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Automatic Planetary Gears Train Conception : Optimization using Gravitational Search Algorithm

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DEDICATION

I would like to dedicate this work:

To my father "**Rabah** ", whose presence has been a constant source of inspiration throughout my academic journey. and also, to my mother, my dearest best friend "**Fatima** ". for her unwavering support, sacrifices, and presence you have made a profound impact into my life. With heartfelt gratitude, I express my deepest appreciation for their tireless efforts in shaping me into the person who I am today.

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To all the members of the «Masterminds» club which I consider my second family. To all the friends and colleagues of IMSI and all those who value me and think of me.

BOUNAB Sana

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DEDICATION

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Résumé

La synthèse du nombre de dents des engrenages pour les transmissions planétaires automatiques utilisées dans les automobiles pose un problème complexe d'optimisation avec contraintes. Ce travail explore l'application de l'algorithme de recherche gravitationnelle (GSA) pour résoudre ce problème. Les paramètres de conception pris en compte sont le nombre de dents pour chaque engrenage, le nombre de planètes multiples et le module des engrenages. La fonction objectif est définie comme la différence entre les rapports de transmission souhaités et réels. Pour assurer un système de transmission fiable, plusieurs contraintes sont prises en compte, notamment l'évitement du sous-creusement des dents, la limitation du diamètre total maximal et un espacement adéquat des planètes multiples. Le cas spécifique d'une transmission planétaire Ravigneaux à 3+1 vitesses est utilisé comme référence pour explorer l'espace de conception. L'algorithme GSA, largement reconnu comme une méta-heuristique, est utilisé pour parcourir l'espace de conception et étudier les effets des différentes contraintes sur le processus de synthèse. Les résultats de la recherche mettent en lumière l'optimisation du nombre de dents des engrenages dans les transmissions planétaires automatiques, fournissant ainsi des informations précieuses pour améliorer les performances, la fiabilité et l'efficacité des transmissions.

Mots clés: synthèse du nombre de dents des engrenages, transmission planétaire automatique, optimisation contrainte, algorithme de recherche gravitationnelle, évitement du sous-creusement des dents, diamètre total maximal, planètes multiples, transmission planétaire Ravigneaux.

Abstract

The gear-teeth number synthesis for automatic planetary transmissions in automobiles poses a challenging constrained optimization problem. This work explores the application of the Gravitational Search Algorithm (GSA) to solve this problem. The design parameters considered are the teeth number of each gear, the number of multiple planets, and the gear module. The objective function is defined as the deviation between the desired and actual transmission ratios. To ensure a reliable transmission system, several constraints are incorporated, including teeth-undercut avoidance, limitation on the maximum overall diameter, and proper spacing of multiple planets. The specific case of a 3+1 speed Ravigneaux planetary transmission is used as a benchmark to explore the design space. The GSA, a widely recognized meta-heuristic algorithm, is employed to navigate the design space and investigate the effects of different constraints on the synthesis process. The research findings shed light on the optimization of gear-teeth numbers in automatic planetary transmissions, providing valuable insights into improving transmission performance, reliability, and efficiency.

Keywords : gear-teeth number synthesis, automatic planetary transmission, constrained optimization, Gravitational Search Algorithm, teeth-undercut avoidance, maximum overall diameter, multiple planets, Ravigneaux planetary transmission.

ملخص

تواجه عملية توليف عدد أسنان التروس في ناقلات تروس كوكبية تلقائية في السيارات تحدياًا كبيراً كمشكلة تحسين مقيدة. تستكشف هذه الرسالة لنيل درجة الماجستير تطبيق خوارزمية البحث الجاذبية (ضا) لحل هذه المشكلة. تشمل المعاملات التصميمية عدد أسنان كل تروسة وعدد الكواكب المتعددة وحجم التروس. تعرف الدالة الهدف بالانحراف بين نسب التروسيب المطلوبة والفعلية. ولضمان نظام نقل موثوق به، تتضمن الرسالة العديد من القيود، بما في ذلك تجنب اختراق الأسنان وتحديد القطر الكلي الأقصى وتوزيع مناسب للكواكب المتعددة.
تستخدم حالة محددة لناقلة تروس كوكبية رافينيو بسرعة ٣"١ كمرجع لاستكشاف مجال التصميم. يتم استخدام خوارزمية البحث الجاذبية، وهي خوارزمية ميتاهيرستيك معروفة جيداً، لاستكشاف مجال التصميم ودراسة تأثير مختلف القيود على عملية التوليف. تسلط نتائج البحث الضوء على تحسين عملية توليف عدد أسنان التروس في ناقلات تروس كوكبية تلقائية، مما يوفر رؤى قيمة لتحسين أداء وموثوقية وكفاءة نظام النقل.

الكلمات الرئيسية : توليف عدد أسنان التروس، ناقلة تروس كوكبية تلقائية، تحسين مقيد، خوارزمية البحث الجاذبية، تجنب اختراق الأسنان، القطر الكلي الأقصى، الكواكب المتعددة، ناقلة تروس كوكبية رافينيو.

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GENERAL INTRODUCTION

Mechanical systems play a crucial role in achieving efficiency and optimal performance in engineering. Among various components, gears and transmissions have a profound impact on numerous industries, serving as the backbone of countless machines and mechanisms. Their wide range of applications includes automotive, aerospace, and robotics, highlighting their significance.

Planetary gearing stands out due to its compact design, high ratio potential, and ruggedness, making it ideal for unique applications. However, the design and optimization of planetary gears remain challenging, primarily due to the complex interactions between their components and the intricate design space. One particular pressing issue that has garnered considerable attention is the generation of noise. The noise produced not only impacts system performance and reliability but also poses negative effects on human comfort and environmental concerns.

To address these issues, this thesis aims to leverage meta-heuristics as effective tools to assist mechanical systems in overcoming their design challenges. Meta-heuristics are renowned for their capacity to solve optimization problems across a wide range of domains. Specifically, this research will focus on employing the gravitational search algorithm (GSA), a nature-inspired optimization technique that simulates the gravitational forces between celestial bodies. By utilizing GSA, we aim to enhance the performance and efficiency of planetary gear trains and the objective is to determine the optimal number of gear teeth that not only meet the required transmission ratios but also minimize noise. This approach holds great potential in addressing the previously mentioned issue of noise generation and improving overall system performance.

In order to achieve this objective, the thesis is structured into three chapters as follows :

- The first chapter, provides a comprehensive review of gears in general, with a specific focus on planetary gear trains. It covers various aspects such as their design, types, and the basics foundation necessary to understand their mechanical system.
- In the second chapter, we delve into optimization techniques. Without further ado, we specifically focus on the gravitational search algorithm (GSA) and explain in detail how we will implement it on the planetary gear train. This includes providing a detailed pseudo-code of the GSA.

- The third chapter presents a detailed formulation of the optimization problem, considering various design constraints and objectives. The mathematical model represents the planetary gear system, incorporating relevant parameters such as gear ratios, contact ratios, and the number of planet gears. This model will be evaluated through case studies and comparative analyses with existing optimization techniques, using the GSA implemented in MATLAB. The effectiveness of this methodology will be assessed to demonstrate its efficacy.
- Finally, we conclude our work with some results and a general conclusion.

CHAPTER 1

AUTOMATIC PLANETARY GEARS TRAIN

1.1 Introduction and history

Around 500 BCE, the Greeks invented the idea of epicycles which refers to circles travelling on the circular orbits. This concept is also known as planetary gears. With this theory *Claudius Ptolemy* in the *Almagest* in 148 CE was able to approximate planetary paths observed crossing the sky[1] and were initially intended to help predict the movements of planets in the solar system. They were long known primarily as clockworks [2], but did not find industrial application until the late 18Th century, at the end of the 18Th century, the sun and planet gear method of converting reciprocating motion to rotary motion and was used in the first rotative beam engines. was invented by the Scottish engineer *William Murdoch*, an employee of *Boulton* and *Watt*, but was patented by *James Watt* in October 1781 [3]. It was invented to bypass the patent on the crank, already held by *James Pickard.*[4]. It played an important part in the development of devices for rotation in the Industrial Revolution. , the planetary gear trains are nowadays increasingly widely used in the different fields of engineering and in particular in the mechanical engineering sector. Also, Planetary gear are used to transmit power in various industrial applications, including automotive and off-road transmissions, wheel drive motors, industrial conveying applications, and others. In addition, they can be used as a power train between internal combustion engines or connected to electric motors [5]. All planets and planetary gears have three main bodies, which we call a central element: the planet carrier, the ring gear, and the sun gear. The planet gears are connected to the planet carrier by bearings and mesh with the sun gear and the ring gear[6]. The number of planetary gears depends on the design load of the system.Planetary gears (or epicyclic gears) are usually categorised as simple or complex. Simple planetary gears feature a single sun, ring, carrier, and planet set. Compound planetary gears use one or more of the following three structures: meshed-planet (at least two more planets in each planet train mesh with each other), stepped-planet (a shaft connection exists between two planets in each planet train), and multi-stage structures (the system contains two or more planet sets). Compound planetary gears feature a higher reduction ratio, a higher torque-to-weight ratio, and more versatile combinations than basic planetary gears.

1.2 Exploring the World of Gears

Exploring the World of Gears provides a comprehensive examination of the fundamental components that drive mechanical systems.

1.2.1 Overview

A gear is a circular machine part with teeth that rotate and connect with another toothed part to transfer power and speed. The sizes of the gears affect how fast they rotate and how much force they can generate. Gears are employed to transmit motion and power from one revolving shaft to another [7]. The gear shafts can only be rotated one position at a time. They can be parallel, cross-sectional, or have an angle or intersect at an arbitrary point. Because of this, modern industrial machinery can operate with no limit on the applications of these components.

1.2.2 Classification of gears

In gear engineering, it is essential to categorize types of gears based on their specific properties and uses, which is referred to as gear classification. Engineers obtain valuable insights into their unique properties, enabling them to select the most suitable gear types for specific tasks. The main classifications of gears can be broadly divided into three categories, which are:

1.2.2.1 Gears for Parallel shafts

The motion between parallel shafts is same as to the rolling of two cylinders.

Spur Gears Spur gears are the most commonly used gear type. They are by far the most common affordable option. When the axes are parallel, the teeth of the meshing gears can be cut in a straight line on the surface of the gear blank. There are many special types of spur gears, some of which are less common. Although these special shapes do not differ significantly from ordinary spur gears in tooth action, it may refer to one or two of these shapes that are sometimes found in special applications. The spur gear meshes with an element called a rack. A rack can be thought of as a small segment of an infinitely large spur gear, a gear whose diameter is so large that the teeth are almost in a straight line, spur gears generally cannot be used when a direction change between the two shafts is required [8].

Figure 1.1: Spur Gear.[8]

Helical Gears Used with parallel shafts similar to spur gears, helical gears are spur gears with serpentine tooth lines. They have better meshing, are quieter and can carry higher loads than spur gears, making them suitable for high-speed applications. When using helical gears, they generate axial forces in the axial direction, which necessitates the use of thrust bearings. Single helical gears impose both radial loads and thrust loads on their bearings and so require the use of thrust bearings[9]. The helix angles on the pinion and gear must be the same magnitude but opposite, the right pinion meshes with the left gear.

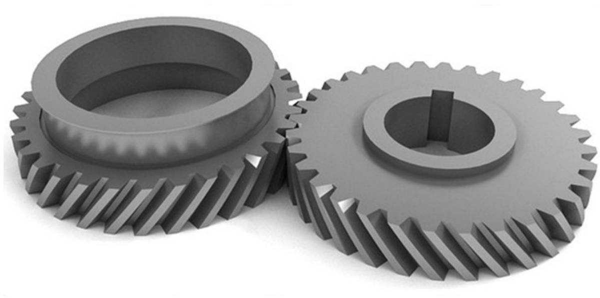


Figure 1.2: Helical gear.[9]

Herringbone Gears It is two sets of opposing helical teeth placed side by side[10]. They are commonly referred to as having a double helical gear arrangement with balanced thrust. There is no thrust load on the bearing. Like helical gears, they have the advantage of transmitting power smoothly because more than two teeth are meshing at any one time.

Figure 1.3: Herringbone gears.[10]

Rack and Pinion In these gears the spur rack can be considered to be spur gear of infinite pitch radius with its axis of rotation placed at infinity parallel to that of pinion. The pinion rotates while the rack translates.

Figure 1.4: Rack and Pinion.[11]

1.2.2.2 Gears for Intersecting Shafts

The motion between two intersecting shafts is equivalent to the rolling of two cones. The gears used for intersecting shafts are called bevel gears.

Bevel/Miter Gear It is conical in shape and is used to transmit power between two shafts that intersect at a point. Its rolling surface is a conical surface, and the teeth are cut along the conical surface.

Figure 1.5: Bevel Gea

1.2.2.3 Gears for Skew Shafts

A worm gear is sometimes called a worm wheel, it has teeth that are oblique to the axis of rotation and cut radially into the gear face. The teeth are helical to match the helix angle of the teeth on the auger. They are usually used in speed reducers. Worm gears are quiet, vibration free and give a smooth output[11].

Figure 1.6: A worm gear.[11]

Hypoid Gears The Hypoid Gears are made from special shapes called frusta of hyperboloids of revolution. When two hypoid gears have the same line of contact, they are created by rotating it. However, it's important to note that these gears are not interchangeable.

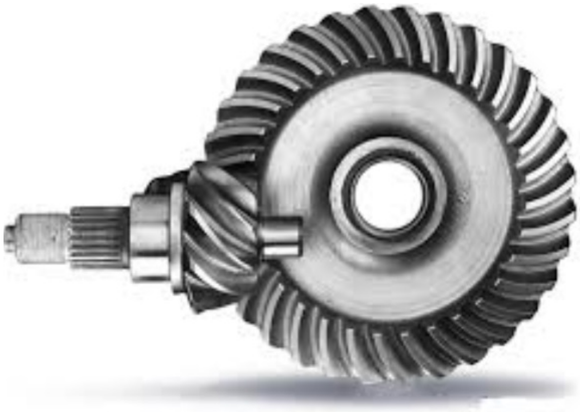


Figure 1.7: A Hypold gear.[11]

1.3 Planetary Gear Train

1.3.1 Overview

A planetary gear is a type of gear system comprised of spur gears. In planetary gearing there is a central gear known as the sun gear, serves as the input and driver of the set. Three or more "driven" gears (referred to as planets) rotate around the sun gear. Finally, the planets engage with a ring gear from the inside, which makes an internal spur gear design. Because the planet gears are evenly distributed around the sun, planetary gear trains are known to be extremely rugged designs. Another benefit of a planetary gear set is that it is easy to convert to a different ratio by simply changing out the carrier and sun gears.,and is widely used in power transmission and serves as the most critical component. Planetary gears are often used to adjust inertia, reduce motor speed, and increase torque while providing a robust mechanical interface. the planetary gears systems have high torque density, compact, low inertia and can be grease lubricated for life, which are demands of industrial applications [12].

A planetary gear set uses spur gears that move opposite of each other within the same plane. While spur gears are a more basic type of gear in terms of engineering since they do not utilize speciaL angles or cuts like bevel or herringbone gearing, they are complex in the tooth shape design. Depending on the application, this tooth design will determine where the teeth make contact, which then determines the available power, torque, and speed potential of the gears.

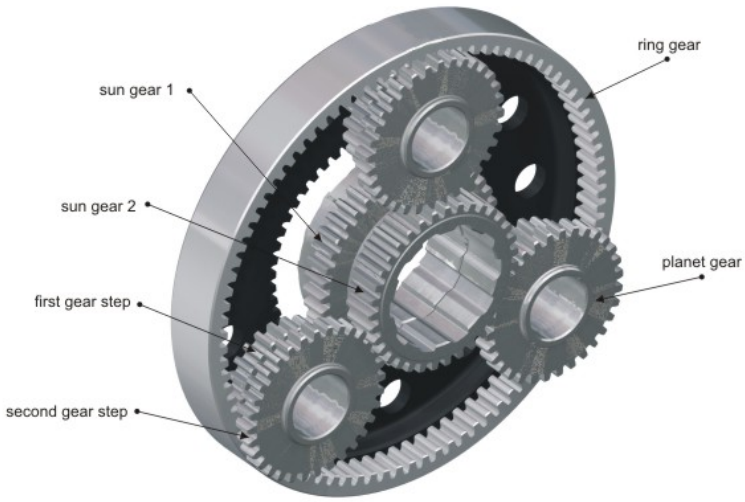


Figure 1.8: Planetary Gear System.[12]

1.3.2 Why is it Named a Planetary Gearbox?

The term "planetary gearbox" originated from the synchronized movement of its various gears. It consists of a sun gear, a ring gear (also called a satellite gear), and two or more planet gears. The sun gear is typically the driving gear, which in turn rotates the planet gears that are attached to a carrier, ultimately forming the output shaft. The satellite gears remain fixed in position relative to the outer components. This arrangement resembles the structure of our solar system, hence the name "planetary." Interestingly, ancient gear systems used in astrology for tracking celestial bodies shared similarities with this gearbox design.

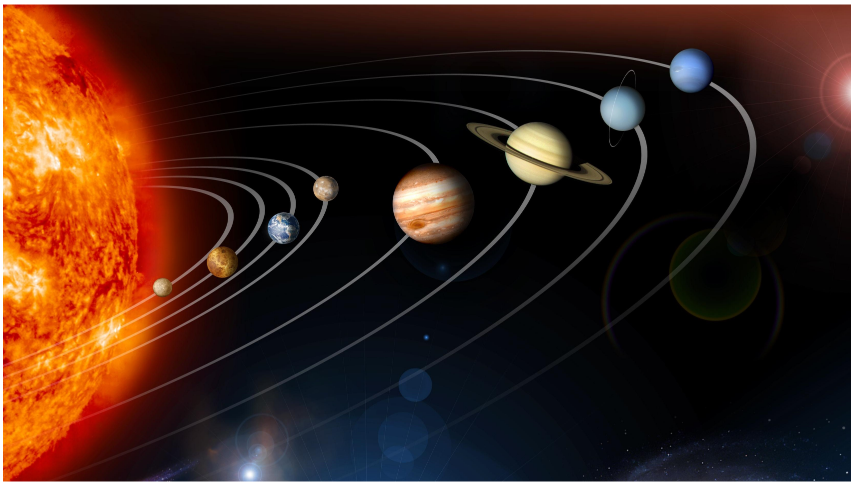


Figure 1.9: Solar system.

However, in practical discussions regarding industrial applications, we focus on the functionality of planetary gearboxes. Thus, we refer to the sun gear as the input shaft, the planet gears as the carrier, the output shaft, and the satellite gear (or ring component) as the housing.

1.4 Design and Analysis of Planetary Gear Trains

A planetary gear train combines multiple parts to efficiently transmit torque, relying on their precise design for optimal performance and power distribution.

1.4.1 Parts of PGT

consists of several parts, each playing an important role in transmitting power from the input shaft to the output shaft. Here are the main parts of a planetary gear train:

1.4.1.1 Sun Gear

The sun gear is the central gear in a planetary gear train and is usually driven by the input shaft. The planet gears rotate around the sun gear and transmit power to the output shaft.

1.4.1.2 Planet Gears

The planet gears are typically mounted on a carrier that rotates around the sun gear. The number of planet gears can vary depending on the desired gear ratio and torque capacity.

1.4.1.3 Ring Gear

the ring gear is the outermost gear in a planetary gear train and is usually fixed to the gearbox casing. The planet gears mesh with the ring gear, transmitting power to the output shaft.

1.4.1.4 Carrier

The carrier holds the planet gears and allows them to rotate around the sun gear. The carrier can be fixed or rotating, depending on the gear train configuration.

1.4.1.5 Bearings

The bearings support the rotating parts of the planetary gear train and allow them to rotate smoothly with minimal friction.

These are the main parts of a planetary gear train, but some gear trains may have additional components such as thrust washers, seals, and lubrication systems to ensure smooth and efficient operation.

1.4.2 Design of PGT

A planetary gear train is a compact and efficient gear system that relies on several components to transmit torque and rotation. The central component of the system is the sun gear, which is surrounded by several planet gears that are mounted on the carrier. The planet gears rotate around the sun gear and mesh with a ring gear that encloses them, providing the outer surface of the gear system. Each component of the planetary gear train plays a crucial role in the system's overall operation and performance. To gain a better understanding of how these components work together, we will examine the design of each part in detail:

1.4.2.1 Sun Gear and Planets Design

The design of a sun gear largely depends on how the load distribution between the planets is equalized. Most often, the sun gear is made of carbonized steel.

Planets are intermediate wheels, which, in a certain sense, act as parasitic (auxiliary) wheels as they do not affect the speed ratio. Most often planets are made of the same steels as the sun gear and are also carbonized and case hardened. It should be remembered that in the same gear train, it is desirable that the matched gears are made of a different material (different grades of steel) in order to reduce the risk of scuffing.

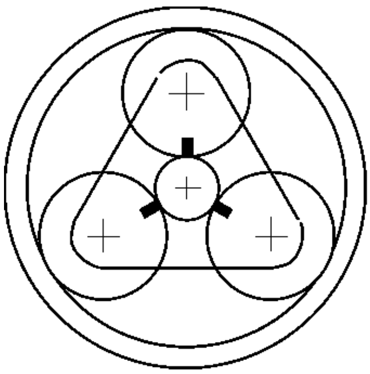


Figure 1.10: Sinphase montage of planets, with radial orientated run-out to the center of sun gear [2]

The faces of all planets of the gear train are simultaneously ground to be parallel. When toothing (cutting or grinding) a package, the orientation of planets can be marked with paint, so that the so-called sinphase montage can be carried out.

1.4.2.2 Ring Gear Design

Ring gear is a specific gear of Abrasion-Inhibited Planetary Gear train(AI-PGT). Unlike the sun gear and planets, the ring gear does not usually harden and very rarely grind. It is made of hardened (tempered), alloy or non-alloy steel, through hardening (tempering), for easy machining. Since the ring gear is a thin-walled and easily deformable part, it is necessary that when tightened on the gear-cutting machine, there are no deformations which will subsequently occur in the performance of the gear train in a very unfavorable manner.

1.4.2.3 Gears Thermal and Chemico-thermal Treatment

For PGTs gears, the following thermal and chemico-thermal treatments are the most common:

- Carburizing and case hardening.
- Through hardening (tempering).
- Nitriding, respectively, ionnitriding.

1.4.2.4 Gears Accuracy Measurement

From every point of view, gears require special attention to design, high-quality machining, and reliable quality control. Quality of PGT (its reliability, durability, heating, noise and vibration, etc.) first depends on its gears. The type and number of accuracy measurements of gears depend on the requirements and responsibility of the PGT (on the estimations of the designer, manufacturer, and user).
The gear accuracy measurements are as follows: On the cutting machine, in all cases, the base tangential length (span measurement, measurement of Wildhaber) of gears with external teeth is measured (Figure 1.9), and in some cases (a large module), this is also possible for gears with internal teeth. Span length is determined as follows:

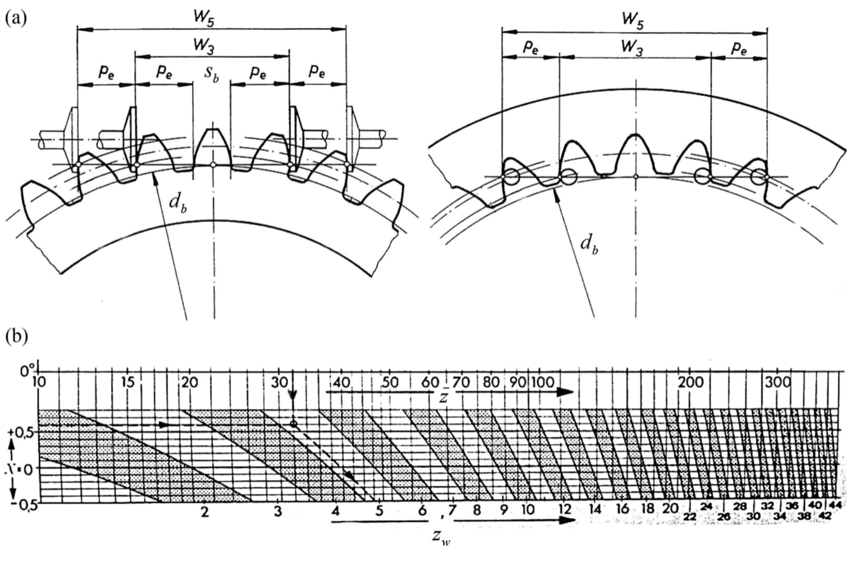


Figure 1.11: Base tangential length (span) W measurement of external and internal teeth: (a) Ways of measuring; (b) determining of the number of measured teeth w... [2]

Over $zw = 3$ teeth

$$W = 2pb + sb = (zw - 1)pb + sb; \tag{1.1}$$

Over $zw = 5$ teeth

$$W = 4pb + sb = (zw - 1)pb + sb; \tag{1.2}$$

where pb is the base pitch, pe is the meshing pitch, sb is the external tooth thickness at the base circle with diameter db, and $s = \pi m + 2mx \tan\alpha$.is the external tooth thickness at the reference circle with diameter d.

$$pb = pe = \pi m \cos\alpha \tag{1.3}$$

$$sb = db\left(s + \frac{1}{\alpha}\right) \tag{1.4}$$

1.5 Types of PGTs

By manipulating various components of a planetary gear train, such as the number of gears or the types of gears used, it is possible to create multiple variations adapted to specific requirements. PGTs can differ in various features, including:[13]:

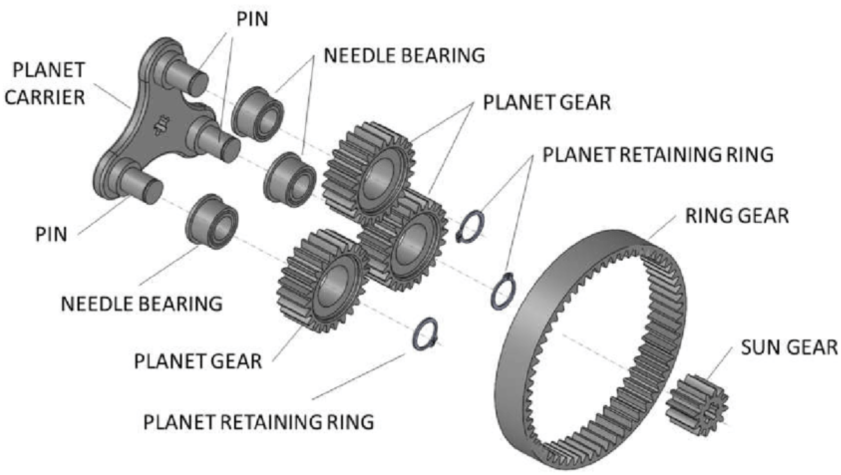


Figure 1.12: Components of a PGT.[13]

1.5.1 According to the carrier number

- **Simple Planetary Gear (single carrier):** This type of planetary gear has only one gear set, consisting of a sun gear, planet gears, and a ring gear. The planet gears are mounted on a single carrier pin, which is fixed to the gearbox housing. The planet gears rotate around the sun gear and mesh with the ring gear to produce the gear reduction.

- **Compound Planetary Gear (Multi-carrier):** This type of planetary gear has two gear sets, each with its own planet carrier. The sun gear is in the middle and meshes with both sets of planet gears. The planet gears in each set rotate in opposite directions and mesh with the ring gear to produce the gear reduction.

- **Epicyclic Planetary Gear (planet carrier):** This type of planetary gear has three or more gear sets, each with its own planet carrier. The sun gear is in the middle, and the planet gears in each set rotate around the sun gear and also rotate around their respective planet carriers. The planet carriers themselves rotate around a fixed annulus gear to produce the gear reduction.

1.5.2 According to the component PGTs number

- **Simple Planetary Gear:** It is the most basic form of planetary gear and has the fewest components.
- **Compound Planetary Gear:** This type of planetary gear has additional components such as a carrier, which holds the planet gears in one set and meshes with the planet gears in the other set. It also has a set of idler gears to transmit power between the two sets of planet gears.
- **Complex Planetary Gear:** This type of planetary gear has more than two sets of planet gears, and the planet gears in each set can mesh with more than one ring gear. It also has additional components such as multiple carriers, sun gears, and idler gears to transmit power between the different sets of planet gears.

1.5.3 According to the gear wheels type

- **Spur Planetary Gear:** All the wheels are spur gears, which have straight teeth and are parallel to the axis of rotation. the gear reduction is achieved through the interaction of these gears.
- **Helical Planetary Gear:** Which are at an angle to the axis of rotation. The helical teeth provide smoother and quieter operation than spur gears and can transmit more torque.
- **Bevel Planetary Gear:** which have conical shaped teeth and are mounted at an angle to the axis of rotation. Bevel planetary gears are used when the direction of the input and output shafts needs to be changed, such as in a differential.
- **Hypoid Planetary Gear:** which have curved teeth and are mounted at an angle to the axis of rotation. Hypoid planetary gears are used in applications where high torque is required and where the input and output shafts are not in the same plane.

1.5.4 According to the gears tooting and meshing

- **With external meshing:** The planet gears mesh externally with both the sun gear and the ring gear. The sun gear and the ring gear are typically stationary, while the planet gears rotate around the sun gear and mesh with the ring gear.
- **With Novikov meshing:**It is a specific form of external meshing; the planet gears are mounted on a carrier that is connected to the output shaft. The carrier rotates around the sun gear, and the planet gears mesh with both the sun gear and the ring gear simultaneously.

- **With internal meshing:** the planet gears mesh internally with both the sun gear and the ring gear. The sun gear and the ring gear are typically rotating, while the planet gears are stationary and mesh with the sun gear and the ring gear from inside.
- **Hybrid Meshing:** Some of the planet gears mesh externally with the sun gear and internally with the ring gear, while others mesh vice versa. This configuration can provide a balance between torque capacity and compactness.
- **Involute:** The teeth are in the form of involutes, which are curves generated by unwinding a taut string from a circle. Involute gears are known for their smooth and quiet operation.
- **Cycloidal:** The teeth are in the form of cycloids, which are curves generated by tracing a point on a circle as it rolls along a straight line. Cycloidal gears are known for their high torque capacity and their ability to transmit power smoothly.

1.5.5 According to the basic speed ratio i0

- **Positive-ratio PGTs:** The output shaft rotates in the same direction as the input shaft. In other words, the basic speed ratio of a positive-ratio PGT is greater than 1.
- **Negative-ratio PGTs:** Also known as counter-rotating PGTs, the output shaft rotates in the opposite direction to the input shaft. In other words, the basic speed ratio of a negative-ratio PGT is less than 1.

1.5.6 According to the external shafts number

- **Single-shaft planetary gears:** This type of planetary gear has only one external shaft, which can be either the input or output shaft. The other end of the gear system is typically connected to a fixed frame or housing.
- **Multi-shaft PGTs:** Have two external shafts, one for the input and one for the output. The sun gear is typically connected to the input shaft, and the ring gear is typically connected to the output shaft.
- **Three-shaft PGTs:** Has three external shafts, which are typically arranged in a T-shape. The input shaft is typically connected to the sun gear, and the output shafts are typically connected to the carrier and ring gear.

1.5.7 According to the external shafts coaxiality

- **Coaxial PGTs:** The external input and output shafts are aligned along a common axis, and it is the most common.
- **Uncoaxial:** The external input and output shafts are not aligned along a common axis.

1.5.8 Applications of PGT

PGT have a wide range of applications in various industries such as in:

1.5.8.1 Wind turbines

Wind turbines are ecologically friendly energy sources that use the power of the wind to create electricity. One critical component of these turbines is the gearbox, which suffers the highest downtime and loss. To assure their lifespan, a flexible pin based on the original straddle-mounted pin design was created [14]. This redesigned pin allows for better load sharing and distribution within a wind turbine gearbox's planetary gear set (PGS). Wind turbines are used to transform the kinetic energy of the wind into electrical energy. They are made up of revolving blades positioned on a rotor that provide power to the main shaft. A generator is used to transform mechanical energy into electrical energy, and a gearbox is used to modify the rotation speed of the main shaft to meet the rated speed of the generator. The turbine is additionally supported by components such as the tower and the rotor yaw mechanism. The blades and rotor typically revolve at a modest speed of 10-20 rpm, imparting significant torque. Induction generators, on the other hand, produce power effectively at 1000-2000 rpm. As a result, most wind turbines have a gearbox to enhance rotor speed. Because of its high-power density and concentric input and output shafts, planetary gear sets (PGS) are the preferable choice for this application. Because of the substantial input torque from the blades, the first PGS in the system suffers the highest stress. Furthermore, the gearbox is a complicated component of a wind turbine and hence has the longest downtime, making it a key area of worry. As a result, several researches have been undertaken to improve the durability of wind turbine gearboxes (WTGBs).

Figure 1.13: Planetary Gear Train used in a wind turbine.[14]

1.5.8.2 Helicopters

Planetary gear systems are commonly utilized as the final step of transmission in helicopters. These systems generally have 3 to 18 gears, with planetary gear ratios ranging from 5:1 to 7:1 [15].

A planetary gear train is used in the primary transmission of a rotor craft, which consists of an inner "sun" gear surrounded by five revolving "planets." The sun gear transfers torque to the planets, which are mounted on a planetary carrier. The torque is subsequently transmitted to the main rotor shaft and blades through the planetary carrier plate. Epicyclic gears are used extensively in rotor craft transmission systems.

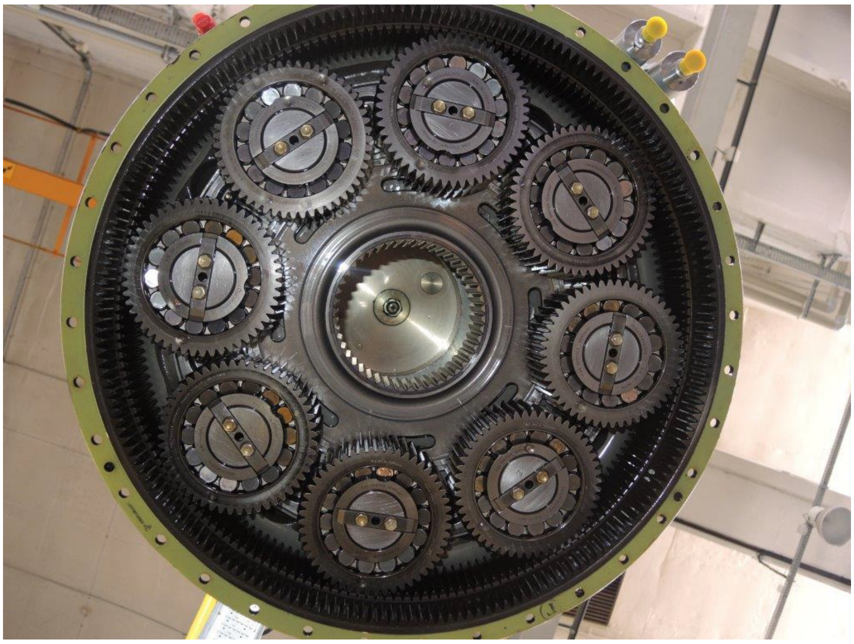


Figure 1.14: Super Puma Epicyclic Gear.
[15]

1.6 Pros and Cons of Planetary Gear Trains

Planetary gear systems are a popular choice for situations where higher gear ratios are needed in a compact space. These arrangements are preferred for reducing speed in tight areas. Compared to traditional gearboxes, planetary systems are lighter weight for similar gear ratios. They also have a higher power transmission efficiency, meaning that a larger proportion of the input energy is delivered to the output. Additionally, they have a higher torque transmission capability and lower inertia, which leads to better load distribution and increased torque transmission. In planetary systems, the driving and driven members are concentric, allowing for equipment to be installed in the same line and saving space. Planetary gear systems also provide higher stability and a longer service life compared to traditional gearboxes for similar loads.

Planetary gear systems offer many advantages, but there are also some drawbacks. One of the most significant disadvantages is the noise generated during operation. Some planetary gearheads can be quite noisy, which can be problematic in applications where noise levels need to be kept low. The complexity of planetary gears makes them more difficult to manufacture and maintain, and this complexity can exacerbate noise issues. In addition to noise, high bearing loads resulting from the use of planetary gears can lead to early wear in dead stud or sleeve bearing construction, which can cause even more noise and reduce the lifespan of the gear system. Determining the efficiency of a planetary gear system can also be difficult, and the higher level of internal friction compared to other types of gears can lead to more energy being lost as heat and noise, further contributing to noise issues. Finally, the multiple stages of planetary gears can result in a high ratio of length to diameter, resulting in a long gearhead. This can be problematic in applications with limited space and may worsen noise issues.

1.7 Conclusion

Planetary gears are commonly used in various industries. Since the gear is one of the most important components of the planetary gear mechanism, these gears will affect the entire transmission system. Planetary gears have proven themselves to provide the necessary stability in mechanical systems. The gearbox is also lighter in weight compared to other boxes. On the other hand, planetary gears are difficult to maintain compared to more traditional systems However, research clearly shows that most planetary gearboxes can outlast the design life of the machine. Another common problem associated with these transmission systems is noise. However, planetary systems still face many challenges that conventional gears cannot solve. To sum up, the planetary gear system has low inertia, high torque density and compact structure. These properties explain why the planetary principle has recently attracted a lot of attention and have convinced mechanical engineers that planetary gear drives will continue to be widely used in various machines, toys, electric motors and automation systems in the future.

CHAPTER 2

META-HEURISTICS OPTIMIZATION: GRAVITATIONAL SEARCH ALGORITHM

2.1 Introduction

Planetary gear trains are commonly used in a wide range of industrial applications due to their compactness and high-power transmission capabilities. They produce high speed reductions in compact spaces, greater load sharing, higher torque to weight ratio, diminished bearing loads, and reduced noise and vibration[16], despite their advantages, the noise induced by a variety of sources, including gear meshing, bearing vibration, and transmission error, remains a key concern. With the advancement of technologies in engineering science, there has always been an advent of optimization for further refinement, researchers have turned to optimization techniques that aim to reduce noise levels while maintaining the necessary levels of power transmission and efficiency. Optimization seeks the maximum or minimum value of an objective function corresponding to variables defined in a feasible range or space. More generally, optimization is the search of the set of variables that produces the best values of one or more objective functions while complying with multiple constraints. In the context of planetary gear trains, optimization can be used to find the optimal gear tooth geometry, gear materials, lubricants, and other design parameters that minimize noise while satisfying other performance requirements. Optimization techniques have been successfully applied to a range of planetary gear train applications, including wind turbine gearboxes, automotive transmissions, and industrial gearboxes. By reducing noise levels, optimization can improve the overall performance, reliability, and durability of planetary gear trains, making them more suitable for a wide range of applications.

2.2 Optimization problems

The word “optimum” is Latin, and means “the ultimate ideal;” similarly, “Optimus” means “the best”. Therefore, to optimize is to make an effort to move whatever we’re working on closer to its ideal condition. Getting the best configuration (optimal solution) out of all feasible configurations under specific conditions, and doing it with reference to a particular criterion, is what is meant by optimization in the broadest sense.

In mathematics, optimization frequently entails identifying the values of one or more variables that maximize or minimize a certain objective function while meeting a given set of restrictions. The optimization problem $P(\Omega, f)$ is characterized by a feasible set Ω and an objective function f. The formulation of the optimization problem requires the specification of the following notations:

- **Objective function**: The "objective function" is the criterion that should be optimized and is an objective measure of the quality of the solution. It allows us to maximize or minimize a numerical value, such as a project's cost, profit value, or even the noise level of a material. The goal of using the objective function is to attain a desired target for the output. From a mathematical perspective, the technical representation of the objective function is:

$$\text{Minimize or Maximize } = \sum_{i=1}^{n} c_i X_i$$

- **Decision variables**: they are unknown and controllable parameters of the problem whose objective is to find their value to solve the optimization problem. The value of the decision variables determines the value of the objective function. Depending on the problem under consideration; they can take discrete (integer) or continuous (real) values. Often these variables are restricted or constrained, i.e. they must check certain conditions called constraints. They take their values in a domain called search space.

- **Search space**: The "search space" is the set of solutions in which the desired solution exists, encompassing the problem's upper and lower boundaries. This space can be a discrete and well-defined data structure in computer science or, in the case of decision theory, an expansive and possibly infinite set that necessitates the generation of individual elements throughout the search process.

- **Candidate or feasible solution**: The candidate or feasible solution, also known as a vector of decision variables satisfying all constraints of the optimization problem, is a set of values that forms the feasible region. This set of feasible solutions defines the feasible space where the decision variables are grouped together.

A minimization problem of an objective function $f(x)$, subject to inequalities (and sometimes qualities) constraints, is presented as:

$$\min_{x \in \Omega} f(x) : Sc \begin{cases} g(x) \leq 0 & \text{(m inequality constraints)} \\ h(x) = 0 & \text{(p equality constraints)} \end{cases} \tag{2.1}$$

Noting that each minimization problem can be transformed into a maximization problem and vice versa.

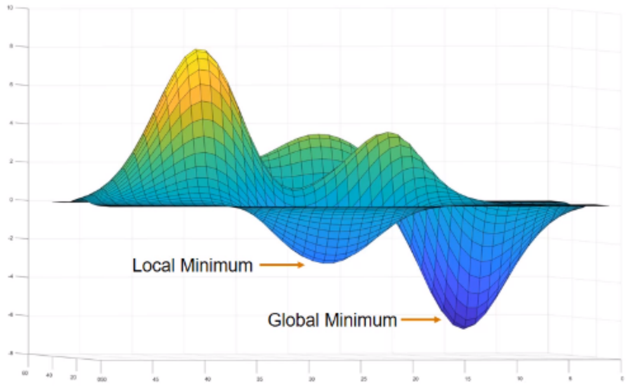


Figure 2.1: "Global Optimization".

2.2.1 Types of optimization methods

The diversity of optimization problems implies different types of optimization methods. We can distinguish between two global types: Deterministic optimization methods (called exact) and Non-deterministic optimization methods (heuristic and metaheuristic).

2.2.1.1 Deterministic methods

A deterministic method is the method of choice if it can solve an optimization problem with the effort that grows polynomially with the problem size. These methods take advantage of the analytical properties of the problem such as convexity, continuity, and differentiability to obtain the optimal solution in a finite time and to prove its optimality[17]. We mention here the two most recognized methods: Newton's method and gradient methods. The situation is different if the problem is NP-Hard, where the exact optimization techniques require exponential effort. In that case, even medium-sized problem instances become intractable and cannot be solved using these methods. Therefore, non-deterministic techniques are the best alternative to solving NP-Hard problems.

2.2.1.2 Non-deterministic methods

Some optimization problems remain beyond the reach of exact methods. A certain number of characteristics can be problematic, such as the absence of strict convexity (multimodality), the existence of discontinuities, and a non-derivable. In addition, determinist methods may take time that grows exponentially with the problem size. The optimization problem in this case is said to be NP-hard and cannot be solved using exact methods.
Thus, non-deterministic methods (heuristic and metaheuristic) has been specifically developed for these type of optimization problems. They are stochastic iterative algorithms that can provide approximate solutions of good quality in a reasonable time without guaranteeing optimality. Heuristic algorithms are commonly problem-specific as they exploit the properties of the problem. When a heuristic can be generalized to several types of problems without significant modification, one speaks then of metaheuristics. The latter will be discussed in more detail in the next section.

2.3 Meta-heuristic optimization techniques

When discussing optimization techniques, the conversation inevitably turns to meta-heuristics. However, before delving further into the topic, it is important to provide a brief overview of the history of meta-heuristics.

2.3.1 History of meta-heuristics

The term "meta-heuristics" was first coined by *Fred W. Glover* in the late 1970s[18], the prefix Meta is derived from the Greek word "metá," which means "beyond" or "transcending." In modern usage, the prefix "meta-" is often used to indicate something that is higher or more abstract than the thing it modifies. In the context of problem-solving and optimization, "meta" is used to refer to higher-level strategies that operate beyond the level of individual solutions. While heuristics comes from the Greek word "heuriskein", which means "to find" or " to discover". In modern usage, heuristics refer to problem-solving strategies or rules of thumb that help individuals or machines find solutions to complex problems quickly and efficiently. So meta-heuristics, for example, are optimization strategies that operate at a higher level than the individual search algorithms used to find solutions[19]. In the 1990s, meta-heuristics started gaining wider recognition and popularity in the scientific community. More sophisticated algorithms were developed, such as Ant Colony Optimization, Particle Swarm Optimization, and Simulated Annealing, which showed promising results in various problem domains. Since then, meta-heuristics have continued to evolve and diversify, with new algorithms and hybrid methods being developed regularly. With the growth of computational power and the availability of large data sets, meta-heuristics are becoming increasingly important and have found applications in various fields such as engineering, finance, medicine, and logistics, among others. Since then, meta-heuristics have continued to evolve and diversify, with new algorithms and hybrid methods being developed regularly. With the growth of computational power and the availability of large data sets.

2.3.2 Overview

Meta-heuristic (MH) algorithms have received wide attention and have been employed to solve various optimization problems. Due to their unique capabilities in solving them. These algorithms are developed by taking inspiration from natural phenomena or the behavior of living organisms, such as animals, insects, and other organic beings. Over time, numerous meta-heuristic algorithms have been introduced and applied to a variety of real-world optimization problems across various domains.

Also, they are problem-independent optimization techniques that can be applied to a wide range of combinatorial optimization problems. They are heuristic methods that use higher-level strategies to find appropriate values for the decision variables of an optimization problem so that the objective function is optimized [20]. There are many different types of meta-heuristics, each with their own strengths and weaknesses. In general, meta-heuristics are used when traditional optimization methods are not sufficient, due to the complexity or size of the problem, or the presence of non-linear or non-convex constraints. They are widely used in many fields, including operations research, computer science, engineering, finance, and biology Generally the complexity of the real-life problems are in increasing in a manner that it become Difficult for the traditional mathematical programming methods to solve and optimize them. Most of the real-life optimization's problems are non-linear, complex, multi-modal, and they have an incompatible objectives functions in which the process of obtaining an optimal or even near-optimal solutions is a very difficult task, generally, there is no guarantee of getting an optimal solution for real-life problems [21] [22].

2.3.3 Types of meta-heuristics

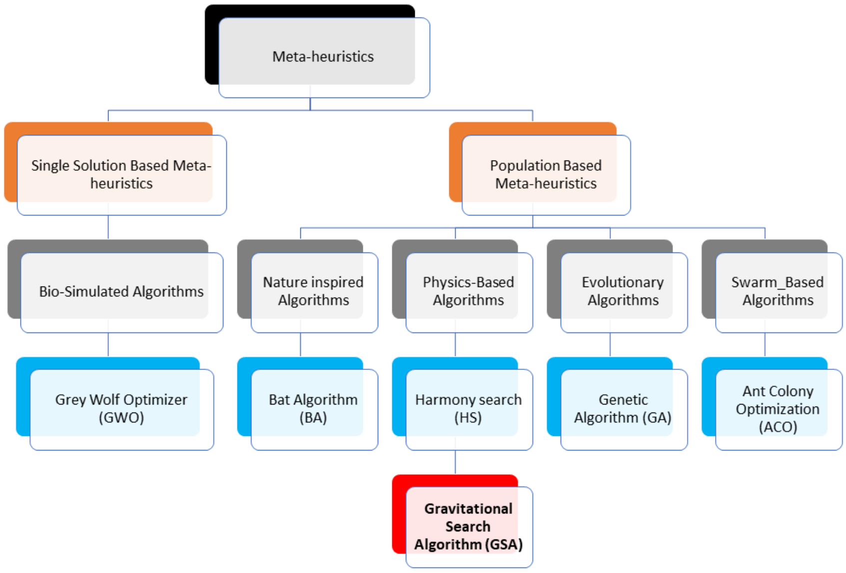


Figure 2.2: Taxonomy of meta-heuristic optimization algorithms.Source:EL-Ghazali Talbi "FROM DESIGN TO IMPLEMENTATION"

Over the last decades, there has been a growing interest in algorithms inspired by the behaviors of natural phenomena. Each algorithm has its own strengths and weaknesses, making them suitable for different types of optimization problems. These are just a few examples of the many types of meta-heuristics available:

2.3.3.1 Genetic Algorithms (GA)

The term genetic algorithm, almost universally abbreviated nowadays to GA, was first used by John Holland [23], is a meta-heuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators. The basic idea behind genetic algorithms is to simulate the process of evolution by creating a population of potential solutions, applying genetic operators such as selection, crossover, and mutation to generate new candidate solutions, and then evaluating the fitness of these solutions to select the best ones for the next generation

2.3.3.2 Simulated Annealing

This technique is emulating the physical annealing of solids to solve optimization problems. Is so named because of its similarity to the process of annealing in metallurgy[24], where a material is heated and slowly cooled to achieve a desired structure. In optimization, simulated annealing gradually cools a system to find the global minimum. The algorithm works by generating a set of candidate solutions and evaluating their fitness based on a specified objective function. It then iteratively adjusts the candidate solutions by applying a perturbation function that adds random noise to the current solution. The perturbation function is controlled by a temperature parameter that determines the level of randomness in the search process. As the temperature decreases, the perturbation function becomes less random and the search process becomes more focused on the best solutions found so far. The process of generating new solutions as the system is cooled is repeated until termination criteria are satisfied.

2.3.3.3 Particle Swarm Optimization

The PSO Algorithm is a population-based stochastic optimization technique first invented in 1995.and inspired by the social behavior of birds flocking or fish schooling [25]. the PSO has been used to solve a wide range of optimization problems, including function optimization, feature selection, and parameter tuning. The advantages of PSO include its simplicity, fast convergence, and ability to handle high-dimensional search spaces. However, PSO can sometimes get stuck in local optima, and the performance of the algorithm depends heavily on the choice of parameters.

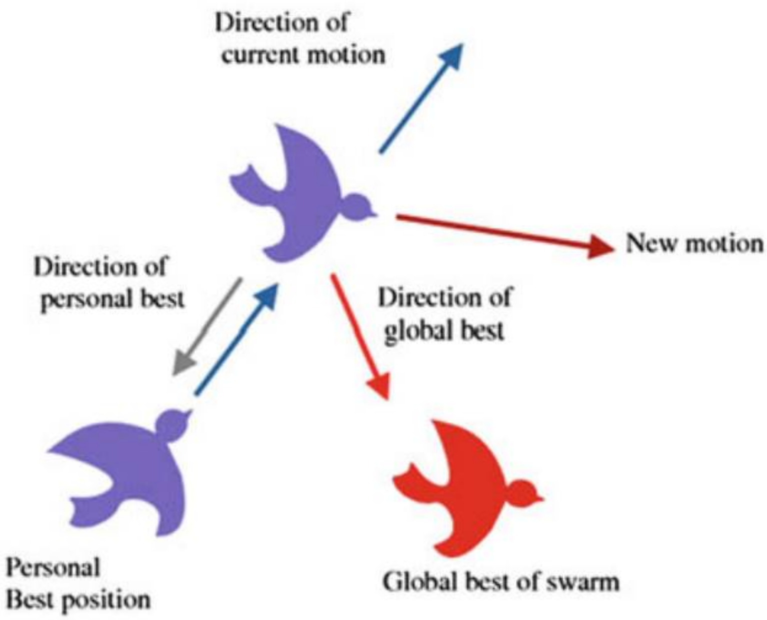


Figure 2.3: "Schematic representation of updating the velocity of a particle".[25]

2.3.3.4 Harmony Search

The HS is a meta-heuristic algorithm inspired by artificial phenomena found in musical compositions [26]. The algorithm was first proposed by Geem in 2001[27]. Musicians test different possible mixtures of musical pitches. Such a process of search for a fantastic harmony can be simulated numerically to find the optima of optimization problems. The algorithm works by generating a set of candidate solutions, or "harmonies," and then refining these solutions through an iterative process of evaluation and modification. The algorithm evaluates the quality of each harmony and uses this information to guide the generation of new candidate solutions. This process continues until a satisfactory solution is found, or until a predefined termination criterion is met.

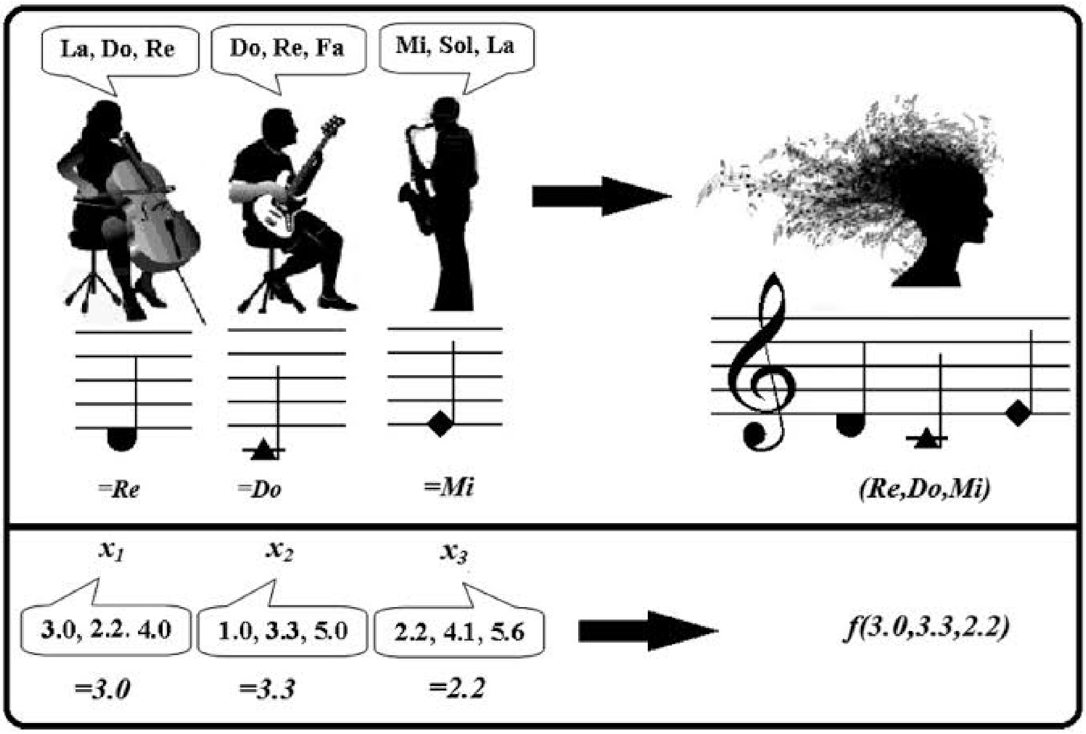


Figure 2.4: "An Illustration of the Harmony Search Algorithm Using Musical Notes".[27]

2.3.3.5 Tabu Search

The tabu search (TS) was developed by Glover (1986) [28]. It is based on the principle of making local moves in a search space to find a better solution while avoiding getting trapped in local optima. Tabu Search employs a tabu list that keeps track of the recently visited solutions and prevents the algorithm from revisiting them. This allows the algorithm to explore other regions of the search space that may lead to better solutions. At each iteration of the algorithm, a new candidate solution is generated by making a small change to the current solution. The quality of the new solution is then evaluated, and if it is better than the current solution, it is accepted as the new current solution. If the new solution is worse than the current solution, it may still be accepted with a certain probability, based on a temperature parameter that controls the probability of accepting worse solutions.

2.3.3.6 Ant Colony Optimization

Was introduced by Dorigo et al. (1991, 1996), It attempts to simulate in algorithmic fashion the foraging behavior of ants [29]. The ACO takes inspiration from the foraging behavior of some ant species that deposit pheromone on the ground to mark favorable paths for colony members to follow to procure food. In ACO, a set of artificial ants are used to search for the best solution in a given search space. Each ant constructs a solution by iteratively selecting a next move based on a combination of pheromone trails and heuristic information. The pheromone trails represent the collective experience of the colony, while the heuristic information guides the ants towards better solutions. The pheromone trails are updated after each iteration based in the quality of the solutions found by the ants.

Figure 2.5: "Ant Colony Optimization (ACO) algorithm".

2.3.4 Applications of meta-heuristics

Meta-heuristic algorithms are a popular and fascinating field of study among scientists, researchers, and academics. They can be applied to various domains with different requirements. This is achieved by utilizing a combination of techniques to navigate the search space, avoid getting stuck in local optimal solutions, and determine when acceptable solutions have been discovered. Meta-heuristics enable the management of the trade-off between performance and solution quality, making them highly relevant to practical applications. As meta-heuristics are motivated by pragmatic purposes, their connection to real-world scenarios is strong. Classical meta-heuristics, have shown their suitability to solve complex scheduling problems, space allocation problems, and clustering problems, among others [30]. Here are a few examples of how meta-heuristics have been applied in practice:

2.3.4.1 Optimization of industrial processes

M-H, such as genetic algorithms and particle swarm optimization, has been used to optimize complex industrial processes, such as chemical production, manufacturing, and logistics. By exploring a large design space and identifying the best solution that meets the desired criteria, such as cost, quality, and efficiency, meta-heuristics can help improve the productivity and profitability of industrial operations.

2.3.4.2 Portfolio optimization in finance

MH, such as simulated annealing and genetic algorithms, have been applied to portfolio optimization, where the goal is to allocate assets in a way that maximizes returns while minimizing risks. By finding the optimal combination of assets that balances risk and reward, portfolio managers can improve the performance of investment portfolios and reduce the impact of market volatility.

2.3.4.3 Resource allocation in healthcare

MH, such as ant colony optimization and tabu search, have been used to optimize patient scheduling and resource allocation in hospitals. By reducing wait times, minimizing costs, and improving patient outcomes, meta-heuristics can help healthcare providers improve the efficiency and effectiveness of healthcare delivery.

2.3.4.4 Traffic management

MH, such as ant colony optimization and genetic algorithms, have been used to optimize traffic flow, route planning, and vehicle routing, with the goal of reducing congestion, minimizing travel times, and improving safety. By identifying the best routes for vehicles or pedestrians, traffic engineers can improve the performance of transportation networks and enhance the mobility of people and goods.

2.3.4.5 Design optimization

MH, such as genetic algorithms and simulated annealing, have been used to optimize the design of complex systems, such as aircraft structures, power grids, and communication networks. By exploring a large design space and identifying the best solution that meets the desired criteria, such as performance, reliability, and cost, meta-heuristics can help engineers design better products and systems.

Overall, meta-heuristics have broad applications and are particularly useful for solving complex optimization problems where traditional methods are not effective.

2.3.5 Hybrid meta-heuristics

Hybrid meta-heuristics: Are optimization algorithms that combine two or more different meta-heuristics to create a new, more powerful algorithm. The goal of hybridization is to leverage the strengths of each individual algorithm and to compensate for their weaknesses [31]. The combination of different meta-heuristics can lead to improved performance and faster convergence to better solutions. There are several ways to combine different meta-heuristics to create a hybrid algorithm. One approach is to combine them sequentially, where one meta-heuristic is used to explore the search space initially, and then another is used to refine the solutions obtained by the first algorithm. Another approach is to combine the algorithms in parallel, where they run simultaneously, and their solutions are merged periodically to create a new population.

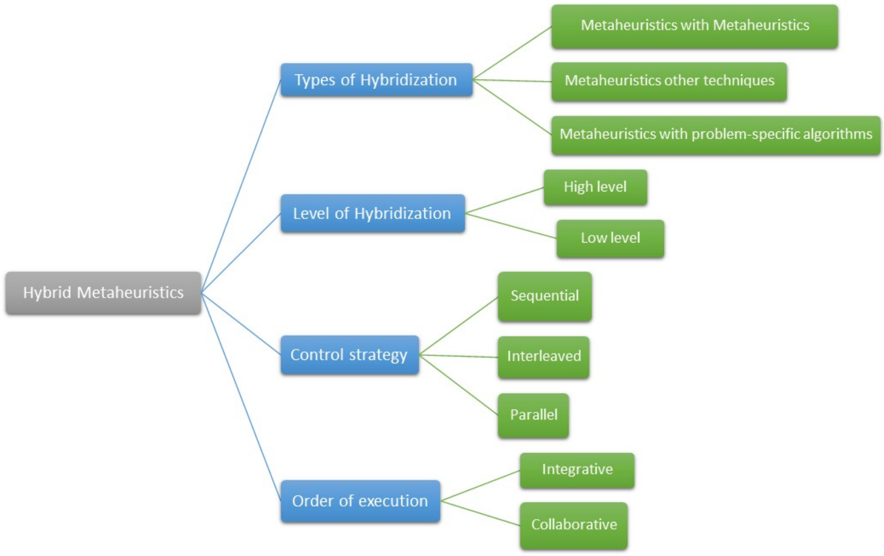


Figure 2.6: "Classification of Hybrid Meta-heuristics".

There are many examples of hybrid meta-heuristics, some of which include:

2.3.5.1 Ant Colony Optimization with Tabu Search

This hybrid algorithm combines the global search capabilities of an ant colony optimization algorithm with the local search capabilities of a tabu search algorithm. It works by using the pheromone trails created by the ants to guide the search towards promising regions of the search space, and then applying tabu search to refine the solutions found by the ants.

2.3.5.2 Particle Swarm Optimization with Simulated Annealing

This hybrid algorithm combines the swarm-based search of a particle swarm optimization algorithm with the stochastic search of a simulated annealing algorithm. It works by using the particle swarm to explore the search space and identify promising regions, and then applying simulated annealing to further refine the solutions found by the swarm.

2.3.5.3 Genetic Algorithm with Differential Evolution

This hybrid algorithm combines the population-based search of a genetic algorithm with the mutation and recombination operators of a differential evolution algorithm. It works by evolving a population of solutions using genetic operators such as crossover and mutation, and then applying differential evolution to generate new solutions and improve the quality of the population. The goal is to create an algorithm that is able to find high-quality solutions efficiently and effectively, even for complex and challenging optimization problems

2.3.6 Applications: Parameter tuning

is an important aspect of meta-heuristic optimization, as it can greatly affect the performance of the algorithm. Meta-heuristics often have several parameters that must be set before the optimization process can begin. These parameters can include things like population size, mutation rate, crossover rate, selection strategy, and stopping criteria. Choosing the right values for these parameters can be a challenging task, and often requires a significant amount of trial and error. There are several methods for parameter tuning in meta-heuristics, including:

2.3.6.1 Grid search

This method involves testing the algorithm with a range of parameter values and selecting the combination that gives the best performance.

2.3.6.2 Random search

This method involves randomly selecting parameter values within a given range and evaluating the algorithm's performance.

2.3.6.3 Evolutionary algorithms

These algorithms can be used to optimize the parameter values by treating them as a set of decision variables and applying a meta-heuristic algorithm to find the optimal values.

2.3.6.4 Bayesian optimization

This method involves constructing a probabilistic model of the algorithm's performance based on previous evaluations and using this model to guide the selection of new parameter values. Parameter tuning processes usually requires a large number of runs of the algorithm to analyze its performance on one instance or a set of problem instances with different parameter settings [32].

2.4 Gravitational Search Algorithm

The Gravitational Search Algorithm (GSA) is a recent addition to the collection of meta-heuristic algorithms that draw inspiration from celestial mechanics. By using masses to represent candidate solutions, GSA has demonstrated its effectiveness in solving challenging optimization problems, making it an interesting alternative to other popular optimization techniques.

2.4.1 Overview

The Gravitational Search Algorithm (GSA) is a meta-heuristic optimization algorithm that is inspired by the law of gravity and the motion of celestial objects. It was proposed in 2009 by *Rashedi, Nezamabadi-Pour*, and *Saryazdi*[33]. and has since become a popular choice for solving a variety of optimization problems in engineering, science, and other fields. The algorithm is grouped under population-based method which is consisting of different masses. Based on the gravitational force, the masses are sharing information to direct the search towards the best location in the search space. This algorithm which is based on the physics' laws seems to demonstrate better characteristics when compared with bio-inspired or other nature-inspired algorithms such as GA, PSO, and ACO. The basic idea behind GSA is to simulate the interactions between celestial bodies in space, where each body represents a potential solution to an optimization problem. The bodies are attracted to each other by the force of gravity, which is proportional to their masses and inversely proportional to the distance between them. As the bodies move towards each other, they undergo a process of acceleration, velocity, and position update, which allows them to converge towards the optimal solution[34]. In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function[35]. In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, we expect that masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space.

The GSA could be considered as an isolated system of masses. It is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion.

2.4.1.1 Law of gravity

It states that every particle of matter in the universe attracts every other particle with a force that is proportional to the product of their masses and inversely proportional to the square of the distance between them. The mathematical formula for the gravitational force between two objects is:

$$F(i,j) = \frac{G * m_i(t) * m_j(t)}{r(i,j)^2} \tag{2.2}$$

Where F is the force of gravity, G is the gravitational constant, m_i and m_j are the masses of the objects, and r is the distance between them.

2.4.1.2 Law of motion

The current velocity of any mass is equal to the sum of the fraction of its previous velocity and the variation in the velocity. Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by mass of inertia.

2.4.1.3 Newton's First Law

The law of inertia An object at rest will remain at rest, and an object in motion will continue to move at a constant velocity in a straight line, unless acted upon by an external force.

2.4.1.4 Newton's Second Law

The law of acceleration, the acceleration of an object is directly proportional to the force applied to it and inversely proportional to its mass. The direction of the acceleration is in the direction of the applied force.

2.4.1.5 Newton's Third Law

The law of action and reaction for every action, there is an equal and opposite reaction. This means that when one object exerts a force on another object, the second object exerts an equal and opposite force back on the first object.

the searcher agents are a set of masses that affect each other's according to New- ton's gravity law and move according to Newton's second law. Now, consider a system with N objects. The position of each object is considered as an answer for the optimization problem which represents a point in the search space. The position of the object (Xi) in the search space is defined as follows:

$$\Xi = (x_1, \ldots, x_d, \ldots, x_D) \quad \text{for } i = 1, 2, \ldots, N \tag{2.3}$$

where x_d represents the positions of the ith agent in the dth dimension, N denotes the total number of particles, and D denotes the dimension of the search space. In the initialization phase, a population of particles is generated, in which their positions are determined randomly in the search space. Although the initial velocity of the particles is considered to be zero, it can be a different value if it is necessary. After evaluating the fitness of particles, the position vector of the best particle which has the highest fitness is specified by X best. Now, the gravitational mass and inertial mass of objects are calculated by the following relations:

$$m_i(t) = \frac{\text{fit}_i(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)}, \quad i = 1, 2, \ldots, N \tag{2.4}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{2.5}$$

$$M_{ai} = M_{pi} = M_{ii} = M_i \tag{2.6}$$

where $f_{\text{it}}(t)$ is the fitness value of the ith particle at time t, M_{ai} is the active gravitational mass of particle i, M_{pi} is the passive gravitational mass of particle i, and M_{ii} is the inertia mass of particle i. In this algorithm, best(t) and worst(t) represent the fitness of the best particle and the worst particle, respectively. In a minimization problem, these parameters are defined in the following form:

$$f_{\text{it}}(t) = \frac{G \cdot M_{\text{ai}} \cdot M_{\text{pi}}}{r_{\text{it}}^2} \tag{2.7}$$

$$M_{\text{ai}} = \frac{\text{best}(t) - f_{\text{it}}(t)}{\text{best}(t) - \text{worst}(t)} \cdot M_{\text{ii}} + M_{\text{ii}} \tag{2.8}$$

As mentioned before, in GSA each particle attracts the other particles. The attractive gravitational force acting on particle i from particle j in the dth dimension can be calculated in the following form:

$$F_{\text{attr}_{ij}^d}(t) = \frac{G(t) \cdot M_{pi}(t) \cdot M_{aj}(t)}{r_{ij}(t)^p + \epsilon} \cdot (x_j^d(t) - x_i^d(t))$$
$$d = 1, 2, \ldots, D$$
$$i, j = 1, 2, \ldots, N$$

where $M_{pi}(t)$ is the passive gravitational mass of particle i, $M_{aj}(t)$ is the active gravitational mass of particle j, ϵ is a small value, p is the power of distance, and $r_{ij}(t)$ is the Euclidean distance between particles i and j, which is defined as follows:

$$r_{ij}(t) = \| X_i(t), X_j(t) \|_2 \tag{2.9}$$

The gravitational constant G(t) is calculated as follows:

$$G(t) = G_0 \exp\left(-\frac{\alpha t}{t_{\max}}\right) \tag{2.10}$$

where $t_{\max}$ is the total number of iterations, G_0 is the gravitational constant at time 0, and α is a shrinking constant which controls the decay rate of the exponential function.

After that, the total force that acts on the ith agent in dimension d ($F_i^d(t)$) is defined as follows:

$$F_i^d(t) = \sum_{j \in K_{\text{best}}, j \neq i} rand_j \times F_{\text{attr}_{ij}}^d(t) \tag{2.11}$$

where rand$_j$ is a uniformly distributed random number in the interval $[0,1]$, K_{best} represents the K particles with the best fitness value and biggest mass, which is a function of time. K_0 is its initial value at the beginning.

In the last step, the particles move with respect to the total gravity forces acting on them. For this purpose, the following equation is used:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{2.12}$$

where $x_i^d(t)$ represents the current positions of the ith agent in the dth dimension, $x_i^d(t+1)$ represents the positions of the ith agent in the dth dimension in the next iteration, and $v_i^d(t+1)$ defines the velocity of the ith agent in the dth dimension in the next iteration, which is calculated as follows:

$$v_i^d(t+1) = \text{rand}_i \times v_i^d(t) + a_i^d(t) \tag{2.13}$$

where rand$_i$ is a uniformly distributed random number in the interval $[0,1]$, $a_i^d(t)$ is the acceleration of particle i in direction d, which is calculated as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{2.14}$$

where $M_{ii}(t) = M_i(t)$ is the inertial mass of the ith particle.

2.4.2 Application of GSA

The GSA has been successfully applied to various optimization problems, Table 2.1 summarizes only the major utilization of GSA in some of the optimization problems:

Table 2.1: GSA Utilization and Performance Summary in Various Optimization Problems

Application	GSA Utilization	Objective function	GSA Performance	Ref.
Power system	used for voltage control by adjusting the reactive power variables	Minimize active power losses in transmission line	High-quality solutions with more reliability and efficiency	[36]
power dispatch	Solving multi objective optimal reactive power dispatch problems	Minimize transmission loss while maintaining the quality of voltages	Converged to better solutions much faster	[37]
Economic load dispatch	Finding optimum emission dispatch,optimum fuel cost,best emission and fuel cost	Minimizing the emission level and cost of generation	Outperformed other available techniques in terms of solution quality and computational efficiency	[38]
Optimal power flow(OPF)	Determine the optimal settings of control variables of OPF problem	Minimize the settings of control variables subjected to various equality and inequality constraints	Effective and robus high quality solution	[39]
Classification	Determine the optimal values of fuzzy ARTMAP training parameters	Optimize training parameter of a fuzzy ARTMAP neural network	Performed better in terms of detection rate,false alarm rate,and cost per example in classification problems.	[40]

2.5 The Advantages of Choosing the Gravitational Search Algorithm for Optimization

In this study, we sought to reduce the noise in a planetary gear train using a meta- heuristic optimization approach. Through a comprehensive review of the literature and a careful valuation of different meta-heuristic methods, we selected Gravitational Search Algorithm (GSA) as the most suitable technique for our optimization problem. Our decision was based on GSA's ability to handle non-linear and non-convex optimization problems, as well as its ease of implementation and computational efficiency. Additionally, previous research has shown the effectiveness of GSA in engineering optimization problems related to gear design and vibration reduction, which gave us further confidence in its suitability for our specific application. Planetary gear trains are known for their complex non-linear dynamics, which can make it difficult to achieve optimal design parameters using traditional optimization techniques. However, GSA is well-suited to handle such problems and has been shown to produce high- quality solutions even in the presence of non-linearity's. Another factor that influenced our decision was the ease of implementation and computational efficiency of GSA. Compared to other meta-heuristics, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), GSA is relatively straight forward to implement and requires fewer computational resources. This allowed us to perform a larger number of simulations and explore a wider range of design parameters, ultimately leading to more accurate and robust results. Finally, previous studies [41] [42] [43],have demonstrated the effectiveness of GSA in solving similar engineering optimization problems, including those related to gear design and vibration reduction. These studies provided us with confidence in the efficacy of GSA for our specific application and motivated us to choose it as our primary optimization tool. Overall, we believe that the Gravitational Search Algorithm is a powerful and effective meta- heuristic optimization technique for reducing noise in planetary gear trains. Its ability to handle non-linear and non-convex optimization problems, combined with its ease of implementation and computational efficiency, made it an ideal choice for our study.

2.6 How we implement planetary gear train

To implement the GSA for planetary gear train optimization, we first define the design parameters of the gear train, which may include the number of teeth on the gears, the gear ratios, and the gear module. Next, we define the objective function, which represents the noise level of the gear train. This objective function is evaluated for each set of design parameters, and the resulting value is used to calculate the gravitational force between the masses. The GSA algorithm then iteratively updates the positions of the masses based on the gravitational force, with the goal of finding the optimal set of design parameters that minimizes the noise level of the gear train. As the algorithm progresses, the masses move towards the location of the minimum gravitational potential, which represents the optimal solution. To evaluate the effectiveness of the GSA in reducing noise in planetary gear trains, we are going to conduct simulations on a variety of gear train designs. Our goal is to determine whether the GSA can identify optimal design parameters that lead to a significant reduction in gear train noise levels, when compared to traditional optimization methods. The Gravitational Search Algorithm (GSA) is a promising optimization tool for reducing noise in planetary gear trains. By simulating the interaction between masses in a gravitational field, the GSA has the potential to optimize the design parameters of the gear train and achieve significant noise reductions. If our upcoming experiment confirms the effectiveness of the GSA, it could provide engineers with an efficient and reliable method for improving the performance of these critical mechanical systems.

2.7 The pseudo-code of GSA

GSA, like any other algorithm, is a set of instructions or rules that is used to solve problems or perform specific tasks. Algorithms are the backbone of computer programming, and every computer program can be broken down into a series of logical steps or instructions that must be executed in a specific order to achieve the desired outcome. These steps must be unambiguous and well-defined so that they can be executed by a computer or other machine. Algorithm steps provide a systematic approach to problem-solving, allowing for complex tasks to be broken down into smaller, more manageable parts.

The steps involved in the GSA algorithm are as follows:

2.7.1 Define initial parameters

setting up the initial values for variables such as the number of agents, maximum iterations, and gravitational constant.

- Population size (N)
- Number of iterations
- Gravitational constant (G)
- Acceleration due to gravity (A)
- Range for the position vector (lower and upper bounds)

2.7.2 Create the initial population randomly

This means that a set of solutions is generated without any prior knowledge or bias towards the problem at hand. The randomness in the initial population helps to ensure that the algorithm explores a wide range of potential solutions.

- Randomly initialize the position vector (Xi) within the specified bounds
- Calculate the objective function value (Fitness) for each particle
- Set the initial velocity vector (Vi) to zero

2.7.3 Calculate the fitness function for all object

The fitness function Is a measure of how well each object solves the problem at hand. And it is calculated by applying the objective function to each object in the population. The objective function is a mathematical function that takes the object as input and returns a value that represents how well the object solves the problem.
The fitness function allows us to rank the objects in the population based on how well they perform. This ranking is used in the next step to select the objects that will be used to create the next generation.

$$f(\vec{x}) = \max_{k=1}^{R} |i_k - i_{0k}|,$$

2.7.4 Calculate G , Worst and Best

Calculate G : This value affects the movement of the agents and their convergence to the optimal solution.

Worst:

$$\text{Worst} = \max_{j=1}^{M} [F(X_j)]$$

Helps to identify the least fit or the poorest performing individual in the current population.

Best :

$$\text{Best} = \min_{j=1}^{M}[F(X_j)]$$

The best solution is the one with the highest fitness value among all solutions in the population.

- Then, the reltive normalized fitness value is calculated as follows:

$$\psi(X_j) = \frac{F(X_j) - \text{"Worst"}}{\text{"Best"} - \text{"Worst"}}, \quad \forall j = 1, 2, \ldots, M$$

2.7.5 Calculate mass value for all objects

You can think of the mass of an agent as a measure of its influence on other agents in the swarm. Agents with higher fitness values (i.e., better performance) will have higher masses, and therefore, will have a greater influence on the movement of other agents in the swarm The mass of an agent is calculated using a simple formula, where the mass is inversely proportional to the fitness value:

$$\text{Mass}(X_j) = \frac{\psi(X_j)}{\sum_{j=1}^{M}\psi(X_j)}, \quad \forall j = 1, 2, \ldots, M$$

2.7.6 Calculate the acceleration and update velocity and position of objects

This helps agents move towards better solutions in the search space, by:

- Calculating the acceleration of each agent using Newton's second law of motion.
- Updating the velocity and position of each agent based on its acceleration.

$$A_i = \left(\frac{F_{\text{total}}}{\text{mass of particle } i}\right) \cdot (\text{position of the best particle} - X_i)$$
$$V_i = V_i + A_i$$
$$X_i = X_i + V_i$$

2.7.7 Perform Genetic operators

Involves applying genetic operators such as crossover and mutation to the agents in the swarm to introduce diversity and prevent the algorithm from converging to a local minimum.

Crossover :

Crossover is a genetic operator that involves combining genetic information from two parent agents to produce offspring agents. In the context of GSA, crossover can be applied to the position vectors of agents. Let's denote the position vectors of two parent agents as P1 and P2. The crossover operation can be performed as follows:

- Select a crossover point randomly within the length of the position vectors.
- Create two offspring agents, O1 and O2.
- Assign the genetic information before the crossover point from P1 to O1 and from P2 to O2.
- Assign the genetic information after the crossover point from P2 to O1 and from P1 to O2.
- The crossover operation allows the exploration of different combinations of genetic information, facilitating the search for improved solutions.

Mutation :

Mutation is a genetic operator that introduces random changes to an agent's genetic information. In GSA, mutation can be applied to the position vectors of individual agents. Let's consider an agent with a position vector P. The mutation operation can be performed as follows:

- Select a mutation point randomly within the length of the position vector.
- Perturb the genetic information at the mutation point by adding a small random value to it.
- Update the position vector of the agent with the mutated information.

The mutation operation helps introduce diversity in the population and allows exploration beyond the influence of gravitational forces.

2.7.8 Perform local search for best solution of the current iteration

The algorithm examines the neighborhood of the best solution and tries to find a better solution within that neighborhood. This can be done by making small perturbations to the current solution and evaluating their fitness. If a better solution is found, it replaces the current best solution.

2.7.9 Stop criteria is reached ?

refer to the conditions that determine when an algorithm should halt its execution. These criteria are essential to ensure that the algorithm stops running when it has achieved a satisfactory solution or when it is unlikely to improve further. include:

- Maximum number of iterations:The algorithm terminates after a predefined number of iterations have been reached.

- Convergence criteria:The algorithm stops when the solution has converged to a stable state or when the improvement in the objective function becomes negligible.
- User-defined criteria: determining when an algorithm should stop its execution. are specific to the user's requirements or preferences.

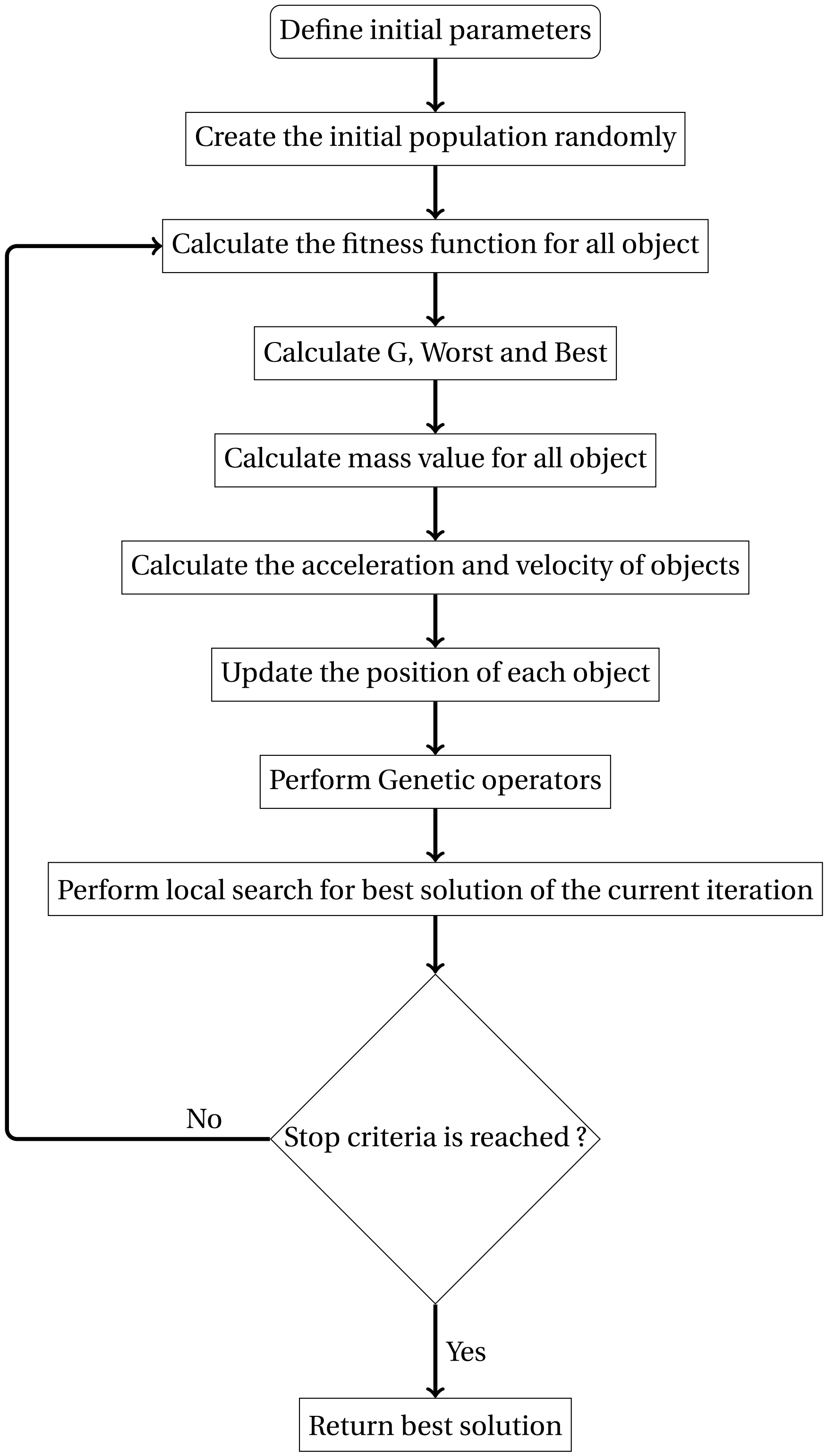


Figure 2.7: "The pseudo code of Gravitational search algorithm(GSA)".

2.8 Conclusion

We have explored the concept of meta-heuristics that have proven to be effective in solving a wide range of complex problems in various domains. and We have discussed in detail the specific meta-heuristic that we have chosen for our work the gravitational search algorithm (GSA). Despite being a relatively recent algorithm, GSA shows great promise in solving complex optimization problems. Through our analysis, we have found that GSA is a powerful meta-heuristic with many benefits, such as its ability to quickly converge and find optimal solutions. However, one potential limitation of GSA is its sensitivity to initial conditions, which may impact its performance. Nonetheless, despite this limitation, GSA has been successfully used in other fields and industries, demonstrating its versatility and potential. We remain confident in the potential of GSA to reduce sound of planetary gear train and look forward to investigating its performance further in the next chapter.

CHAPTER 3

IMPLEMENTATION OF GRAVITATIONAL SEARCH ALGORITHM FOR NOISE REDUCTION IN PLANETARY GEARS TRAIN

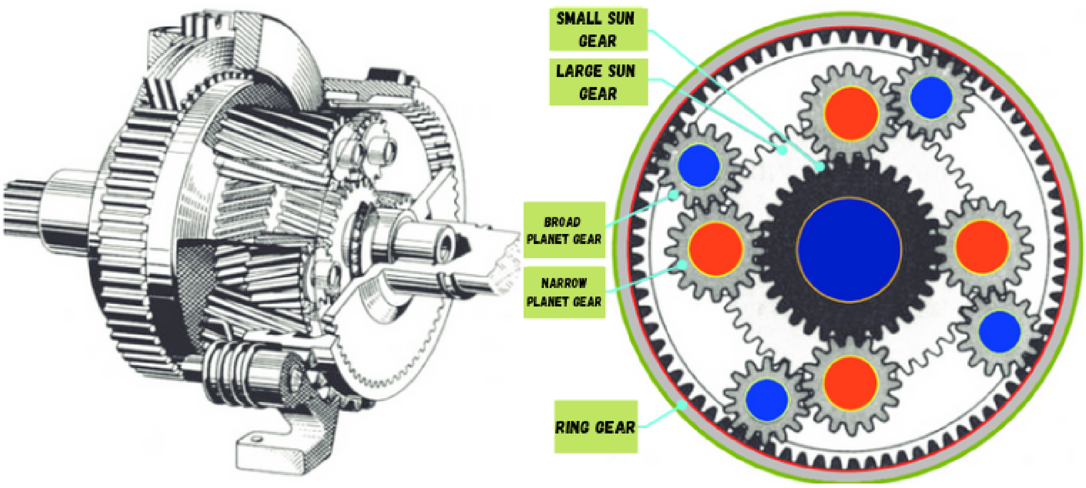
3.1 Introduction

The third chapter focuses on the implementation of the Gravitational Search Algorithm (GSA) to the problem of noise reduction in planetary gear trains within the realm of conventional automatic transmissions. To accomplish this, A crucial step is the formulation of a mathematical model that accurately describes the planetary gear system. This model includes several important features, such as design variables, constraints, and objective functions, which aid in the optimization process. To provide a thorough foundation for this work, relevant scholarly resources have been used, including Gisbert Lechner's book "Automatic Transmissions" [44] along with articles authored by Esmat Rashedi[45], P. A. Simionescu[46], and Hammoudi Abderazek[47]. These resources contain valuable insights about automatic transmission systems, teeth-number synthesis, and the optimal design of planetary gear trains.

Building upon the foundational knowledge, the subsequent section of this chapter explores the complex mechanisms of conventional automatic transmissions. We can develop a solid framework for understanding the special issues offered by noise reduction in planetary gears trains by delving into the characteristics, components, and operating principles of these transmissions. This understanding provides a solid basis for implementing the Gravitational Search Algorithm (GSA) optimization strategy into this complex system. By efficiently combining the GSA with traditional automatic transmissions, we may develop improved noise reduction solutions, thereby improving the overall performance and efficiency of the planetary gears train.

3.2 Conventional Automatic Transmission

A conventional automatic transmission, also known as an "automatic transmission," is a fully automatic transmission system commonly found in passenger cars. It includes a torque converter and a planetary gearbox, enabling smooth gear shifting without interrupting power delivery. The torque converter acts as a fluid coupling, transferring power from the engine to the gearbox. The planetary gearbox has multiple gear sets, allowing the transmission to select the appropriate gear ratio based on the vehicle's speed and driving conditions. This system automatically adjusts the gear ratio to optimize performance and fuel efficiency. The planetary gearbox consists of gear sets that can engage or disengage to achieve different gear ratios, adapting to various driving conditions such as starting, cruising, or climbing uphill. Gear changes happen seamlessly, providing a comfortable driving experience without noticeable power interruptions. The Simpson planetary gear-set is advantageous for manufacturing due to its symmetrical arrangement and equal number of gearwheels in the input and output sections, simplifying production and reducing costs. The Ravigneaux planetary gear-set, widely used in automatic transmissions, consists of two sun gears, multiple planet gears, and a ring gear, allowing up to four usable forward gears and one reverse gear.



[44]

Figure 3.1: Ravigneaux planetary gear.

3.2.1 The Ravigneaux 3+1 gear transmission

Is a planetary transmission commonly used in automobiles. It has three forward gears and one reverse gear, with different gear configurations requiring specific clutch and brake activations.

Table 3.1: Clutch/Brake Activation table

	Clutch (C)		Brake (B)	
Speed	C1	C2	B1	B2
First	Engage		Engage	
Second		Engage		
Third	Engage	Engage	Engage	
Reverse		Engage		

[44]

The table provided represents a Clutch/Brake Activation table, which illustrates the engagement of different clutch and brake components at various speeds and gear steps. There are two types of brakes commonly used: the belt brake and the multi-disc brake. It is worth noting that the multi-disc brake shares components with the multi-disc clutch, which connects the moving parts of the transmission together. Hydraulic fluid is used to control the clutches and brakes mentioned above.

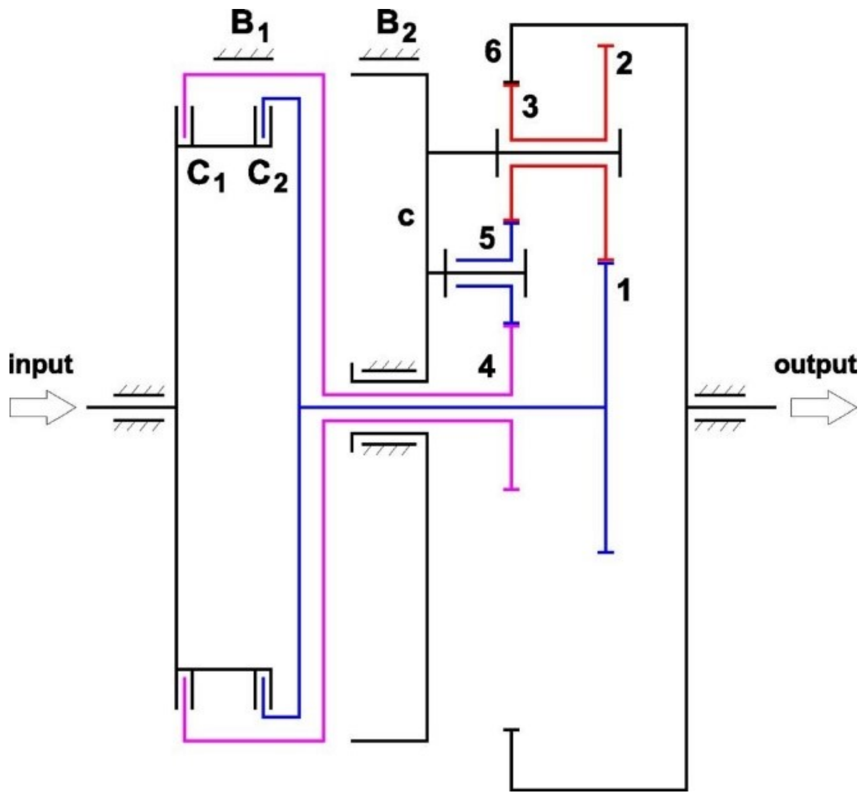


Figure 3.2: kinematic diagram for ravigneaux 3+1 transmission ratios.[44]Automative transsmition

3.2.1.1 Transmission Ratios

The transmission ratios determine the speed and torque relationships between different gears in the transmission. The following transmission ratios are defined:

First Gear and Reverse Gear: the planet carrier remains stationary, and the transmission acts as a fixed-axle system. The transmission ratios for these gears can be calculated using the number of teeth on certain gears. It's given by:

$$i_1 = \frac{N_6}{N_4}, \tag{3.1}$$

and

$$i_R = -\frac{N_2 N_6}{N_1 N_3}. \tag{3.2}$$

Second Gear: The second gear is the only case where the transmission functions as a planetary gear set. The transmission ratios for this gear can be determined by considering the planet carrier as immobile. Three basic transmission ratios can be defined:

$$i_{16}^c = -\frac{N_2 N_6}{N_1 N_3}, \quad i_{46}^c = \frac{N_6}{N_4}, \quad i_{14}^c = -\frac{N_2 N_4}{N_1 N_3}. \tag{3.3}$$

Third Gear: In the third gear, the planet carrier, sun gears, and ring gear rotate together, providing a direct drive and improving mechanical efficiency,the transmission ratio is :

$$i_3 = 1. \tag{3.4}$$

3.2.1.2 Optimization Problem

The optimization problem aims to find the optimum number of gear teeth to fulfill the desired transmission ratios. The problem involves finding the minimum or maximum of a function of various design variables subject to side constraints, inequality constraints, and equality constraints.

Design Variables: The design variables include the number of teeth for gears 1, 2, 3, 4, 5, and 6. Additionally, the number of equally spaced, identical planets on the planet carrier is considered. The module values $(m_1, m_2, m_3, m_4, m_5, m_6)$ can also be design variables with discrete values according to gear standards.

Objective Function: The objective function measures the departure between the actual (i_k) and desired (i_{0k}) transmission ratios. Two common objective functions are defined: Maximum-error based : given by

$$f_1(N_1, ...N_n, p, m_j) = \max_k(w_k|i_k - i_{0k}|), \tag{3.5}$$

and

$$f(\mathbf{x}) = \max_{k=1}^{R} |i_k - i_{0k}|.$$

Sum of squared residuals : given by

$$f_2(N_1, ...N_n, p, m_j) = \sum_k w_k(i_k - i_0)^2, \tag{3.6}$$

is the number of transmission ratios, and the weighting coefficients (w_k) allow adjusting the importance of different transmission ratios during optimization.

Constraints: Several constraints are imposed on the optimization problem, including gear teeth constraints, diameter constraints, center-distance constraints, interference constraints, and spacing constraints for equally spaced planets. These constraints ensure the gears operate properly and do not interfere with each other.

- Gear Size Limitations: The number of teeth on the sun gear (S), ring gear (R), planet gears (P), and planet carrier (C) should be within the specified permissible ranges. with ns=2 the number of sun gears, np=3 the number of distinct planet gears (gears 2,3, and 5), and nr=1 the number of ring gears, the lower side constraints have the following general expressions:

$$N \min_j \leq N_j (1 \leq j \leq n_s + N_P), \tag{3.7}$$

where $N \min_j$(the minimum number of teeth the sun or planet gears can have) are specified from the condition of undercut avoidance as 17 or if the use of nonstandard gears is acceptable, 14 even 12 teeth.

- Maximum Outer Diameter Constraint: The maximum outer diameter of the transmission, denoted as D max, can be imposed by limiting the standard root diameter of the ring gear.

$$m_3(N_6 + 2.5) \leq D\max. \tag{3.8}$$

- Workspace Diameter Constraints: The outside diameters of planet 2 and idler 5 should not exceed D max. This can be expressed as inequalities involving the gear teeth numbers and module values.

$$2[m_1(N_1 + N_2)/2 + m_1(N_2/2 + 1)] \leq D\max, \tag{3.9}$$

$$2[m_3(N_4 + N_5)/2 + m_3(N_5/2 + 1)] \leq D\max, \tag{3.10}$$

- Coaxial Axes Constraint: The solar and ring gears should have coaxial axes. This can be expressed as an inequality constraint to ensure that the difference in the standard center-distances of the gears is less than an average modulus.

$$|m_1(N_1 + N_2)/2 - m_3(N_6 - N_3)/2| \leq (m_1 + m_3)/2. \tag{3.11}$$

- Neighborhood Distance Constraint: The distance between adjacent, non-meshing gears should be greater than a certain minimum value. This constraint ensures that the teeth of neighboring gears operate at a sufficient distance.

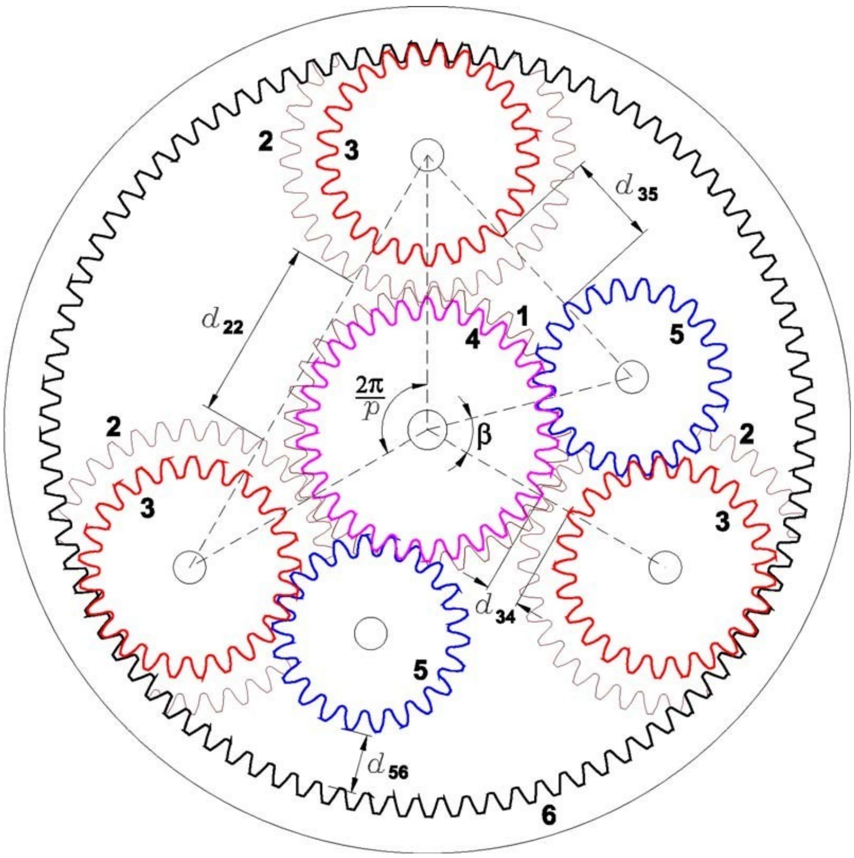


Figure 3.3: Schematic for calculating distances. [46]

The distances can be approximated using equations involving gear teeth numbers and module values.

$$dij \geq d\min_{ij}, \tag{3.12}$$

where ,(d_{ij})is the distance between the addendum circles of the respective neighboring wheels. And $d\min_{ij}$ can be approximated as follows:

$$d_{22} = 2\left[m_1 \frac{N_1 + N_2}{2} \sin\left(\frac{\pi}{p}\right) - m_1\left(\frac{N_2}{2} + 1\right)\right], \tag{3.13}$$

$$d_{33} = 2\left[m_3 \frac{N_6 + N_3}{2} \sin\left(\frac{\pi}{p}\right) - m_3\left(\frac{N_3}{2} + 1\right)\right], \tag{3.14}$$

And

$$d_{55} = 2\left[m_3 \frac{N_4 + N_5}{2} \sin\left(\frac{\pi}{p}\right) - m_3\left(\frac{N_5}{2} + 1\right)\right]. \tag{3.15}$$

- Interference Constraint: The interference between planets 3 and 5 should be checked by evaluating a distance expression. If the distance is less than a certain value, it indicates interference.

$$d_{35} = \sqrt{C_{36}^2 + C_{45}^2 - 2C_{36}C_{45}\cos\left(\frac{2\pi}{p} - \beta\right)} - m_3\left(\frac{N_3}{2} + 1\right) - m_3\left(\frac{N_5}{2} + 1\right), \tag{3.16}$$

where:

$$\beta = \cos^{-1}\left(\frac{C_{36}^2 + C_{45}^2 - C_{35}^2}{2C_{36} + C_{45}}\right),$$

$$C_{36} = m_3 \frac{N_6 - N_3}{2},$$
$$C_{45} = m_3 \frac{N_4 + N_5}{2},$$

and

$$C_{35} = m_3 \frac{N_3 + N_5}{2}.$$

- Lubricant Flow Constraint: The distances between the addendum circles of gear pairs 3-4 and 5-6 should be larger than a certain value to allow for satisfactory lubricant flow.

$$d_{34} = m_3 \frac{N_6 - N_3}{2} - m_3\left(\frac{N_3}{2} + 1\right) - m_3\left(\frac{N_4}{2} + 1\right), \tag{3.17}$$

$$d_{56} = m_3\left(\frac{N_6}{2} - 1\right) - m_3 \frac{N_4 + N_5}{2} - m_3\left(\frac{N_5}{2} + 1\right). \tag{3.18}$$

- Equally Spaced Planets Constraint: The equally spaced identical planets 2-3 constraint requires that a specific equation involving gear teeth numbers and partial bosic ratios of the planetary gear is satisfied.

$$\text{Frac}\left(\frac{1}{p}\left|\frac{1}{i^c_{1-2}} - \frac{1}{i^c_{6-3}}\right|\right) = \left|\frac{A}{N_2} + \frac{B}{N_3}\right|, \tag{3.19}$$

where

- Frac(...) is the factional part of the expression in parentheses.

$$\begin{aligned} A &\longleftarrow N_2/2, \\ B &\longleftarrow N_3/2, \\ i^c_{1-2} &= -N_2/N_1, \\ i^c_{6-3} &= N_3/N_6. \end{aligned}$$

- Idler Planets Constraint: An additional assembly condition must be imposed on idler planets 5, which can be expressed as an equation involving gear teeth numbers.

$$(N_6 - N_4)/p = \text{integer}. \tag{3.20}$$

These equations represent the mathematical expressions for the given constraints in the optimization problem for the Ravigneaux 3+1 gear transmission. The goal is to find feasible values for the gear teeth numbers (N_S, N_R, N_P) and the module values (m_1, m_3) that satisfy these constraints while optimizing the transmission performance.

3.2.1.3 Numerical results

- The design problem focused on a Chevrolet Corvette manual transmission with a maximum outer diameter of 220 mm and specific forward and reverse transmission ratios ($i_{01} = 3.11, i_{02} = 1.84, i_{03} = 1.0, i_R = -3.11$) although in the original transmission this was slightly higher, viz. -3.22 .

3.2.2 Key components

Before we embark on our programming environment with MATLAB, it is essential to delve into the key components of the Gravitational Search Algorithm (GSA). This exploration will help us gain a deeper understanding of how these components contribute to the algorithm's effectiveness. By studying its inner workings, we can acquire valuable insights and appreciate how well-suited it is for implementation in MATLAB.

The key components of the GSA algorithm include:

1. **Mass and Position Initialization**
   In the GSA, each potential solution is represented as a "mass" with an associated position in the search space. The masses are initially randomly distributed within the search space.

2. **Calculation of Gravitational Force**
   The gravitational force is calculated between the masses based on their positions and masses. The positions and masses of the masses influence the gravitational force acting on them.

3. **Update of Acceleration and Velocity**
   The acceleration and velocity of each mass are updated based on the gravitational forces acting upon them. This simulates the movement of masses in search of better solutions.

4. **Mass Interaction and Movement**
   The masses interact with each other, exchanging information and influencing their movements. The stronger masses exert greater gravitational forces and attract weaker masses towards them, fostering exploration and exploitation in the search space.

5. **Local and Global Best Update**
   The algorithm maintains the best local and global solutions found so far, updating them if a better solution is discovered during the search.

By understanding and implementing these key components, we can effectively utilize the power of the Gravitational Search Algorithm within the MATLAB programming environment.

3.3 Problem Formulation of the Planetary Gear Train

The problem addressed in this paper revolves around the optimization of a planetary gear train, originally proposed by Simionescu et al. in 2006[46]. The aim is to develop a mathematical model that allows for the efficient determination of optimal design parameters for the gear train. These design parameters comprise a combination of integers and discrete values, which directly influence the performance of the gear train.

Specifically, the optimization problem involves nine decision parameters. These parameters include the number of teeth for six gears, denoted as $N1$, $N2$, $N3$, $N4$, $N5$, and $N6$. Additionally, the number of planet gears, referred to as P, and the gear module values, denoted as $m1$ and $m2$, attre also part of the decision parameters.

Table 3.2: Optimization Problem

Decision Parameter	**Symbol**
Number of teeth for Gear 1	$N1$
Number of teeth for Gear 2	$N2$
Number of teeth for Gear 3	$N3$
Number of teeth for Gear 4	$N4$
Number of teeth for Gear 5	$N5$
Number of teeth for Gear 6	$N6$
Number of planet gears	P
Gear module value 1	$m1$
Gear module value 2	$m2$

Throughout the subsequent sections of the paper, a comprehensive explanation of the objective function, constraints, and the limits defining the search space design is provided.

These aspects play crucial roles in the optimization process and aid in obtaining optimal solutions for the planetary gear train.

Objective: The goal here is to minimize the maximum errors in the gear ratio in order to reduce vibration noise. According to the mathematical model, the objective function is as follows:

$$f(\vec{x}) = \max_{k=1}^{R} |i_k - i_{0k}|,$$

where:

$\mathbf{x} = (x_1, x_2, \ldots, x_R)$ represents the design variables,
i_k is the calculated gear ratio for the k-th gear,
i_{0k} is the target gear ratio for the k-th gear, and
R is the total number of gears in the gear train.

The specific gear ratios and target gear ratios for each gear are given by:

$$\begin{aligned}
i_1 &= \frac{N_6}{N_4}, \quad i_{01} = 3.11, \\
i_2 &= \frac{N_6(N_1 \times N_3 + N_2 \times N_4)}{N_1 \times N_3(N_6 - N_4)}, \quad i_{02} = 1.84, \\
i_R &= \frac{N_6}{N_4}, \quad i_{0R} = -3.11,
\end{aligned}$$

where N_1, N_2, N_3, N_4, N_6 are the specific gear parameters.

The objective function seeks to minimize the maximum absolute difference between the calculated gear ratios and the target gear ratios for each individual gear in the gear train. By minimizing these errors, the objective is to achieve a more uniform and balanced gear system, resulting in reduced vibration noise.

Design constraints:There are eleven design constraints that are applied to the planetary gear train. The purpose of these constraints is to address the undercutting phenomenon, the maximum overall transmission diameter, as well as the spacing between multiple planets. Please refer to [46] for a detailed description of the optimization formulation of the problem.

$$
\begin{aligned}
g_1(\vec{x}) &= m_3(N_6 + 2.5) - 220 \geq 0, \\
g_2(\vec{x}) &= m_1(N_1 + N_6) + m_1(N_1 + N_6) - 220 \geq 0, \\
g_3(\vec{x}) &= m_3(N_4 + N_5) + m_3(N_5 + 2) - 220 \geq 0, \\
g_4(\vec{x}) &= |m_1(N_1 + N_2) - m_3(N_6 + N_3)| - (m_1 + m_3) \geq 0, \\
g_5(\vec{x}) &= (N_1 + N_6)\sin\left(\frac{\pi}{p}\right) - N_2 - 2 - d_{22} \leq 0, \\
g_6(\vec{x}) &= (N_6 - N_3)\sin\left(\frac{\pi}{p}\right) - N_3 - 2 - d_{33} \leq 0, \\
g_7(\vec{x}) &= (N_4 + N_5)\sin\left(\frac{\pi}{p}\right) - N_5 - 2 - d_{55} \leq 0, \\
g_8(\vec{x}) &= (N_6 - N_3)^2 + (N_4 + N_5)^2 - 2(N_6 - N_3)(N_4 - N_5)\cos\left(2\pi/p - \beta\right) - (N_3 + N_5 + 2 + d_{35})^2 \leq 0, \\
g_9(\vec{x}) &= N_6 - 2N_3 - N_4 - 4 - 2d_{34} \geq 0, \\
g_{10}(\vec{x}) &= N_6 - N_4 - 2N_5 - 4 - 2d_{56} \geq 0, \\
h(\vec{x}) &= \frac{N_6 - N_4}{p} = \text{integer},
\end{aligned}
$$

where:

$$
\beta = \frac{\cos^{-1}\left((N_6 - N_3)^2 + (N_4 + N_5)^2 - (N_3 + N_5)^2\right)}{2(N_6 - N_3)(N_4 + N_5)}.
$$

And the variable ranges are:

$$
\begin{aligned}
m_1, m_3 &= \{1.75, 2.0, 2.25, 2.5, 2.75, 3.0\}, \\
d_{22}, d_{33}, d_{55}, d_{34}, d_{35}, d_{56} &= 0.5, \\
17 \leq N_1 &\leq 96, \\
14 \leq N_2 &\leq 54, \\
14 \leq N_3 &\leq 51, \\
17 \leq N_4 &\leq 46, \\
14 \leq N_5 &\leq 51, \\
48 \leq N_6 &\leq 124.
\end{aligned}
$$

3.4 Experimental results and analysis

In this section, several optimization algorithms, namely FA (Firefly Algorithm) proposed by Yang in 2010, ISA (Improved Shuffled Frog-Leaping Algorithm) presented by Gandomi in 2014 and further improved by Gandomi and Roke in the same year, MVO (Moth-Flame Optimization) developed by Mirjalili et al. in 2016, HFPSO (Hybrid Firefly Particle Swarm Optimization) introduced by Aydilek in 2018, ReDE (Reformulated Differential Evolution) proposed by Ho-Huu et al. in 2018, and GWO-CS (Grey Wolf Optimization with Chaotic Search) presented by Abhishek in 2019, were examined to address the problem of designing a 3+1 speed Ravigneaux planetary gear train. It is important to note that the methodologies employed in this study have not been elaborated on in this particular paper. For a more comprehensive understanding of these algorithms, interested readers are encouraged to refer to the original works by the respective authors. These optimization algorithms were selected and utilized in the context of designing a 3+1 speed Ravigneaux planetary gear train. The aim of the study was to identify the optimal configuration of the gear train that would maximize its performance according to predefined objectives and constraints. Each algorithm was applied to the problem, and the obtained results were analyzed and compared. The experimental results indicated that the FA algorithm, which is inspired by the behavior of fireflies, demonstrated promising performance in optimizing the design of the gear train. It effectively explored the design space and identified a set of optimal solutions. The ISA algorithm, based on the concept of a shuffled frog-leaping process, also exhibited competitive performance, converging to near-optimal solutions.

The MVO algorithm, inspired by the behavior of moths and flames, showed encouraging results as well. It effectively balanced exploration and exploitation of the design space, leading to the identification of high-quality designs. The HFPSO algorithm, combining the principles of firefly and particle swarm optimization, demonstrated good performance by efficiently exploring the search space and converging to optimal solutions.

The ReDE algorithm, which is a reformulated version of the differential evolution algorithm, provided competitive results by effectively handling the design constraints and searching for globally optimal solutions. Lastly, the GWO-CS algorithm, which combines the Grey Wolf Optimization with Chaotic Search, exhibited promising performance in terms of convergence and solution quality.

Overall, the experimental analysis demonstrated the effectiveness of these optimization algorithms in solving the problem of designing a 3+1 speed Ravigneaux planetary gear train. The results obtained from each algorithm showcased their capabilities in exploring the design space, identifying optimal solutions, and providing valuable insights for improving the performance of the gear train.

3.4.1 Constraint handling

Two kinds of penalties are used to deal with the constraints of the design. A death penalty (equation (**??**)) is used with GSA algorithm.

$$F(\mathbf{x}) = f(\mathbf{x}) + \lambda \left(\sum_{i=1}^{10} \max(0, g_i(\mathbf{x}))^2 + \sum_{j=1}^{1} \max(0, |h_j(\mathbf{x})| - \epsilon \leq 0) \right), \tag{3.21}$$

where λ is a large positive value, called penalty factor ($\lambda = 10^{25}$). The equality constraints are transformed into inequalities by using a tolerance value $\epsilon = 1, \ldots, 10$ and $h_j, j = 1$ are the number of inequality and equality constraints, respectively. The tolerance value for the equality constraint is set as 0.0001.

Whereas, FA, MVO, HFPSO, ReDE, and GWO-CS adopt another penalty function which is introduced by Kaveh and Zolghadr (2014). The mathematical expression of the penalty function can be expressed as follows:

$$F(\mathbf{x}) = (1 + \epsilon_1 \cdot \Phi(\mathbf{x}))^{\epsilon_2} \cdot f(\mathbf{x}) \tag{3.22}$$

The value of ϵ_1 is equal to 1, and ϵ_2 is linearly increased from 1.5 to 6 with iterations (Kaveh and Zolghadr, 2014). The sum of constraint violation $\Phi(\mathbf{x})$ is given by the following equation:

$$\Phi(\mathbf{x}) = \left(\sum_{i=1}^{10} \max\big(0, g_i(\mathbf{x})\big) + \sum_{j=1}^{1} \max\big(0, |h_j(\mathbf{x})| - \epsilon \leq 0\big) \right), \tag{3.23}$$

ISA implemented Deb's (Deb, 2000) rules to solve the design constraints of the pedantry gear problem.

3.4.2 Parameter settings

In this study, the parameter settings were specifically defined for the Gravitational Search Algorithm (GSA) to facilitate a fair comparison with other optimization methods. The GSA algorithm was implemented in MATLAB and executed on a PC equipped with an Intel (R) Core (TM) i7-6600U CPU operating at 2.60x2.81 GHz and 8.0 GB of RAM memory, running the Microsoft Windows 10 Professional operating system.

To ensure consistency and comparability, the following parameter values were employed exclusively for GSA:

- Population size (np) = 50
- Maximum number of iterations (t_{max}) = 500.

These specific parameter settings were chosen to create a level playing field when comparing GSA with other optimization algorithms used in the study.

Please note that these parameter settings are exclusive to GSA and may differ for the other algorithms analyzed in the research.

3.4.3 Results and discussions

In this study we have compared the performance of various optimization algorithms, namely FA, ISA, MVO, HFPSO, ReDE, and GWO-CS, with GSA. The results obtained from these algorithms are presented in Table 2.
Upon examining the results in Table 2, it is evident that ReDE achieves the best value for the "maximum transmission error" among all the algorithms considered. This implies that ReDE demonstrates superior performance in reducing noise in planetary gears train, as compared to the other optimization techniques utilized in this study. It is worth noting that the results are all relatively close, with values ranging from 0.5255 to 0.5273.
The results achieved using GSA are notable. GSA achieves a transmission error value of 0.5257, which compares favorably to the top-performing algorithms in this investigation. This demonstrates that GSA is capable of generating good noise reduction results for planetary gears trains. Furthermore, these findings illustrate GSA's potential as a reliable optimization algorithm for noise reduction in planetary gear trains, and further validate its competitiveness within the existing literature on this subject.

3.4.4 Statistical comparaisons

In this step, a statistical comparison is conducted to evaluate the introduced algorithms in terms of solution quality, robustness, convergence behavior, and average computational time. The evaluation is performed over 25 independent runs, both quantitatively and qualitatively. The best results obtained from all the runs are summarized in Table 3. The table clearly demonstrates that all the algorithms utilized in this study successfully find the optimal solution without any violations of the constraints. Furthermore, the comparison reveals that the ReDE algorithm achieves the lowest transmission error, denoted as $f(\mathbf{x}^*) = 0.5255886$, corresponding to the solution vector $\mathbf{x}^* = \{33, 25, 34, 32, 30, 116, 4, 2.5, 1.75\}$.

In contrast, the Gravitational Search Algorithm (GSA) produces a slightly higher transmission error, represented as $f(\mathbf{x}^*) = 0.525714$, with the corresponding solution vector $\mathbf{x}^* = \{28, 20, 19, 19, 15, 69, 2, 2, 4\}$. Despite this marginally higher error, it is important to note that GSA still achieves a commendable level of performance, demonstrating its capability to find a solution that is comparable to the best-performing algorithms in the study.

Table 3.3: The best results for the planetary gearbox attained by different optimisers

Implemented optimisation methods							
M-H	FA	ISA	MVO	HFPSO	ReDE	GWO-CS	GSA
Best value	0.5257	0.5261	0.5273	0.5262	0.5255	0.5257	0.5257

Table 3.4: The best simulated results achieved by used algorithms for the planetary gear train problem.

	Optimisation method						
Variables	F A	ISA	M V O	HFPSO	ReDE	G W O-C S	GSA
N_1	35	29	49	37	33	35	28
N_2	26	25	35	22	25	26	20
N_3	25	29	32	20	34	25	19
N_4	24	24	32	24	32	24	19
N_5	21	22	29	26	30	19	15
N_6	87	87	116	87	116	87	69
p	3	3	4	3	4	3	4
m_1	2	2.5	1.75	2.25	2.5	2	2
m_3	2	2.25	1.75	2	1.75	2	2
$f_{\min}$	0.5257687	0.5261740	0.5273469	0.5262805	0.5255886	0.5257687	0.525714

Note :
The unit of a transmission ratio is dimensionless. It represents the ratio of the input speed or torque to the output speed or torque in a transmission system. Since it is a ratio, it does not have any physical units associated with it. The transmission ratio is often expressed as a decimal or a fraction, indicating how much the output is scaled relative to the input in the transmission system.

3.4.5 Convergence analysis

In this section, we present a comprehensive convergence analysis of the Gravitational Search Algorithm (GSA) using three different gravity functions: the dynamic gravity function3.4, linear GSA3.5, and logsigmoid GSA3.6. The dynamic gravity function was defined as follows:

$$G = G_0 \cdot \exp\left(-\alpha \cdot \frac{\text{iteration}}{\text{max\_it}}\right),$$

where α is set to 20, G_0 is set to 70, and iteration represents the current iteration while max_it denotes the maximum iteration (set to 90 in our experiments). The linear GSA gravity function is given by:

$$G = G_0 \cdot \left(1 - \frac{\text{iteration}}{\text{max\_it}}\right),$$

with G_0 set to 70. Lastly, the logsigmoid GSA gravity function is defined as:

$$G = \frac{G_0}{1 + \exp\left(\frac{\text{iteration} - \frac{\text{max\_it}}{2}}{100}\right)},$$

with G_0 also set to 70. Each gravity function was evaluated using a population size of 50 ($N = 50$) and a dimensionality of 9 ($d = 9$). The algorithm was run 10 times for each function, and the best $f_{\min}$ value obtained from each run was recorded. The convergence analysis primarily focuses on the behavior of the algorithm over iterations, aiming to assess the rate at which it converges to the optimal solution. We observe that the best $f_{\min}$ values obtained for the dynamic gravity function, linear GSA, and logsigmoid GSA are 0.5400, 0.5264, and 0.5422, respectively. Although these values show slight differences, indicating similar performance across the gravity functions, further investigation is necessary to determine the convergence rate and stability.

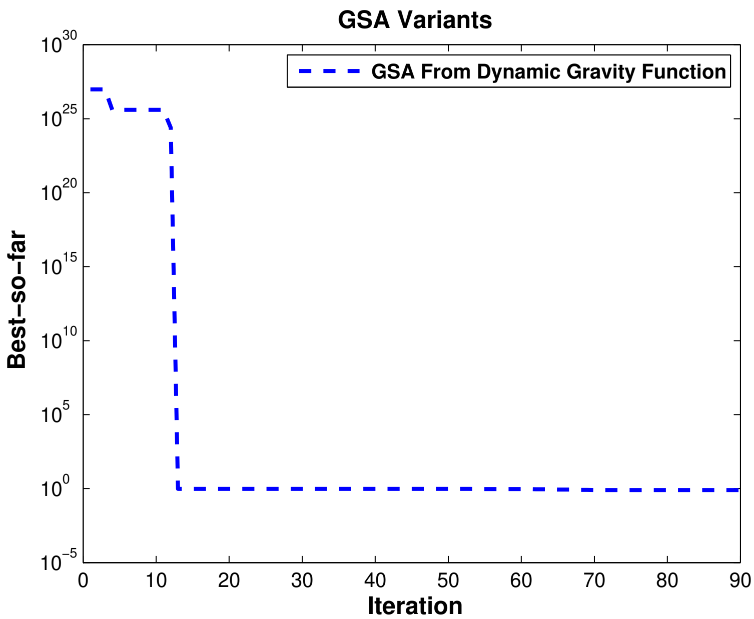


Figure 3.4: Performance of GSA Using Dynamic Gravity Function.

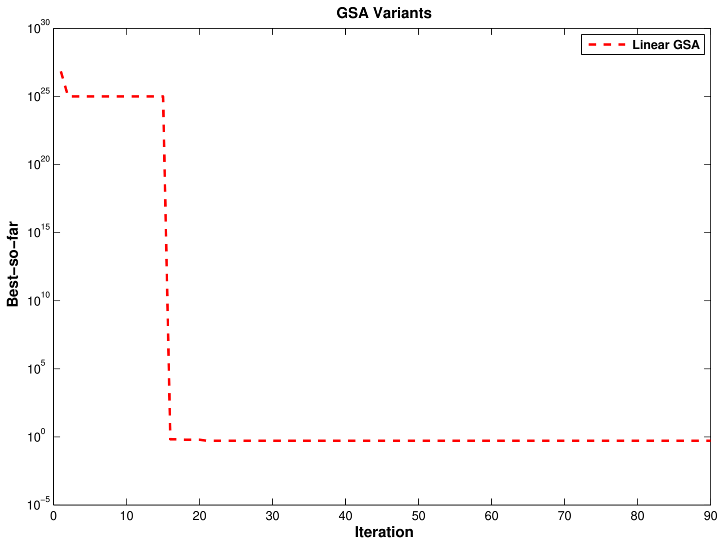


Figure 3.5: Linear GSA Performance Analysis.

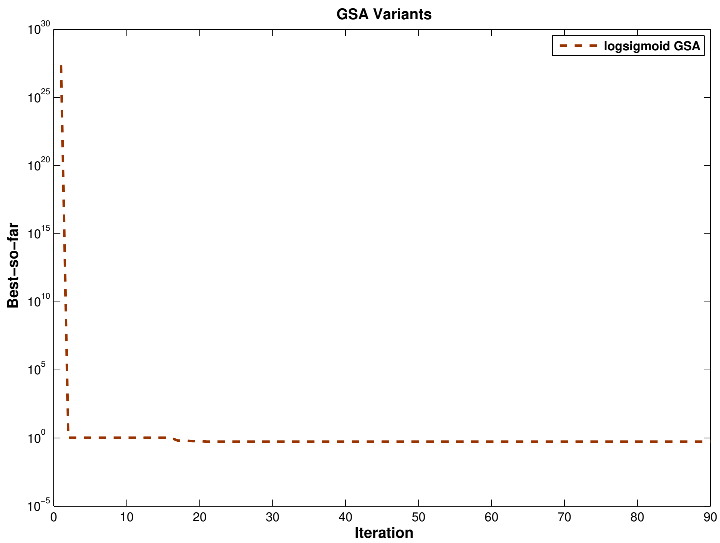


Figure 3.6: Logsigmoid GSA Performance.

3.5 Conclusion

In this chapter, we focused on the implementation of the Gravitational Search Algorithm (GSA) for noise reduction in the planetary gear train of conventional automatic transmissions. Its primary objective was to determine the optimal number of gear teeth that would meet the transmission ratios while minimizing noise. we attempted to achieve a more balanced and uniform gear system by formulating an objective function that minimizes maximum errors in the gear ratios. the implementation involved addressing design constraints related to undercutting, maximum transmission diameter, and spacing between multiple planets. These constraints were carefully considered to ensure the feasibility and functionality of the optimized gear train designs. By comparing the results obtained from GSA with other meta-heuristics, namely FA, ISA, MVO, HFPSO, ReDE, and GWO-CS, we were able to assess GSA's performance in reducing noise in planetary gear trains. GSA achieved competitive noise reduction results, with a transmission error value comparable to the top-performing algorithms in this study, according to the results. This proves GSA's capability as a reliable optimization approach for noise reduction in planetary gear trains.

In conclusion, the Gravitational Search Algorithm (GSA) implementation for noise reduction in planetary gear trains showed good results. GSA has the potential to enhance automatic transmission performance by lowering noise levels, thereby benefiting the automotive industry with quieter and more efficient vehicles.

CONCLUSION

In this thesis, we focused on the conception of automatic planetary gears trains (PGT) and employed the power of meta-heuristics(M-H), specifically the Gravitational Search Algorithm (GSA), as an optimization technique inspired by the law of gravity and motion. Our primary objective was to enhance the efficiency and performance of PGT by minimizing the maximum errors in gear ratios, thereby reducing vibration noise.

Drawing upon existing research, we established appropriate design parameters and formulated an objective function. By leveraging the intelligent exploration capabilities of GSA, which emulates the gravitational forces and motions experienced by celestial bodies, we effectively managed the trade-offs between various performance criteria, converging towards optimal solutions. Our specific objective was to determine the ideal number of gear teeth that would fulfill transmission ratios while minimizing noise.

While comparing GSA with other M-H, we found that it yielded notable results, although it did not achieve the best outcome. Nevertheless, it exhibited good results in minimizing transmission error, achieving a value of 0.5257. This outcome highlights the effectiveness of GSA in optimizing automatic PGT configurations, reaffirming its valuable role in the field of mechanical engineering.

As technology continues to advance, the exploration and refinement of M-H optimization algorithms, such as GSA, will undoubtedly play a crucial role in continuously improving and innovating automatic PGT systems. We hope that the findings of this research contribute to a broader understanding of gear technology and provide insights into the application of meta-heuristics in the field.

BIBLIOGRAPHY

[1] Wright M,T . *"The Antikythera Mechanism reconsidered*". (2007). p27-43

[2] K, Arnaudov & D, Karaivanov. *"Planetary gear trains*". Sofia:Bulgarian Academy of Sciences Publ. “Prof, Marin Drinov”. May 2017. 5p.

[3] Eric Robinson. *"James watt and the law of patents"*. Journal of Technology and Culture.(1972). pp 115–139

[4] Symonds, R,W. *"Catalogue of the Mechanical Engineering Collection in the Science Division of the Victoria and Albert Museum, South Kensington.*" (1924).

[5] ISL DIGI-KEY Electronics. (n,d). *"Planetary gear motors*". Retrieved from https://islproducts.com/component/planetary-gear-motors/: :text=A

[6] Christopher G, Cooley & Robert G, Parker . *"planetary and epicyclic gear dynamics and vibration"*.july2014.

[7] Sharma, V *"Gears and their lubrication evolution of gears*".academia . (2017, 26 mai).P 01

[8] Halah, Y . *" Manufacturing of Gears* ". academia . (2016, 9 décembre). P 05.

[9] Hussein, M. *"GEARS Information about Gears"*. academia. (2016, 4 novembre).P 03.

[10] Salihin. *"T.Gear-Box-Report*".(2015, 26 octobre). P 02.

[11] Hussein, M. *"GEARS Information about Gears"*. ". academia. (2016, 4 novembre).P 03.

[12] P,V Pawar & P,R Kulkarni. *"Design of two stage planetary gear train for high reduction ratio"*. International Journal of Research in Engineering and Technology . (2016, 2 février).p 150-157.

[13] KHK Gear Manufacturer . *"Types of Gears "*.

[14] Yoo H,G & Chung W,J. *"Application of flexible pin for planetary gear set of wind turbine gearbox"*. Journal of Renewable Energy Engineering. 2022(1). p23-37.

[15] A,S Robleda. *"Split Torque Gearboxes: Requirements, Performance and Applications"*.April 2012. p56-74

[16] S,H Gawande & S,N Shaikh. *"Experimental investigations of noise control in planetary gear "*.25 NOV 2014.

[17] Lin, Ming-Hua & Tsai, Jung-Fa & Yu, Chian-Son. *review of deterministic optimization methods in engineering and management*. Mathematical Problems in Engineering. 2012.

[18] Holland J,H. *"Adaptation in Natural and Artificial Systems"*University of Michigan Press. (1975).

[19] Glover, F. *"Tabu search—part I"*.ORSA Journal on computing. (1989). p190-206.

[20] O.Bozorg-Haddad & M, Solgi & H,A Loáiciga *"Meta-heuristic and Evolutionary Algorithms for Engineering Optimization"*.John Wiley and Sons. (2017).p 21.

[21] S, Almufti & R, Asaad & B, Salim.*"Review on Elephant Herding Optimization Algorithm Performance in Solving Optimization Problems"*.Sciencepubco.com. 2019.

[22] S, Almufti. *"U-Turning Ant Colony Algorithm powered by Great Deluge Algorithm for the solution of TSP Problem"*.(Hdl.handle.net). 2018.

[23] Holland J,H. *"Adaptation in Natural and Artificial Systems"*.University of Michigan Press.re-issued by MIT Press .(1992) .

[24] O,Bozorg-Haddad & M, Solgi. & H. A Loáiciga *"Meta-heuristic and Evolutionary Algorithms for Engineering Optimization"*.John Wiley and Sons. (2017).

[25] Sholedolu M,O .*"Nature-inspired optimization Improvements to the Particle Swarm Optimization Algorithm and the Bees Algorithm"*.A Thèses Submitted to C Ardiff University. (2009).

[26] O,Bozorg-Haddad & M, Solgi . & H,A Loáiciga. *"Meta-heuristic and Evolutionary Algorithms for Engineering Optimization"*.John Wiley and Sons. (2017).

[27] E, Rashedi. *"Recent Developments in Intelligent Nature-Inspired Computing"*.(2022, November 30)

[28] F,Glover. *"Future paths for integer programming and links to artificial intelligence"*.Computers and Operations Research. 13(5). (1986). p 533-549.

[29] O,Bozorg-Haddad & M, Solgi . & H,A Loáiciga. *"Meta-heuristic and Evolutionary Algorithms for Engineering Optimization"*.John Wiley and Sons. (2017).

[30] J,T Jiménez& J, Pavon . *"Applications of meta-heuristics in real life problems"*.12 April 2014.

[31] C,Blum & A,Roli *"Meta-heuristic in combinatorial optimization: Overview and conceptual comparison"*.ACM Computing Surveys (CSUR), (2003). p 268-308

[32] C, Huang & Y, Li & X, Yao . *"A Survey of Automatic Parameter Tuning Methods for Metaheuristics"*. IEEE Transactions on Evolutionary Computation. (2019).

[33] E,Rashedi & H,Nezamabadi-pour& S,Saryazdi *"GSA: A gravitational search algorithm"*.Information Sciences. 2009. p 2232-2248.

[34] J, Smith. *"Gravitational search algorithm for optimization problems."*.Journal of Optimization. 20(1). (2021). 45-58.

[35] E,Rashedi & H,Nezamabadi-pour& S,Saryazdi *"GSA: A gravitational search algorithm"*.Information Sciences. 2009. p 2232-2248.

[36] O,Penangsang & M, Abdillah & A, Soeprijanto . *"Voltage Control on 500 kV Java-Bali Electrical Power System for Power Losses Minimization Using Gravitational Search Algorithm"*.First International Conference on Informatics and Computational Intelligence. 2011. no2. pp 11.

[37] P, K Roy & B, Mandal & K, Bhattacharya *"Gravitational Search Algorithm Based Optimal Reactive Power Dispatch for Voltage Stability Enhancement"*.Electric Power Components and Systems, vol 40, no 9. 2012.pp 956–976.

[38] S, Monda & A, Bhattacharya & S, H nee Dey. *"Multiobjective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration"*International Journal of Electrical Power & Energy Systems, vol 44, no 1 Jan 2013. pp 282–292.

[39] S, Duman & U, Güvenç& Y, Sönmez & N, Yörükeren *"Optimal power flow using gravitational search algorithm"*.Energy Conversion and Management, vol. 59. Jul 2012.pp 86–95.

[40] L,N De Castro. *"Fundamentals of natural computing: an overview"*.vol 4. 2007. pp1–36.

[41] H, Liu & J, Wu & X, Chen & Q, Liao. *"Gearbox fault diagnosis using optimized empirical mode decomposition and Hilbert spectrum based on gravitational search algorithm"*. Mechanical Systems and Signal Processing. 84. (2017). p 424-437.

[42] Y, Zhang & X, Xu & B, Liu& Q, Zhang. *"An effective Gravitational SearchAlgorithm with mutation for multi-objective optimization of spur gear design"*.Engineering Optimization. 51. (2019). p1256-1271

[43] M,Esmail & M, Sabaghi & S,M Jafari. *"Design optimization of the planetary gear train by an efficient gravitational search algorithm"*.Mechanism and Machine Theory.132.(2019). p 205-219.

[44] G, Lechner & H, Naunheimer *"Automotive Transmission"* .1999.

[45] H, Zandevakili & E,Rashedi & A,Mahani *"Gravitational Search Algorithm with both attractive and repulsive forces"*.2017.

[46] P,A Simionescu & D,Beale & G,V Dozier *"Teeth-Number Synthesis of a Multispeed Planetary Transmission Using an Estimation of Distribution Algorithm"*.2006.

[47] A,Hammoudi & M, Sadiq Sait & Ali Riza Yildiz. *"Optimal design of planetary gear train for automotive transmission using advanced meta-heuristics"*. 2019.