated Annealing, Variable Neighborhood Search, Genetic Algorithms, and Ant Colony Optimization.

Podolski, Michał (2022) proposes the use of two metaheuristic methods the simulated annealing algorithm and the tabu search algorithm, completing each other to solve scheduling optimization problem. The simulated annealing algorithm is used to find the global optimum by iteratively searching for better solutions and accepting worse solutions with a certain probability. The tabu search algorithm is used to explore the search space by maintaining a tabu list that prevents revisiting previously visited solutions **[52]**.

Khan, Muhammad (2023) presents different types of metaheuristic algorithms can be used to optimize industrial processes, thus making them more sustainable in the context of Industry 4.0, such as design, product development, forecasting, scheduling, and so on **[53]**.

1.4 Conclusion

The optimization of industrial schedules is a complex and evolving field, driven by the increasing demands for efficiency, cost-effectiveness, and sustainability across various industries. This literature review has explored a range of strategies, methodologies, and technological advancements applied to industrial scheduling, highlighting the significant role of artificial intelligence, safety improvements, and the development of intelligent maintenance and production systems. Several trends have emerged from the review. First, the integration of digital tools and artificial intelligence has proven critical in improving operational efficiency and safety within industries, especially in sectors like petrochemicals. Techniques such as metaheuristic algorithms (e.g., genetic algorithms, ant-colony optimization) have been instrumental in addressing complex scheduling problems, providing near-optimal solutions in diverse contexts such as production planning, maintenance scheduling, and safety management. Second, despite the progress made, certain challenges and gaps persist. Many studies focus on isolated aspects of optimization without offering comprehensive, integrated solutions that consider both technical and organizational factors. Additionally, the cost of implementing advanced technologies, such as AI systems, can be prohibitive, especially when dealing with legacy systems that may not easily accommodate new innovations. These gaps present opportunities for future research and development, particularly in creating cost-effective, scalable solutions that balance technological advances with practical, real-world applications. In conclusion, this review has underscored the importance of continuous improvement in industrial scheduling optimization. The insights gathered from the literature provide a foundation for further investigation into more adaptive and integrated approaches. Future research should focus on addressing the current limitations by developing more comprehensive frameworks that combine technical, environmental, and human factors, ultimately driving industries toward more efficient and sustainable operations.

Part 2: Maintenance Smart Scheduling

1.1 Introduction

In the realm of process industries where safety is paramount, the effective functioning of safety systems, such as Safety Instrumented Systems (SIS), is crucial for preventing accidents, mitigating risks, and ensuring the well-being of personnel and the environment. A key aspect of optimizing safety system performance lies in the realm of scheduling of maintenance practices. Traditional maintenance approaches often rely on fixed schedules or reactive responses to failures, which may lead to inefficiencies, downtime, and increased risk exposure. However, the advent of smart scheduling of maintenance techniques offers a transformative opportunity to enhance the reliability, availability, and effectiveness of safety systems while optimizing maintenance costs and resources. This chapter explores the intersection of smart scheduling and maintenance strategies with safety systems,

This part aims to provide insights and guidance for leveraging smart scheduling of maintenance practices to optimize safety system performance and foster a culture of safety

1.2. Smart Scheduling:

1.2.1 Traditional scheduling

Generally, a schedule is intended to produce certain patterns of behavior in the manufacturing facility for which it was generated. In traditional industrial contexts, Scheduling is the process of assigning tasks to resources or allocation of resources to perform tasks over a period of time to obtain a good solution within a reasonable computational time. Schedules play a pivotal role in orchestrating the sequence of tasks and activities to ensure smooth and efficient operations. Lot of factors affecting scheduling include external elements like customer demand, delivery dates, and existing stock, as well as internal factors such as equipment availability, manpower, and material availability. The prioritization of jobs based on the earliest available time slots is a common practice aimed at expediting task completion and minimizing idle time. By assigning tasks to these early time slots, manufacturers can capitalize on available resources and equipment effectively, thereby striving to meet production deadlines and customer demands. However, this approach often results in the accumulation of in-process inventory, which can incur additional costs and strain production capacities. Nevertheless, the emphasis on prompt task completion remains a fundamental objective. Conversely, in certain assembly-type industries, an alternative scheduling method gains prominence. Here, jobs are strategically allocated to the latest available time slots, with the primary aim of achieving just-in-time (JIT) production. By completing tasks precisely when they are due, this approach minimizes the need for excess inventory and optimizes resource utilization. Furthermore, it streamlines the flow of work through the manufacturing process, facilitating seamless transitions between work centers. Thus, while traditional scheduling methods may vary in their priorities and strategies, their overarching goal remains consistent: to drive operational efficiency and productivity within manufacturing facilities.

Traditional scheduling strategies and methodologies have several historical foundations. These include Henry Gantt created Gantt charts in the early 20th century, and they are used in industrial project management. Additionally, Frederick Taylor adopted scientific management techniques in the late 19th century, emphasizing the need of scheduling and planning in raising output. Moreover The application of scheduling in the manufacturing sector dates back to Henry Ford's invention of the assembly line in the early 1900s. The use of motion and time studies to task completion and resource allocation in the early 20th century. These historical foundations molded and affected the conventional scheduling approaches and procedures that are still in use today. **[54]**
Overall, traditional industrial scheduling methods focus on optimizing resource usage, meeting delivery deadlines, and minimizing costs through efficient planning and coordination of production activities.

1.2.2 Limitation of traditional scheduling approaches

The question "What makes a good schedule good?" is relevant. Any schedule must first meet the requirement of,
Feasibility, meaning it cannot go against any limitations in the production system in which it is to be implemented. Stated differently, it must be physically possible to carry out; It needs to designate tasks to machines that can complete them.
Acceptability is the second requirement imposed on a timetable. A timetable is considered suitable when it cannot be enhanced by little adjustments and does not conflict with another easily accessible schedule in every way. For example, it might be possible to conduct operation A on either Machine 1 or Machine 2, but since Machine 1 can satisfy stricter standards, it might be best to use it whenever possible. It is obvious that employing Machine 1 will improve a timetable that uses Machine 2 to conduct Operation A when Machine 1 is idle. Clearly, the specifics of what defines a "trivial change" will differ from system to system based on how complicated the scheduling issue at hand is. **[54]**
Traditional and conventional scheduling methods face lot of limitation in the way to achieve these requirements, limitations that can affect their effectiveness. Traditional scheduling techniques are known to lack flexibility and struggle with deterministic instances, especially when transitioning from small to large-scale datasets **[55] [56].** The utilization of these methods has been complex and cumbersome for project managers, often requiring extensive preparation time **[57].**
We can elaborate on these limitations by explaining them as follows:

Limited Adaptability: Traditional scheduling methods often rely on fixed rules and formulas that may lack the flexibility to adapt to changing demand patterns, resource availability, or production constraints. Leading to inefficiencies in resource allocation and production planning, such as underutilized resources during periods of low demand or bottlenecks when demand unexpectedly increases. **[58]**
Lack of adaptability to complex constraints: These approaches may struggle to handle complex constraints such as resource limitations, multiple dependencies, and intricate human

aspects involved in scheduling tasks, fluctuating demand, unexpected disruptions, or changing priorities. **[58]**

Limited Optimization: Rudimentary scheduling approaches typically prioritize tasks based on simple rules or criteria such as first-come-first-served or earliest due date. This simplistic approach may not consider all relevant factors and constraints, resulting in suboptimal schedules that fail to maximize resource utilization or minimize production costs.

Lack of Coordination: Rudimentary scheduling approaches may lack coordination between different departments or work centers within the organization especially in coordinating multiple tasks. This can lead to suboptimal scheduling decisions, conflicts over resource allocation, and inefficiencies in production workflows. **[59]**

High Inventory Levels: Rudimentary scheduling approaches often result in the accumulation of in-process inventory due to the prioritization of tasks based on their earliest available time slots. This excess inventory ties up capital, increases storage costs, and can lead to obsolescence or waste if products become outdated or perishable. **[60]**

Suboptimal Resource Allocation: Without sophisticated optimization techniques, rudimentary scheduling approaches may allocate resources inefficiently, leading to underutilization of machinery, labor, or other assets. This can result in decreased productivity and increased production costs.

Limited Visibility: Traditional scheduling techniques may lack the visibility and real-time adaptability offered by modern digital scheduling systems, making it challenging to monitor and adjust schedules efficiently in dynamic manufacturing environments. **[60]**

Overall, while traditional scheduling approaches may suffice for simple or low-volume production environments, they are often inadequate for addressing the complexities and challenges present in modern industrial settings. As industries strive to improve efficiency, reduce costs, and enhance customer satisfaction. Due to these limitations of traditional approaches, there is a growing need to transitioning to more advanced and adaptable scheduling methods that leverage technology and data-driven insights to optimize the performances of industrial systems.

1.2.3 What is smart scheduling?

Smart scheduling involves the application of advanced algorithms, data analytics, and automation techniques to enhance and streamline scheduling processes across various industrial sectors such as manufacturing, production, and logistics **[61]**. It ensures adaptability, flexibility, and collaboration within scheduling systems by leveraging technologies like the Internet of Things (IoT) and artificial intelligence (AI). This leads to increased productivity and operational efficiency [62]. Smart scheduling systems analyze data to determine the optimal allocation of resources through artificial intelligence and machine learning; ensuring resources are utilized in the most efficient manner **[63]**. These systems enable effective resource utilization, task adaptability and synchronization, real-time optimization, improved operational visibility and responsiveness, allowing for better time management, cost reduction, and minimized energy consumption while meeting deadlines **[64]**.

Efficient scheduling affects manufacturing industries by Develop innovative strategies to enhance flexibility and adaptability in response to evolving market trends driven by technological advancements and the growing consumer preference for highly tailored products. Additionally, ensure accurate and timely completion of all plant operations **[65]**. Efficient scheduling of production tasks results in quicker lead times, facilitate rapid order execution and increase customer satisfaction **[66]**. Smart scheduling maximizes the utilization of resources such as labor, machinery, and materials, in other hand minimizing downtime and enhancing productivity and cost-effectiveness **[63]**. Also Strategic scheduling allows for rapid adjustments and responsiveness to shifts in demand, resource availability, or unforeseen circumstances **[63]**. By adapting production to actual demand and avoiding overstocking, effective scheduling helps reduce excess storage **[65]**.

1.2.4 Characteristics of Smart Scheduling:

In order to optimize and improve scheduling procedures in manufacturing and optimizing production, logistics, and other industrial sectors. In addition, to overcome the limitation of traditional approaches, modern technologies and methods was used to develop the scheduling process to the smart scheduling Which refers to the application of optimization algorithms, data analytics, and automation techniques **[61]** to ensures scheduling systems' scalability, modularity, adaptability, flexibility, and collaboration. Smart scheduling systems are characterized by their advanced capabilities in leveraging technology, data analytics, and optimization techniques to optimize scheduling processes in industrial environments. **[67]** If we compare smart scheduling with traditional and conventional schedule approaches, we can find that smart scheduling contain sort of characteristics that make them faster, more cost savings, flexible and increases productivity. Those characteristics aim to enhance resource utilization, minimize conflicts, and improve efficiency in resource allocation and management **[68].** Some of those characteristics are

This system leverages the power of Artificial Intelligence (AI) and Machine Learning (ML) techniques to efficiently generate and manage timetables while considering various constraints and preferences. **[69][70]**

Smart scheduling systems gather data from various sources to create a unified repository for scheduling purposes, enabling comprehensive analysis and decision-making. **[71]**

Smart scheduling systems use real-time control and monitoring to monitor machine status, production progress, and resource use. They gather and evaluate data continuously in order to identify schedule irregularities and facilitate risk prevention. **[70]**

Smart scheduling systems utilize predictive analytics techniques by analyze historical data and trends to make informed predictions about future scheduling requirements, enabling proactive decision-making and risk management. **[72]**

Smart scheduling systems employ advanced optimization algorithms such as genetic algorithms, simulated annealing, and particle swarm optimization to solve complex scheduling problems with multiple objectives and constraints and generate optimal schedules that maximize efficiency, minimize costs, and meet production targets.

Smart scheduling systems facilitate collaboration and communication among different departments, teams by providing digital platforms, collaborative tools, and real-time communication channels to enable information sharing, coordination, and consensus-driven decision-making. **[72]**

They enable continuous improvement through feedback loops, iterative refinement of scheduling algorithms, and learning from past scheduling experiences.

1.3 Maintenance

1.3.1. Definition

The term maintenance is based on the Latin roots manus and tenere. According to Larousse, the word "maintenance" refers to anything that keeps or restores a system in working order. According to AFNOR (NF X60-010), " Maintenance is the combination of all technical and associated administrative actions intended to retain an item in, or restore it to, an acceptable condition." **[73] [74].**

1.3.2 Maintenance Types

Maintenance work can be put into one of two main categories: preventative maintenance and corrective maintenance **[74]**.

a. **Preventative maintenance** includes all acts aimed at preventing a failure or decline in an item's state of repair. It seeks to reduce the likelihood of a failure occurring. This type of work is invaluable as it reduces the amount of work and cost in repairs that are incurred when an item has failed. Preventative maintenance also helps to preserve and restore equipment availability by replacing worn components before they lead to system failure. There are several preventive maintenance policies. The most common are:
   - **Systematic maintenance**: preventive maintenance carried out at pre-established time intervals or according to a defined number of usage units, but without prior inspection of the item's condition. We determining maintenance dates, depending on the importance of a given item in a system. **[73]**
   - **Conditional maintenance**: consists in periodically checking the condition of parts that are degrading, and intervening only if the state of degradation is sufficiently advanced to affect the availability of the item. It requires measurement or tests to assess the state of degradation. **[75]**
   - **Predictive maintenance**: conditional maintenance carried out according to forecasts extrapolated from the analysis and evaluation of significant parameters of the asset's deterioration. It enables us to anticipate and predict as accurately as possible the moment when the intervention will need to be carried out. When it is technically feasible and economically profitable, this form of maintenance is undoubtedly the most sophisticated, and leads to the best maintenance optimization. **[75]**

b. **Corrective maintenance:** Corrective maintenance is reactive, responding to identified issues after they occur it addresses existing issues, such as damaged components, designed to restore an item to a condition where it can perform its required function. **[76]** we can devise this strategy into two types:
   - **Palliative maintenance**: means dealing with the symptoms but not the cause in order to temporarily lessen the impact of a failure and allow the asset to continue operating.

Troubleshooting is typically the action that is conducted. The failure in issue is likely to recur and is therefore called a repetitive failure if this maintenance is not complemented by a basic intervention intended to remedy the primary cause. **[77]**

- **Curative maintenance**: it really gets to the root of the problem, by trying to "cure" the problem and treating the root cause, if the diagnosis can be traced back to the root cause. **[73]**

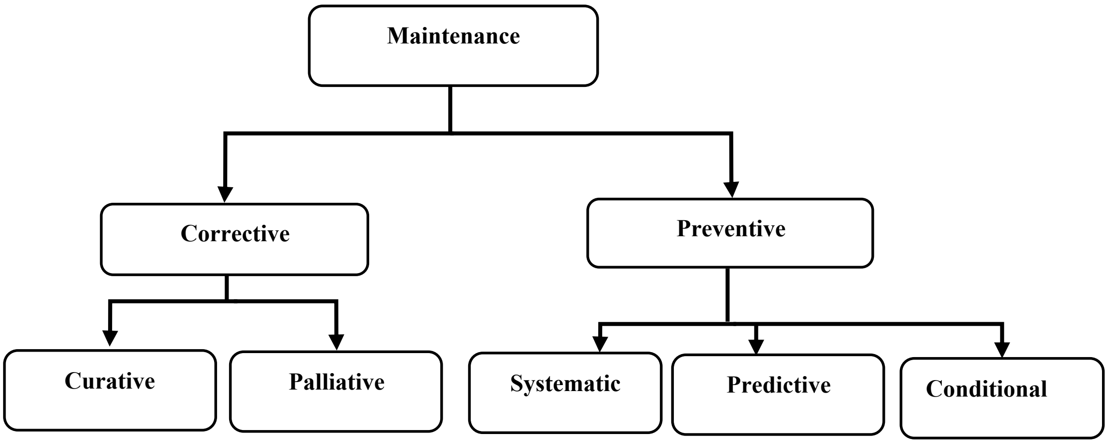


Figure 1. 1: Types of maintenance

1.3.3 Advantage and limitations of each maintenance strategy

Maintenance strategies play a crucial role in ensuring the availability, performance, and longevity of industrial equipment and systems. However, it is important to recognize that each maintenance strategy “whether it's preventive, or corrective” comes with its own set of advantages and limitations. Understanding the advantages and limitations of each strategy is essential to develop effective maintenance plans tailored to operational requirements.

1.3.3.1 Corrective Maintenance:

Corrective maintenance is the simplest and quickest response to equipment failures, requiring minimal planning and resources. In addition, it may be more cost-effective than preventive maintenance when the cost of downtime is relatively low. Moreover, it focuses resources only on equipment that has actually failed, avoiding unnecessary maintenance tasks. However, in other hand corrective maintenance can result in unplanned downtime, leading to disruptions in production schedules and potential revenue loss. In addition, we can consider that the delayed repairs or neglecting maintenance needs can lead to further damage to equipment and increase repair costs and downtime in the long term. In order to explain the advantages and limitations of each type of this strategy, we can detail the following:

a. Palliative Maintenance:

Palliative maintenance provide immediate response allow quick interventions to address issues and minimize disruptions to operations. In addition, it provides temporary fixes to keep equipment operational until permanent repairs or replacements can be implemented. In other hand, those temporary fixes may not fully address underlying issues, leading to the risk of additional equipment damage or failures, increase complexity of maintenance processes, and increase the risk of errors or oversights. In addition relying too heavily on palliative measures without addressing root causes can result in decreased equipment availability and increased downtime in the long term. **[78]**

b. Curative Maintenance:

By identifying and rectifying underlying issues, curative maintenance can help improve equipment availability and reduce the likelihood of future failures. It aims to address root causes of equipment failures so it leads to more sustainable and long-lasting repairs. In addition, Curative maintenance may include preventive actions to mitigate the risk of similar failures occurring in the future. However, curative maintenance often requires more time, planning, and resources for diagnosing and addressing complex issues, which may involve extended downtime or equipment outages, affecting production schedules and revenue generation. The upfront costs of repairs measures may be high due to the implementation of preparing all the necessary resources while the equipment or even the system is in a down status due to the aimed failure. **[78]**

1.3.3.2 Preventive Maintenance

Preventive maintenance helps identify and address potential issues before they escalate into major failures, resulting in improved equipment availability and uptime. By performing routine inspections, lubrication, and replacement of worn components, preventive maintenance can help avoid costly breakdowns and emergency repairs, which can prolong the lifespan of equipment and items and reduce the need for premature replacements and capital expenditures. Performing maintenance tasks based on fixed schedules (like systematic maintenance) may result in unnecessary or excessive maintenance, leading to wasted resources and increased downtime, affecting production schedules and potentially causing production losses. In addition, Preventive maintenance (predictive) may not always detect or predict all potential failures, especially for unpredictable or non-linear failure modes. We can go over the following to clarify the advantages and limitations of every variant of this strategy:

a. Systematic Maintenance:

By prioritizing maintenance tasks based on criticality and system dependencies and considering the entire system or process rather than individual components, systematic maintenance optimizes resource and ensures efficient use of resources, and focuses efforts on areas with the greatest impact. In additional, systematic maintenance can enhance overall system availability and performance by addressing interdependencies and interactions between system components. As limitations of this strategy we can talk about its complexity; implementing systematic maintenance may require detailed knowledge of system architecture, dependencies, and failure modes, which can be challenging to manage and maintain and requiring significant time, effort, and resources. **[79]**

b. Conditional Maintenance:

By monitoring equipment health indicators such as temperature, vibration, or fluid levels, conditional maintenance focuses maintenance efforts on equipment that exhibits specific signs or conditions indicating the need for repair or servicing, reducing unnecessary maintenance and prevent unexpected failures and minimize unplanned downtime. However, Conditional maintenance relies on accurate and reliable condition monitoring systems to detect potential issues, requiring investment in sensors, data collection, and analysis tools. Those condition-monitoring systems may not always detect early signs of equipment degradation or failures, leading to missed maintenance opportunities and increased risk of unexpected downtime. Also determining the appropriate maintenance actions can be complex. **[78] [79]**

c. Predictive Maintenance:

Predictive maintenance leverages advanced analytics and machine learning algorithms to predict equipment failures before they occur, allowing for timely interventions and minimizing unplanned downtime. By predicting when maintenance is needed, based on equipment performance data, predictive maintenance enables optimization of maintenance schedules, reducing unnecessary downtime and maximizing equipment uptime. Predictive maintenance can lead to significant cost savings in terms of reduced repair costs, production losses, and equipment replacements by addressing issues proactively and avoiding costly breakdowns **[80]**. Like other strategies, predictive maintenance has its own challenges and limitations due to its dependence on accurate and reliable data from sensors, monitoring systems, and historical records, setting up predictive maintenance capabilities may require significant upfront investment in sensors, data infrastructure, and analytics tools, which can be a costly. Also poor data quality or incomplete data sets can undermine the effectiveness of predictive maintenance algorithms. In additional, implementing predictive maintenance requires expertise in data analytics, machine learning, and condition monitoring technologies, as well as integration with existing maintenance processes and systems. In order to avoid the limitations of maintenance strategies, maximize the benefits of an efficient strategy and develop the best maintenance plan that would boost system availability and save maintenance costs. It is crucial to carefully analysis the costs and complexity of implementing each maintenance program and make sure that the technology employed is accurate and dependable and have a solid understanding of the targeted system's current state.

Regular maintenance activities, such as inspections, servicing, and repairs, can help identifying and addressing potential issues before they lead to equipment breakdowns, ensuring that systems are always in optimal working condition and significantly improve productivity and efficiency of industrial equipment. In industry, there are systems that have the priority in maintenance schedules due to their importance and influence overall plant. Safety systems are one of those systems, due to their role in preventing accident and protecting lives and equipment, safety systems should take into consideration when planning an optimal maintenance schedule to ensure their availability to perform the safety function when it is needed. By implementing well-planned maintenance procedures, components of safety systems can be serviced and changed when necessary, also improve their efficiency and prolonging their useful lives, and without proper maintenance, safety systems may become unreliable or malfunction, increasing the risk of accidents and injuries.

1.4 Smart scheduling of maintenance activities

The main problem in choosing the optimal maintenance schedule is that the decision is actually easy to make if the company is facing unexpected but urgent orders or machine fails, i.e., the rescheduling procedure should be run as soon as possible. More in general, within a manufacturing system, rescheduling is necessary whenever unexpected events occur and the planned schedule becomes unfeasible. On the contrary, without obviously serious disruptions, the production plan seems feasible and then the potential problem becomes rather tough to figure out. The choice of a schedule of operations is part of a production planning process. More precisely maintenance scheduling. Scheduling involves the allocation of the available maintenance resources. As it is intuitively evident, these decision problems have a strong combinatorial nature and consequently a high complexity. Maintenance activities need to be scheduled according to the availability of the system and the cost of maintenance, these two factors should be satisfied in the maintenance schedule. In addition, to making sure of that, schedule will be assess to check the suitability of this schedule with the system otherwise, the process of scheduling will keep repeating (rescheduling) until factors satisfaction is met. Given the combinatorial nature and the complexity of most scheduling problems, the satisfaction of all factors during the process of maintenance scheduling is hard. A failure in the safety system means the inability of the SIS to take the process to a safe state when required. In some cases, a failure could be potentially hazardous due to the importance of the safety system in the process and the severity of the accident in the protected system. Maintenance can reduce the level of risk for the process by identifying and implementing changes to the safety system and prevent its failure or maintain it as soon as possible if a failure occurs, to ensure the current safety level is maintained **[81].** To increase the availability of the safety system, to reduce maintenance costs, and despite the complexity problem finding optimal schedule that satisfies all factors is mandatory. To achieve this level of optimality we propose to integrate the optimization metaheuristics technics in smart scheduling. The following chart explain the combination of scheduling and metaheuristics technics.

1.4.1 Maintenance scheduling process

The maintenance scheduling process begins with identifying the initial state, where the system requiring maintenance is selected based on its criticality and operational importance. Following this, the planning phase commences, incorporating resources and data gathered from the system to devise an effective maintenance schedule. Once the schedule is in place, the system undergoes maintenance according to the plan. Subsequently, the system's availability is assessed; if there is an increase, the system continues to be monitored with the maintenance schedule intact. However, if the availability does not improve as expected, a rescheduling of maintenance occurs. The process restarts, with the system undergoing maintenance again, followed by another assessment of its availability. This cycle repeats until the desired level of system availability is achieved, ensuring optimal operational performance.

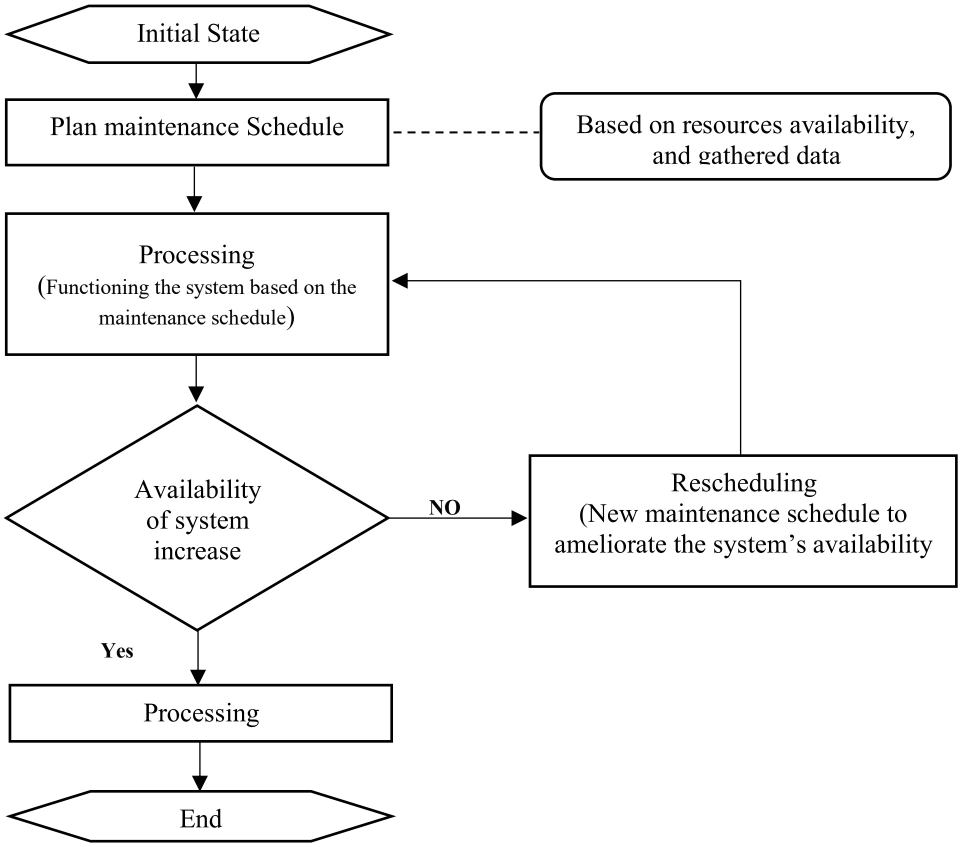


Figure 1. 2: Maintenance scheduling process

In order to accelerate rescheduling process and assessing the maintenance plan by monitoring the availability of the system undergoes maintenance. We can use an optimization algorithm, which have the ability of exploring potential solutions and evaluating them based on an objective function, which quantifies the quality of a solution. The goal is iteratively refine the solutions until an optimal or near-optimal solution is found. These algorithms facilitate the process of choosing the best maintenance schedule; that increase the system's availability, and reduce the costs of system shutdown even due to a failure or to unnecessary maintenance activities.

1.4.2 Smart scheduling benefits for maintenance processes

Smart scheduling brings transformative advantages to maintenance activities and industrial processes by leveraging advanced technologies like AI, IoT, and predictive analytics. It optimizes resource allocation, ensuring that labor, tools, and machinery are used efficiently, which reduces downtime and maximizes productivity. By predicting maintenance needs, smart scheduling allows maintenance activities to be planned during non-peak hours, minimizing disruptions and enhancing overall operational efficiency. Predictive maintenance is a key benefit, as it helps forecast potential equipment failures, enabling timely interventions that prevent costly unscheduled downtime. This not only extends the lifespan of machinery but also significantly reduces maintenance costs by minimizing the need for emergency repairs and spare part inventories. In terms of safety, smart scheduling proactively addresses potential issues, creating a safer work environment and ensuring compliance with safety regulations, thus reducing the risk of accidents and associated fines.

The flexibility offered by smart scheduling is another critical advantage, as it can adapt maintenance schedules in real-time based on changing conditions, such as fluctuating production demands or machine performance data. This adaptability, coupled with the system's scalability, ensures that as industrial operations grow or evolve, maintenance activities remain efficiently managed. Data-driven decision-making is at the core of smart scheduling, enabling managers to analyze historical data and trends to make more informed decisions about maintenance timing and methods. This continuous flow of insights supports the ongoing refinement of processes, leading to continuous improvement in operational efficiency. Additionally, smart scheduling enhances workforce management by aligning tasks with employee skills and availability, reducing the need for overtime and improving work-life balance for employees.

Furthermore, smart scheduling contributes to environmental sustainability by optimizing energy use, reducing waste, and preventing equipment malfunctions that can lead to material loss or environmental harm. By integrating all these benefits, smart scheduling not only improves the efficiency and cost-effectiveness of industrial operations but also supports safer, more sustainable, and more resilient processes that can adapt to future challenges and opportunities.

1.5 Conclusion

In conclusion, the integration of smart scheduling into maintenance strategies and safety systems marks a significant advancement in industrial operations. By leveraging the power of AI, IoT, and predictive analytics, smart scheduling not only optimizes resource allocation and reduces downtime but also enhances the overall safety and efficiency of production processes. The ability to anticipate maintenance needs and adjust schedules in real-time ensures that machinery and equipment are maintained in peak condition, which not only extends their lifespan but also minimizes unexpected failures and costly disruptions. Furthermore, by aligning maintenance activities with broader safety systems, smart scheduling contributes to a safer working environment, reducing the risk of accidents and ensuring compliance with regulatory standards. Ultimately, the smart scheduling of maintenance plans plays a crucial role in boosting production efficiency and system performance, leading to more reliable, cost-effective, and sustainable industrial operations. This holistic approach to maintenance and safety underscores the critical importance of integrating advanced technologies into the core of industrial processes, paving the way for future innovations and continuous improvement.

Chapter 2: Safety Instrumented System

2.1 Introduction

In complex industrial processes, the prevention of catastrophic failures and the protection of people, assets, and the environment are paramount. One of the most critical safeguards used to achieve these objectives is the Safety Instrumented System (SIS), a dedicated control mechanism designed to bring a process to a safe state upon the detection of predefined hazardous conditions. The implementation of SIS is rooted in the layered safety approach, where multiple independent protective barriers work together to reduce risk to a tolerable level.

This chapter explores the fundamental concepts and technical components of Safety Instrumented Systems, as defined primarily by international safety standards such as IEC 61508 and IEC 61511. It introduces the classification of safety layers in industrial environments, explains the core elements of SIS—sensors, logic solvers, and final elements—and discusses the role of Safety Instrumented Functions (SIFs) in achieving functional safety. Emphasis is placed on Safety Integrity Levels (SILs) and the quantitative/qualitative techniques used to evaluate and design for risk reduction.

Furthermore, the chapter delves into the failure classifications that can affect SIS reliability, including random hardware failures and systematic failures, and explains how these failures influence the safety function. Various architectures (KooN systems) are analyzed for their impact on both safety and availability, using modeling techniques such as Reliability Block Diagrams (RBDs), Fault Tree Analysis (FTA), and Markov approaches. Lastly, the chapter investigates the phenomenon of spurious activations, offering a quantitative insight into their occurrence and providing analytical methods for their estimation.

2.2 Types of safety layers

We can classify the safety systems into layers. Each layer is a set of preventive/protective measures implemented to prevent or mitigate the effects of process deviations, equipment failures, and human errors **[82].** Each of these protection layers plays a crucial role in safeguarding process industries against accidents and ensuring the safety of personnel, facilities, and the surrounding environment. By implementing multiple layers of protection, organizations can establish robust safety barriers that reduce the likelihood and severity of process safety incidents.

Safety systems or layers can be classified into four categories

- Process Design Basic
- Process Control System (BPCS)
- Alarms and Operator Intervention
- Safety Instrumented Systems (SIS, ESD)

The classification of these layers is carried out according to the onion model

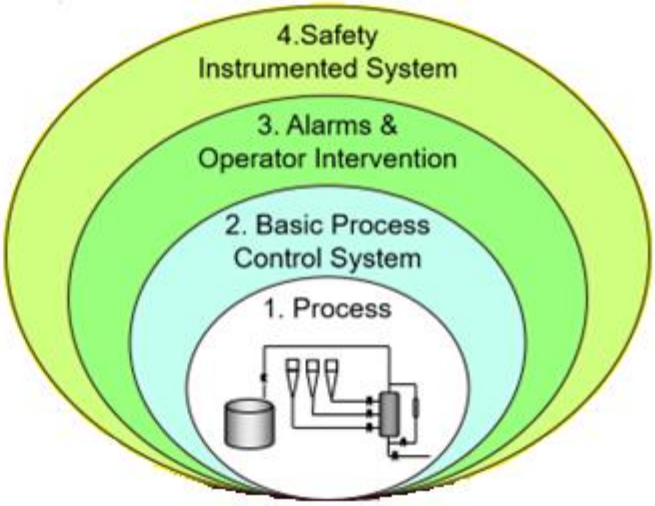


Figure 2. 1: Layer of safety in Process Industry

Process Design Basics: This layer focuses on the fundamental design aspects of the process itself. It involves engineering the process in a way that inherently reduces risks and hazards. Elements of process design basics include selecting appropriate equipment, designing effective ventilation systems, ensuring adequate containment measures for hazardous materials, and implementing inherently safer design principles. The goal is to design the process in such a way that hazards are minimized from the outset, reducing the likelihood of accidents. **[83]**

Process Control System (BPCS): The Process Control System (BPCS) is responsible for monitoring and controlling the various parameters of the process to maintain it within safe operating limits. This includes regulating factors such as temperature, pressure, flow rates, and chemical concentrations. The BPCS employs sensors to continuously monitor process variables and actuators to adjust control parameters as needed. By maintaining process conditions within safe limits, the BPCS helps prevent deviations that could lead to hazardous conditions. **[83]**

Alarms and Operator Intervention: Alarms and operator intervention serve as early warning systems to alert operators to abnormal conditions or potential hazards within the process. These alarms are triggered when certain predefined thresholds or conditions are exceeded. Operators are trained to recognize and respond to alarm notifications promptly. They may intervene by taking manual control of the process, initiating corrective actions, or implementing emergency shutdown procedures if necessary. Alarms and operator intervention are critical for enabling timely responses to abnormal situations and preventing accidents. **[83]**

Safety Instrumented Systems (SIS, ESD): Safety Instrumented Systems (SIS) are independent layers of protection designed to mitigate the consequences of process safety incidents. SIS typically A SIS comprises input elements (e.g., sensors), logic solvers (e.g., programmable electronic solver [PLC]), and final elements (e.g., safety valves, circuit breakers, alarms) that actuate in response to predetermined safety conditions. These systems are specifically designed to address scenarios where the BPCS and other layers of protection fail to prevent or mitigate hazardous conditions. SIS automatically initiate safety measures, such as shutting down the process or isolating equipment, to prevent escalation of incidents and protect personnel, the environment, and assets and to keep the process running safely or return it to a safe state. **[83]** This function of detects a specific hazard and brings the process to a safe state is defined in IEC61511 as safety instrumented function which means “function to be implemented by a SIS, intended to achieve or maintain a safe state for the process, with respect to a specific hazardous event. Taking into consideration that a SIS is composed of several Safety Functions.

2.3 Safety instrumented system

A safety system is a designed system that responds to hazardous or potentially hazardous conditions within a plant or facility. It is engineered to take the process to a safe state when dangerous situations are detected. Safety systems are crucial components in various industries, including oil and gas, chemical plants, and manufacturing facilities, where they play a vital role in preventing accidents, protecting personnel, and ensuring operational safety. These systems typically consist of hardware and software controls that provide a protective layer to shut down or control a process in case of an emergency or hazardous condition. The primary function of a safety system is to maintain a safe operating environment by detecting abnormal conditions, initiating appropriate responses, and minimizing risks to personnel and equipment. **[84]**

IEC 61508 defines a SIS as: E/E/PE (electrical/electronic/programmable electronic) system related to safety applications comprises all system elements necessary to perform the safety function’.

IEC 61511 defines safety instrumented systems as "an instrumented system used to implement one or more safety instrumented functions. A SIS consists of any combination of sensor(s), logic unit(s) and terminal element(s)".

S: Sensors: made up of a set of input elements (sensors, detectors) which monitor changes in parameters representative of the EUC's behavior (temperature, pressure, flow rate, level, etc.).

LS: Logic Solver: comprises a set of logic elements (PLC, API) which collect the information coming from the S subsystem and carry out the decision-making process which may end, if one of the parameters deviates beyond a threshold value, with the activation of the FE subsystem.

Final Elements (FE): act directly (emergency stop valve) or indirectly (solenoid valve, alarm) on the process to neutralize its drift, generally placing it in a safe state.

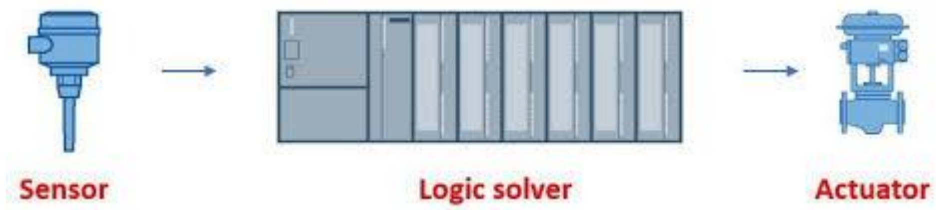


Figure 2.2: Architecture of a SIS

2.4 The security function and integrity level of a SIS

It is recognized that in order to reduce the risks associated with the EUC (Equipment under Control) and its control system to a certain tolerable level, it is generally necessary to employ a number of safeguards using different technologies which intervene in a certain predetermined manner. These interventions called safety functions.

A Safety Instrumented Function (SIF) is a function to be performed by a SIS designed to ensure or maintain a safe state of the equipment to be protected (EUC) in relation to a specific hazardous event. For a given situation, several safety functions can lead to a reduction in the frequency of occurrence of a hazardous event. The functional architecture of a SIS is a set of RIS comprising three basic functions: detection (or measurement), processing (or decision) and actuation. Safety functions are measured using the concept of Safety Integrity Level (SIL), the SIL of a function represents the level of risk reduction it is capable of or assigned to achieve. IEC 61508-4 defines it as follows: 'the probability that a safety-related system (SRS) will satisfactorily perform the required safety functions under all specified conditions and for a specified period of time'. It also indicates that this definition focuses on the reliability of SRSs in performing their safety functions.

The same standard specifies that safety integrity includes hardware safety integrity and systematic safety integrity. These are defined below.

- Hardware safety integrity: part of the safety integrity of systems relating to safety linked to random failures of hardware in dangerous failure mode.

- Systematic safety integrity: that part of the safety integrity of safety-related systems which relates to systematic failures in a hazardous failure mode, noting that systematic integrity cannot normally, or precisely, be quantified, but merely considered from a qualitative point of view.

2.4.1 Failure measures concept

SILs are characterized by discrete indicators positioned on a four-level scale set by the standard as a function of the average probability of failure on demand (PFDavg) for SISs subject to low demand operation (less than one intervention per year). On the other hand, as a function of the probability of failure per hour (PFH) for SISs subject to continuous demand operating or continuous mode (Table 2.1). The required (actual) SIL can be determined using several quantitative, semi-quantitative (e.g. layer of protection analysis (LOPA)) or qualitative (e.g. risk graph method) methods.

The usual methods for calculating the PFDavg of SISs (or PFH) are probabilistic methods derived from traditional operational safety studies where the reliability data relating to components (failure rate, repair rate, etc.) can be known with a greater or lesser degree of accuracy and are validated by feedback. Part 5 of the IEC61508 standard provides a detailed description of these methods as well as some factors that could be useful in choosing the most appropriate.

Table 2.1: Safety Integrity Levels (SIL) as a function of target failure measures.

SIL	Low demand operation		Continuous demand operation	
	PFD	**PFD (power)**	**PFH**	**PFH (power)**
1	0.1–0.01	$10^{-1} - 10^{-2}$	0.00001-0.000001	$10^{-5} - 10^{-6}$
2	0.01–0.001	$10^{-2} - 10^{-3}$	0.000001-0.0000001	$10^{-6} - 10^{-7}$
3	0.001–0.0001	$10^{-3} - 10^{-4}$	0.0000001-0.00000001	$10^{-7} - 10^{-8}$
4	0.0001–0.00001	$10^{-4} - 10^{-5}$	0.00000001-0.000000001	$10^{-8} - 10^{-9}$

In addition to the quantitative (probabilistic) requirements that show the adequacy of the SIS to the required SIL, the IEC61508 standard also requires qualitative requirements that serve to minimize the occurrence of systematic failures through the application of the various requirements during the different phases of the SIS safety life cycle, and another requirement, that of architectural constraints. The aim of the constraint is to encourage architectures that are robust to hardware failures and avoid choosing an architecture solely on the basis of PFD_{avg}. With reference to table 2.2, two new terms are introduced by the standard:

- A hardware fault tolerance of N means that (N+1) faults are likely to cause the loss of the safety function.
- The proportion of safe failures of a subsystem (SFF: Safe Failure Fraction) is defined by the ratio of the average rate of safe failures plus detected dangerous failures to the total average failure rate of the subsystem.

2.4.2 Basic architectural constrains concepts

Architectural constraints SIL calculation is simple enough, when calculations are performed by engineer in analytical way. But when we want to automate this task, the challenge arises, which algorithm to choose for calculation of architectural constraints for loop of any complexity and any structure. In this article we describe, how SIL from architectural constraints is calculated in SIL Toolbox. If you know better or more accurate way to perform this task, please comment this article or contact us at

Safe Failure Fraction (SFF) the fraction of failures which can be considered "safe" because they are detected by diagnostic tests or do not cause loss of the safety function.

In SIL Toolbox during calculation of SIL solution checks for every part of loop if all necessary data for SFF calculation is present in assigned instrument properties. SFF is calculated for every instrument using formula:

$$\lambda_{total} = \lambda_s + \lambda_{dd} + \lambda_{du}$$

$$\boldsymbol{SFF} = \frac{\lambda_{total} - \lambda_{du}}{\lambda_{total}}$$

Hardware Fault Tolerance (HFT) determines, how many faults can occur before losing safety function. HFT is calculated for combinations of elements with voting MooN:

HFT = N – M

Unit type is contained in assigned instrument properties. If Unit type is not entered by user, it is assumed to be B type (worst case).

For type A elements all possible failure modes can be determined for all constituent components, whereas for type B elements the behavior under fault conditions cannot be completely determined. In general type B components contain microprocessor, complex electronics and software, while type A components are electromechanical.

Architectural constraints SIL calculation is started from lowest level elements (i.e. tags with assigned instruments). When all lowest level instrument architectural constraints SIL have been calculated, solution starts calculating of higher level groups/subsystems until whole loop is covered.

Following rules apply for different types of structures.

For simple elements, architectural constraints SIL is calculated from SFF, HFT and unit type data using following table:

Table 2.2: architectural constraints SIL

Type A

SFF	HFT		
	0	1	2
<60%	SIL1	SIL2	SIL3
60%-90%	SIL2	SIL3	SIL4
90%-99%	SIL3	SIL4	SIL4
>99%	SIL3	SIL4	SIL4

Type B

SFF	HFT		
	0	1	2
<60%	-	SIL1	SIL2
60%-90%	SIL1	SIL2	SIL3
90%-99%	SIL2	SIL3	SIL4
>99%	SIL3	SIL4	SIL4

For chains of elements solution searches for element with lowest architectural constraints SIL. Such element restricts whole chains performance.

For groups and subsystems solution searches for element with lowest architectural constraints SIL. This value is increased by HFT calculated from group's voting.

Finally, when all subsystems have their architectural constraints SIL calculated, lowest SIL is taken as whole loop's architectural constraints SIL, exactly as it is done for chains.

2.5 Classification of SIS failures:

Generally, a system (SIS) can be in one of four states:

- Normal state: The safety function of the system is validated and there are no failures.
- Normal degraded state: The safety function is enabled, but system components may fail. The system can react as soon as a dangerous event occurs.
- Safe state: This is a state of the system for which safety has been achieved. The system can converge towards this state as soon as a failure occurs, for example in one or more components. In this case, the failure may be either detected or not detected, but it has no harmful effect on safety.
- Dangerous failure state: This is a state of the system where the safety function is no longer achieved, one or more components have failed. The system enters this state as soon as an accident risk appears and the system does not respond to a request to activate the safety function. **[85]**

There are several ways of classifying failures; generally, failures can be classified according to their causes and effects **[86]**.

2.5.1 Classification of failures by cause

In a more general sense, there are two categories of failure:

- Random hardware failures (physical): failures occurring at random and resulting from various degradation mechanisms within the hardware.

- Systematic failures: failure linked in a deterministic way to a certain cause, which can only be eliminated by a change in the design or manufacturing process, operating procedures, documentation or other appropriate factors.

Random equipment failures are caused by age-related degradation of components - natural or primary failures – **[87]** which can be accelerated by stress factors - secondary failures - **[88]**.

Systematic failures, on the other hand, are caused practically by any other cause apart from degradation, such as: failures due to errors in design, specification, operation, maintenance and installation, human error, etc.

Systematic failures can lead to common cause failures (CCF = Common Cause Failure). They can also prevent a component from fulfilling its function even when it is still capable of (reliable) operation **[88]**.

IEC 61508 recommends that only random failures should be considered in SIS performance calculations, as systematic failures generally cannot be quantified. However, the IEC61508 standard implicitly includes the quantification of certain systematic failures in the method for quantifying equipment-related common cause failures **[88]**.

2.5.2 Classification of failures according to their effects on the safety function

As mentioned above, some safety system failures can lead to dangerous situations and others to false activations (but without any danger), so SIS failures (either random hardware failures or systematic failures) can be classified according to their effects into two categories:

1) Dangerous failures: A failure that has the potential to place the safety-related system in a dangerous state or unable to perform its function.

2) Safe failures: failures which do not have the potential to place the safety-related system in a dangerous state or make it impossible to perform its function.

Faults detected on-line by diagnostic test are referred to as detected faults. Those which are not detected are referred to as undetected faults. The breakdown of faults and their rates according to standard IEC 61508 is therefore as follows:

- Dangerous Detected Failures (DD): failures detected immediately after their occurrence by on-line tests. Their failure rate is noted λDD.

- Dangerous Undetected Failures (DU): failures which can only be revealed during periodic off-line tests (with a period equal to T). Their failure rate is noted λDU .

- Safe Detected Failures (SD). Their failure rate is noted λSD.

- Safe Undetected Failures (SU). Their failure rate is noted λSU.

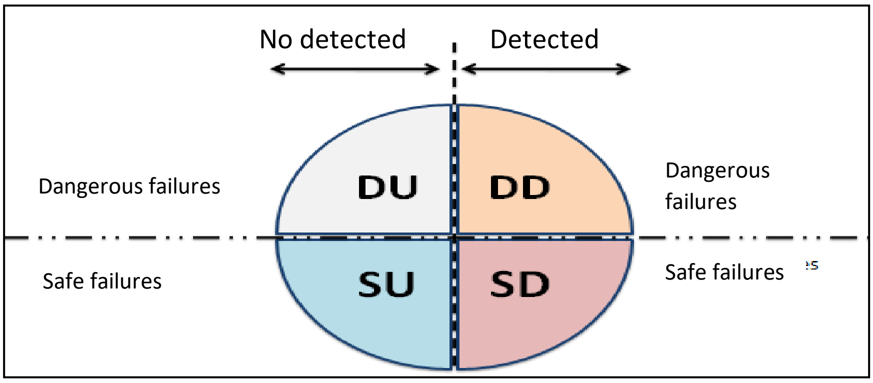


Figure 2.3: Classification of faults according to the standard

Taking this decomposition into account, the total random equipment failure rate (λ) has two components:

$$\lambda = \lambda_D + \lambda_S$$

With:

λ_D: random safe failure rate of equipment

λ_S: random safe failure rate of equipment

The sum of the detected and undetected safe failure rates represents the safe failure rate (λ_S):

$$\lambda_S = \lambda_{SD} + \lambda_{SU}$$

The sum of the rates of detected and undetected dangerous failures gives the dangerous failure rate (λ_D)

$$\lambda_D = \lambda_{DD} + \lambda_{DU}$$

By introducing diagnostic coverage, we can rewrite the different failure rates, mentioned above, as follows:

$$\lambda_{DD} = DC \,.\, \lambda_D$$

$$\lambda_{DU} = (1\text{-}DC).\, \lambda_D$$

Where: DC represents the diagnostic coverage of dangerous random faults.

$$\lambda_{SD} = DC_S \,.\, \lambda_S$$

$$\lambda_{SU} = (1\text{-}\ DC_S)\,.\, \lambda_S$$

Here, DCS represents the diagnostic coverage of random failures in safety.

In the case of common cause failures (CCF) the N constituent channels of a redundant architecture fail simultaneously; to estimate the failure rate (λ_{DCC}), IEC 61508 uses the β-factor model:

$$\lambda_x = \lambda_{xind} + \lambda_{xDCC} = (1\text{-}\ \beta_x)\ \lambda_x + \beta_x . \lambda_x$$

β_x is the percentage of DCCs. The subscript 'ind' means independent failures whose occurrence affects only one component of the KooN architecture, while 'x' is used to account for the previous partition of failures (DU, DD, SU, SD).

2.6 Modelling the performance of the safety instrumented system using KooN architectures

Improving safety is necessary, but it should not be forgotten that the availability of installations is in most cases just as important as safety (or at least one of the priorities of manufacturers).

In order to achieve a compromise between the safety and availability of installations, certain methods have been developed in terms of modelling the dependence of safety instrumented systems on KooN architectures, such as the reliability block diagram (RBD) and the fault tree (FTA). These are static models that can be used to calculate point or average values. RBDs are generally useful for non-repairable systems. FTA can handle repairable systems, but for systems with sophisticated repair strategies or temporal dependencies, other state-based approaches, such as Markov methods, are better suited to systems with dynamic behaviors.

In order to reduce the likelihood of an SIS not fulfilling its safety function at the time it is called upon, one solution is to redundantly (totally or partially) integrate certain components of the SIS (sensors, logic unit, actuators, terminal elements and even transmission media). It should be noted that redundancy could be achieved using identical equipment or different technologies. There are several types of redundancy:

1) Active redundancy: which is redundancy such that all the means of performing a required function operate simultaneously.

2) Passive redundancy: which is redundancy such that only part of the means of performing a required function is in operation, the rest being used on demand only in the event of failure of the part in operation.

3) KooN type redundancy: is a so-called majority redundancy such that a function is only ensured if at least K of the N existing means (channels) are in working order or in operation. In this thesis, it is assumed that all channels are designed with the commonly used 'de-energized to trip concept, i.e. the principle of current at rest (i.e. the outputs are activated during normal operation of the process).

Systems based on this principle are designed to remove energy following an error (a power supply failure, for example). To perform the safety function, the relays have to be opened (the power supply to the load has to be cut off). In this case, dangerous faults result in the power supply to the load being maintained (closed relays), the relays being initially closed, whereas safe faults result in the relays being opened. The most frequently encountered architectures and their models are as follows:

- Architecture 1001

The one-in-one architecture provides no fault tolerance, which means that the occurrence of a safe failure will result in an untimely shutdown of the entire process, and the loss of the safety function on demand if the failure is unsafe **[89]**.

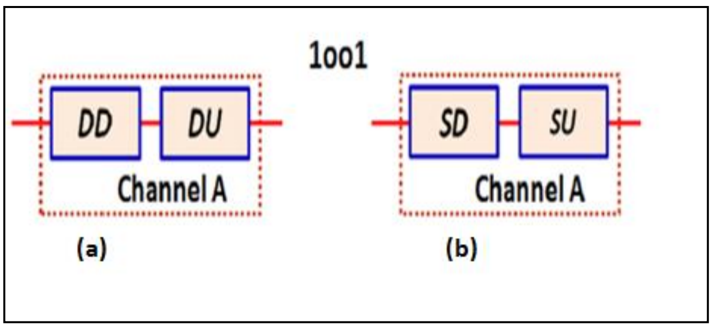


Figure 2.4 : Reliability block diagram relating to (a) unsafe and (b) safe behaviour (left) and the 1001 Electrical Schematic (right) [89].

- Architecture 1002

This configuration consists of two identical channels wired in series. This architecture offers a high level of safety compared with (1001), by tolerating the occurrence of a dangerous failure in one of the two channels.

As far as spurious activation is concerned, the safe failure of either of the two channels leads the monitored system to a safe fallback state (activation of the safety function) - worse than 1001 - since it increases the probability of safe failures.

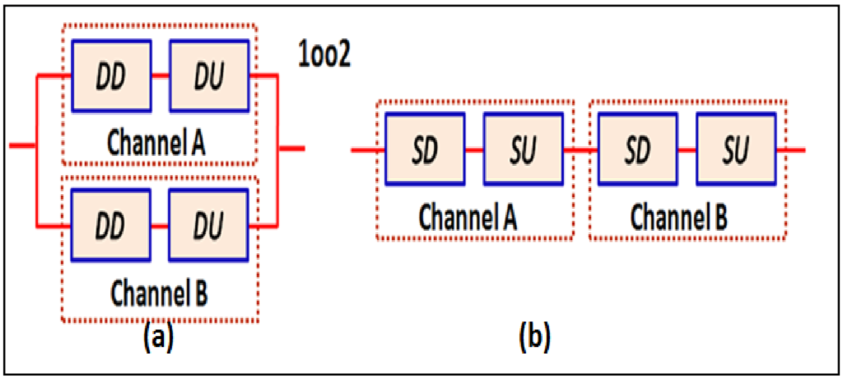


Figure2.5 : Reliability block diagram relating to (a) unsafe and (b) safe behavior (left) and the 1002 electrical diagram (right). [89]

- Architecture 2002

This architecture consists of two channels wired in parallel. In fact, nuisance tripping (activation of the safety function in the absence of demand) only occurs if these two channels observe safe failures, whereas a single dangerous failure can lead to the loss of the safety function.

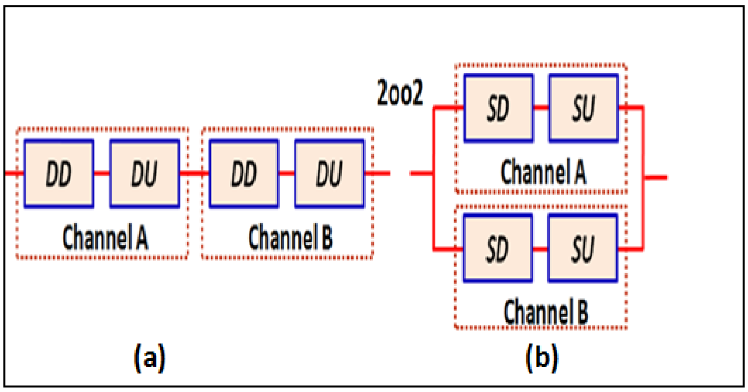


Figure 2.6 : Reliability block diagram relating to (a) unsafe and (b) safe behaviour (left) and the 2002 Electrical Schematic (right). [89].

- Architecture 1003

The 1oo3 design has three channels wired in series, which means that it is capable of tolerating two unsafe failures at the same time. In addition, a safe failure can bring the whole system (EUC) to a safe state.

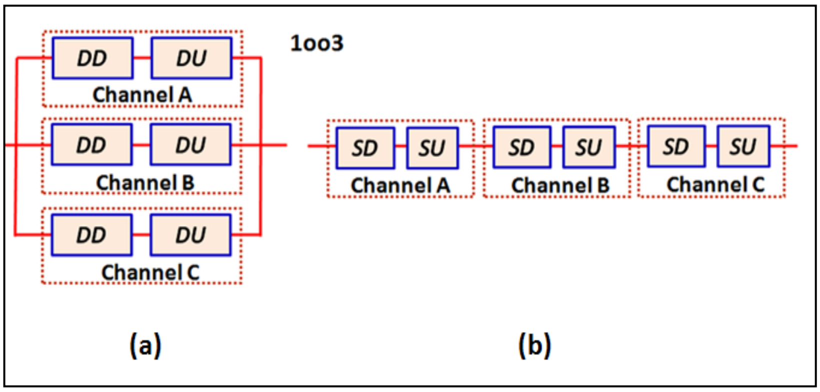


Figure 2.7 : Reliability block diagram relating to (a) dangerous and (b) safe behavior (left) and the 1oo3 electrical diagram (right).

- Architecture 2oo3

This configuration has been developed to tolerate both safe and unsafe failures. In order to lose the safety function, two dangerous failures must occur and at least two safe failures are required for SIS to be triggered unexpectedly.

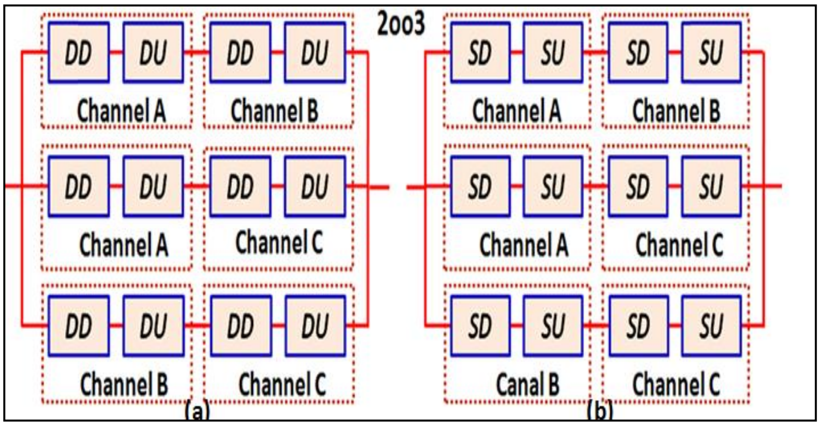


Figure 2.8 : Reliability block diagram relating to (a) unsafe and (b) safe behaviour (left) and the 2oo3 Electrical Schematic (right) [89].

Generally speaking, for a KooN architecture these two numbers are established as follows:

- N - K+1 represents the number of dangerous failures whose occurrence leads to the loss of the safety function.

- K represents the number of safe failures whose occurrence leads to the untimely activation of this same function.

2.7 Analytical formulas for SIS performance

2.7.1 The average probability of failure on demand (PFD_{avg})

The probability of failure at stress noted PFD_{avg} as mentioned in chapter 2 corresponds to the value of the probability of failure at stress PFD(t) averaged over the period of time separating two tests noted TI. This probability is expressed as follows **[90]**

$$PFD(t) = Pr(T \leq t) = F(t) = 1 - R(t)$$

So

$$PFD_{avg} = \frac{1}{TI}\int_0^{TI} PFD(t)dt = \frac{1}{TI}\int_0^{TI} F(t)dt = 1 - \frac{1}{TI}\int_0^{TI} R(t)dt$$

It is often assumed that: (i) DU (Dangerous Undetected) failures are the main contributor to PFD, (ii) the time to a DU failure is exponentially distributed **[86]**

The calculation formulae (relating to the reliability block diagrams presented in the previous paragraph) used to evaluate the overall PFD of each sub-system are as follows:

Parallel block : $PFD_{globale} = \prod_{i=1}^{n} PFDi$.

Block in series: $PFD_{globale} = \sum_{i=1}^{n} PFDi$.

The PFD_{avg} of the SIS is deduced by the sum of the PFD_{avg} of the various elements that compose it.Generally speaking the SIS is composed of the three subsystems and for each subsystem, depending on its architecture(KooN) and knowledge of reliability data (λ, MTTR, TI, etc.).

$$PFD_{avg} = PFD_{avg}(S) + PFD_{avg}(LS) + PFD_{avg}(FE). \quad \textbf{(1)}$$

2.7.2 Spurious Activations

2.7.2.1 Definitions

Spurious activations are known in the literature under various names, such as spurious operation (SO), spurious trip, false triggering, and premature shutdown, etc. In this thesis, the term "spurious activation" is used as a collective term.

The word "activation" implies that there is a transition from one state to another, and the word "spurious" indicates that the causes of the triggering are false, incorrect, or not real **[86]**.

In an industrial process, spurious activations of SIS (Safety Instrumented Systems) can lead to partial or complete shutdowns of the facilities. Therefore, it is necessary to reduce their occurrence in order to:

Avoid production losses resulting from shutdowns,

Avoid the risks that may arise during the restart phase.

2.7.2.2 Classification of Spurious Activations

There are three different types of spurious activations in Safety Instrumented Systems (SIS):

2.7.2.2.1 Spurious Operation (SO):

A spurious operation is the activation of a single element of the SIS in the absence of a real demand from the EUC (Equipment Under Control), i.e., without any actual deviations.

For example:

A false high-level signal emitted by a level transmitter due to an internal failure.

Note: A spurious operation of a gas detector in a 2oo3 voting configuration, for instance, will not lead to a spurious activation of a Safety Instrumented Function (SIF) within the SIS.

2.7.2.2.2 Spurious Trip:

This is the activation of one or more SIS components in such a way that it executes a SIF without the presence of a real demand from the EUC.

For example:

Two flame detectors in a 2oo3 configuration emit a false fire signal, which causes final elements to trip and the Safety Instrumented Function (SIF) to be activated.

The premature closure of an Emergency Shut-off Valve (ESV) in a 1oo2 configuration due to an internal failure.

2.7.2.2.3 Spurious Shutdown:

A spurious shutdown is a partial or total shutdown of systems without an actual activation demand (i.e., in the absence of real deviations) of a specified process **[86]**.

2.7.2.3 The spurious activation rate (STR)

The spurious activation rate (STR) is defined as the average number of spurious activations of the safety instrumented function (SIF) per unit of time.

The STR of a well-defined safety function, provided by a given SIS, is determined by calculating and combining the STR of its three subsystems (S, LS and FE). This can be expressed by the following general formula:

$$STR_{moySIS} = STR_{moy}\,(S) + \ (LS) + STR(FE). \qquad \textbf{(2)}$$

Naturally, each of these three sub-systems is represented by a KooN architecture **[86]**.

2.7.2.3.1 IEC 61508 standard

This standard provides simplified calculation formulas that allow the evaluation of the average PFD PFD_{avg} upon demand for some KooN redundancies (Table 5).

Table 2.3: Analytical formulas related to the average PFD of KooN architectures according to IEC 61508-6 (PFD_{avg})

Architecture	PFD_{avg} [IEC 61508-6,2009]
1oo1	$(\lambda_{SU} + \lambda_{SD})t_{CE}$
1oo2	$2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}\, t_{GE} + \beta_D\lambda_{DD} MTTR + \beta\lambda_{DU}\left(\frac{T1}{2} + MRT\right)$
1oo3	$6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^3\, t_{CE}\, t_{GE}\, t_{G2E} + \beta_D\lambda_{DD} MTTR + \beta\lambda_{DU}\left(\frac{T1}{2} + MRT\right)$
2oo2	$2\lambda_D t_{CE}$
2oo3	$6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}\, t_{GE} + \beta_D\lambda_{DD} MTTR + \beta\lambda_{DU}\left(\frac{T1}{2} + MRT\right)$
With: $t_{CE} = \frac{\lambda_{DU}}{\lambda_D}\left(\frac{T1}{2} + MRT\right) + \frac{\lambda_{DD}}{\lambda_D} MTTR$ $t_{GE} = \frac{\lambda_{DU}}{\lambda_D}\left(\frac{T1}{3} + MRT\right) + \frac{\lambda_{DD}}{\lambda_D} MTTR$ $t_{G2E} = \frac{\lambda_{DU}}{\lambda_D}\left(\frac{T1}{4} + MRT\right) + \frac{\lambda_{DD}}{\lambda_D} MTTR$ $\beta_{DU} = \beta;\ \beta_{DD} = \beta_D$	

Spurious failures are not even mentioned in the classification adopted by this standard, only the two versions [IEC 61508-6, 1998] and 2.3 [IEC 61508-6, 2009] consider that the detection of a dangerous failure, for a non-redundant SIS (1oo1 and 2oo2) and operating in high demand or continuous demand mode, leads to the emergency shutdown (activation of the safety function) of the monitored system. The current version of the standard goes beyond this assumption, considering that it remains valid even for redundant architectures (1oo2, 1oo3, 2oo3), i.e. the detection of a dangerous failure leads to the activation of the safety function, if the elements have not been restored within the mean time to restore indicated MTTR.

2.7.2.3.2 Markovian approach

Le principe de cette approche est résumé selon **[91]** comme suit :

- Approximate the multi-phase Markov model (exact) by a continuous model (approximate), without taking into account the DCC.

- Determine rates of return for failure states.

- Calculate asymptotic probabilities (continuous model).

- Calculate MDT.

- Calculate asymptotic failure frequency w: 1/MTBF=PFH.

- Deduce the PFD: MDT/MTBF.

Table 2.4 : Analytical formulas for the PFD_{avg} of KooN architectures obtained using an approximate Markovian approach.

Arcitectures	PFD_{avg}
1oo1	$\lambda_{DU}\,(\frac{T1}{2}+MTTR) + \lambda_{DD}\,.MTTR$
1oo2	$2\lambda_D{}^2\left[\frac{(1-\beta)\lambda_{DU}}{\lambda_D}\left(\frac{T1}{2}+MTTR\right)+\frac{(1-\beta)\lambda_{DU}}{\lambda_D}\ MTTR\right]\times\left[\frac{\lambda_{DD}}{\lambda_D}MTTR+\frac{\lambda_{DU}}{\lambda_D}\left(\frac{T1}{3}+MTTR\right)\right]+\beta_D\,\lambda_{DD}\,MTTR+\beta\,\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)$

1oo3	$6\lambda_D[(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}]\Big[(1-\beta_D)\lambda_{DD}MTTR + (1-\beta)\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)\Big] \times \Big[\frac{(1-\beta_D)\lambda_{DD}MTTR}{(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}} + \frac{(1-\beta)\lambda_{DU}}{(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}}\left(\frac{T1}{3}+MTTR\right)\Big] \times \Big[\frac{\lambda_{DD}MTTR}{\lambda_D} + \frac{\lambda_{DU}}{\lambda_D}\left(\frac{T1}{4}+MTTR\right)\Big] + 3[\beta_D\lambda_{DD}+\beta\lambda_{DU}]\Big[(1-\beta_D)\lambda_{DD}MTTR + (1-\beta)\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)\Big] \times \Big[\frac{\beta_D\lambda_{DD}MTTR}{\beta_D\lambda_{DD}+\beta\lambda_{DU}} + \frac{\beta\lambda_{DU}}{\beta_D\lambda_{DD}+\beta\lambda_{DU}}\left(\frac{T1}{3}+MTTR\right)\Big] + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)$
2oo2	$2[(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}]\times\Big[\frac{(1-\beta_D)\lambda_{DD}MTTR}{(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}} + \frac{(1-\beta)\lambda_{DU}}{(1-\beta_D)\lambda_{DD}+(1-\beta)\lambda_{DU}}\left(\frac{T1}{3}+MTTR\right)\Big] + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)$
3oo3	$3[(2-\beta_D)\lambda_{DD}+(2-\beta)\lambda_{DU}]\Big[(1-\beta_D)\lambda_{DD}MTTR + (1-\beta)\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)\Big]\times\Big[\frac{(2-\beta_D)\lambda_{DD}MTTR}{(2-\beta_D)\lambda_{DD}+(2-\beta)\lambda_{DU}} + \frac{(2-\beta)\lambda_{DU}}{(2-\beta_D)\lambda_{DD}+(2-\beta)\lambda_{DU}}\left(\frac{T1}{3}+MTTR\right)\Big] + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T1}{2}+MTTR\right)$

The same steps mentioned above were followed for safe failures

Table 2.5: STR formulas for KooN architectures using a Markovian approach.

Architecture	STR
1oo1	$\lambda_{SU}+\lambda_{SD}$
1oo2	$2((1-\beta_{SD})\lambda_{SD}+(1-\beta_{SU})\lambda_{SU})+\beta_{SD}\lambda_{SD}+\beta_{SU}\lambda_{SU}$
1oo3	$3((1-\beta_{SD})\lambda_{SD}+(1-\beta_{SU})\lambda_{SU})+\beta_{SD}\lambda_{SD}+\beta_{SU}\lambda_{SU}$
2oo2	$2(\lambda_{SU}+\lambda_{SD})\Big[(1-\beta_{SD})\lambda_{SD}MTTR+(1-\beta_{SU})\lambda_{SU}\left(\frac{T1}{2}+MTTR\right)\Big]+\lambda_{SDCC}$
2oo3	$3((2-\beta_{SD})\lambda_{SD}+(2-\beta_{SU})\lambda_{SU})\Big[(1-\beta_{SD})\lambda_{SD}MTTR+(1-\beta_{SU})\lambda_{SU}\left(\frac{T1}{2}+MTTR\right)\Big]+\lambda_{SDCC}$

2.7.2.3.3 Binomial approach

it is based on the following formulas **[92]**:

$$PFD_{avg}\,(KooN) = A_N^{N-K+1} \lambda_{Dind}^{N-K+1} \prod_{i=1}^{N-K+1} [\frac{\lambda DU}{\lambda D} (\frac{T1}{i+1} + MRT) + \frac{\lambda DD}{\lambda D} . \mathrm{MTTR}] + \beta\, \lambda_{DU}\, (\frac{T1}{2} + MRT) + \beta_D\, \lambda_{DD} . MTTR. \quad \textbf{(3)}$$

$$STR_{(KooN)} = A_N^K . \lambda_{Sind} . \prod_{i=1}^{K-1} \left[\lambda_{SUind} . (\frac{T1}{i+1} + MRT_S) + \lambda_{SDind} . MTTR_S\right] + \beta_{SU} . \lambda_{SU} + \beta_{SD} . \lambda_{SD} \quad \textbf{(4)}$$

With :

$A_N^{N-K+1} = \frac{N!}{(K-1)!}$

$A_N^K = \frac{N!}{(N-K)!}$

$\lambda_D = \lambda_{DD} + \lambda_{DU}$

$\lambda_{Dind} = (1 - \beta)\, \lambda_{DU} + (1 - \beta_D)\, \lambda_{DD}$

$\lambda_S = \lambda_{SD} + \lambda_{SU}$

$\lambda_{Sind} = (1 - \beta_{SU})\, \lambda_{SU} + (1 - \beta_{SD})\, \lambda_{SD}$

$MTTR_{SD}$: Mean time to restoration for SD failures

MRT_S : mean repair time for SU failures

2.8 Conclusion

Safety Instrumented Systems (SIS) are at the heart of modern industrial safety, serving as the final line of defense when other protective layers fail. The reliability and effectiveness of these systems depend not only on their design and technology but also on a thorough understanding of their behavior under failure conditions and their ability to perform as intended during demand.

Through the detailed study presented in this chapter, we have examined the structure, functionality, and evaluation of SIS from both a theoretical and analytical perspective. We classified safety layers, defined SIS components, and outlined the standards that govern their design. A critical analysis of SIS failure modes and architectural constraints highlighted the importance of considering both **random** and **systematic** failures, while the modeling of KooN architectures demonstrated how redundancy strategies can improve reliability without compromising availability.

Moreover, the inclusion of spurious activation analysis—often overlooked in conventional safety assessments—provides a balanced view of both **safety and operational continuity**. By employing analytical and probabilistic methods, including Markov and binomial approaches, practitioners can better predict system performance and optimize designs to meet required SIL targets.

Overall, this chapter underscores the necessity of a robust and well-documented approach to SIS design, validation, and maintenance, aligned with international safety standards, to ensure safe, reliable, and efficient industrial operations.

Chapter 3:
Introduction to modern optimization

3.1 Introduction

In industrial settings, optimization plays a crucial role in enhancing productivity, reducing waste, and improving the overall performance of systems. Whether it is the design of a manufacturing process, the scheduling of tasks in a production line, or the management of a supply chain, the need for efficient and effective optimization methods is ever-present.
The complexity of industrial problems often stems from their large-scale, non-linear, and multi-objective nature. Traditional optimization techniques, such as linear programming and gradient-based methods, while powerful, frequently struggle to address these complexities. These methods often require the problem to be simplified, assume linear relationships, or may be trapped in local optima, failing to find the best possible solution. As industrial systems grow in complexity and the demand for optimal performance increases, there is a pressing need for more robust and flexible optimization methods. This need has led to the rise of metaheuristic algorithms high-level problem-solving frameworks that offer an alternative to traditional optimization methods. Metaheuristics are designed to efficiently explore large and complex search spaces, making them particularly well-suited for solving difficult industrial problems. Unlike traditional methods, metaheuristics do not rely on gradient information or other problem-specific features, which allows them to be applied to a wide variety of problems with minimal modifications. From optimizing production schedules and supply chain management to improving the design of industrial systems and processes, metaheuristics have proven to be highly effective in delivering solutions that meet the demanding requirements of modern industry. Among the most widely used metaheuristic algorithms are Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Manta Ray foraging optimization (MRFO). Each of these methods draws inspiration from natural or physical processes and has been successfully applied to a wide range of industrial optimization problems.

This chapter delves into the world of optimization, with a particular focus on the concept and application of metaheuristic methods to industrial problems. It begins by exploring the fundamental concepts of optimization, including the types of problems encountered in industrial settings and the challenges associated with solving them. The chapter then provides an overview of metaheuristic algorithms, discussing their: general characteristics, strengths and how they compare to traditional optimization techniques. Following this, the chapter offers detailed explanations of some of the most widely used metaheuristic methods: Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Manta Ray foraging optimization illustrating their principles, applications, and effectiveness in solving industrial optimization problems. By the end of this chapter, the reader will not only highlight the power of these algorithms but also provide practical guidance on selecting and implementing the most appropriate optimization method for specific industrial problems.

3.2 Optimization of Industrial Problems

3.2.1 Terminology of optimization

- **Convergence**: The process of an algorithm approaching an optimal solution over time.
- **Near Optimum**: A solution close to the best possible, but not necessarily the global best.
- **Local Optimum**: A solution better than its neighbors but not the best overall.
- **Sub-optimum**: A solution that is not the best (could be local or near-optimal).

- **Global Optimum**: The best possible solution across the entire search space.
- **Objective Function**: The function to be minimized or maximized in an optimization problem.
- **Feasible Region**: The set of solutions that satisfy all problem constraints.
- **Search Space**: The domain of all possible solutions the algorithm explores.
- **Exploration and Exploitation**: Balancing between searching new areas (exploration) and improving the current best solution (exploitation).
- **Fitness Function**: Measures how good a solution is.

3.2.2 Optimization

The word "optimum" is Latin and means "the ultimate ideal"; similarly, "optimus" means "the best". Consequently, optimizing means trying to bring everything we deal with back to its ultimate state **[93]**.

Optimization is a fundamental concept that underpins a vast array of scientific, engineering, and industrial processes. It is about achieving the best result under given circumstances. In the design, construction and maintenance of any engineering system, engineers have to make numerous technology and management decisions at several stages. The ultimate goal of all these decisions is to minimize the effort required or maximize the desired benefit.

Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions giving the maximum or minimum value of a function.

Optimization consists in selecting the values of a problem's input variables in order to find the optimum solution. Input variables are those that can be controlled or modified by the optimizer. Optimization seeks to minimize or maximize certain objectives specific to the problem in question, which are the outcome of the problem. Each objective is defined by an objective function **[94]**.

3.2.3 The optimization problem

An optimization problem, denoted P(X, f), is characterized by a nonempty feasible or admissible set X and an objective function f that associates a scalar in $\mathbb{R}$, with each element x of the set X. The elements of X are called feasible solutions. Solving the problem P(X, f) amounts to finding, among the feasible solutions, one that minimizes or maximizes f, i.e. in the case of a minimization problem, finding a solution $x* \in X$ such that $f(x) \geq f(x*)$ for any element x in X. Such a solution is called optimal and will be denoted x(X, f) **[94]**.

The feasible set X is usually defined as a part of R^n where n is a positive integer denoting the size of the problem. Feasible solutions can then be represented as vectors whose n components are the problem variables. The set X is commonly delimited by a system of inequalities called problem constraints. The constraints are constructed using combinations of the variables, and make it possible to characterize the properties common to the solutions of X in order to distinguish them among all the solutions of R^n **[94]**.

The description of the set X is therefore implicit. Linear programs are probably the best-known optimization problems. The objective function and constraints of these problems are linear **[94]**.

3.2.3.1 The objective/adaptive function

The quantities to be optimized may be, for example, consumption, efficiency, transmission factor, profit, technological feasibility, cost, test period and so on. An optimization algorithm generally requires the definition of a function that accounts for the suitability of potential solutions, based on the quantities to be optimized. This is the fitness function f(x) **[95]**.

The algorithm's convergence towards the optimum of this function f, whatever its definition, is the main consequence. In this way, the relevance of the solution is at stake in the question posed to the computer. The function f is the translation into mathematical language of the user's desire.

An objective function $f : X \rightarrow Y$ with $Y \subseteq R$ is a mathematical function subject to optimization. The Co-domain Y of an objective function as well as its range must be a subset of the real numbers ($Y \subseteq R$). The domain X of f is called the problem space (Phenome) and can represent any type of element such as numbers, lists, construction plans, etc. It is chosen according to the problem to be solved. It is chosen according to the problem to be solved with the optimization process. Objective functions are not necessarily simple mathematical expressions, but can be complex algorithms involving, for example, several simulations. Global optimization comprises all techniques for finding the best elements x* in X with respect to these criteria $f \in F$ /F is the set of objective functions. **[94]**.

3.2.3.2 Optimization process

The optimization process usually starts with a real problem, full of details and complexities, some of which are relevant and some not. From this, an extraction of the essential elements is necessary to create a model and choose an algorithm or technical solution to apply. In practical problems, the computer will perform the necessary calculations.

The transition from real-world problem to algorithm, model or solution technique is known as analysis.

In the analysis phase, we always start by identifying the data needed to solve the problem, such as consumption values or item data sheets, the quantity of available resources, maintenance costs, production capacity, the gains generated by each item or the expenses established for carrying out an action. In this phase, we determine the components, issues and limits of the problem. All this information is essential for problem formulation **[95]**.

Next, Modeling the problem or moving from text to mathematical equations: To describe (and eventually solve) an optimization problem we use mathematical modeling. The modeling approach involves three steps **[95]**:

- Step 1: Choose the decision variables, which are the components of the system on which we can act. The decision variables are represented by a vector $x = (x_1, x_2, x_3, .. ,x_n)^t \in R^n$ (column vector).
- Step 2: Describe the state of the system, given a configuration of decision variables. This is mathematically equivalent to giving ourselves a function $f : R^n \to R$, which is called an objective function and which we want to make as small or as large as possible.
- Step 3: Describe the constraints that the decision variables satisfy. This amounts to defining a set of constraints $U \subset R^n$ and imposing to have $x \in U$.

To sum up, to describe an optimization problem, we give ourselves

A function $f : R^n \to R$ (cost function, for example)

A set $U \subset R^n$ (set of constraints)

We seek to minimize f on U, i.e., we look for $x* \in U$ such that

$$f(x*) = \min_{x \in U} f(x)$$

Or equivalent

$$f(x*) \leq f(x), \forall\ x \in U.$$

The transition from algorithm, model or solution technique to computer implementation is usually a matter for numerical methods (and other computational techniques). This covers issues such as the accuracy of numerical calculations when using computers, the efficient implementation of matrix inversion techniques, etc. In-depth knowledge is not normally necessary, but some familiarity is useful when trying to adjust the control parameters of solvers you may be using **[95]**.

Moving from the computer implementation to the algorithm, model or solution technique is called verification. The main idea is to make sure that the computer implementation actually executes the algorithm as it is supposed to.

Great concern should be given to validation and sensitivity analysis, the process of transitioning the algorithm, model or solution technique to the real-world problem. This is where the loop is closed and a comparison is made between the results obtained and the real situation. Are the results appropriate? Do they make sense? Should the model be modified or another technical solution chosen? If so, the loop starts again.

Validation involves ensuring that the model or solution technique is appropriate to the real situation. Sensitivity analysis examines the effect of specific data on results.

Sensitivity analysis asks how sensitive the results are to variations in the data (the study of how uncertainty in the output of a code or system (digital or otherwise) can be attributed to uncertainty in its inputs **[95]**. This may show, for example, that the final solution changes very little, even if the inputs vary significantly. In this case, you will breathe a sigh of relief. On the other hand, if it turns out that the results change radically when the inputs change very slightly, you may be worried, especially if there are millions of dollars riding on the outcome of your analysis! In this case, running a number of scenarios showing how things will play out at different input values is necessary in order to arrive at a final recommendation **[95].**

3.2.4 Classification of optimization problems

The classification is based on the main characteristics of an optimization problem. The characteristics differentiating optimization problems are related to the number of objectives (Single-objective, Multi-objective) and constraints (inequality, equality constraint), the type of design variables (i.e. continuous integer, discrete or mixed) and the mathematical properties of all functions (namely linearity or non-linearity, convexity and differentiability),also may be related to the type of data used **[96]**.

None, one or more objectives

Most optimization problems have a single objective function, however, there are interesting cases when optimization problems have no objective function or multiple objective functions. Feasibility problems are problems in which the aim is to find values for variables that satisfy the constraints of a model without any particular objective to optimize.

Complementarity problems are ubiquitous in engineering and economics. The aim is to find a solution that satisfies the complementarity conditions. Multi-objective optimization problems arise in many fields, such as engineering, economics and logistics, when optimal decisions have to be made in the presence of trade-offs between two or more conflicting objectives. For example, developing a new component may involve minimizing weight while maximizing strength, or selecting a portfolio may involve maximizing expected return while minimizing risk. In practice, multi-objective problems are often reformulated as single-objective problems either by forming a weighted combination of the different objectives (aggregation), or by replacing some objectives with constraints **[96]**.

Unconstrained and constrained optimization

Another important distinction concerns problems in which there are no constraints on variables and problems in which there are constraints on variables. Unconstrained optimization problems arise directly in many practical applications; they also arise when reformulating constrained optimization problems in which constraints are replaced by a penalty term in the objective function **[96]**.

Constrained optimization problems arise from applications in which there are explicit constraints on the variables. The constraints imposed on the variables can vary considerably, from simple bounds to systems of equalities and inequalities modeling complex relationships between variables. Constrained optimization problems can be classified according to the nature of the constraints (e.g. linear, non-linear, convex) and the regularity of the functions (e.g. differentiable or non-differentiable) **[96]**.

Continuous versus discrete optimization

Some models only make sense if the variables take values from a discrete set, often a subset of integers, while other models contain variables that can take any real value. Models with discrete variables are discrete optimization problems; models with continuous variables pose continuous optimization problems **[96]**.

Continuous optimization problems tend to be easier to solve than discrete optimization problems; the finesse of the functions means that the values of the objective function and the constraint function at a point x can be used to infer information about points in a neighborhood of x. However, improvements in algorithms, combined with advances in computer technology, have considerably increased the size and complexity of discrete optimization problems that can be solved efficiently. Continuous optimization algorithms are important in discrete optimization because many discrete optimization algorithms generate a sequence of continuous sub-problems **[96]**.

Deterministic versus stochastic optimization

In deterministic optimization, it is assumed that the data for a given problem is known precisely. However, for many problems, the data cannot be known precisely for a variety of reasons. The first reason is simple measurement error. The second, more fundamental reason is that some data represent information about the future (for example, demand for a product or a price for a future period) and simply cannot be known with certainty **[96]**. In optimization under uncertainty, or stochastic optimization, uncertainty is incorporated into the model. Robust optimization techniques can be used when the parameters are known only within certain limits. The aim is to find a solution that is feasible for all data and optimal in one direction. Stochastic programming models take advantage of the fact that the probability distributions governing the data are known or can be estimated; the aim is to find a strategy that is feasible for all (or almost all) possible data instances, and to optimize the model's expected performance **[96].**

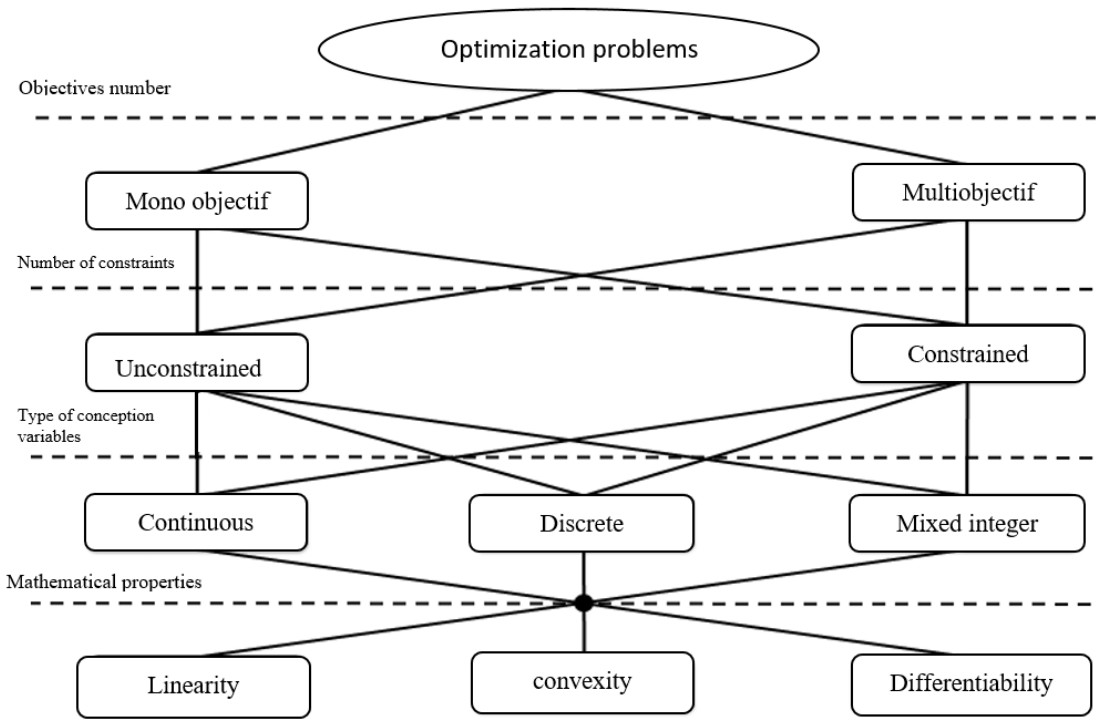


Figure 3. 1: Classification of optimization problems according to [97].

3.3 Multi-objective optimization

As mentioned previously, there are several types of optimization problems, including multi-objective optimization problems.

3.3.1 Basic concepts and terminology

Multi-objective optimization (MOP) problems

Multi-objective optimization (MOP) problems are commonplace. For example, consider the design of a complex hardware/software system such as a Fire andGas system, ESD, cell phone, automobile, etc. The cost of such systems often needs to be minimized, while seeking to maximize performance. Depending on the application, other objectives may be important, such as reliability and power dissipation. These can be defined explicitly as separate optimization criteria, or formulated as constraints, e.g. the system size must not exceed given dimensions.

The general MOP comprises a set of n parameters (decision variables), a set of k objective functions and a set of m constraints. The objective functions and constraints are functions of the decision variables. The optimization objective is to:

Minimize :

$$\boldsymbol{y} = f(\mathrm{x}) = (f_1(\mathrm{x}), f_2(\mathrm{x}), f_3(\mathrm{x}), \ldots\ldots f_m(\mathrm{x})),\ m \geq 2$$

Under the constraints:

$$\boldsymbol{e}(x) = (\mathrm{e}_1(\mathrm{x}), \mathrm{e}_2(\mathrm{x}), \mathrm{e}_3(\mathrm{x}), \ldots\ldots\ \mathrm{e}_m(\mathrm{x})) \leq 0$$

Where $x = (\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots\ldots \mathrm{x}_n) \in \boldsymbol{X}$

$$y = (y_1, y_2, y_3 \ldots\ldots \mathrm{y}_k) \in \boldsymbol{Y}$$

x is the decision vector, y is the objective vector, $\boldsymbol{X}$ is referred to as a decision space and $\boldsymbol{Y}$ is called the objective space (the criteria space) **[98]**.

The constraints $\boldsymbol{e}(x) \leq 0$ determine the set of feasible solutions.

It is generally impossible to find a single solution that optimizes all objectives at the same time. In its place is a set of non-dominated optimal solutions, containing the best solutions in the decision space $\boldsymbol{X}$, called the Pareto-optimal set, which constitutes the Pareto front. This implies that a single solution must be selected from this set of alternative solutions by the decision-maker, who is usually a human.

The feasible set $\mathbf{X}_f$ is defined as the set of decision vectors x satisfying the constraints e(x)

$\mathbf{X}_f$ = {x ∈ X/ e(x) ≤ 0}

The image of $\mathbf{X}_f$, i.e. the feasible region in the objective space, is denoted by :

$\mathbf{Y}_f = f(\mathrm{X}_f) = \cup_{x \in \mathrm{X}_f} \{f(\mathrm{x})\}$.

Since the decision variable vector is in correspondence with the objective function vector, there is a correspondence between the decision space (where the search is performed) and the objective space: there exists a solution in the objective space corresponding to each point in the decision space. The limits of the objective space, being those imposed by the variable limits or the constraint vector, constitute the feasible region of the search space. **Figure 5** shows the correspondence between the decision space and the objective space.

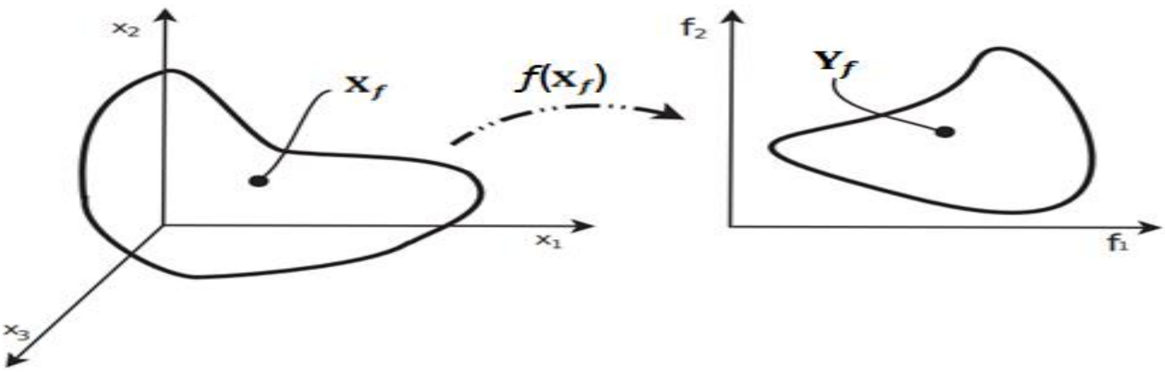


Figure 3. 2: basic concepts: space of decision variables (left) and space of objectives (right).

What makes MOPs difficult is the common situation where the individual optima corresponding to distinct objective functions are sufficiently different. Then, the objectives are in conflict and cannot be optimized simultaneously. Instead, a satisfactory compromise has to be found. For example, the two objective functions (***f1***) for cost unavailability ***(f2)*** are generally in competition: high-performance architectures increase costs considerably, while low-cost architectures generally offer low performance. Depending on market needs, an intermediate solution (medium performance, medium cost) may be an appropriate compromise. This discussion clearly shows that a new notion of optimality is required for MOPs **[99]**.

In single-objective optimization, the set of feasible solutions $\mathbf{Y}_f$ is totally ordered according to an objective function f: let two solutions a, b of $\boldsymbol{X}_f$ be either f(a) ≤f(b) or f(b) ≥ f(a). The aim is to find the solution (or solutions) that gives the minimum value to f. However, when several objectives are involved, the situation changes. The set $\boldsymbol{X}_f$ is, in general, not totally ordered, but partially ordered (Pareto 1896). This is illustrated in **figure 6** on the left.

The solution represented by point B is better than the solution represented by point C: it delivers better performance at a lower cost. The same applies to solution C, which is better than solution D for the same cost. In order to express this situation mathematically, the =, <= and < relations are extended to objective vectors by analogy with the case of single objectives **[100]**.

Les relations

Let us consider two objective vectors u and v,

$$u = v \Leftrightarrow \forall i \in [1, n] : \mathbf{u}_i = \mathbf{v}_i$$

$$u \leq v \Leftrightarrow \forall i \in [1, n] : \mathbf{u}_i \leq \mathbf{v}_i$$

$$u < v \Leftrightarrow \forall i \in [1, n] : \mathbf{u}_i < \mathbf{v}_i$$

The relationships ≥ and > are similarly defined. Using these notions, it turns out that B < C, C < D and, consequently B < D. However, when comparing solutions B and E, neither is inferior to the other, since B ≮ E and E ≮ B. Although the solution associated with E is less costly, it provides poorer performance than the solution represented by B. Therefore, two decision vectors **a** and **b** can have three types of relationship in multi-objective optimization (with respect to the operator): f(a) ≤ (b), f(b) ≤ f(a) or f(a) ≮ f(b) ∧ f(b) ≮ f(a) **[100]**

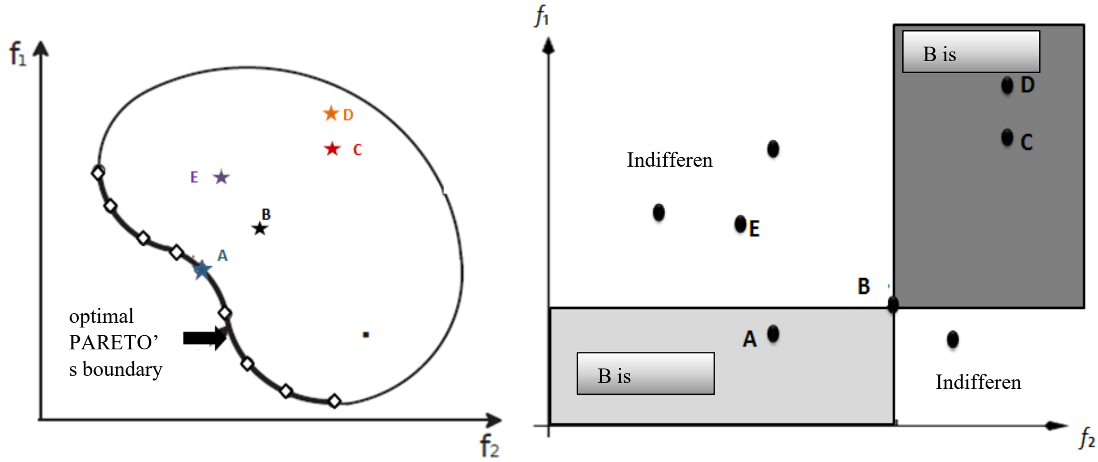


Figure 3. 3: An illustrative example of Pareto optimality in objective space (left) and possible solution relationships in objective space (right).

Pareto domination and optimality

The criteria for determining which of all the solutions in the feasible space are optimal are based on the concept of Pareto dominance and optimality. These allow us to compare any two solutions in the search space in terms of their multiple objectives and determine which are optimal. **[100]**, The solution A dominates another solution B if :

Solution A is no worse than B in all objectives, and

Solution A is better than B in at least one objective.

In the case of minimization, this means:

$\boldsymbol{f_i}$**(A)** $\leq$ $\boldsymbol{f_i}$**(B)** for all **i**$\in$ {1……n}, and

$\boldsymbol{f_i}$**(A)** $<$ $\boldsymbol{f_i}$**(B)** for at least **i**$\in$ {1……n}.

So we say : **A** $\prec$**B**

In the **figure 6** (right), the dark gray rectangle surrounds the region in the objective space that is dominated by the decision vector represented by B. The light gray rectangle contains the objective vectors that correspond to the decision vectors dominating the solution associated with B. All solutions whose corresponding decision vector is neither in the light nor in the dark rectangle are indifferent to the solution represented by B **[100]**.

Based on Pareto's concept of dominance, optimality criteria for POMs can be introduced. **In Figure 6**, A dominates points B, C, D and E: its decision vector a is not dominated by any other decision vector. This means that a is optimal in the sense that it cannot be improved on any objective without causing the degradation of at least one other objective .such solutions are called Pareto optimal solutions **[100]**.

3.3.2 Multi-objective optimization techniques

The multi-objective optimization problem is a vector optimization problem. The generation of the Pareto-Optimal set by classical methods is based on the aggregation principle; other numerical methods based on heuristic and meta-heuristic methods, notably genetic algorithms, provide better solutions to so-called difficult optimization problems.

Treating a multi-objective problem as a single-objective problem

Consists in optimizing a single objective function composed of the sum of all normalized objectives, each multiplied by a user-provided weight, called weighted sum methods. Weights are chosen according to the relative importance of each objective.

Another approach is to optimize only one objective at a time, with the other objectives used as constraints included in an ε-vector. This is known as the ε-contraint method; this method 'often leads to a solution that cannot be the best or most satisfactory **[88].** Goal Programming methods aim to find solutions to achieve a goal or a predefined reference for one or more objectives. If the solution is unattainable, the method seeks to minimize deviations from the target. Methods can use weighted factors for deviations (weighted goal programming) and minimize the weighted sum of deviations (which in effect becomes a single-goal optimization) **[93]** Aggregating multiple objectives into a single optimization criterion has the advantage that classical single-objective optimization strategies can be applied without further modification. However, this requires extensive domain knowledge, which is often not available. Performing the search before the decision is made removes this disadvantage, but excludes the articulation of preferences by the decision-maker, who must reduce the complexity of the search space **[100]**.

3.4 Industrial Optimization

3.4.1 An Overview

Optimization in industrial settings is a critical process that directly impacts the efficiency, productivity, and profitability of manufacturing and production systems. Industrial optimization involves the application of mathematical, computational, and analytical techniques to improve various aspects of industrial operations. These aspects include minimizing costs, maximizing output, reducing waste, improving quality, and ensuring timely delivery of products and services. Industrial optimization can be applied at multiple levels, from the optimization of individual machines and processes to the optimization of entire supply chains and production networks. **[101]**

In a highly competitive global market, industries are continually seeking ways to enhance their performance. This drive for improvement is fueled by the need to meet increasing customer demands, comply with stringent regulatory requirements, and respond to the rapid pace of technological advancements. Optimization allows industries to achieve these objectives by enabling them to make informed decisions about the allocation of resources, the scheduling of tasks, and the design of processes.

One of the primary challenges in industrial optimization is the complexity of the systems involved. Industrial systems are often characterized by a large number of interconnected components, each with its own set of constraints and objectives. This complexity makes it difficult to find optimal solutions using simple, rule-based approaches. Instead, sophisticated optimization techniques are required to navigate the vast solution space and identify the best possible outcomes.

3.4.2 Traditional vs. Modern Optimization Techniques

Traditional optimization techniques, such as linear programming, integer programming, and gradient-based methods, have long been used to solve industrial optimization problems. These techniques are effective when the problem is well-defined, linear, and involves a relatively small number of variables. For example, linear programming is commonly used in operations research to solve problems related to resource allocation, production planning, and transportation. However, traditional methods have several limitations when applied to complex industrial problems. Many industrial systems are inherently nonlinear, meaning that the relationship between variables cannot be accurately captured by linear equations. In addition, industrial problems often involve a large number of variables and constraints, making them computationally expensive to solve using traditional methods. Moreover, these methods are typically designed to find a single, optimal solution, which may not be suitable for problems with multiple conflicting objectives **[102]**. As industrial problems have grown in complexity, the limitations of traditional optimization methods have become increasingly apparent. This has led to the development and adoption of modern optimization techniques, particularly metaheuristic algorithms, which are better suited to handling the challenges of industrial optimization.

Metaheuristic algorithms differ from traditional methods in several key ways. First, they are designed to handle nonlinear, complex, and large-scale problems. Second, they do not require gradient information or other problem-specific details, making them more flexible and widely applicable. Third, metaheuristics are capable of exploring a vast solution space to find near-optimal solutions, even for problems that are difficult or impossible to solve exactly. Finally, many metaheuristic algorithms are population-based, meaning that they maintain and evolve a set of candidate solutions simultaneously, which enhances their ability to avoid local optima and converge to a global solution. **[102]**

3.4.3 The Rise of Metaheuristic Methods

The growing complexity of industrial problems has driven the rise of metaheuristic methods as a powerful alternative to traditional optimization techniques. Metaheuristics are particularly well-suited to solving industrial optimization problems because they are designed to explore large and complex search spaces efficiently. Unlike traditional methods, which may struggle to find optimal solutions in the presence of nonlinearity, multiple objectives, and a large number of constraints, metaheuristics are capable of navigating these challenges effectively **[103].**

Natural processes, such as evolution, the behavior of swarms, inspire metaheuristic algorithms. These algorithms mimic the strategies used by biological or physical systems to find optimal solutions in complex environments. For example, Genetic Algorithms (GAs) simulate the process of natural selection, while Particle Swarm Optimization (PSO) is inspired by the social behavior of birds and fish. Ant Colony Optimization (ACO) models the foraging behavior of ants, and Manta Ray foraging optimization (MRFO) mimics the foraging behavior of manta ray.

The success of metaheuristic methods in industrial optimization can be attributed to several factors **[103]**:

- **Flexibility**: Metaheuristics are not limited by the assumptions of linearity or differentiability, making them applicable to a wide range of industrial problems.

- **Robustness**: These algorithms are capable of handling noisy, dynamic, and uncertain environments, which are common in industrial settings.
- **Scalability**: Metaheuristics can be applied to large-scale optimization problems with many variables and constraints, making them suitable for complex industrial systems.

- **Multi-objectivity**: Many industrial problems involve multiple conflicting objectives. Metaheuristic algorithms, particularly multi-objective metaheuristics, are designed to find a set of trade-off solutions that balance these objectives.

- **Global Search Capability**: Metaheuristics are designed to explore the global solution space, reducing the risk of getting trapped in local optima and increasing the likelihood of finding the best possible solution.

Due to these advantages, metaheuristic methods have become increasingly popular in industrial optimization. They are now widely used in various industrial applications, including production scheduling, supply chain management, process optimization, quality control, and resource allocation.

3.5 Metaheuristic Methods for Industrial Optimization

Metaheuristic methods have emerged as powerful tools for solving complex optimization problems, particularly in industrial contexts. These methods offer a flexible and robust approach to finding near-optimal solutions in environments where traditional optimization techniques may fail due to the complexity, non-linearity, and scale of the problems. This section provides an in-depth exploration of metaheuristic algorithms, focusing on their general characteristics, effectiveness, and classification, and highlighting their significant impact on industrial optimization.

3.5.1 Overview of Metaheuristic Algorithms

Metaheuristics are high-level strategies that guide the search process for optimal solutions in complex optimization problems. Unlike exact optimization methods, which guarantee finding the optimal solution but may be computationally infeasible for large-scale problems, metaheuristics focus on finding good enough solutions within a reasonable time frame. They are particularly valuable in industrial applications where the solution space is vast, and the relationships between variables are non-linear and complex **[103]**.

The core idea behind metaheuristics is to combine different search strategies to explore the solution space effectively. These strategies involve both exploration and exploitation:

- Exploration refers to the process of searching through new, unexplored regions of the solution space. This helps to avoid getting trapped in local optima and ensures a comprehensive search for the global optimum.
- Exploitation involves refining the best-known solutions to improve their quality. This process is essential for converging towards the optimal solution once promising regions of the solution space have been identified.

Metaheuristic algorithms are designed to balance these two processes, ensuring that the search is both broad enough to explore the entire solution space and focused enough to converge on high-quality solutions. This balance is crucial for the success of metaheuristics, especially in solving industrial optimization problems, where the solution landscape is often rugged and multi-modal **[103]**.

3.5.2 Effectiveness of Metaheuristic Methods

The effectiveness of metaheuristic methods in industrial optimization stems from their ability to handle the inherent complexity and uncertainty of industrial systems. These methods are designed to find high-quality solutions in a reasonable amount of time, making them ideal for real-world industrial applications where time and computational resources are often limited.

Several factors contribute to the effectiveness of metaheuristics in solving industrial optimization problems **[104]**:

- Ability to Handle Non-linearity and Discontinuity: Industrial problems often involve non-linear relationships between variables, as well as discontinuities in the solution space. Metaheuristics do not require gradient information, making them well-suited for optimizing non-linear and discontinuous functions.
- Multi-objective Optimization: Many industrial problems involve multiple conflicting objectives, such as minimizing cost while maximizing quality. Metaheuristics, particularly those designed for multi-objective optimization, can generate a set of Pareto-optimal solutions that provide a trade-off between competing objectives. This capability is essential for decision-makers in industry, who must often balance multiple factors when selecting the best solution.
- Robustness to Noise and Uncertainty: Industrial environments are often subject to noise, uncertainty, and changing conditions. Metaheuristic algorithms are robust to these

challenges, as they can adapt their search strategies in response to changing information and are less sensitive to noisy data compared to traditional optimization methods.

- Scalability: Industrial optimization problems can involve a large number of variables and constraints. Metaheuristics are scalable and can be applied to large-scale problems without a significant loss of performance. This makes them suitable for optimizing complex industrial systems that involve many interacting components.
- Global Search Capabilities: One of the key strengths of metaheuristics is their ability to perform a global search across the solution space. This reduces the likelihood of the algorithm getting trapped in local optima, which is a common issue with traditional optimization methods. By exploring the solution space more broadly, metaheuristics increase the chances of finding the global optimum or a solution close to it.
- Adaptability: Metaheuristics are highly adaptable and can be customized to suit specific industrial problems. This adaptability allows them to be fine-tuned to the characteristics of the problem at hand, improving their performance and the quality of the solutions they produce.

Given these advantages, metaheuristic methods have been successfully applied to a wide range of industrial optimization problems, including production scheduling, supply chain management, resource allocation, and process optimization. Their ability to provide high-quality solutions in complex and dynamic environments has made them indispensable tools in modern industrial optimization.

3.5.3 Classification of Metaheuristic Algorithms

Metaheuristic algorithms can be classified based on various criteria, such as the nature of their search strategies, the inspiration behind their design, and their application domains. A common way to classify metaheuristics is by dividing them into two broad categories: nature-inspired algorithms and non-nature-inspired algorithms **[105]**.

Nature-Inspired Algorithms

Nature-inspired metaheuristics draw their inspiration from natural processes, such as biological evolution, the behavior of social animals, or physical phenomena. These algorithms are often designed to mimic the strategies used by nature to find optimal solutions in complex environments. Some of the most well-known nature-inspired metaheuristics include **[105]**:

- Genetic Algorithms (GA): Inspired by the process of natural selection and genetics, GAs use a population of candidate solutions that evolve over generations. The algorithm applies operators such as selection, crossover, and mutation to create new solutions, gradually improving the quality of the population. GAs are particularly effective in solving problems where the solution space is large and the relationships between variables are non-linear.
- Particle Swarm Optimization (PSO): PSO is inspired by the social behavior of birds flocking or fish schooling. In PSO, a swarm of particles moves through the solution space, with each particle adjusting its position based on its own experience and the experience of its neighbors. This collaborative approach allows the swarm to efficiently search for the global optimum, making PSO a powerful tool for continuous optimization problems.
- Ant Colony Optimization (ACO): ACO is inspired by the foraging behavior of ants. Ants communicate with each other using pheromone trails, which guide other ants to food

sources. In ACO, artificial ants explore the solution space by constructing paths based on pheromone information and heuristic factors. ACO is particularly well-suited for combinatorial optimization problems, such as routing and scheduling.

- Manta Ray foraging optimization (MRFO): Manta Ray foraging optimization Manta rays employ various foraging strategies that optimize their feeding efficiency in natural habitats. These strategies are reflected in the development of algorithms inspired by their foraging behavior, which can be applied to solve complex optimization problems.

Non-Nature-Inspired Algorithms

While nature-inspired algorithms are the most popular and widely used, there are also several metaheuristics that are not directly inspired by natural processes. These non-nature-inspired algorithms include **[105]**:

- Tabu Search (TS): Tabu Search is a neighborhood-based search algorithm that uses a memory structure (the "tabu list") to keep track of recently visited solutions and avoid cycling back to them. TS explores the solution space by moving from one solution to a neighboring solution, with the tabu list helping to prevent the search from getting trapped in local optima.
- Greedy Randomized Adaptive Search Procedure (GRASP): GRASP is a multi-start metaheuristic that constructs solutions by combining greedy heuristics with randomization. Each iteration of GRASP generates a new solution, which is then refined using local search. The best solution found over multiple iterations is selected as the final solution.
- Variable Neighborhood Search (VNS): VNS is a systematic approach that explores different neighborhoods of the current solution. By changing the neighborhood structure during the search process, VNS can escape local optima and explore different regions of the solution space, increasing the chances of finding a global optimum.

Single-Solution-Based vs. Population-Based Metaheuristics

Another way to classify metaheuristics is based on whether they operate on a single solution or a population of solutions **[105]**:

- **Single-Solution-Based Metaheuristics**: These algorithms work with a single candidate solution at any given time and iteratively improve it through local search or other operators. Examples include Simulated Annealing, Tabu Search, and Variable Neighborhood Search. Single-solution-based metaheuristics are often more straightforward to implement and can be highly effective for specific types of problems.
- **Population-Based Metaheuristics**: These algorithms maintain a population of candidate solutions that evolve or are refined simultaneously. The population-based approach allows for greater diversity in the search process, reducing the risk of getting trapped in local optima. Examples include Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization. Population-based metaheuristics are generally more robust and are well-suited for complex optimization problems with large solution spaces.

Hybrid Metaheuristics

In many cases, combining different metaheuristic methods can yield better results than using a single algorithm. Hybrid metaheuristics take advantage of the strengths of multiple algorithms to improve the overall performance and solution quality. For example, a hybrid approach might use a Genetic Algorithm to explore the solution space globally, followed by manta ray foraging optimization to fine-tune the best solutions locally. Such combinations can be particularly effective in industrial optimization, where different aspects of the problem may require different optimization strategies **[103]**.

3.5.4 Applications of Metaheuristic Methods in Industrial Optimization

Metaheuristic methods have found wide-ranging applications in various industrial optimization problems, reflecting their versatility and effectiveness. Some of the key areas where metaheuristics have been successfully applied include **[103]**:

- **Production Scheduling**: Production scheduling is a critical aspect of industrial operations, involving the allocation of resources, machines, and labor to produce goods within specified timeframes. Metaheuristic algorithms, such as Genetic Algorithms and Ant Colony Optimization, have been used to solve complex scheduling problems, optimizing the sequence of tasks to minimize production time, reduce costs, and meet delivery deadlines.
- **Supply Chain Management**: Supply chain management involves coordinating the flow of materials, information, and products across multiple stages of production and distribution. Metaheuristics have been applied to optimize various aspects of supply chain management, including inventory control, transportation logistics, and supplier selection. For example, Particle Swarm Optimization has been used to optimize inventory levels in dynamic supply chains, while manta ray foraging optimization has been applied to optimize transportation routes and reduce costs.
- **Process Optimization**: In industrial processes, optimization is often required to improve the efficiency and quality of production. Metaheuristic methods have been used to optimize process parameters, such as temperature, pressure, and flow rates, to achieve desired outcomes. For example, Genetic Algorithms have been used to optimize chemical processes, while Artificial Bee Colony algorithms have been applied to optimize machining operations in manufacturing.
- **Quality Control**: Ensuring the quality of products is essential in industrial operations. Metaheuristics have been used to optimize quality control processes, such as inspection scheduling and defect detection. For example, Ant Colony Optimization has been applied to optimize inspection routes in manufacturing plants, while Particle Swarm Optimization has been used to optimize defect detection algorithms in automated inspection systems.
- **Resource Allocation**: Resource allocation involves assigning limited resources, such as machines, labor, and materials, to various tasks in an industrial setting. Metaheuristics have been used to optimize resource allocation in manufacturing, construction, and service industries. For example, Genetic Algorithms have been applied to optimize the allocation of resources in construction projects, while manta ray foraging optimization has been used to optimize the allocation of machines in manufacturing plants.
- **Energy Optimization**: Energy consumption is a significant cost factor in industrial operations. Metaheuristics have been used to optimize energy usage in various industries, such as optimizing the operation of HVAC systems in buildings, optimizing the scheduling of energy-intensive processes, and optimizing the operation of renewable energy systems. For example, Particle Swarm Optimization has been applied to optimize the operation of

wind farms, while Genetic Algorithms have been used to optimize the scheduling of energy-intensive processes in manufacturing.

- **Maintenance Scheduling**: Maintenance scheduling involves planning and scheduling maintenance activities to ensure the reliability and availability of industrial equipment. Metaheuristics have been applied to optimize maintenance schedules, balancing the need for preventive maintenance with the desire to minimize downtime and costs. For example, Particle Swarm Optimization has been used to optimize the scheduling of maintenance activities in manufacturing plants and power plants.

3.5.5 Challenges and Future Directions

While metaheuristic methods have proven to be effective tools for industrial optimization, several challenges remain. These challenges include the need for improved scalability, the development of more efficient algorithms, and the integration of metaheuristics with other optimization techniques and technologies **[106]**.

- **Scalability**: As industrial systems become increasingly complex, the scalability of metaheuristic algorithms becomes a critical issue. Developing metaheuristics that can handle large-scale problems efficiently is an ongoing challenge.
- **Algorithm Efficiency**: While metaheuristics are effective at finding near-optimal solutions, they can be computationally expensive. Developing more efficient algorithms that can find high-quality solutions with less computational effort is a key area of research.
- **Integration with Other Techniques**: Integrating metaheuristics with other optimization techniques, such as machine learning and artificial intelligence, holds great promise for improving the performance of these algorithms. For example, combining metaheuristics with data-driven approaches can enhance their ability to adapt to dynamic environments and make better use of available data.
- **Real-time Optimization**: In some industrial applications, optimization needs to be performed in real-time. Developing metaheuristics that can provide high-quality solutions within tight time constraints is an important area of research.
- **Adaptability and Robustness**: As industrial environments become more dynamic and uncertain, the need for adaptable and robust optimization algorithms increases. Developing metaheuristics that can adapt to changing conditions and maintain their performance in the face of uncertainty is a key challenge.

Despite these challenges, the future of metaheuristic methods in industrial optimization is bright. Advances in computing power, the availability of large datasets, and the development of new algorithms and techniques are likely to further enhance the effectiveness of metaheuristics in solving complex industrial optimization problems. As industries continue to face increasing pressure to improve efficiency, reduce costs, and enhance quality, metaheuristic methods will play an increasingly important role in helping them achieve these goals.

In the following sections, we will explore some of the most widely used metaheuristic algorithms Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and manta ray foraging optimization. We will discuss their principles, applications, and effectiveness in solving industrial optimization problems, providing a comprehensive understanding of how these powerful tools can be used to tackle the complex challenges faced in industrial systems.

3.6 Metaheuristic methods

3.6.1 Genetic algorithm

3.6.1.1 Introduction to Genetic Algorithms

Genetic Algorithms (GAs) are a class of optimization techniques inspired by the principles of natural selection and genetics. First introduced by John Holland in the 1970s, GAs have since become a popular tool for solving complex optimization problems, particularly in scenarios where traditional methods struggle due to the size, complexity, or non-linearity of the problem space. GAs simulate the process of evolution, using mechanisms such as selection, crossover, and mutation to evolve a population of potential solutions toward an optimal or near-optimal solution **[107]**.

3.6.1.2 Conceptual Foundations of Genetic Algorithms

The core idea behind GAs is the representation of potential solutions as individuals in a population, which evolves over successive generations. Each individual, often encoded as a string of binary digits (though other representations like real numbers or permutations can be used), represents a candidate solution. The evolutionary process is driven by the following key components **[107]**:

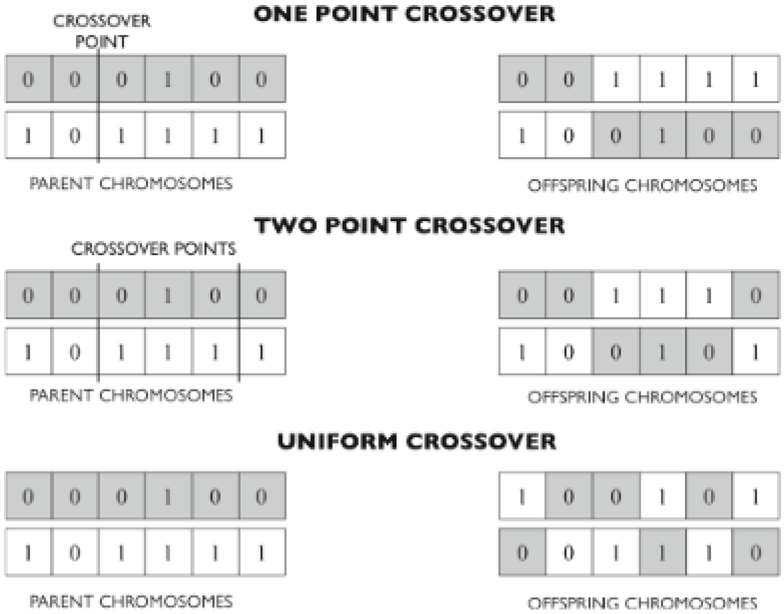
- **Population**: A group of individuals, each representing a potential solution to the problem.
- **Fitness Function**: A function that evaluates how good a solution is by assigning a fitness score to each individual based on how well it solves the problem.
- **Selection**: A process that selects individuals from the current population to act as parents for the next generation. Fitter individuals have a higher probability of being selected.
- **Crossover (Recombination)**: A genetic operator that combines two parent solutions to produce offspring, potentially inheriting characteristics from both parents.
- **Mutation**: A genetic operator that introduces small, random changes to an individual, promoting diversity within the population and helping to explore new areas of the solution space.

3.6.1.3 Steps of Genetic Algorithms

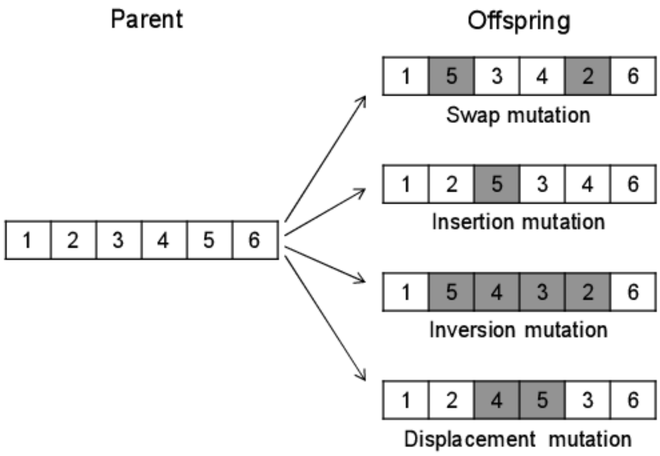
A typical GA involves the following steps:

- ✓ **Initialization**:
  - Randomly generate an initial population of NNN individuals.
  - Encoding: Genetic algorithms operate by initially defining a population of candidate solutions (each of which is called an individual). Individuals are encoded in an abstract representation, known as a chromosome
- ✓ **Evaluation**:
  - Compute the fitness of each individual using the fitness function.
- ✓ **Selection**:
  - Select individuals for reproduction based on their fitness. Common selection methods include roulette wheel selection, tournament selection, and rank-based selection.
- ✓ **Crossover**:

- Apply crossover to selected pairs of individuals to produce offspring. Crossover generate new solutions from an existing population, it can be single-point, multi-point, or uniform, depending on how the parents' genes are combined. **[108]**



- ✓ **Mutation**:
  - The mutation operator is used for exploration with randomly altering genes in chromosomes to discover new horizons and new traits. Mutation helps to diversify the population, thus helping GAs to avoid local optima and pave the way towards global optima The mutation rate determines how often mutations occur **[109].**



- ✓ **Replacement**:
  - Replace the current population with the new generation, usually by selecting the best individuals from both the parents and offspring.
- ✓ **Termination**:
  - Repeat the evaluation, selection, crossover, and mutation steps until a stopping criterion is met (e.g., a fixed number of generations, convergence to a solution, or achieving a desired fitness level).

3.6.1.4 Advantages of Genetic Algorithms in Industrial Optimization

Genetic Algorithms offer several advantages when applied to industrial optimization problems **[107]**:

- **Global Search Capability**: GAs are well-suited for exploring large and complex search spaces, often finding global optima where traditional methods might get trapped in local optima.
- **Versatility**: GAs can be applied to a wide range of optimization problems, including those that are nonlinear, discontinuous, or have multiple conflicting objectives.
- **Parallelism**: The population-based approach of GAs allows for parallel processing, which can significantly speed up the search process.
- **Flexibility in Representation**: GAs can handle various types of solution representations (binary, real-valued, permutations), making them adaptable to different problem domains.

3.6.1.5 Applications of Genetic Algorithms in Industrial Systems

Genetic Algorithms have been successfully applied to various industrial optimization problems, including **[107]**:

- **Scheduling**: GAs are used to optimize production schedules, balancing multiple objectives such as minimizing completion time, reducing setup costs, and maximizing resource utilization.
- **Design Optimization**: GAs help in optimizing the design of products and systems, such as aerodynamic shapes, circuit layouts, and mechanical structures, to improve performance and reduce costs.
- **Control Systems**: GAs are applied in the optimization of control system parameters, enhancing the stability and responsiveness of industrial processes.
- **Logistics and Supply Chain Management**: GAs optimize routing, inventory management, and distribution strategies, reducing costs and improving service levels in supply chains.

3.6.1.6 Challenges and Limitations of Genetic Algorithms

While GAs are powerful optimization tools, they are not without challenges **[107]**:

- **Parameter Sensitivity**: The performance of GAs depends on the proper tuning of parameters, such as population size, crossover rate, and mutation rate. Poorly chosen parameters can lead to premature convergence or inefficient searches.
- **Computationally Intensive**: GAs can be computationally expensive, particularly for large populations or complex fitness evaluations, making them less suitable for real-time or resource-constrained applications.
- **No Guarantee of Optimality**: GAs do not guarantee finding the global optimum, especially in highly complex or noisy search spaces. They may instead converge to a near-optimal solution.

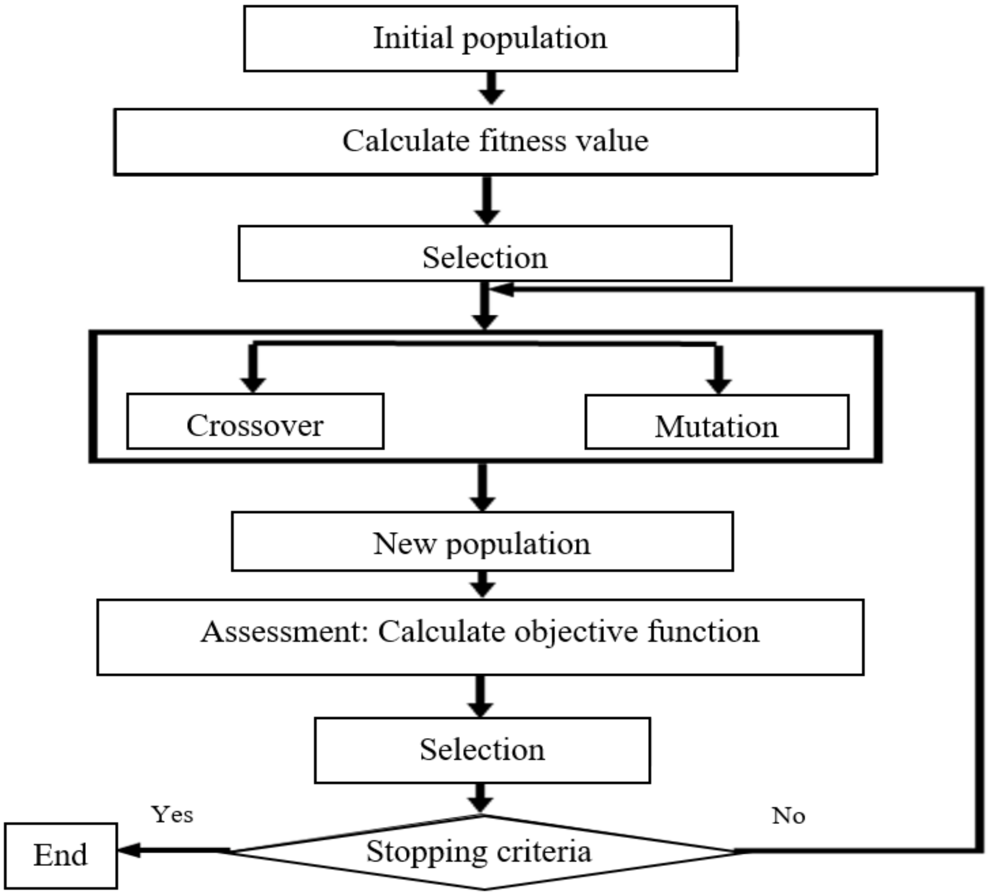


Figure 3. 4: Flowchart of a genetic algorithm.

3.6.2 Particle swarm optimization algorithm

3.6.2.1 Particle swarm optimization

In computational science, Particle Swarm Optimization (PSO) is an optimization technique that iteratively (iterative method is a mathematical procedure that uses an initial value to generate a sequence of improving approximate solutions for a class of problems, in which the i^{th} approximation is derived from the previous ones) seeks to enhance a candidate solution based on a specific quality measure. This method involves a population of candidate solutions, referred to as particles, which navigate the search space by following mathematical rules governing their position and velocity. Each particle's movement is influenced by its own best-known position and is also guided towards the best-known positions discovered by other particles in the swarm. As the search progresses and better positions are identified, the swarm collectively gravitates towards optimal solutions. **[110]**

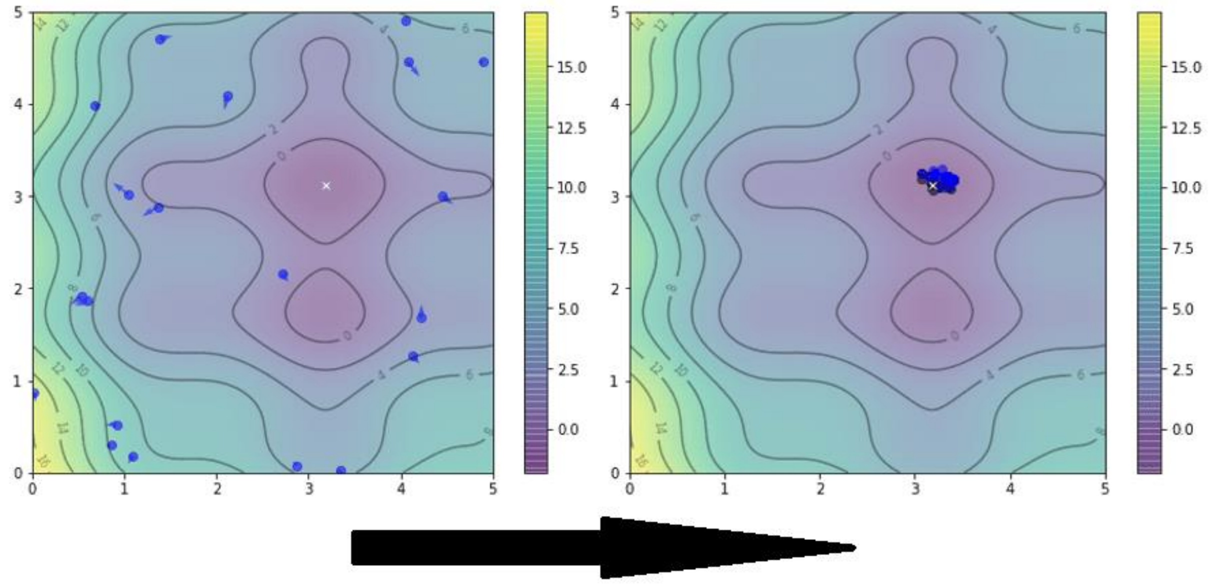


Figure 3. 5: illustration of swarm gathered around the optimal solution in the search space.

Kennedy and Eberhart developed particle swarm optimization, or PSO, in 1995 **[111]** as a model for simulating social behavior, specifically the movement patterns of organisms like birds in a flock or fish in a school. Over time, the algorithm was simplified, and it was discovered that it could effectively be used for optimization tasks. Due to its versatility and ease of use, PSO has developed to become one of the most widely used swarm-intelligence-based algorithms.

3.6.2.2 Conception of PSO

PSO uses global communication and real-number randomization among the swarm particles **[112].** By randomly reshaping the particle trajectories in piecewise ways according to positional vectors, the PSO algorithm explores the space of an objective function **[112]**. There are two main parts to the formation of a swarming particle a deterministic component and a stochastic component. While moving randomly, each particle is drawn in the direction of its individual optimal location Xi and the current global best g. A particle upgrades a location to the current best for particle i when it finds one that is more optimal than all previously discovered regions. Through iterations, a current best is found for all n particles. The goal is to identify the global best solution out of all the existing best arrangements until the goal is no longer met or after a predetermined number of repetitions **[112].** Every particle's position is a possible solution to the optimization problem; the method iteratively updates these positions by taking into account both the best places that their surrounding particles have obtained and their own previous best positions.

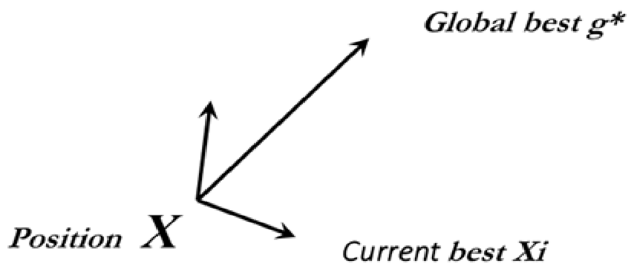


Figure 3. 6: Schematic representation the particle i moving toward the global best and the current best Xi.

In PSO, each particle has the following attributes:

Position: Represents a candidate solution in the solution space.

Velocity: Determines the direction and speed of the particle's movement.

Personal Best Position (P_{Best}): The best position that a particle has found so far.

Global Best Position (G_{Best}): The best position found by any particle in the entire swarm.

3.6.2.3 Math of particle swarm optimization

The mathematical representation of the PSO algorithm involves updating the position and velocity of each particle at each iteration. Each particle tries to modify its position *X*i at a moment t to another position Xi at the net moment t+1 by a velocity Vi(t), using the following formula **[112]**:
Every iteration of the PSO algorithm's mathematical formulation entails updating each particle's position and velocity (moving speed). Each particle attempts to change its position Xi at a moment t to another position Xi at the moment t+1 by a velocity Vi (t). Using the following formula,

$Xi\,(t+1) = Xi(t) + Vi(t+1)$

Where Vi(t+1) is the velocity (speed) of the particle i at time t+1.

Vi(t+1) discussed with the formula:

$Vi(t+1) = Wi.Vi(t) + c_1.rand().(X_{\mathbf{pbest}} - Xi(t)) + c_2.rand().(X_{\mathbf{gbest}} - Xi(t))$

Where ‘Xpbest’ is the particle's best position, ‘Xgbest’ is the global best position, and ‘Wi’ is the inertia weight. Learning and accelerating variables are represented by ‘c1’ and ‘c2’, and a random number between 0 and 1 is represented by ‘rand ()’. Until a stopping condition is satisfied, such as reaching a maximum number of iterations or arriving to a workable solution, the algorithm keeps on iterating.

3.6.2.4 Particle swarm optimization parameters and their effect on the algorithm

Several optimization parameters are included in the PSO algorithm, including the maximum iteration number T_{max}, the inertia weight w, the particle number m, and the accelerate constants c1 and c2. **[113]**

Inertia weight: demonstrates how speed in the past affects speed in the present. Its selection could adjust PSO's ability to search both locally and globally **[114]**.

Particle numbers: Considering that a large uniform initialization conspire is used to initialize the particles. Larger swarms allow larger portions of the search space to be covered per iteration **[114].**

Accelerate constant ‘c1’ and ‘c2’: weight toward the personal best (p best) and the global best (g best) is the particle stochastic speeding up. However, a large acceleration constant may cause the molecule to go quickly to the target location and even fly there. A little acceleration constant may cause the particle to drift missing in the objective area **[114].**

Number of iterations: the number of cycles (iteration) required to reach the optimal configuration varies based on the type of problem. Moreover, the search may end abruptly after a few cycles. On the other hand, too many cycles result in superfluous computational complexity **[114].**

3.6.2.5 Steps of swarm optimization algorithm

Based on the above the PSO algorithm operates according to the following steps **[115]**:

- Initialization: Disperse a population of particles at random throughout the search space. Everybody starts at a randomly determined position and speed.
- Evaluation: Determine each particle's fitness by applying the goal function to its current position and comparing it to the necessary fitness value.
- Update each particle's optimal location: Every particle strives to achieve its optimal position, taking into account its current fitness level. If the particle's current fitness is higher than its prior best, update the particle's best position.
- Update the global best position by identifying the particle in the population with the highest fitness score. The ideal global position is determined by this particle's optimum position.
- Update particle velocity and position based on current positions (personal best) and the best positions found thus far (global best).
- The loop: Continue updating and evaluating until a termination condition is satisfied. This criterion may be the attainment of a target fitness value, a maximum number of iterations, or the inability to progress after a predetermined number of iterations.

- Output: The method shows the best result, which is represented by the global best position, after the termination requirement is satisfied.

3.6.2.6 Advantages of PSO in Industrial Optimization

PSO offers several advantages when applied to industrial optimization problems **[115]**:

- **Simplicity and Ease of Implementation**: PSO is easy to implement and requires few parameters to be adjusted, making it accessible for a wide range of problems.
- **Robustness**: PSO is robust and can effectively handle complex, nonlinear, and multi-objective optimization problems.
- **Flexibility**: PSO can be adapted to various types of optimization problems, including continuous, discrete, and combinatorial problems.
- **Convergence**: PSO typically converges quickly to a good solution, especially in well-defined search spaces.

3.6.2.7 Applications of PSO in Industrial Systems

PSO has been successfully applied to various industrial optimization problems **[115]**, such as:

- **Scheduling**: PSO is used to optimize production schedules, minimizing production time and costs while maximizing resource utilization.
- **Supply Chain Management**: PSO helps optimize the design and operation of supply chains, improving efficiency and reducing costs.
- **Energy Systems**: PSO is applied in the optimization of energy systems, including the scheduling of power generation and the management of renewable energy resources.
- **Manufacturing Processes**: PSO is used to optimize various manufacturing processes, such as machining operations and assembly line balancing, to improve productivity and reduce waste.

3.6.2.8 Challenges and Limitations of PSO

1. While PSO is a powerful optimization tool, it is not without its challenges and limitations **[115]**:

- **Local Minima**: PSO may converge prematurely to a local minimum rather than the global optimum, especially in complex landscapes.
- **Parameter Sensitivity**: The performance of PSO is sensitive to its parameters (inertia weight, cognitive and social coefficients), requiring careful tuning.
- **Scalability**: As the dimensionality of the problem increases, the performance of PSO may degrade, requiring modifications to maintain effectiveness.

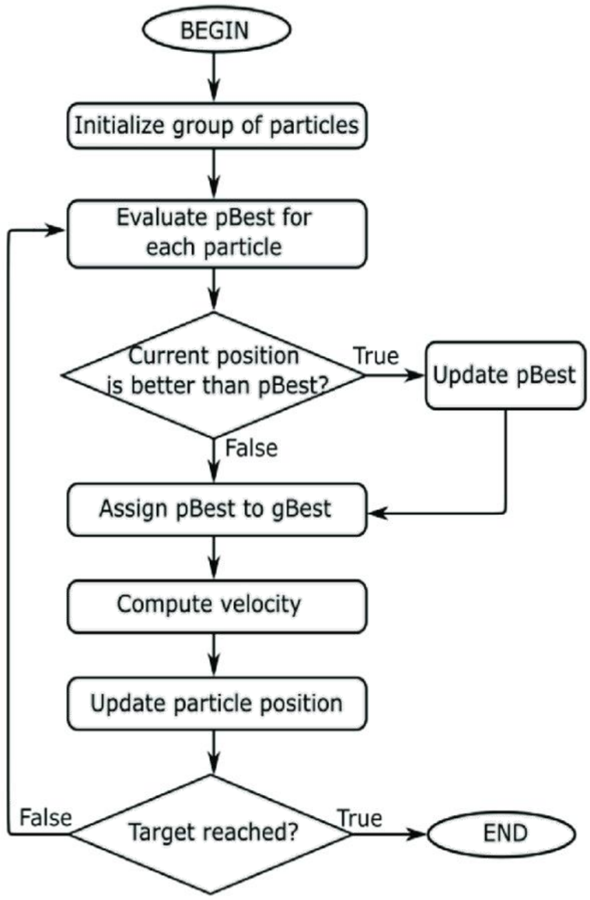


Figure 3. 7: Particle swarm optimization Flow chart. [40]

3.6.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a widely recognized metaheuristic algorithm inspired by the foraging behavior of ants. This algorithm has proven to be highly effective in solving complex discrete optimization problems, making it particularly useful in industrial applications. The section provides an in-depth exploration of ACO, discussing its foundational principles, algorithmic structure, and diverse applications in industrial optimization.

3.6.3.1 Inspiration and Biological Background

The inspiration for ACO comes from the way real ants search for food and establish the shortest paths between their colony and food sources. In nature, ants deposit a chemical substance known as pheromone on the ground as they move. This pheromone trail acts as a communication mechanism among ants. When an ant finds a food source, it returns to the colony, reinforcing the path with additional pheromone. Over time, shorter paths, which are traversed more frequently, accumulate more pheromone, thereby attracting more ants. This positive feedback loop naturally leads to the emergence of the optimal path to the food source **[116]**.

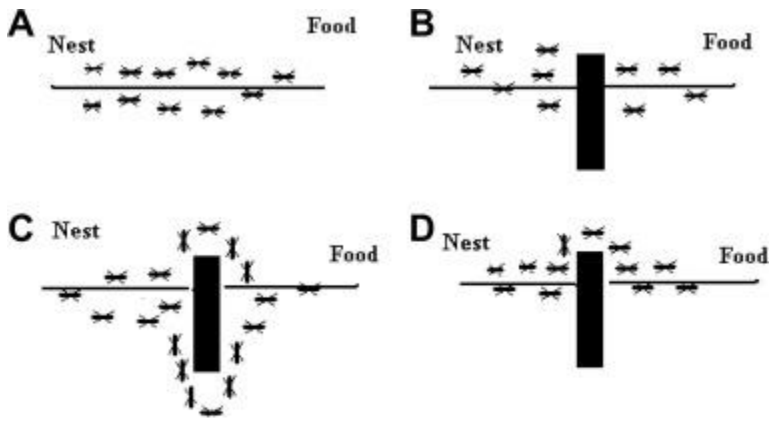


Figure 3. 8: Real ants behavior [116].

The **figure 11** illustrates the behavior of ants in finding the shortest path to a food source through pheromone-based communication. Initially, as shown in Panel A, ants leave the nest and explore randomly in search of food, moving directly toward the source with uniformly distributed pheromone trails along their path. In Panel B, an obstacle is introduced, blocking the direct route. This forces some ants to choose between going left or right around the obstacle, with the pheromone trails remaining evenly distributed since the ants are encountering the obstacle for the first time.

In Panel C, as the ants navigate around the obstacle, they begin to lay pheromones on the paths they take, with some choosing the left and others the right path. Initially, both paths around the obstacle accumulate pheromones at a similar rate. However, by Panel D, more ants start following the shorter path as it becomes reinforced with more pheromone due to its quicker traversal time. Over time, this positive feedback loop leads to the majority of ants selecting the shorter path, resulting in the optimal route being established. This behavior exemplifies how ants, through simple local interactions and pheromone trails, collectively discover the most efficient path, even in the presence of obstacles, a process that forms the basis of the Ant Colony Optimization (ACO) algorithm.

Marco Dorigo and his colleagues first introduced ACO in the early 1990s as a computational algorithm that simulates this ant behavior to solve discrete optimization problems. The algorithm models the collective foraging process of ants to explore and exploit the search space, ultimately converging on high-quality solutions **[117].**

3.6.3.2 Basic Structure of Ant Colony Optimization

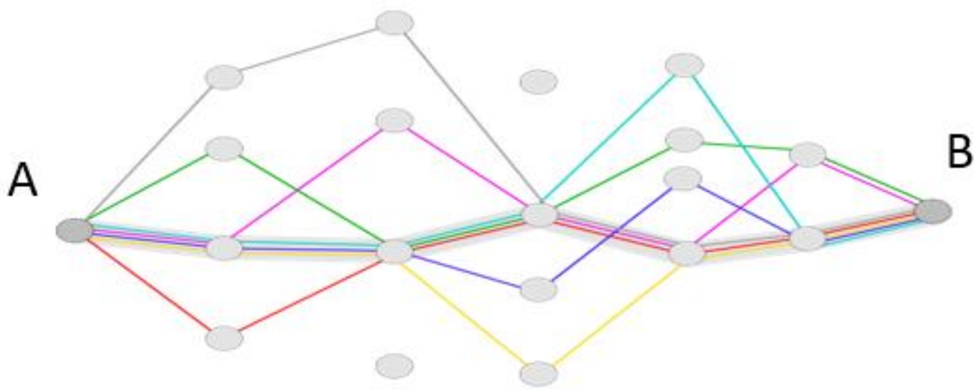


Figure 3. 9: Ants paths from nest to food.

The basic structure of ACO revolves around a population of artificial ants that construct solutions to an optimization problem iteratively. The key components of ACO are as follows **[118]**:

- **Representation of Solutions**: Each ant constructs a solution incrementally by moving from one decision point to another. The problem is represented as a graph, where the nodes represent decision points, and the edges represent possible choices.
- **Pheromone Update**: As ants construct their solutions, they deposit pheromone on the edges of the graph. The amount of pheromone deposited is proportional to the quality of the solution. Over time, edges that are part of better solutions accumulate more pheromone, making them more attractive to other ants. Pheromone evaporation is also applied to avoid the algorithm converging too quickly on suboptimal solutions. This evaporation ensures that the algorithm continues to explore new regions of the search space.
- **Solution Construction and Evaluation**: Each ant builds a complete solution by traversing the graph. Once all ants have constructed their solutions, the quality of each solution is evaluated. The best solution found by the colony during an iteration is used to update the pheromone levels, reinforcing the paths that contribute to the best solution.
- **Iteration and Convergence**: The process is repeated over many iterations, with the pheromone levels continually updated based on the quality of solutions found. As the algorithm progresses, the colony converges towards the optimal or near-optimal solution. The balance between exploration and exploitation is controlled by the parameters of the algorithm, such as the rate of pheromone evaporation and the weight given to heuristic information.

3.6.3.3 Steps of ACO

Key terms of ACO

- Ant **K**: any possible solution.
- Population **N**: group of all ants.
- Search space **[lb,ub]**: all possible solutions to the problem.
- Step size: search space is divided by step size **h.**
- Pheromone trail **Ͳ.**
- scaling parameter **ʐ.**
- Evaporation rate **P.**

- **Step 1: Initialization**

- Assume a suitable number of ants in the colony (population **N**).
- Assume a set of permissible discrete values **m** for each of the design variables (step size **h**).
- Initialize all discrete values of design variables equal amounts of pheromone **Ͳ**.

- **Step 2: build a tours**

- From the home node, ants start travelling through the various paths and end at the destination node in each iteration (discrete value f design variables).
- The probability to select discrete values of design variables $\boldsymbol{P_j^K} = \frac{Ͳ_j}{\sum_{j=1}^{m} Ͳ_j}$.
- Find the cumulative probability ranges associated with different discrete values based on its probabilities.
- The specific discrete values chosen by ant K will be determined using the roulette-wheel selection.
- Generate N random number r in the range (0, 1), one for each ant.
- Determine the discrete value by ant K for variable as the one for which the cumulative probability range includes the random numbers r.

- **Step 3: update trail**

- Once the path is complete, the ant deposits some pheromone on the path.
- Evaluate the objective function values of each ant.
- Determine the best $\boldsymbol{f_{best}}$ and worst $\boldsymbol{f_{worst}}$ objective function of the discrete value among ants.
- Update the pheromone:
  - Best ants: reinforcement the pheromone of the best path by: $Ͳ_j^{new} = Ͳ_j^{old} + \sum_K \Delta Ͳ_j^{(K)}$

$$\Delta Ͳ_j^{(K)} = \frac{ʐ \cdot \boldsymbol{f_{best}}}{\boldsymbol{f_{worst}}}$$

  - Other ants: evaporates the pheromone of other paths by: $Ͳ_j^{new} = (1-P)\, Ͳ_j^{old}$

- **Step 4: Termination**

The president steps are iteratively repeated until number of iteration is reached or a termination criterion is met.

Pseudo Code

- Input
  - ✓ Objective function (fitness function), upper bound (ub), lower bound (lb), Population size (**N**), number of iteration (**T**), scaling parameter **ζ**, evaporate rate (**P**), step size(**h**) (or number of discrete value **m**).
- Initialization
  - ✓ Initialize all discrete values **m** of design variables equal amount of pheromone **Ƭ.**
- Loop
  - ✓ For t=1:T
    - o Find probability to select discrete values of design variables is $\boldsymbol{P_j^K} = \frac{Ƭ_j}{\sum_{j=1}^{m} Ƭ_j}$
    - o Find the cumulative probability range associated with different discrete values based on its probabilities (design roulette-wheel).
    - o For i= 1:N
      - ▪ Generate a random number **r.**
      - ▪ Find corresponding discrete value
      - ▪ Evaluate the objective function $\boldsymbol{f_{xj}}$
    - o Determine the best $\boldsymbol{f_{best}}$ and worst $\boldsymbol{f_{worst}}$ objective function of the discrete value among ants
    - o Update best path by: $Ƭ_j^{new} = Ƭ_j^{old} + \sum_K \Delta Ƭ_j^{(K)}$ and other paths by: $Ƭ_j^{new} = (1-P)\, Ƭ_j^{old}$
    - o If there is no convergence of the current solution and if t > T go to loop
- Print $\boldsymbol{f_{best}}$ and x_{fbest}

3.6.3.4 Applications of Ant Colony Optimization in Industrial Optimization

ACO has been successfully applied to a wide range of industrial optimization problems, demonstrating its versatility and effectiveness. Some of the key applications include **[118]**:

- **Production Scheduling**: In manufacturing, production scheduling involves determining the optimal sequence of tasks to be performed on a set of machines to minimize production time, reduce costs, and meet delivery deadlines. ACO has been applied to solve various production scheduling problems, including job shop scheduling, flow shop scheduling, and flexible manufacturing systems. The ability of ACO to handle complex constraints and multi-objective optimization makes it particularly well-suited for these applications.
- **Supply Chain Management**: Supply chain optimization involves coordinating the flow of materials, information, and products across multiple stages of production and

distribution. ACO has been applied to optimize various aspects of supply chain management, including inventory control, supplier selection, and transportation logistics. For example, ACO has been used to optimize the design of supply chain networks, balancing the trade-offs between cost, service level, and supply chain resilience.

- **Robotics and Autonomous Systems**: ACO has been applied to optimize the path planning and coordination of autonomous robots. For example, in robotic swarm systems, ACO is used to coordinate the movements of multiple robots to achieve collective goals, such as area coverage, target tracking, and object manipulation. The algorithm's ability to find optimal paths in dynamic and uncertain environments makes it highly effective for these applications.
- **Energy Optimization**: In industrial energy systems, optimizing the generation, distribution, and consumption of energy is crucial for reducing costs and minimizing environmental impact. ACO has been applied to optimize various energy systems, such as optimizing the operation of smart grids, designing energy-efficient buildings, and scheduling the operation of renewable energy systems. The algorithm's ability to handle complex, dynamic optimization problems makes it well-suited for these applications.

3.6.3.5 Advantages and challenges of Ant Colony Optimization

Advantages

- **Flexibility**: ACO is highly flexible and can be adapted to solve a wide range of optimization problems across different industries. Its ability to handle complex constraints and multi-objective optimization makes it particularly useful for industrial applications **[118]**.
- **Scalability**: ACO is scalable and can be applied to large-scale optimization problems without a significant loss of performance. This makes it suitable for optimizing complex industrial systems that involve many interacting components **[118]**.
- **Robustness**: ACO is robust to noise and uncertainty, making it well-suited for industrial environments where conditions may change dynamically. The algorithm's ability to adapt to changing information and maintain its performance **[118].**

Challenges

- **Slow Convergence**: ACO's reliance on pheromone accumulation leads to slow convergence, especially in large or complex problems. It often requires many iterations to find optimal solutions compared to other metaheuristic methods **[118]**.
- **Premature Convergence**: The algorithm can settle on suboptimal solutions early on if certain paths are reinforced too strongly by pheromones, reducing exploration and diversity in the search process **[118]**.
- **Scalability Issues**: As problem size increases, the computational complexity of managing pheromone levels and simulating multiple ants grows, making ACO less suitable for large-scale optimization tasks **[118]**.

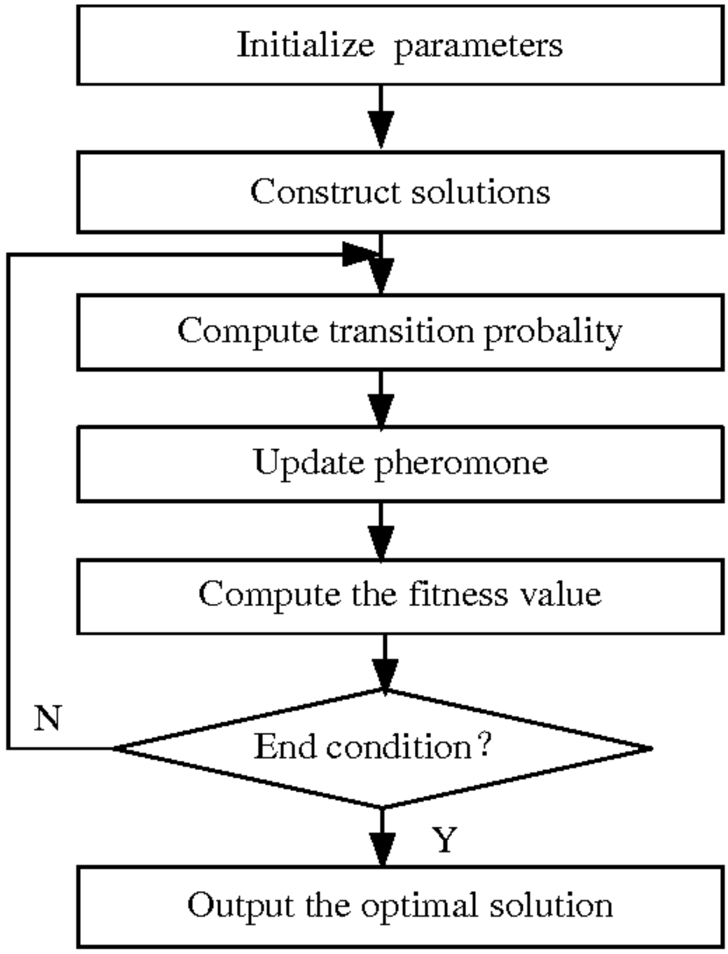


Figure 3. 10: Ant Colony Optimization flowchart [119].

3.6.4 Manta Ray foraging optimization algorithm

Manta Ray Foraging Optimization (MRFO) is a relatively new nature-inspired metaheuristic algorithm, designed based on the unique foraging behaviors of manta rays. These rays are known for their coordinated movements and swarm intelligence, which they utilize to efficiently locate and capture food. MRFO has gained significant attention due to its effectiveness in solving complex optimization problems, especially in industrial applications. In this section, we will explore the biological inspiration of the algorithm, its structure, and its various applications in industrial optimization **[120]**.

3.6.4.1 Inspiration and Biological Background

The Manta Ray Foraging Optimization algorithm is inspired by the foraging behavior of manta rays, large marine animals known for their group behavior while searching for plankton and other small organisms. Manta rays exhibit three distinct foraging strategies that form the foundation of the MRFO algorithm **[120]**:

- **Chain foraging**: Manta rays often form a chain-like structure while foraging. This formation allows the rays at the front to stir plankton and other small prey, which those at the back consume. By working together in this coordinated manner, manta rays increase their foraging efficiency.
- **Somersault foraging**: Another unique behavior is somersault foraging, where manta rays rotate their bodies in a somersault-like motion, continuously trapping prey in their mouths. This behavior maximizes their prey intake and ensures that they can consume food in dense patches.
- **Cyclone foraging**: Manta rays sometimes create cyclone-like structures as a group, swirling together to concentrate prey into dense areas, making it easier to capture them. This coordinated group movement demonstrates an intelligent swarm behavior that can be effectively mimicked in computational optimization.

MRFO uses these behaviors to mimic the search for optimal solutions in a solution space, exploiting both individual and collective foraging strategies to explore and exploit the search area effectively.

3.6.4.2 Basic Structure of Manta Ray Foraging Optimization Algorithm

The basic structure of the Manta Ray Foraging Optimization (MRFO) algorithm involves using artificial manta rays as agents to explore the search space and converge toward the best solution. The algorithm consists of three phases, corresponding to the different foraging behaviors of real manta rays: chain foraging, somersault foraging, and cyclone foraging.

- **Chain Foraging**

In this strategy, a group of manta rays move in the form of an organized line, lining up one behind the other, they travel forward and backward their fins open in front of their mouth**121]]**. We also notice in this movement the support of the smaller male manta rays by the females, by swimming over their back bellies **[121]**. The first manta ray updates its location (current position) based on the best solutions obtained so far, while the rest of the manta ray updates its current position according to the best solution and the location of the manta ray in front of it in the search area. This can be translated by the following equation:

$$x_i^{t+1} = \begin{cases} x_i^t + r\,(G_{best}^t - x_i^t) + 2.r.\sqrt{|\log(r)|}.(G_{best}^t - x_i^t), & and\,i = 1 \\ x_i^t + r\,(X_{i-1}^t - x_i^t) + 2.r.\sqrt{|\log(r)|}.(G_{best}^t - x_i^t), & and\,i = 2, \dots N \end{cases}$$

where, r is a random vector in [0, 1], N is the size of population, x_i^t is the position or the ith manta ray in the iteration t and x_i^{t+1} is its new position in the next iteration, and G_{best} represent the global best solution within the entire population.

- **Cyclone Foraging**

This strategy is used in places rich in food, where dozens of manta ray fish gather to form a spiral. This circle's diameter is proportional to the number of manta rays (approximately 15-20 m), and this cyclone always rotates and clockwise this is to create a current that attracts prey outside the feeding circle towards them **[121]**. To simulate this motion, a spiral equation is used to update the position of the population

$$x_i^{t+1} = \begin{cases} G_{best} + r\,(G_{best}^t - x_i^t) + 2.e^{r_1 \frac{T_{max}-t+1}{T_{max}}}.\sin(2\pi r_1).(G_{best}^t - x_i^t), & and\,i = 1 \\ G_{best} + r\,(X_{i-1}^t - x_i^t) + 2.e^{r_1 \frac{T_{max}-t+1}{T_{max}}}.\sin(2\pi r_1).(G_{best}^t - x_i^t), & and\,i = 2, \dots N \end{cases}$$

where: T_{max} is the maximum number of iterations and r1 is a random number in [0, 1]. In order to improve the exploratory ability, each individual updates his position away from the current best position and according to a new random position in the entire search space as follows:

$$x_i^{t+1} = \begin{cases} X_{rand} + r\,(X_{rand}^t - x_i^t) + 2.e^{r_1 \frac{T_{max}-t+1}{T_{max}}}.\sin(2\pi r_1).(X_{rand}^t - x_i^t), & and\,i = 1 \\ X_{rand} + r\,(X_{i-1}^t - x_i^t) + 2.e^{r_1 \frac{T_{max}-t+1}{T_{max}}}.\sin(2\pi r_1).(X_{rand}^t - x_i^t), & and\,i = 2, \dots N \end{cases}$$

Where, x_{rand} is a random reference point in the search space given by:

$x_{rand} = LB + r.\,(UB - LB)$

LB: lower boundary of the search space.
UB: upper boundary of the search space.

- **Somersault Foraging**

This strategy of feeding is typically used when the prey is concentrated near the surface to limit mobility and improve feeding effectiveness. The manta ray performs a series of backwards somersaults, which are random, repetitive, local and cyclical movements, and it is one of the most beautiful scenes in nature **[121]**. In this strategy, the manta ray update their position around the best position found so far by performing a somersault movements. Therefore, its mathematical model is given by:

$$X_i^{t+1} = X_i^t + S.(r_2.G_{best} - r_3.X_i^t), \qquad i = 1, \dots, N$$

S is the somersault factor that defines the somersault range of manta rays and it is set to 2. r_2 and r_3 are random numbers between 0 and 1.

3.6.4.3 Applications of Manta Ray Foraging Optimization in Industrial Optimization

Manta Ray Foraging Optimization has shown promise in a variety of industrial applications, particularly in solving complex optimization problems where traditional methods struggle. Some of the key applications include **[122]**:

- **Production Scheduling**: MRFO has been applied to production scheduling problems, where the objective is to find the optimal sequence of tasks to minimize production time, reduce costs, and meet delivery deadlines. The algorithm's ability to balance exploration and exploitation makes it highly effective for these multi-objective problems, which often involve conflicting goals and constraints.
- **Supply Chain Optimization**: In supply chain management, MRFO has been used to optimize the flow of materials and goods between suppliers, manufacturers, and customers. The algorithm's ability to explore a wide range of solutions while refining the best ones makes it particularly well-suited for complex supply chain problems, where decisions such as inventory management, transportation, and demand forecasting must be optimized simultaneously.
- **Energy Management**: The optimization of energy systems, such as smart grids, renewable energy systems, and industrial energy consumption, is another area where MRFO has been successfully applied. The algorithm has been used to optimize the scheduling and operation of energy resources, reduce energy costs, and minimize environmental impact.
- **Robotic Path Planning**: In robotics, MRFO has been used to optimize the path planning of autonomous robots, ensuring that they navigate efficiently through complex environments. The algorithm's swarm intelligence and foraging behaviors enable it to find optimal paths while avoiding obstacles and adapting to changes in the environment.
- **Industrial Process Optimization**: MRFO has been applied to optimize various industrial processes, such as the design of manufacturing systems, the allocation of resources, and the optimization of chemical processes. The algorithm's flexibility and ability to handle complex, nonlinear problems make it an attractive choice for optimizing large-scale industrial systems.

3.6.4.4 Advantages and Challenges of Manta Ray Foraging Optimization

Advantages:

- **Efficient Exploration and Exploitation**: MRFO's ability to balance exploration (through chain foraging) and exploitation (through somersault and cyclone foraging) makes it highly effective at finding high-quality solutions. This is particularly useful in industrial applications where the search space is large and complex **[122]**.

- **Adaptability to Different Problems**: MRFO can be easily adapted to a wide range of optimization problems, including continuous, discrete, and combinatorial problems. Its flexibility makes it a valuable tool for solving diverse industrial optimization challenges **[122]**.
- **Swarm Intelligence**: Like other swarm-based algorithms, MRFO benefits from collective intelligence, where multiple agents (manta rays) collaborate to find optimal solutions. This distributed approach improves robustness and helps the algorithm avoid being trapped in local optima **[122]**.

Challenges:

- **Parameter Sensitivity**: Like many metaheuristic algorithms, MRFO's performance is sensitive to the choice of parameters, such as the number of manta rays, the influence of chain foraging, and the rate of somersault movement. Fine-tuning these parameters can be challenging and may require problem-specific adjustments **[122]**.
- **Convergence Speed**: While MRFO is effective at exploring the search space, it may suffer from slower convergence compared to other algorithms in certain cases. This is especially true when the problem landscape is highly rugged or contains many local optima **[122]**.
- **Computational Complexity**: The algorithm's complexity increases with the number of manta rays and the size of the search space. In large-scale industrial problems, the computational cost of running MRFO may become a limiting factor, especially if hybrid or parallel implementations are not used **[122]**.

The Manta Ray Foraging Optimization algorithm offers a novel and effective approach to solving complex optimization problems, particularly in industrial contexts. By mimicking the intelligent foraging behaviors of manta rays, MRFO provides a powerful mechanism for balancing exploration and exploitation, making it well-suited for applications ranging from production scheduling to energy management. Despite some challenges, such as parameter sensitivity and computational complexity, MRFO holds great promise as a versatile and adaptable tool for industrial optimization.

3.7 Recapitulative Analysis of Metaheuristic Methods

In this section, we conduct a comparative analysis of four prominent metaheuristic algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Manta Ray Foraging Optimization (MRFO). The comparison focuses on several key factors: problem-solving effectiveness, convergence behavior, adaptability, computational complexity.

3.7.1 Problem-Solving Effectiveness

When evaluating the effectiveness of different metaheuristic algorithms in solving optimization problems, each method demonstrates unique strengths and weaknesses.

- **Genetic Algorithm (GA)** is known for its adaptability to a wide range of problem types, including both continuous and discrete optimization. By utilizing crossover and mutation operations, it effectively explores large, complex solution spaces. However, GAs are prone to premature convergence, particularly in multimodal landscapes where many local optima exist. This premature convergence can limit the search's thoroughness and result in suboptimal solutions if proper diversity mechanisms are not maintained.
- **Particle Swarm Optimization (PSO)** is particularly effective in continuous optimization problems. Its simplicity and rapid convergence make it an attractive option for industrial applications where quick solutions are needed. PSO benefits from the collective behavior of the swarm, which helps it avoid local minima, but it can struggle with slower convergence as the optimization process progresses, especially in high-dimensional or complex landscapes.
- **Ant Colony Optimization (ACO)** excels in combinatorial problems, such as scheduling and routing, where its pheromone-based communication system allows efficient exploration of solution paths. Its ability to refine solutions over time makes it particularly suitable for complex discrete problems. However, ACO is less effective when applied to continuous optimization and may require significant computational resources to simulate the behavior of ants and manage the pheromone levels.
- **Manta Ray Foraging Optimization (MRFO)**, although relatively new, has shown impressive performance in both continuous and discrete optimization problems. It balances exploration and exploitation effectively, thanks to its foraging strategies that mimic the behavior of manta rays. However, the method requires careful tuning of parameters for specific problem contexts, making it somewhat challenging to apply in some cases.

3.7.2 Convergence Behavior

Each metaheuristic method exhibits different convergence characteristics, which can influence the speed and accuracy of finding optimal solutions.

- **Genetic Algorithm (GA)** typically starts with good exploration of the search space but may converge slowly, particularly when faced with complex or rugged landscapes. The balance between exploration (mutation) and exploitation (crossover) affects the convergence speed, and without proper mechanisms to maintain population diversity, GAs are prone to getting stuck in local optima, resulting in premature convergence.

- **Particle Swarm Optimization (PSO)** is known for its rapid initial convergence, especially in continuous problem spaces. However, its performance can plateau later in the search process, leading to slower convergence as particles settle near local optima. Proper tuning of parameters, such as velocity and inertia weight, is necessary to strike the right balance between exploration and exploitation to ensure efficient convergence.
- **Ant Colony Optimization (ACO)** tends to converge more slowly due to the gradual pheromone-based feedback system, which relies on multiple iterations for pheromones to build up and guide ants toward optimal paths. While this slow convergence allows ACO to explore the search space extensively, it can delay finding a final solution, especially for larger or more complex problems.
- **Manta Ray Foraging Optimization (MRFO)** demonstrates balanced convergence behavior. Its three distinct foraging strategies help maintain a good balance between exploration and exploitation throughout the search process. The cyclone foraging phase, in particular, allows MRFO to focus on promising regions of the solution space once identified, leading to faster convergence compared to ACO and GA.

3.7.3 Adaptability to Different Problem Types

The adaptability of each metaheuristic algorithm to different types of optimization problems varies significantly, depending on the algorithm's design and intended application.

- **Genetic Algorithm (GA)** is highly adaptable and can be applied to continuous, discrete, multi-objective, and combinatorial optimization problems. However, its effectiveness often depends on problem-specific modifications, such as tailored crossover and mutation operators, making it less general-purpose unless carefully adapted to specific applications.
- **Particle Swarm Optimization (PSO)** is best suited for continuous optimization problems but can also be adapted for discrete and combinatorial problems with suitable modifications. These adjustments may involve altering the particle representation or developing custom velocity update rules. PSO's general simplicity and effectiveness make it highly adaptable to a variety of industrial optimization tasks.
- **Ant Colony Optimization (ACO)** shines in combinatorial optimization problems like the Traveling Salesman Problem (TSP) and scheduling tasks, where its pheromone system helps efficiently identify optimal solutions. However, its applicability to continuous optimization is limited, and specialized variants of ACO are required to address these challenges.
- **Manta Ray Foraging Optimization (MRFO)** stands out for its adaptability to both continuous and discrete optimization problems. The manta ray's natural foraging strategies, which MRFO mimics, allow the algorithm to tackle various types of optimization tasks without requiring extensive modifications, making it highly flexible in industrial contexts.

3.7.4 Computational Complexity

The computational complexity of each algorithm plays a critical role in determining its suitability for large-scale or real-time optimization problems.

- **Genetic Algorithm (GA)** is computationally expensive due to the need to maintain and evolve large populations over many generations. The application of crossover and mutation operations, along with the selection and reproduction of individuals, increases the computational burden, especially for high-dimensional or complex problems.

- **Particle Swarm Optimization (PSO)**, on the other hand, is computationally less expensive compared to GA, as it involves simpler operations for updating particle positions and velocities. However, when dealing with high-dimensional problems, PSO may still require many iterations to achieve an optimal solution, potentially increasing its overall computational time.
- **Ant Colony Optimization (ACO)** is computationally demanding, primarily because it simulates the behavior of numerous ants and requires continuous updates to pheromone trails. As the number of potential solution paths grows, the computational effort required to manage pheromone levels and calculate probabilities for each ant's movement also increases, making ACO resource-intensive for large-scale problems.
- **Manta Ray Foraging Optimization (MRFO)** is relatively efficient in terms of computational complexity. Although it incorporates three distinct foraging strategies, the overall computational cost is moderate, making it well-suited for large-scale optimization problems. Its complexity generally falls between that of PSO and ACO, with the added benefit of balancing exploration and exploitation without excessive computational overhead.

Table 3.1: Recapitulation

Algorithm	Problem-Solving Effectiveness	Convergence Speed	Adaptability	Computational Complexity
GA	Versatile, handles various problem types, but can suffer from premature convergence	Moderate, can be slow in complex landscapes	Highly adaptable to different problem types	High, especially for large populations
PSO	Excellent for continuous problems, struggles with local optima in large search spaces	Fast in early iterations, may stagnate later	Best for continuous, can be adapted for discrete problems	Moderate, less expensive than GA and ACO
ACO	Best for combinatorial problems, strong at finding optimal paths	Slow due to pheromone updating and probabilistic search	Highly effective for discrete, less so for continuous problems	High, due to pheromone management
MRFO	Balanced for both continuous and discrete problems, versatile in performance	Fast, particularly in cyclone foraging phase	Flexible and adaptable to both continuous and discrete problems	Moderate, efficient for large-scale problems

The selection of **Particle Swarm Optimization (PSO)** and **Genetic Algorithm (GA)** is highly appropriate for optimizing maintenance schedules in a combined cycle power plant. These methods are proven to be effective, particularly in handling complex, continuous optimization problems. Their ability to balance exploration (searching new areas of the solution space) and exploitation (refining known solutions), coupled with their computational efficiency, makes them ideal for this type of industrial task. While alternatives like **Ant Colony Optimization**

(ACO) and **Manta Ray Foraging Optimization (MRFO)** offer interesting approaches, PSO and GA provide a more reliable and robust solution for maintenance schedule optimization. In the case of optimizing maintenance schedules to reduce spurious activations of the emergency shutdown system, these techniques are particularly well-suited because they can efficiently handle complex, continuous, and multi-dimensional search spaces. PSO is known for its ability to quickly converge on optimal or near-optimal solutions with minimal parameter tuning, while GA excels in exploring large search spaces, handling constraints, and avoiding local optima, making it perfect for intricate optimization tasks. A key element in optimization is balancing exploration and exploitation. PSO's swarm behavior promotes effective exploration, allowing particles to share information and converge toward the best-known solution. GA, with its crossover and mutation operations, ensures both exploration and exploitation, refining solutions while searching across diverse regions of the solution space. In contrast, newer algorithms like Manta Ray Foraging Optimization (MRFO) are still in the early stages of development and have not been extensively tested in real-world applications. Similarly, Ant Colony Optimization (ACO) is more commonly applied to discrete problems like routing and scheduling, making it less efficient for continuous optimization tasks such as maintenance schedule optimization. ACO tends to focus more on exploitation after an initial exploration phase, which can limit its ability to find optimal solutions in large, continuous spaces. MRFO, while promising in terms of exploration, has yet to demonstrate the refined exploitation capabilities of PSO and GA.

3.8 Conclusion

This chapter has provided an in-depth exploration of optimization techniques, specifically within the context of solving industrial problems. We began by discussing the importance of optimization in enhancing industrial processes, improving efficiency, reducing costs, and maximizing output. The increasing complexity of industrial systems has necessitated the use of advanced optimization techniques, particularly metaheuristic methods, which have shown great promise in handling large, complex, and non-linear optimization problems.

Metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Manta Ray Foraging Optimization (MRFO), were examined for their effectiveness in solving industrial optimization problems. These techniques are especially useful in scenarios where traditional optimization methods fail to provide satisfactory solutions due to complex landscapes or large search spaces.

Each method brings its own strengths: GA excels in adaptability and can be tailored to a wide variety of problems, PSO is renowned for its simplicity and fast convergence in continuous optimization tasks, ACO is particularly effective in combinatorial optimization problems like routing and scheduling, and MRFO, as a newer method, strikes an excellent balance between exploration and exploitation across both discrete and continuous problems.

In the comparative analysis, we found that no single method is universally superior; the effectiveness of each algorithm is problem-dependent. Factors such as convergence speed, computational complexity, adaptability, and real-world applicability vary across methods and must be considered when selecting the right optimization technique for a specific industrial problem.

Overall, metaheuristic optimization methods have proven to be powerful tools in addressing the challenges of modern industrial systems. Their flexibility, adaptability, and capability to provide near-optimal solutions make them indispensable in real-world applications where traditional methods fall short. As industrial systems continue to evolve, so too must the optimization methods that support them, ensuring that industries remain efficient, sustainable, and competitive in an increasingly complex world.

Chapter 4: Case Study: Optimizing Maintenance Schedules for a Combined Cycle Power Plant

4.1 Introduction

In this chapter, we apply the optimization methods discussed in Chapter 3 to a real-world industrial problem within a combined cycle power plant. Specifically, the focus is on the plant's emergency shutdown system, a critical safety mechanism designed to prevent catastrophic events such as fires or explosions. In power plants, ensuring the reliability and proper functioning of such systems is vital for both operational continuity and personnel safety.

The emergency shutdown system, though essential, can face challenges during the commissioning phase, where spurious activations frequently occur. These unintended activations not only disrupt plant operations but also introduce unnecessary downtimes and maintenance costs. This issue highlights the importance of optimizing maintenance schedules to minimize spurious activations and ensure that the emergency shutdown system performs optimally.

In this chapter, we aim to solve this problem by utilizing metaheuristic optimization methods, specifically Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). These techniques, which have proven effective in solving complex optimization problems, are applied to develop a maintenance schedule that minimizes the likelihood of spurious activations. Through this case study, we will assess the performance of GA and PSO in addressing the specific challenges faced by the power plant's safety system.

This chapter is divided into three main sections: an introduction to the combined cycle power plant and the role of its emergency shutdown system, an explanation of the spurious activation problem, and the application of GA and PSO to optimize maintenance strategies. The results of the optimization will provide insights into the effectiveness of these methods in enhancing the reliability and safety of industrial systems.

4.2 Introduction to the System

4.2.1 Overview of Combined Cycle Power Plants

A **gas turbine** is a device that converts fuel energy into mechanical power through the **Brayton cycle**. It works by compressing air, mixing it with fuel, and igniting the mixture in a combustion chamber. The high-temperature gases expand and drive a turbine, which spins a shaft connected to a generator, producing electricity. Gas turbines often use natural gas as fuel.

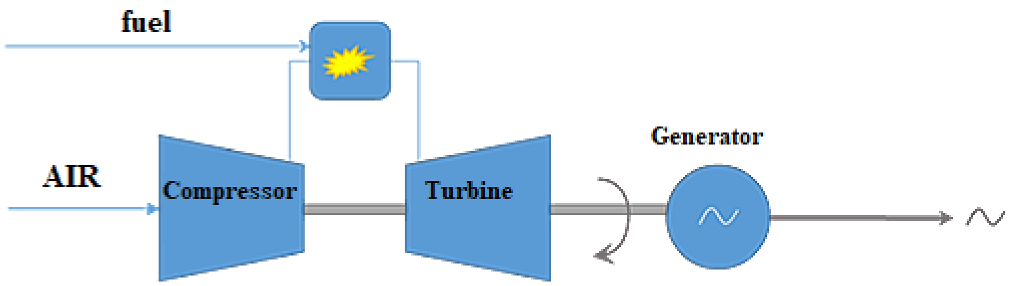


Figure 4. 1: gas turbine.

Combined cycle power plants (CCPP) have revolutionized electricity production by significantly improving efficiency compared to single-cycle plants. Traditional fossil-fuel plants, which use only one type of turbine (typically steam turbines), operate at efficiency levels of around 35-40%. In contrast, CCPPs use both gas and steam turbines in tandem, allowing them to capture and reuse energy that would otherwise be wasted. This results in thermal efficiencies as high as 60%.

The innovation of CCPPs lies in their ability to utilize the hot exhaust gases from a gas turbine, which would otherwise be released into the atmosphere, to produce additional electricity through a steam turbine. The plant operates in two cycles:

- Gas Turbine Cycle: Natural gas or another fuel is burned to generate high-temperature, high-pressure gas, which spins a gas turbine connected to a generator.
- Steam Turbine Cycle: The waste heat from the gas turbine is used to produce steam, which then drives a steam turbine connected to another generator.

This dual process reduces fuel consumption and greenhouse gas emissions per unit of electricity produced, making combined cycle plants a more environmentally friendly and cost-effective solution for large scale power generation.

A combined cycle power plant consists of the following main components:

- **Gas Turbine (Brayton Cycle)**: The first stage of electricity generation occurs in the gas turbine. Natural gas or other fuels are combusted in the turbine, producing high-temperature, high-pressure exhaust gases. These gases drive the gas turbine, which generates electricity. The gas turbine operates on the Brayton cycle, where air is compressed, mixed with fuel, and then combusted, with the expanding gases turning the turbine blades.
- **Heat Recovery Steam Generator (HRSG)**: After passing through the gas turbine, the exhaust gases still contain a significant amount of thermal energy. Instead of wasting

this energy, the HRSG captures it and uses it to convert water into steam. This process is vital to the overall efficiency of a CCPP because it enables the system to generate additional electricity using the steam cycle.

- **Steam Turbine (Rankine Cycle)**: The steam produced in the HRSG is directed to a steam turbine, which operates on the Rankine cycle. As the steam expands and cools, it drives the steam turbine, generating more electricity. This second stage of electricity generation is what distinguishes combined cycle plants from single-cycle gas or steam plants.
- **Condenser and Cooling System**: After passing through the steam turbine, the steam must be condensed back into water before being returned to the HRSG. The cooling system, often using water or air, condenses the steam, and the cooled water is recirculated to continue the cycle.

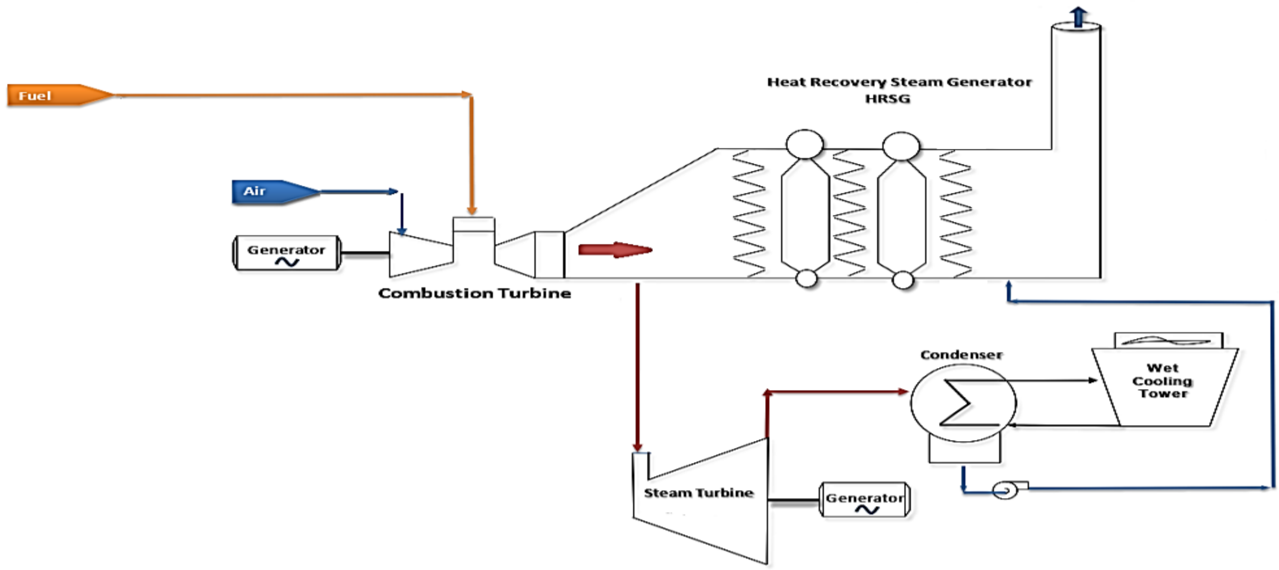


Figure 4.2: combined cycle power plant.

4.2.2 The Emergency Shutdown System

The combined cycle power plant is associated with an emergency shutdown system (ESD), which is a system aim to rapidly and automatically stop the plant in the event of an abnormal situation or when unsafe operating conditions is detected, to limit the damages of the accident. ESD continuously monitors critical parameters such as temperature, pressure, flow rates, and equipment status to detect deviations from normal operating conditions that could indicate potential safety issues, such as overheating, overpressure, or equipment malfunctions. The ESD of CCPP consists of three subsystems as follow:

- **Sensors (S)**: These include temperature sensors, pressure transducers, flow meters, and gas detectors. They provide real-time data to the ESD.
- **Logic Solvers (LS)**: Programmable logic controllers (PLCs) or distributed control systems (DCS) that process the input data from sensors and make decisions based on pre-defined safety logic.

- **Final equipment (SDV)**: Devices such as valves, relays, and circuit breakers that execute the actions determined by the logic solvers, such as shutting down equipment or isolating systems.

The Emergency Shutdown System (ESD) in a combined cycle power plant is critical for ensuring the safety of the plant, its personnel, and the environment. Its primary role is to automatically shut down plant operations in the event of abnormal conditions, preventing equipment damage, accidents, or catastrophic failures like fires or explosions. One of the main functions of the ESD is to protect equipment and personnel. The system continuously monitors key parameters such as pressure, temperature, and vibration in essential components like the gas turbines, steam turbines, and heat recovery steam generator (HRSG). If any of these parameters exceed safe limits, the ESD initiates an automatic shutdown to prevent damage and ensure the safety of workers. The ESD also plays a vital role in preventing fires and explosions. Since combined cycle power plants operate at high temperatures and pressures, any malfunction can lead to serious hazards. The ESD can isolate fuel lines, stop combustion processes, and activate fire suppression systems to minimize these risks. Additionally, the ESD helps maintain system stability during situations such as power grid fluctuations or sudden operational changes. By shutting down key components quickly, it prevents overloading and ensures the plant remains stable. Finally, the ESD helps to avoid environmental hazards by shutting down processes that could lead to the release of harmful substances. This ensures that any potential environmental impact is minimized in case of a system failure. The ESD system intervenes according to the following sequence:

Sort of sensors are spread throughout the plant especially suspicious areas. The logic solver of the ESD system receives a signal from sensors that detect abnormalities. After processing the information and explaining the protected area's status, the logic solver decides whether to shut down the system. A shutdown valve (SDV gas supply line) instantly cuts off the fuel supply to the gas turbine, closing the entire gas pipeline. This is the first step in the shutdown procedure. By using a bypass system, the steam generated in the heat recovery steam generator is sent to the condenser instead of the steam turbine. Another shutdown valve on the SDV steam turbine will likewise close the supply pipe that supplies the steam.

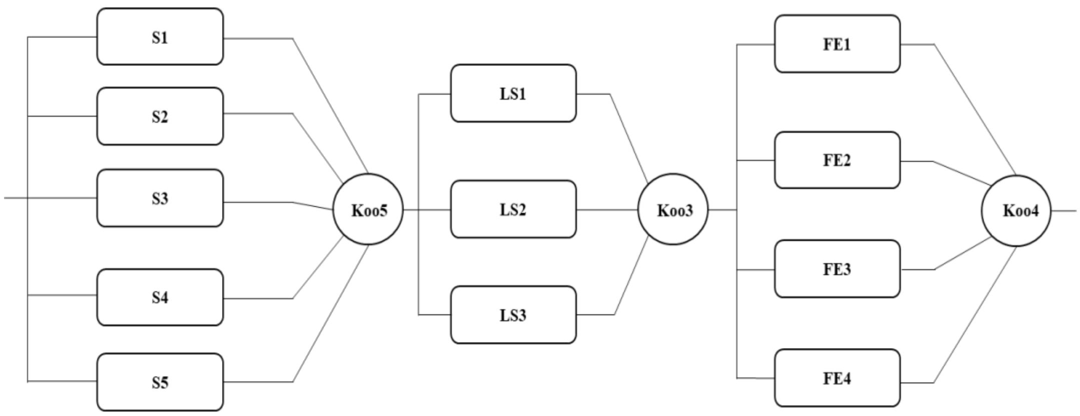


Figure 4. 3: ESD reliability block diagram.

4.3 Problem Definition: Spurious Activations of the Emergency Shutdown System

4.3.1 Impact of Spurious Shutdowns During the Commissioning Phase

The emergency shutdown system in a combined cycle power plant plays a critical role in ensuring the safety of operations by preventing catastrophic events such as fires or explosions. It is designed to immediately halt plant operations in the event of a dangerous malfunction or anomaly. During the commissioning phase of the studied combined cycle power plant, the emergency shutdown system has been experiencing spurious activations, leading to a complete shutdown of the plant each time we initiate the commissioning process.

The commissioning phase of a power plant include thorough testing and careful adjustment of equipment to ensure the best functioning of all systems before to the facility becoming fully operational. During this period, the emergency shutdown system is frequently tested, which can lead to false activations. These spurious activations are typically caused by a variety of factors, including sensor malfunctions, improper calibration, or software bugs. Additionally, the complexity of integrating multiple systems during commissioning can result in miscommunications between different subsystems, further increasing the likelihood of spurious shutdowns. Spurious activations of the emergency shutdown system have a profound impact on plant operations. Each activation halts the entire plant, causing substantial losses in production and increased operational costs due to downtime. The time required to reset the system, verify that no real threat exists, and bring the plant back online can be lengthy. Furthermore, repeated false activations place additional wear and tear on the system, potentially leading to equipment failure or decreased system reliability. From a financial perspective, spurious activations during the commissioning phase can increase the overall cost of the project due to delays and the need for additional maintenance or repairs. The plant's profitability is also affected, as the plant is unable to produce power while it is shut down. These costs accumulate quickly, especially when the frequency of spurious shutdowns is high, making it crucial to address the issue effectively.

4.3.2 Cost of Spurious activations

Spurious activations of the shutdown system in a combined cycle power plant can lead to significant economic losses due to the interruption of power production and the associated costs. The plant in question, with a production capacity of 1338.15 MW, faces substantial financial implications every time an unexpected shutdown occurs. Given that the price of one MWh is $20, a single hour of lost production translates to a direct revenue loss of approximately $26763. This figure can escalate quickly if the shutdown persists, compounding the financial impact. Additionally, these events necessitate maintenance work to restart the system, often requiring workers to engage in extra time work. The cost of this maintenance, which includes the workers' salaries and potential overtime pay **[123]**, further exacerbates the economic burden. Beyond the immediate financial losses, frequent shutdowns can also lead to long-term operational inefficiencies and wear and tear on the equipment, potentially shortening the lifespan of critical components and necessitating more frequent and costly repairs or replacements. Moreover, these disruptions can undermine the reliability and reputation of the power plant, potentially affecting future contracts and partnerships. Therefore, preventing spurious activations and ensuring the reliable operation of the shutdown system is crucial to maintaining the economic viability and operational stability of the power plant.

Given the criticality of this event, standards like OREDA and IEC 61511 classified it as critical failures. In addition, standards require the estimation and consideration of STR when selecting the SIS design to enhance system performance in relation to this type of failure. Therefore, the head office has set an objective to reduce the frequency of these spurious activations to $STR<10^{-4}$. Also we take in consideration the probability of failure in demand PFD in the optimization process, due to its contradiction with the spurious activation rate STR. The best architecture (redundancy) that reduce the STR will we the worst architecture to the PFD. because increasing redundancy to avoid false alarms (lower STR) also increases the risk of missing real faults (higher PFD). Redundancy on 1ooN is the best to reduce the PFD because the system will keep operating with only one element operates properly, in other hand this redundancy means that the spurious activation of one element will lead to the spurious activation the whole system. Otherwise the redundancy of NooN reduces the STR because the system will spuriously activates if all the elements activate in spurious way, in other hand this redundancy will increase the PFD because the system will need all the elements in operational to operates and avoid facing failures.

4.3.3 Equations

SIS performance functions

The STR of a safety function given by a safety-instrumented system is decided by calculating the sum of the STR of its three subsystems (S, LS, and FE). This could be communicated by the taking after equation **[92]**:

$$STR_{(SIS)} = STR_{(S)} + STR_{(LS)} + STR_{(FE)}. \quad \textbf{(2)}$$

The STR of each subsystem with a design of K out of N components can be calculated using Binomial approach with the following equation:

$$PFD_{avg}\,(KooN) = A_N^{N-K+1} \lambda_{Dind}^{N-K+1} \prod_{i=1}^{N-K+1} \left[\frac{\lambda DU}{\lambda D}\left(\frac{T1}{i+1} + MRT\right) + \frac{\lambda DD}{\lambda D}.MTTR\right] + \beta\, \lambda_{DU}\left(\frac{T1}{2} + MRT\right) + \beta_D\, \lambda_{DD}.MTTR. \quad \textbf{(3)}$$

$$STR(_{KooN}) = A_N^K\, .\lambda_{Sind}. \prod_{i=1}^{K-1} \left[\lambda_{SUind}.\left(\frac{T1}{i+1} + MRT_S\right) + \lambda_{SDind}.MTTR_S\right] + \beta_{SU}\,.\,\lambda_{SU} + \beta_{SD}\,.\,\lambda_{SD} \quad \textbf{(4)}$$

With:

$A_N^K = \frac{N!}{(N-K)!}$

$\lambda_S = \lambda_{SD} + \lambda_{SU}$

$\lambda_{Sind} = (1 - \beta_{SU})\,.\,\lambda_{SU} + (1 - \beta_{SD})\,.\,\lambda_{SD}$

$MRT_S = MTTR_S$

$\beta_D = \beta/2$

$DC_S = \lambda_S * DC$

$\lambda_{SU} = (1 - DCS) * \lambda_S$

$\lambda_{SD} = DC_S * \lambda_S$

The values of variables of each subsystem are shown in table 02

Table 4.1: Sub-systems Performance Variables Values.

	Sensors (S)	**Logic Solver (LS)**	**Final Element (SDV)**
λ_S	1.23E-3	3.94E-4	3.08E-4
DC	0.2	0.2	0.2
B	0.02	0.02	0.02
$MTTR_s$ MRT_s [hour]	8	8	8
N	5	3	4

The entire precedent factors depend on the type of element used in the system, except 'T1' and 'K' which depend respectively on the maintenance strategy and the voting mode choosing within the redundancy of the subsystem. Since the system is in the commissioning stage, which implies we cannot adjust the number of components (N) of any subsystem (already existing within the site), neither the factors related to the type of the element. So we are able only to act on the voting (K out of N) of each subsystem and time between periodic tests T1 as a maintenance strategy.
Accomplishing the required level of accessibility involves. Providing sufficient repetition of identical elements;

- Redundancy may be a profitable way to upgrade a system's availability by including plug-ins. Redundancy reduces the probability of total system failure while also lowering downtime and maintenance time and increasing productivity, a system consists of N identical elements, obtains the ability to function even in the presence of failures by including redundant subsystems. **[124]**.
  For a system containing N element, repetition of one component out of N components (1ooN) is the most excellent to guarantee the security work and increment the reliability of the safety system, because the system will be able to finish its safety function with only one element available, which mean that this system tolerates N-1 failure. However, it affects contrarily the rate of spurious trips since with this design the spurious actuation of one component is sufficient to cause the activation of all the system.
- The time between tests, also known as the test interval, is important in terms of system performance and reliability. The test interval defines how frequently preventative maintenance or testing is performed in the system. It is critical to strike the proper balance while determining the test interval. A shorter test period can result in earlier detection of degradation, allowing for quick corrective steps, preventing potential failures and minimizing downtime. However, an extremely short test interval can result in unneeded maintenance and increased operational costs. A longer test interval, on the other hand, may save money in the short term but may increase the risk of undiagnosed problems **[125]**.

Cost function

The cost of a spurious activation event in a system is intricately tied to several key factors: the rate at which these events occur, the time required to repair the system after such an event. Therefore, we can find that the STR cost is the sum of maintenance cost and production loss cost. This relationship can be expressed through the equation:

$$\mathbf{C_{PL} = STR * MTR * PL_h} \quad \mathbf{(5)}$$

The cost of production loss C_{PL}, can be expressed in terms of the production of the price of one megawatt per hour of downtime where the plant will stop producing electricity due the spurious activation event [PL_h]. Multiplied by the time in hours needed to restore the system to its functional state, during which the system is non-operational [MRT]. All multiplied by the rate of occurrence of the spurious activation [STR].

$$\mathbf{C_M = STR * MTR * C_{Labor/h}} \quad \mathbf{(6)}$$

In other hand maintenance cost C_M can be expressed in terms of the production of the cost of labor (workers carry out the maintenance work) per hour until the plant get start again [$C_{Labor/h}$], multiplied by the time in hours required to restart the plant [MRT], all multiplied by the rate of occurrence of the spurious activation [STR].

The cost of STR is so **(4)** + **(5)**

$$\mathbf{C_{STR} = C_{PL} + C_M}$$

$$\mathbf{C_{STR} = STR * MTR * (PL_h + C_{Labor/h})} \quad \mathbf{(7)}$$

4.3.4 Maintenance as a Solution to Minimize Spurious Activations

Maintenance plays a key role in minimizing the occurrence of spurious activations. By ensuring that all components of the emergency shutdown system, such as sensors, Logic solver, and Final equipment, are properly maintained and calibrated, the likelihood of false activation can be reduced. Regular maintenance activities help identify potential issues before they lead to system failures or spurious activations, ensuring that the system operates reliably and only activates in the event of a real emergency. However, determining the optimal maintenance schedule that balances system reliability with cost efficiency can be a complex task. Overly frequent maintenance increases operational costs and downtime, while insufficient maintenance raises the risk of both spurious activations and actual system failures. Therefore, optimizing the maintenance schedule is critical to reducing spurious activations while maintaining the safety and operational continuity of the power plant.

In this case study, we aim to apply Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to develop a maintenance schedule that minimizes the spurious activation rate during the commissioning phase. By optimizing the frequency and scope of maintenance activities, we can ensure that the emergency shutdown system functions reliably without triggering unnecessary shutdowns. This will enhance the overall performance of the plant and reduce both costs and downtime associated with false alarms.

4.4 Application of Optimization Methods

4.4.1 Application of Genetic Algorithm for Optimizing Maintenance Schedules

In this section, we present the results of applying the Genetic Algorithm (GA) to optimize the maintenance schedule of the emergency shutdown system in the combined cycle power plant. The goal of this optimization is to minimize the occurrence of spurious activations while maintaining cost efficiency and ensuring system reliability during the commissioning phase.

4.4.1.1 Problem Formulation

The objective of the optimization process was to design a maintenance schedule that reduces spurious activations of the emergency shutdown system. The problem was formulated with the following components:

- **Decision Variables**: the time between periodic tests T1 and the voting redundancy KooN for each element of the ESD system.
- **Objective Function**: Minimize the rate of spurious activations STR while keeping maintenance costs and downtime within acceptable limits equations **(4)** and **(7)**.

4.4.1.2 Genetic Algorithm Parameters

To implement the GA for optimizing the maintenance schedule, the following parameters were configured:

- **Population Size**: A population of 100 candidate maintenance schedules was initialized.
- **Selection Mechanism**: Tournament selection was used to select the fittest individuals for reproduction.
- **Crossover Rate**: A crossover rate of 0.8 was applied to allow a high probability of mixing genetic information between schedules.
- **Mutation Rate**: A mutation rate of 0.05 was set to introduce variability and prevent premature convergence to local optima.
- **Generations**: The algorithm was run for 300 generations to ensure a thorough exploration of the solution space.

4.4.1.3 Results and Analysis

The Genetic Algorithm successfully generated an optimized maintenance schedule that significantly reduced the spurious activation rate of the emergency shutdown system. The key results are summarized as follows:

Table 4.2: Genetic algorithm optimization results.

	S	**LS**	**SDV**
T1(hour)	4 380	4 380	4 380
KooN	2	2	4
PFD_{ESD}	0,00878		
STR_{ESD} (1/h)	$3{,}55\times10^{-5}$		
C_{STR} (\$/h)	7.60 $		

To ensure minimization of STR at a value = 3.55×10^{-5} /h, this means an untimely activation within an observation period of 3 years. The best voting for the sensors is 2oo5 with a voting

of logic solver 2oo3 and the voting for the shutdown valves is 4oo4 system. In addition the same period between tests for all the subsystems which equal to 4380 hour (a test each 6 months).
Figure 4.4 below shows the evolution of the objective function as a function of generations, reaching a stationary value from the 50th generation onwards.

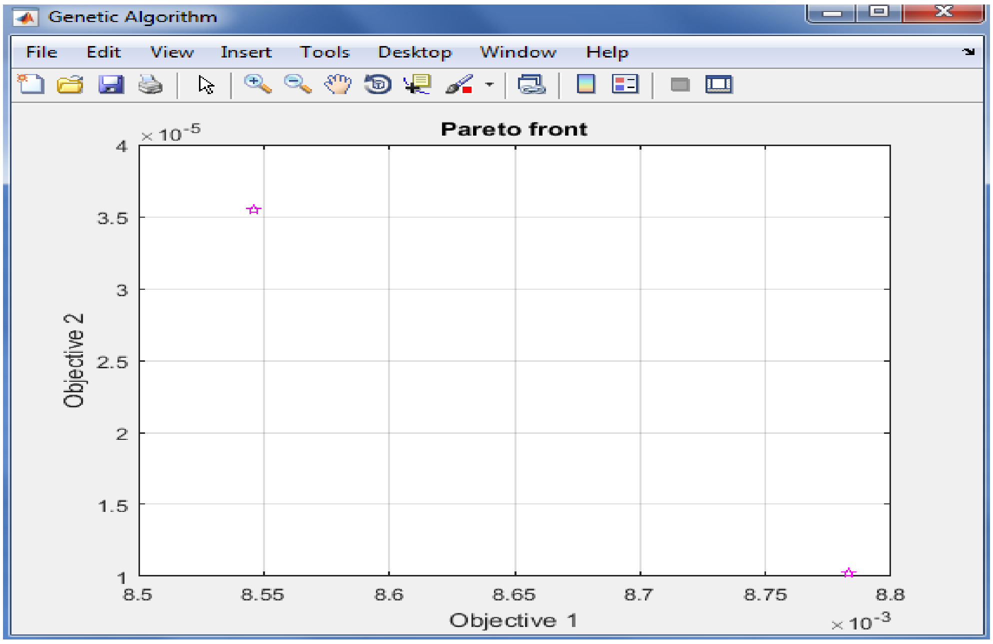


Figure 4. 4: Objective Function STR in term of generations.

We notice the following results:

- **Reduction in Spurious Activations**: The optimized schedule led to reduction in the number of spurious activations in line with the target set by the head office STR<10^{-4}. This demonstrates the GA's ability to effectively balance maintenance activities to address the root causes of false alarms.
- **Maintenance Frequency**: The optimized schedule recommended more frequent subsystems testing during critical phases of plant operation (each 6months). This targeted maintenance approach helped minimize spurious activations.
- **Cost Efficiency**: The GA-optimized schedule maintained cost efficiency by strategically spacing out periodic tests.
- **System Reliability**: The reliability of the emergency shutdown system improved significantly under the optimized schedule. The GA algorithm identified key maintenance interventions at critical junctures that enhanced system performance and minimized unexpected shutdowns.

4.4.1.4 Convergence and Computational Performance

The GA exhibited strong convergence behavior, with the objective function stabilizing after approximately 50 generations. The fitness values of the population steadily improved over time, indicating that the algorithm was effectively exploring the solution space and refining the maintenance schedule. In terms of computational performance, the algorithm was able to generate a high-quality solution within a reasonable runtime. The processing time per generation was acceptable, given the complexity of the problem, and the algorithm efficiently handled the trade-offs between cost, downtime, and system reliability.

4.4.1.5 Practical Implications

The results of this GA-based optimization provide practical insights for power plant operators seeking to minimize spurious activations of their emergency shutdown systems. The optimized schedule can be easily implemented in real-world operations and offers the following benefits:

- **Enhanced Safety**: By reducing false activations, the system can operate more reliably, ensuring that the emergency shutdown mechanism only triggers in genuine cases of system failure, thereby improving overall plant safety.
- **Cost Savings**: The reduced need for excessive maintenance and the minimization of downtime result in lower operational costs, which is crucial during the commissioning phase when cost management is essential.
- **Improved Plant Efficiency**: With fewer unnecessary shutdowns, the plant can maintain higher levels of operational efficiency, leading to better overall performance and less disruption to energy production.

In summary, the Genetic Algorithm proved to be a powerful tool for optimizing the maintenance schedule of the emergency shutdown system in the power plant, delivering a balance between system reliability, safety, and cost efficiency. The success of the GA application in this context sets a strong foundation for further exploration and potential deployment in other critical industrial systems.

4.4.2 Application of Particle swarm optimization for Optimizing Maintenance Schedules

In this section, we present the results of applying Particle Swarm Optimization (PSO) to optimize the maintenance schedule for the emergency shutdown system in a combined cycle power plant. The objective of this optimization is to minimize the frequency of spurious activations STR while maintaining cost efficiency and ensuring system reliability during the commissioning phase by determining the optimal frequency maintenance interventions (periodic tests).

4.4.2.1 Particle Swarm Optimization Parameters

The PSO algorithm was configured with the following parameters to guide the optimization process:

- **Swarm Size**: A swarm of **20** particles (candidate solutions) was initialized.
- **Inertia Weight (w)**: The inertia weight was set to **0.9** to balance exploration and exploitation during the optimization process.
- **Cognitive and Social Constants (c1, c2)**: The cognitive constant C1 and social constant C2 were both set to **C1=C1= 2**, ensuring that particles considered both their own experience and the best experiences of the swarm.
- **Iterations**: The algorithm will run for **100 iterations**, so it stops after the number of iterations is reached.

4.4.2.2 Results and Analysis

The application of PSO to the maintenance scheduling problem yielded significant improvements in reducing spurious activations while optimizing the overall maintenance process. The key results are summarized as follows:

Table 1.3: Particle swarm algorithm results of optimization

	S	LS	SDV
T1(hour)	8 253	7 279	5664
KooN	2	2	3
PFD_{ESD}	0,01081		
STR_{ESD} (1/h)	1.19×10^{-5}		
C_{STR} ($/h)	2.54 $		

The optimization results indicate a significant reduction in the spurious trip rate (STR) of the Emergency Shutdown (ESD) system. This reduction implies that the unwanted and frequent activations of the system, which previously led to plant shutdowns during the commissioning process, have been minimized. Compared to the high frequency of spurious activations observed at the start of the commissioning process, the STR achieved in our study is more favorable for the ESD system's operation. **Table 4.3** outlines the optimal voting redundancy (KooN) and time between tests (T1) required to achieve the desired STR for the ESD system. To attain an STR of 1.19×10^{-5}/h for the emergency shutdown system which mean **one activation in ten years** which means that the C_{STR} will be 214 264$ in five years instead of the same amount every time the system is activated spuriously and frequently at commissioning phase. to achieve this solution the optimal configuration for sensors is a voting redundancy of four out of five sensors (2oo5) with a test interval of 8 253 hours. For the logic solver, the best setup is two out of three logic solvers (2oo3) with a test interval of 7 279 hours. Additionally, for the shutdown valve, the optimal configuration is three out of four valves (3oo4) with a test interval of 5 664 hours.

The **Figure 18** depict the distribution of particles across the search space, with each particle representing a potential solution to the optimization problem. The red spots indicate the best positions of particles within the search space, while the single yellow spot marks the global best or optimal solution.

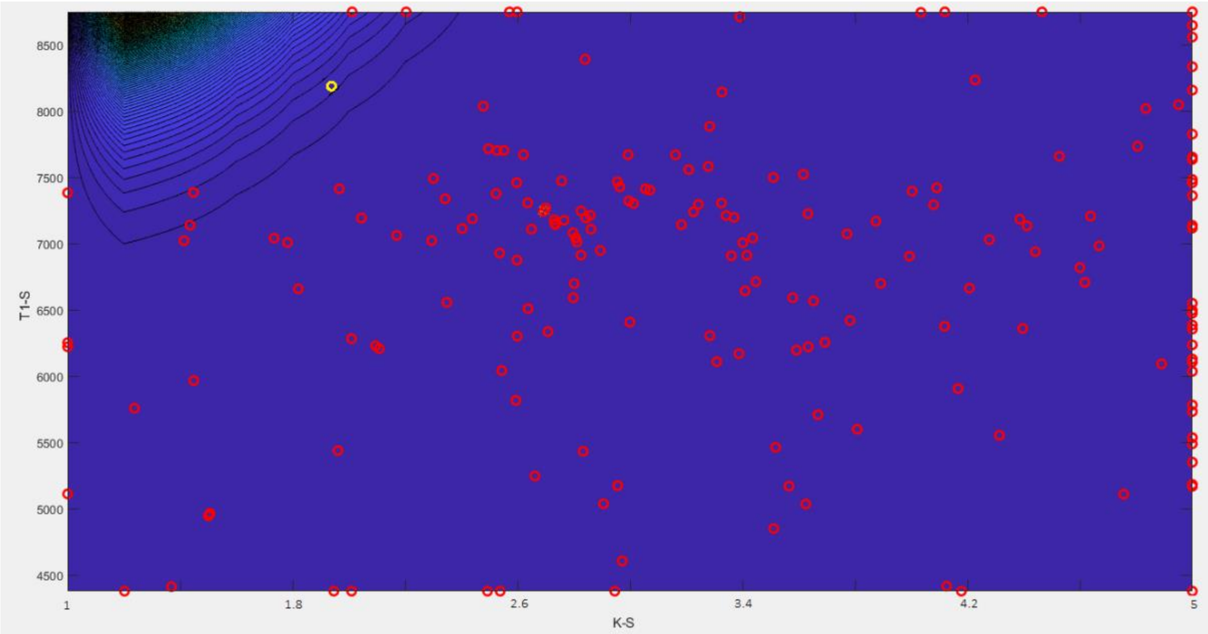


Figure 4. 5: Sensors PSO Particles distribution.

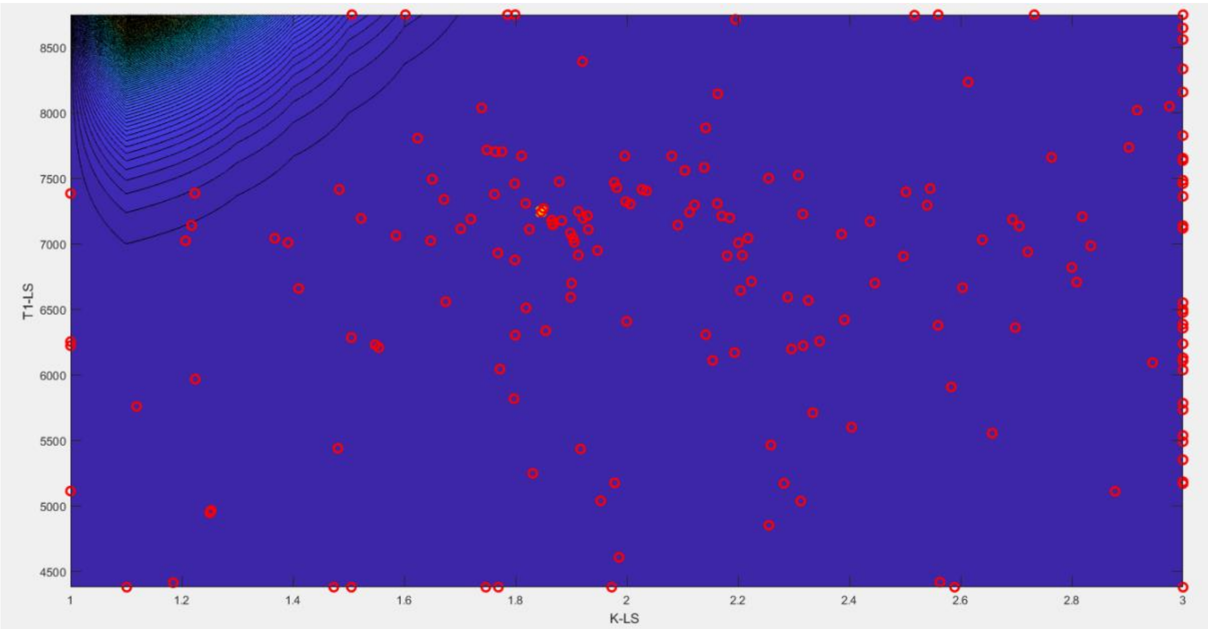


Figure 4. 6: Logic solver PSO Particles distribution.

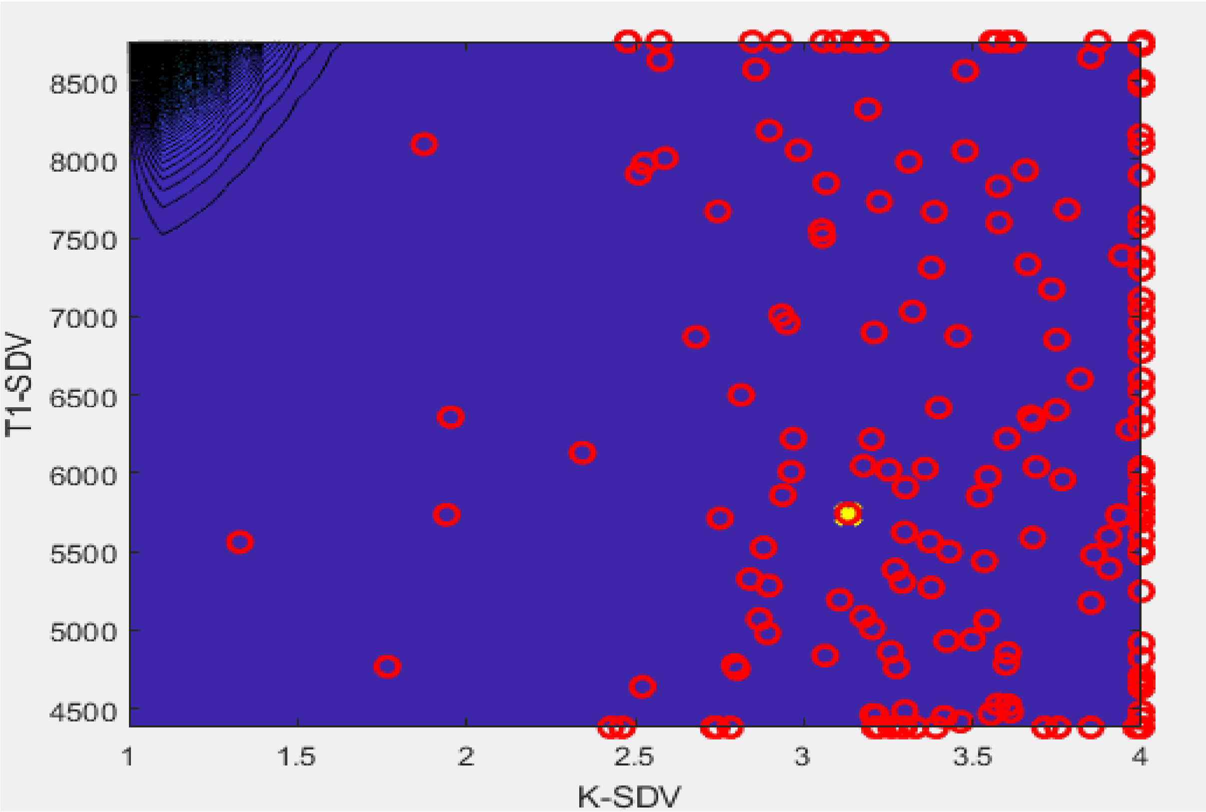


Figure 4. 7: Shutdown valve PSO Particles distribution.

4.4.2.3 Convergence and Computational Performance

PSO demonstrated strong convergence characteristics, with the objective function stabilizing after approximately 50 iterations. The velocity adjustment of particles allowed for a steady improvement in solution quality, and the swarm rapidly homed in on a near-optimal solution within a reasonable number of iterations.

The computational efficiency of PSO was another advantage in this study. Compared to more complex algorithms like GA, PSO required fewer computational resources and iterations to converge to an optimal solution. The simplicity of parameter tuning, combined with the algorithm's fast convergence rate, made it an attractive option for solving this real-world optimization problem.

4.4.2.4 Practical Implications

The optimized maintenance schedule generated by PSO offers several practical advantages for the power plant's operations:

- **Improved Safety and Reliability**: By reducing the frequency of spurious activations, the emergency shutdown system operates more effectively, ensuring that it triggers only in genuine cases of emergency, thus safeguarding the plant's operations.
- **Cost-Effective Maintenance**: The reduction in unnecessary maintenance tasks results in lower operational costs and increased efficiency during the plant's commissioning phase. PSO's ability to fine-tune the balance between maintenance frequency and cost helped achieve these savings.

- **Enhanced Plant Performance**: With fewer interruptions caused by false shutdowns, the plant can maintain higher levels of productivity. The reduced downtime translates into improved overall efficiency and profitability for the power plant during the critical commissioning stage.

In conclusion, Particle Swarm Optimization proved to be a powerful and efficient method for optimizing the maintenance schedule of the emergency shutdown system. The results of this case study highlight PSO's practical utility in minimizing spurious activations, improving system reliability, and reducing maintenance costs in industrial settings.

While both PSO and GA were effective in optimizing the maintenance schedule, PSO demonstrated a slightly faster convergence rate and required fewer iterations to reach an optimal solution. Additionally, PSO produced a marginally higher reduction in spurious activations (1.98×10-5) compared to GA's (4.251×10-5), though both methods resulted in significant improvements over the initial schedule. PSO's advantage in computational simplicity and faster convergence make it a strong candidate for maintenance optimization in industrial applications, though GA's robustness and adaptability still provide value depending on the specific nature of the problem.

4.5 Conclusion

In this chapter, we applied two powerful metaheuristic optimization methods (Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)) to solve a critical industrial problem within a combined cycle power plant. Specifically, we addressed the issue of spurious activations in the emergency shutdown system during the plant's commissioning phase. These activations caused unnecessary downtime, increased costs, and disrupted operations.

By optimizing the maintenance schedule using GA and PSO, we successfully reduced the occurrence of spurious activations, improved system reliability, and achieved significant cost savings. Both GA and PSO provided practical, implementable solutions that strategically balanced the frequency of maintenance tests with operational constraints. GA proved robust in exploring complex solution spaces, generating a maintenance schedule that minimized activations (4.251×10-5) while reducing overall maintenance costs. PSO, on the other hand, achieved slightly better results with a reduction in spurious activations (1.98×10-5), demonstrating its computational efficiency and fast convergence.

The results of this study underscore the effectiveness of metaheuristic methods in addressing complex optimization problems in industrial environments. By optimizing the maintenance strategy, we not only improved the performance of the emergency shutdown system but also provided a framework for enhancing the safety and operational efficiency of the plant. These findings demonstrate the value of applying advanced optimization techniques to real-world industrial systems, paving the way for more reliable and cost-effective maintenance strategies in the future.

General conclusion

General Conclusion

This thesis has embarked on a comprehensive exploration of the optimization of industrial scheduling, addressing the intricate challenges and opportunities that arise in modern industrial landscapes. Through an in-depth analysis of methodologies, technologies, and strategies, the research has sought to enhance the efficiency, safety, and sustainability of industrial operations, particularly within the petrochemical sector. The findings of this work contribute significantly to advancing the state of knowledge and practice in the field of industrial scheduling optimization.

The research began by identifying the pivotal role of scheduling in achieving industrial excellence, emphasizing its impact on resource utilization, operational efficiency, and adaptability. Traditional scheduling methods, while foundational, were shown to fall short in addressing the complexities of contemporary industrial systems. This gap has been effectively addressed through the integration of advanced technologies such as artificial intelligence (AI), machine learning, and metaheuristic algorithms, which form the cornerstone of the proposed optimization frameworks.

One of the key contributions of this thesis is the development of intelligent scheduling strategies that leverage AI to predict, adapt, and optimize operational workflows. These strategies not only enhance the efficiency of resource allocation but also significantly improve the reliability and safety of critical systems. The integration of predictive maintenance models, for instance, has demonstrated the potential to preempt failures, reduce downtime, and mitigate risks, underscoring the practical benefits of adopting smart scheduling approaches.

The petrochemical industry served as a focal domain for this research, providing a rich context to explore the interplay between safety, efficiency, and cost-effectiveness. By addressing challenges such as the scheduling of maintenance activities for Safety Instrumented Systems (SIS), the research has proposed innovative solutions that ensure system availability and compliance with regulatory standards. Furthermore, the incorporation of metaheuristic algorithms has showcased their effectiveness in solving complex scheduling problems, balancing competing objectives, and navigating constraints.

While the findings of this thesis highlight substantial progress, it is important to acknowledge the limitations inherent in the study. The reliance on specific case studies and simulated environments, for instance, calls for further validation of the proposed frameworks in diverse real-world scenarios. Additionally, the implementation of advanced technologies such as AI and IoT in scheduling systems presents challenges related to cost, scalability, and integration with legacy systems. Addressing these limitations requires collaborative efforts between academia, industry, and policymakers to develop more accessible and scalable solutions.

Looking ahead, the research opens several avenues for future exploration. The continued evolution of AI and machine learning technologies holds immense potential for further advancements in industrial scheduling. Future studies could focus on refining predictive models, enhancing data integration, and exploring the use of digital twins to simulate and optimize complex industrial processes. Moreover, interdisciplinary approaches that combine technical, organizational, and human factors could yield more holistic solutions to the multifaceted challenges of industrial scheduling. Additionally, the integration of sustainability metrics into scheduling frameworks could align industrial operations with global environmental goals, fostering a balance between productivity and ecological responsibility.

In conclusion, this thesis has demonstrated that the optimization of industrial scheduling is not merely a technical endeavor but a strategic imperative for modern industries. By bridging theoretical insights with practical applications, the research provides a robust framework for navigating the complexities of industrial operations. The integration of advanced technologies and innovative methodologies represents a transformative step toward achieving efficiency, resilience, and sustainability in industrial systems. As industries continue to evolve, the insights and contributions of this work will serve as a foundation for driving innovation and excellence in the dynamic landscape of industrial management. By fostering a synergy between cutting-edge technologies and practical applications, this thesis paves the way for a future where industrial systems are not only efficient but also adaptable, safe, and sustainable.

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