ONLINE CONTROL AND OPTIMIZATION OF DIRECTIONAL DRILLING

BY

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To my beloved father, mother, siblings, wife

& my son "Youssef"

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LIST OF ABBREVIATIONS

BHA: Bottom Hole Assembly

DD: Directional drilling

DOF: Degree of Freedom

DSS: Directional Steering System

FOB: Force on Bit

GSA: Gravitational Search Algorithm

LQR: Linear Quadratic Regulator

LWD: Logging While Drilling

MD: Measured Depth

MSE: Mechanical Specific Energy

MWD: Measurement While Drilling

PSO: Particle Swarm Optimization

RMSE: Root Mean Square Error

ROP: Rate of Penetration

RPM: Revolution per Minute

RSE: Rock Specific Energy

RSS: Rotary Steerable System

TVD: True Vertical Depth

WOB: Weight on Bit

ABSTRACT

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Directional Steering System (DSS) has been established for well drilling in the oilfield in order to accomplish high reservoir productivity and to improve accessibility of oil reservoirs in complex locations. In this thesis, dynamic modeling of two different DSS were developed and optimized using different control and optimization techniques. Firstly, the Rotary Steerable System (RSS) which is the current state of the art of directional steering systems. In this work, we address the problem of real time control of autonomous RSS with unknown formation friction and rock strength. The work presents an online control scheme for real time optimization of drilling parameters to maximize rate of penetration and minimize the deviation from the planned well bore trajectory, stick-slip oscillations, and bit wear. Nonlinear model for the drilling operation was developed using energy balance equation, where rock specific energy is used to calculate the minimum power required for a given rate of penetration. A proposed mass spring system was used to represent the phenomena of stick-slip oscillation. The bit wear is mathematically represented using Bourgoyne model. Secondly, the autonomous quad-rotor DSS which has 4 downhole motors, is considered. In this work, a novel feedback linearization controller to cancel the nonlinear dynamics of a DSS is proposed. The proposed controller design problem is formulated as an optimization problem for optimal settings of the controller feedback gains. Gravitational Search Algorithm (GSA) is developed to search for optimal

settings of the proposed controller. The objective function considered is to minimize the tracking error and drilling efforts. Detailed mathematical formulation and computer simulation were used for evaluation of the performance of the proposed techniques for both systems, based on real well data.

ملخص الرسالة

الاسم الكامل: محمود عبدالحكيم كامل جمعه

عنوان الرسالة: التحكم والتحسين المستمر في اداء الحفر الموجه

التخصص: هندسة النظم والتحكم

تاريخ الدرجة العلمية: نوفمبر 2016

قد تم إنشاء انظمه الحفر الموجه في مجال البترول من أجل الحصول علي أنتاجية عالية من حزانات البترول و تحسين إماكنية الوصول الي خزانات البترول في الأماكن المعقدة. في هذه الرسالة تم تطوير نظامين مختلفين من أنظمة الحفر الموجه ثم تحسين اداءهم باستخدام تقنيات مختلفة من التحكم والتحسين. النظام الاول هو النظام الدوراني القابل للتوجيه وهو نوع من انواع الحفر الموجه. في هذا الجزء نتناول مشكلة التحكم في الزمن الحقيقي للنظام الدوراني القابل للتوجيه بدون معلومية مقدار الأحتكاك مع جدار البئر و قوة الصخور. هذا العمل يقدم مخطط للتحكم المستمر للتحسين في الوقت الحقيقي للعوامل المتغيرة اثناء الحفر من أجل زيادة نسبة التغلغل و تقليل الأنحراف عن مسار البئر المخطط له مسبقا وتقليل التذبذبات نتيجه الأحتجاز والأنزلاق و تقليل نسبه التآكل فى الحفار. تم تطوير نموذج رياضي غير خطي لتمثيل عملية الحفر بأستخدام معادلة توازن الطاقة حيث أن الطاقة النوعية للصخور تم أستحدامها لحساب أقل طاقة مطلوبة لنسبة محددة من التغلغل. تم أستخدام نظام الكتلة والزنبرك لتمثيل ظاهرة التذبذبات نتيجه الأحتجاز والأنزلاق. نسبة التآكل في الحفار تم تمثيلها بأستخدام النموذج المقترح من بورجيوني. ثانياً نظام الحفر الموجه رباعي المحرك حيث يحتوي علي اربع محركات تيار مستمر. في هذا النظام تم تصميم متحكم جديد باستخدام طرق التحويل الى نظام خطي باستخدام التغذية الخلفية لألغاء الديناميكيات الغير خطيه. تصميم المتحكم المقترح أُعد كوسيلة تحسين معاملات كسب التغذيه الخلفية للمتحكم للوصول للقيمة الأمثل. تم تطوير خوارزميه البحث المبنية علي الجاذبية للبحث عن القيم الأمثل للمتحكم المقترح. داله الهدف المستخدمة في عملية التحسين تهدف الي تقليل نسبة خطأ التتبع و تقليل الجهد المبذول. تم أستخدام معادلات رياضية مفصلة و نظام محاكأه حاسوبي لتقييم اداء التقنيات المقترحه بناء علي بيانات حقيقيه لأبار بترول.

CHAPTER 1

INTRODUCTION

In particular, conventional vertical drilling becomes no longer attractive compared to horizontal drilling. Directional Steering System (DSS) has a considerable importance in the oilfield industry due to its influence on drilling production rate. It can expedite the accessibility of the oil reservoirs with wide surface zone in a slim horizontal coat. The horizontal wells can be extended over a larger area in contact with the reservoir providing higher productivity [1]. Most of the research and development in the oilfield aims at minimizing total costs, minimizing the possibility of encountering drilling problems and maximizing performances. In the recent years, the search for the underground energy has shown significant advances in drilling wells technologies. Different techniques from various disciplines are being developed presently in drilling activities to achieve an environmentally safe and friendly well in addition to cost effective well construction. Among those disciplines the most effective are communication and computer technologies which enabled online optimization of well drilling. Massive data quantity could be transferred from different sites in the world in time efficient and reliable aspects. Advanced computer and network technologies can be used to transfer, store, and retrieve massive amounts of data, and numerically solve sophisticated algorithms and problems [2].

The objective of the online drilling parameters optimization is to optimize each of control parameters and performance parameters. Performance parameters are the parameters used to represent the well status and can be optimized to improve its performance as stick slip oscillation, Technical Hole Deviation, and bit life time. Control Parameters are the tools used to tune performance parameters as weight on bit (WOB) and bit RPM. Optimization of performance parameters may lead to the maximization of drilling rate and minimization of the overall cost of drilling operations. An optimization technique has been applied for the drilling optimization to minimize certain objective function. A comprehensive literature review on drilling optimization has been carried out for the given research work. A mathematical model is implemented for this intent using real-field data gathered via advanced well monitoring systems and data recorders. This model forecasts the rate of penetration (ROP) of any drilling well as a function of available parameters. Computer networks are fundamental tools in drilling process. They can let the drilling parameters be remotely optimized in the field. These networks save the ducted data immediately from the data source, while collects the new data to be fed. The field engineer is responsible to transmit the present parameters back to the main computer. The new amount of parameter's modifications is decided by the headquarters to be modified in the model and optimum drilling parameters using the recently received data. Therefore, this process is considered to be a real-time-optimization. This defined method is going to be extensively used in future drilling works since it could minimize overall drilling costs and reduce the probability of facing troubles.

Some important parameters those of which could be gathered in real time from drilling activities are as

WOB: Stands for weight on bit which considered as essential factor in optimization of the drilling process, where it affects the rate of penetration likewise natural frequencies of the drill string in the vibration bending mode. Also it can be related to the drill string carrying capacity load (buckling load) [3]. It is usually measured through attaching a strain-gauge to the drilling line which works for measuring the magnitude of the tension in the line itself, then gives a calibrated weight reading.

RPM: It stands for "revolution per minute". This parameter represents the angular speed of the drill string.

ROP: Is the Rate of Penetration which is the speed of breaking the rock exerted by the drill bit in order to deepen the borehole, which is considered as the most important drilling parameter, since all the upcoming calculations in this work depend on accurate estimation of ROP.

Torque: This parameter is the torque of the drillstring while it is rotating. The torque is going to be significantly important for inclined and highly deviated wellbores, which is also related with the wellbore cleaning issues.

MWD: Is the Measurement While Drilling where the feedback loop depends on. This drilling instruments produce real-time parameters automatically and continuously such as the location of the bottom hole assembly (BHA) in addition to its orientation, MWD transmits these monitoring parameters to the PC for displaying, recording, printing, and providing the control parameters [4].

1.1 Statement of the Problem

It is shown that for all of the factors determined in the literature contribute to the conclusion that a much enhanced overall ROP will be accomplished while using RSS assembly in drilling operations instead of steerable motors. The use of rotary steerable systems allows drilling variables to be optimized for both formation and bit.

The reactive torque from the bit acts in the opposite direction of the generated bit torque. As the required bit torque increases, the reactive torque increases. Stick-slip occurs when there is an increased torque demand from the bit to achieve penetration that cannot be met by the drilling motor power section, causing bit rotation to slow or stop. It is also concluded that the model for the on-line drilling optimization requires the previous and accumulated practical data in order to be used in tuning parameters in next iterations.

The focus of this thesis is to propose an integrated approach for control and optimization of two different directional drilling (DD) systems,

1- Optimize the drilling parameters and directional steering control of a RSS. An objective function is defined, which compromises between trajectory tracking accuracy, drilling effort, ROP, bit wear and stick-slip oscillations. The optimization problem is solved subject to operations limits and constraints using constraint optimization techniques. Nonlinear model for the drilling operation was developed using energy balance equation, where rock specific energy is used to calculate the minimum power required for a given ROP. The algorithm finds the optimal torque, rpm, WOB, the steering actuators commands, and the drilling fluid feed rate. An adaptive technique is used to estimate the rock specific energy, the lateral rate of penetration coefficient, the bit life time, and rotary string parameters.

2- Control and optimization of the quad-rotor directional steering system. The dynamic analysis and control strategy of the quad-rotor systems are proposed. The proposed strategy aims at designing and controlling the DSS for tracking and stabilization of the drill bit. The proposed control strategy involves linearization of the highly nonlinear dynamics of the system. GSA optimization technique is proposed and developed to optimize the control inputs of the four rotors.

1.2 Research Objectives and Contributions

The research objective of this study is to develop a methodology which would accomplish the following tasks in real-time basis:

1. Develop an adaptive control system for real-time Directional Drilling for RSS and Quad-rotor.
2. Develop an optimization method for optimization of the drilling parameters, Technical Hole Deviation, and cost of bit wear in RSS.
3. Extending of the optimization problem to include the Stick-Slip oscillations in RSS.
4. Develop an optimization and control algorithm for the quad-rotor directional steering system.

1.3 Methodology

The research is planned to be performed as follows:

1- The performance of the Rotary Steerable System is improved by adding more degrees of freedom to its dynamics in order to make its path smooth.

2- The location deviation of the BHA is minimized by online tuning of the control law using real time MWD data, which are assumed to be available at the present time without time delay. MWD data are compared with the preplanned trajectory at each control iteration to compute the tracking error then using an optimization technique this error is reduced by minimizing an objective function. To have more accurate results, more drilling variables are considered as inclination and azimuth angles.

3- Optimizing the input drilling parameters using the concept of mechanical specific energy which is illustrated as the amount of work required to crush a certain volume of the rock. This concept is used as an optimization tool during drilling operations where any change in drilling efficiency is detected in order to enhance instantaneous ROP by optimizing the drilling parameters.

4- The stick-slip oscillation of the drill bit is reduced by online optimization of WOB.

5- Optimizing the life time of the drill bit using Burgoyne and Young model.

6- In order to optimize the performance of the quad-rotor DD system, the proposed controller design problem is formulated as an optimization problem for optimal settings of the controller feedback gains and Gravitational Search Algorithm is developed to search for optimal settings of the proposed controller. The objective function considered is to minimize the tracking error and drilling efforts.

1.4 Thesis Organization

The rest of this thesis is described as follows. Chapter 2, presents the literature review. Chapter 3, illustrates mathematical models for the directional steering systems. Chapter 4, presents the proposed control design. The simulation results and discussion are presented in chapter 5, followed by the conclusions.

CHAPTER 2

LITERATURE REVIEW

Directional drilling refers to the operation of leading the wellbore along some preplanned trajectory towards a prescribed target. Technical Hole Deviation control aims at holding the wellbore within predetermined limits relative to inclination angle, azimuth angle, or both [5].

2.1 Applications of directional drilling

Groups of application of DD include [6]

1- Sidetracking: This refers to drilling around an obstruction (e.g. fish) encountered by a well bore during drilling. Such obstruction may also be result of the failure of drillstring or an intentional back-off with leaving the bottom part of the drillstring in the hole. When this happens, no additional advancement can be done if the obstruction is not removed from the hole. Sidetracking such an obstruction is much cheaper than to relinquish the hole then start drilling a new hole as shown in Figure 2-1.

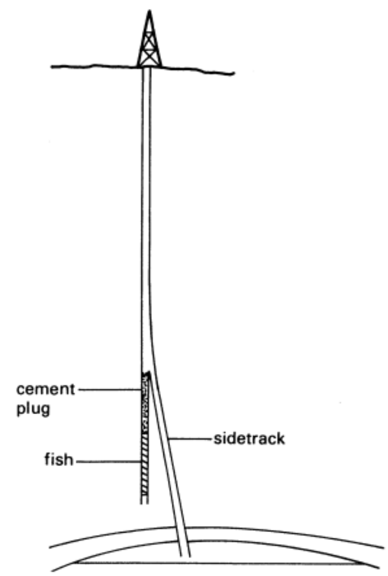

Figure 2-1 Sidetracking around a fish

2- Drilling to avoid geological problems: Salt dome structures are geological features that occasionally occur with petroleum reservoirs. Part of a salt dome may be located directly on top of a reservoir such that a vertical well into the reservoir would have to penetrate the salt formation. Lost circulation, large washouts and corrosion are some of the problems that can be caused by drilling through a salt section. Drilling a directional well in this kind of situation would be wiser as shown in Figure 2-2.

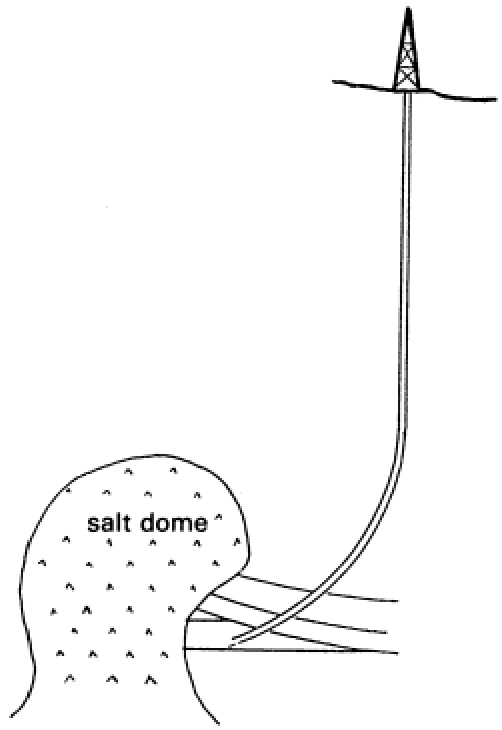

Figure 2-2 Example of drilling a directional well down a salt dome

3- Controlling vertical holes: Directional techniques are needed to keep vertical wells on an appropriate course and prevent them from going over lease boundaries. Altering certain drilling configurations or changing BHA or can be used to correct small deviations from a planned trajectory, while more significant deviations may need the use of a downhole motor and bent sub to make a correction run or drill a sidetrack. Deviation from trajectory may occur in the tangential section of a directional well.

4- Drilling beneath inaccessible locations: When drilling a vertical well means drilling through natural or man-made obstructions such as urban areas or mountainous areas, permissions for such drilling operations may not be granted due to the potential negative impact on the environment. In such cases, drilling directional wells that can be accessed externally from an outer unrestricted location may be a feasible alternative to exploit the reserve as shown in Figure 2-3.

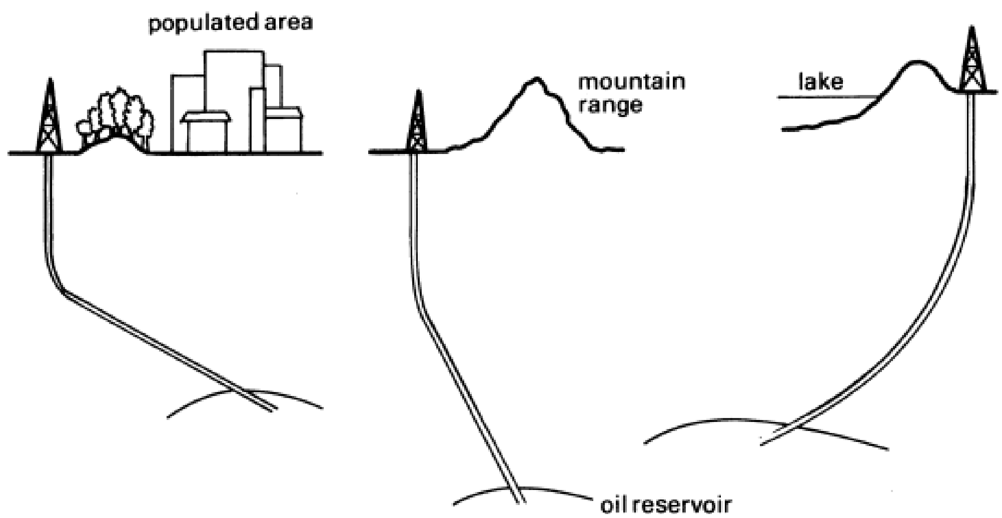

Figure 2-3 Directional wells drilled down some restricted surfaces

5- Offshore development drilling: Using DD in the exploitation of offshore reservoirs is one of the major applications of DD over the past 20 years. To drill a large number of vertical wells from individual platforms in order to develop the many oil and gas reserves that are beyond the reach of land-based rigs is clearly very expensive and impractical. DD enabled a conventional approach where for a large oilfield, a fixed platform is installed on the seabed from which many wells can be drilled directionally. This platform can also be used to centralize all needed production facilities, from which the oil may be exported through tankers or pipelines. Some large platforms can be used to drill up to 50 directional wells Figure 2-4.

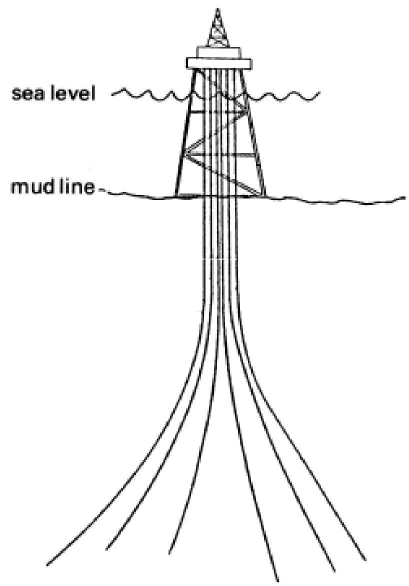

Figure 2-4 Development wells drilled from a fixed platform

6- Horizontal drilling: Drilling wells that are highly deviated from the vertical and horizontal wells have advantages over vertical wells that include increased productivity and reduced costs. Conventional wells may be drilled to an inclination of around 60°, with increased inclinations causing many drilling problems that increase the cost of the well significantly Figure 2-5.

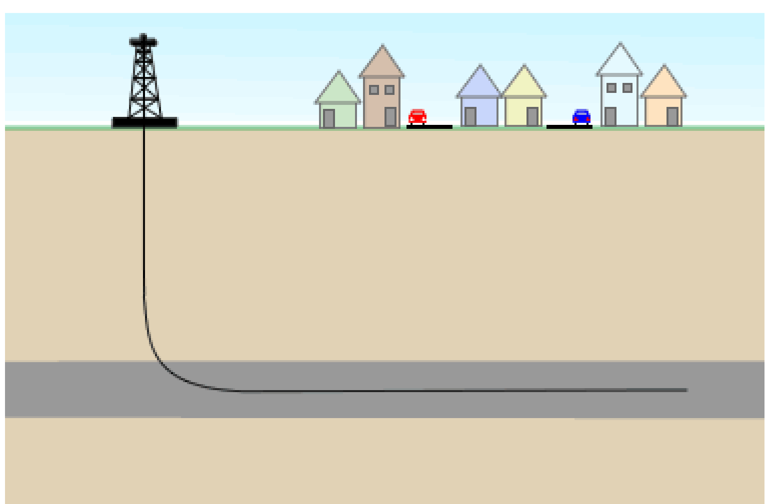

Figure 2-5 Horizontal drilling

7- Non-petroleum uses: DD may be used in other non-petroleum applications. In the mining industry, small-diameter boreholes could be drilled in rocks for production (such as in obtaining methane gas in coal seams) or measurement (such as to measure strata thickness) purposes. DD can also find use in installing pipelines underneath river beds.

2.2 Directional drilling mechanisms

The steering mechanism of DD systems works by applying angular moments and laterals loads to the drill bit in order to modify the direction of the propagation of the borehole. Sensors that are spatially displaced from the drill bit are used to measure the BHA angular orientation. This measurement inferentially gives the local inclination (i.e. pitch angle) of the borehole. The sensors also indicate the azimuthal direction (i.e. deviation from the north direction in the horizontal plane) of the borehole and both the azimuthal direction and local inclination are transmitted to a controller.

The controller, which could be positioned in the drillstring, surface rig or remote location, combines these measurements with data on distance drilled to estimate the position and shape of the borehole with respect to the desired borehole trajectory. The controller then computes and transmits a steering direction correction to the DD mechanism [7] .

Although the California Huntington Beach field drilled in 1933 is regarded as the first directional oil well, different DD techniques have been recently presented. DD systems introduced in 1962 which had developments on the positive displacement motor and bent-sub assembly made the development of offshore fields practical [8]. This technology rapidly extended from California to the Gulf of Mexico and has developed into the steerable motor systems which are in use nowadays [9]. The development of the steerable motor technology has included many improvements to its designs and materials [10].

High precision DD technologies have significant importance in extended mineral and seabed resources exploration. They could be considered as a key task of geological work. In order to enhance the precision and quality of geological exploration, a high accuracy

DD technique is the proper option. DD is used to decrease the overall exploration cost and reduce the total drilling platform number, particularly in the maritime resources exploration [10].

In the last two decades, DD technology has been improved by some oil and gas services companies as Schlumberger, Baker Hughes, Halliburton amongst others. Other companies that carried out subsequent research in directional systems include Precision Drilling Corporation, Pathfinder, Gyrodata Limited, and Noble Downhole Technology [11]–[13]. Researchers of several Chinese companies, including China National Offshore Oil Corporation, Xi'an Petroleum Institute, China Petrochemical Corporation have also investigated DD system control principle 21st century. Key directionally drilling components, particularly the control unit of the system, has however not been fully realized in China [10].

DD assembly designs used to drill directional holes are (1) mechanical, (2) hydraulic, (3) electrical, and (4) natural [14]. The techniques used to drill directional holes are rotary drilling with certain stabilizers arrangements[15], downhole motor with a bent sub [16], rotary steerable system [17], whipstocks [18], and jetting drilling [19]. All of these techniques are classified as mechanical methods except the jetting drilling which is considered as a hydraulic method. Natural method is related to formation geology such as hardness and dipping associated with a certain BHA design. Nowadays, the two most used methods in deep DD are the downhole motor and the RSS.

In order to control the drilling direction, downhole steerable-motor necessitates sliding through the hole without rotating the drillstring.

Odell, Payne and Cocking in 1995 [20] used variable gauge stabilizers for fine tuning control of the hole inclination which can cost effectively deepen the achieve of extended-reach-drilling (ERD) wells and minimize drilling time consuming. A new world record had been set with Wytch Farm the first well drilled using the HVGS technique for reaching the subject reservoir depth where the total depth was 7522 m with a reach of 6732 m. The HVGS can be controlled from the surface via a series of mud pump flow sequences, and communicates the blades' commanded and measured positions to the surface with mud pulse telemetry.

Bruce, Bezant and Pinnock in 1996 [21] pioneered a new technique at BP Wytch Farm which is critical to their ERD where sliding is considered as a problem. GeoSteering Tool near-bit inclination data and a HVGS are combined together and located on the top of the motor. This combination enabled the wells to be drilled almost entirely in rotary mode. But both of [20] and [21]have not been known to control the azimuth angle.

Steerable rotary drilling has better control ability for both angles (inclination and azimuth). It has much more features over previous mechanisms, as Barr, Clegg and Russell have done in 1996 [22]. The proposed system used synchronous polyphase modulation of bias by connecting a rotating mechanism into the drill bit. It is driven by a kind of drilling fluid and can be controlled by a directional sensor package, the orientation of the latter being independent of BHA rotation, stabilized and controlled. Some economic gains are supposed by saving time consuming and enhancing directional control.

Rotary Steerable Systems improve the ROP and extend the reach of ERD wells. This increases the efficiency and lowers the overall cost of ERD processes. Using those systems, operators can optimize the wellbore placement and hole quality to fulfill better ROP and improve the reservoir deliverability. RSSs were applied for various ERD wells at the Wytch Farm by Colebrook, Peach, Allen, and Conran in 1998 [23].

One of the biggest advantages of rotary drilling is the application of weight to the bit in ERD wells [24]. As the departure growth relative to the vertical depth, it becomes more sophisticated to implement this property in order to apply and control weight to the bit because of axial friction [25] and the detailed trajectory design of the well becomes critical in terms of torque and drag optimizing [26]. By optimizing the WOB the lateral vibrations (Stick-Slip oscillations) can be decreased to reduce the probability of drill bit stall and equipment failure [27]. Stick Slip oscillations are introduced as a new methodology to represent the enormous amplitude torsional oscillation of the drill string in drilling wells [28].

Some drilling assembly are composed of a drill bit and mud motor with one or more "bends" immediately above, below, or intermediate the motor. When the bit is being steered in a desired direction, the entire drill string is not rotated in order to maintain the "bends" and the motor directed in the proper orientation. This type of system has several inherent disadvantages such as the mud motor is expensive to manufacture and maintain, the non-rotating drill string also causes cuttings to accumulate on the bottom side of the borehole which may inhibit the removal of the drill string, on-rotation of the drill string results in high frictional contact between the wellbore wall and the drill string which inhibits the smooth application of an axial force to the drill bit which is needed in order to drill efficiently, and the drill string tends to "stick" in the borehole and does not slide down freely. In order to overcome the problems inherent to the above described tools, Tommy

M. Warren (1996) provided a simple and robust shifting mechanism for changing the drilling mode from "straight" to "curved" and vice versa without withdrawing the drilling assembly from the borehole [29].

T. Yonezawa, E. J. Cargill , T. M. Gaynor, J. R. Hardin and Richard T. proposed a new rotary steerable drilling in 2002 [30] which is the Robotic Controlled Drilling. The proposed technique is a bendable shaft where the bit is pointed in the counter direction to the shaft bending direction. The concept of tilting action is triggered from other rotary steerable device concepts where the bit is pushed sideways in order to modify the wellbore trajectory. The combination of the described tilting action and the extended gage bit technology contributes maximum effectiveness in torque and drag reduction while reducing vibration and further improving hole cleaning.

Y. Li , W. Niu , H. Li , Z. Luo , and L. Wang (2015) presented a novel steering mechanism which is installed in a point the bit rotary steerable system for oilfild exploitation [31]. This unique mechanism supports a set of universal joints to relieve the high alternative strain on drilling mandrel and engages a specially designed planetary gear small tooth number difference (PGSTD) to achieve directional steering. The point-the-bit steering mechanism normally utilizes a set of offset mechanisms to deflect the drilling mandrel and hence changes the well direction. The offset mechanism contains various eccentric rings. Each eccentric ring is energized by motors and can rotate, respectively. During the eccentric rings rotation, the offset amplitude and offset phase of the drilling mandrel can be regulated [32][33]. The point-the-bit steering mechanism can introduce greater well holes quality, lower vibration, extended service life time, and greater efficiency of rock removing.

A new high build-up rate (HBR) rotary-steerable drilling system (RSS) with comprehensive logging-while-drilling (LWD) capabilities was developed and commercialized by E. Biscaro, J. D'Alessandro, A. Moreno, M. Hahn, R. Lamborn, M. H. Al-Naabi, and A. C. Bowser in 2015 [34] . The new HBR RSS was designed to provide extensive LWD services, including propagation and deep resistivity, neutron and density porosity measurements, borehole imaging and many others at build-up rates up to 12°/100 ft. With the use of a closed loop control algorithm and a short steering sleeve that decouples steering functionality from dynamics of the drilling system, it becomes able to perform open-hole sidetracks and drill high dogleg severity (DLS) curves and laterals in one run with precise directional control and well placement, without exceeding the fatigue limits of the LWD tools.

A new proposed model of a directional steering system has been developed with different dynamics by M. Talib, et. al. in 2014, which includes 4 DC motors where drill cones are attached. The steering mechanism of quad-motor is comparable to the quad-rotor craft structure. However, designing its control algorithm is more challenging due to the nonlinear coupling in its associated angles, pitch-yaw-roll [1]. Unlike conventional drilling, the drilling power is mainly coming from these downhole motors. The drill string is not rotating and only transmits the drilling fluid and force on bit.

A novel steering mechanism for RSS was presented by Hongtao, Wentie, Shengli and Dawei [35] in 2015,with the use of an multiobjective optimization technique to reach the optimal parameters design using a modified Non-dominated Sorting Genetic Algorithm (MNSGA). The key component of which is a planetary gear set with teeth number difference (PGSTND) [31]. This study aimed to minimize the dynamic responses and outer diameter of steering mechanism with structural parameters as design variables subject to geometric, kinematic, and strength constraints. Based on the established dynamic model, the optimization problem is formulated, and both MNSGAII and NSGA-II are applied to the optimization problem.

2.3 Directional drilling optimization

Plenty of research studies have been developed in the scope of modeling and optimization, of DD. A major part of the reported work aims at minimizing error and cost of the drilling process [36]. Drilling optimization has changed from simply improving the ROP assuming or holding the other factors constant to analyzing all aspects of the drilling process by establishing an integrated workflow that enables different engineering departments to plan and execute the well [37].

Modeling of the drilling operation for control and optimization is a challenging problem due to the diversity of the factors affecting drilling as well as uncertainty in their determination. Among these factors are the BHA dynamics, torques and drags, formation properties, bit formation interaction and drilling fluid properties and its hydraulics [38].

At the while-drilling mode, the DD system should try to coordinate various control actions (RPM, WOB, mud properties, rate and hydraulic pressure, inclination actuators, azimuth actuators, etc) to keep the down hole path close to the preplanned path trajectory. The main task in DD is to properly orientate the down hole tool to steer the wellbore in a desirable location, and minimize the drilling time [39].

The work by Bourgoyne and Young (1974) is one of the most important early investigations on optimal drilling detection. It was based on statistical analysis of the drilling parameters from previous works [38]. In the work, a linear ROP model was constructed and multiple regression analysis of drilling data obtained from the model was done to select the rotary speed, bit hydraulics and bit weight. This model is commonly used in industry due to its robustness. Effects of formation attributes - such as strength, compaction, and depth of the formation in addition to the pressure differential across the hole bottom – as well as drilling features – such as bit diameter, RPM, bit wear, bit weight, and bit hydraulics – were included in model data analysis. It was concluded in the work that about 10% of drilling costs can be saved using fairly uncomplicated drilling optimization equations.

Speer [40] suggested a new comprehensive approach in 1958 to determine optimum drilling techniques. His work showed the empirical interrelationships of ROP, WOB, RPM, hydraulic horse-power and drill ability of the formation. He integrated five relationships into one chart to define optimum drilling technique using minimum field test data.

Graham and Muench [41] are executed one of the earliest evaluations of drilling data in order to determine optimum WOB and RPM combination in 1959. Their approach was to use a method of mathematical analysis of drilling related costs for drilling in optimum conditions. They derived experimental mathematical formulations for bit life anticipation and drilling rate as functions of depth, RPM and bit weight. Their work yielded a means for using calculations with any different drilling conditions to suggest optimum WOB and RPM that minimizes total drilling costs.

Young (1968) [42] achieved improvement in on-site computer systems for bit weight and rotary speed control. A minimum cost drilling terminology was introduced with four main equations; drilling rate as function of WOB and bit tooth height, bit wearing rate as a function of bit rotation speed, bit tooth wear rate and finally drilling cost. The work showed that integration of the equations for optimum WOB and RPM constants yields the best solutions for those parameters.

Wilson and Bentsen [43] investigated various drilling optimization procedures concentrating on optimization of WOB and RPM. In the study, three methods of increasing complexity and data requirements were developed. The first method is a Point Optimization method to minimize the cost per foot during a bit run, while the second method is an Interval Optimization method to minimize the cost of a selected interval. The third and most complex method is a Multi-Interval Optimization method for minimizing the cost of over a series of intervals. The authors concluded that their model of equations could be used as a guide toward good drilling procedures with considerable cost savings.

Reza and Alcocer (1986) used the Buckingham Pi theorem, a theorem for dimension analysis in creating expressions with dimensionless formats, to improve a non-linear, dynamic, multidimensional mathematical formulation for extended applications in drilling. The model consisted of three equations for ROP, rate of bearing wear, and rate of bit dulling. Their work also showed the effect of drilling parameters - WOB, RPM, bit radius, bit nozzle radius, bit bearing radius, characteristics of drilling fluid, differential pressure, etc. – on the developed model [44].

Wojtanowicz and Kuru (1990) proposed a new technique of drilling process planning and control. The proposed method combined theory of single-bit control with an optimal multi-bit drilling program for a well. Comparison of the dynamic drilling strategy to conventional drilling optimization and typical field practices showed an estimated potential cost saving of 25 and 60 respectively. The proposed method was shown to be the most cost effective for expensive and long-lasting PDC bits due to the more effective use of bit performance and reduced number of required bits for the hole [45].

In 1992, Pessier and Fear [46] improved on the Mechanical Specific Energy technique which has been created by Teale [47] . The authors implemented computer simulation and laboratory measurement tests in order to establish an energy balanced formulation for boreholes drilling subject to hydrostatically pressurized conditions. They implemented the derivation for mechanical specific energy formulation and identified methodologies for drill bit bearing problems identification. The identification methods continuously monitor the specific energy and bit-specific coefficient of sliding friction. They are quicker and more reliable than WOB and ROP concentrated evaluation.

Cooper et al. [48] developed a simulator program for well drilling in 1995. This program was aimed to be simple to understand and use. The simulator included characteristics in which drilling engineers could experiment changing effects of the operating parameters in order to optimize drilling operations. The simulator contained an algorithm which determines drilling ROP and wear rate of the bit. The overall cost and time are available together with cost per foot in total and for the bit in use during the drilling run.

Mitchell (1995) demonstrated the purpose of selecting optimal WOB and RPM values in his book [49]. One of the essential reasons was defined to be producing the minimum drilling cost per foot. Also controlling the direction of the borehole and recognizing over-pressured regions were among optimum parameters selection. He also mentioned the contouring method of selecting optimal weight and string speed.

Serpen [50] implemented a computerized drilling optimization research work in 1996. Computer programmes were implemented for the common six different drilling optimization methodologies which mostly made use of graphs. Namely the methods covered were: Constant Energy Drilling approach, Galle-Woods method, drill-off tests approach, modified multiple regression approach, multiple regression approach, drilling hydraulics optimization. The aim of the study was to be useful to field drilling teams in determining optimized drilling parameters, and to planning engineers in making effective parameters estimation.

Dubinsky and Baecker [51] developed a simulation system for several drilling conditions in 1998. They examined dynamic behavior of drill bit, simulating key dynamic drilling dysfunctions such as lateral vibrations, bit bounce, torque shocks, BHA/bit whirl, stick-slip and torsional oscillations. They concluded that the model for the on-line drilling optimization requires the previous and accumulated practical data in order to be used in tuning parameters in next iterations.

Akgun (2002) investigated the controllable drilling parameters that effecting drilling rate [52]. Mud weight, RPM, WOB, bit shape, and hydraulics are considered as the controllable parameters of the drilling process. Selection of the controllable parameters properly was concluded to significantly enhance drilling rate. An upper drilling rate limit or “technical limit” concept has been introduced which can not be passed without hazarding the safety of drilling operations. Values of RPM and WOB variables should be at possible maximum feasible rates taking into consider the minimum bit operational cost and stability of drillstring. Hole cleaning and bit hydraulics must be considered while selecting flow rate at an optimum value.

Ozbayoglu and Omurlu [53] implemented a research to optimize drilling parameters mathematically to decrease the overall well costs in 2005. They treated with WOB, RPM, bit wear and type, and bit hydraulics as explicit influencers on ROP. An analytical formulation of the drilling cost was formed based on a non-linear ROP equation. After using the proposed formula to optimized drilling parameters of the real field data provided from their literature, they discovered that total costs of the drilling process were decreased up to four times.

William and Jeff (2005) showed a method for determining Mechanical Specific Energy (MSE) in real time and in remote monitoring. The work showed how MSE behavior can be effectively understood from conducting real time MSE tests and how it can be an acceptably beneficial tool for drilling technicians and engineers. A practice of tuning drilling parameters in order to reduce MSE amount is shown as a good rule of thumb.

Milter et al. (2006) worked on improving the use of real-time data transfer from offshore to drilling, well intervention and production operations land stations [54]. Emphasis was placed on the piped data quality to multi-disciplinary relevant personnel that are not essentially at a predetermined remote location, but anywhere with high speed internet communication. The efficiency of the optimization was based judgment of the expert involved, which is based on in his/her experience in the process. It was concluded that using real-time data transmission as a means of automatic surveillance, there is a reduction in occurrence of unforeseen events and well shut-ins and improved consistency of operations.

Iqbal (2008) demonstrated a computer algorithm in order to calculate and optimize drilling optimization procedures using real-time parameters for roller cutter insert type of bits [55]. This method is consisted of some steps include calculating weight exponent given in drilling ROP, finding the optimum revolution speed of the string and parameters of WOB using plots or correlation. The relation of lease cost per foot is used to select the optimum parameter. The study concluded that the efficiency of exploratory wells could be enhanced using the same technique where no proven information would be available.

Alum and Egbon (2011) used real-time bit data acquired from wells in Niger Delta reservoirs to develop semi-analytical models for ROP [56]. These models were obtained by carrying out regression analysis of the parameters that contain differential pressure in the equations of the Bourgoyne and Young Model in order to obtain regression constants. Mathematical expressions connecting ROP and drilling fluid properties were then generated using the obtained regression constants.

Rashidi et al. (2008) put forward a novel approach to compute real-time bit wear from a combination of MSE and ROP models. The stated approach, unlike ROP models, takes the major differences between those two models into consideration. Particularly interesting results that were obtained from the work show a linear relationship between rock drillability (Drilling Strength) and MSE (Rock Energy) [57].

Eren and Ozbayoglu (2010) showed the development of a model to minimize cost per foot by maximizing drilling rate through the optimization of parameters in an ongoing drilling operation, such as WOB and bit RPM [2]. Data in the developed model is experimental field data obtained using modern well monitoring systems and data recorders. The acquired data is used to estimate the rate of drilling penetration as a function of available parameters. The work illustrated the use of past drilling trends to achieve relatively accurate prediction of drilling ROP. Optimum WOB and bit RPM could also be regulated in order to accomplish minimum cost drilling.

Koederitz and Johnson (2011) showed the improvement and field testing of an autonomous drilling system that uses a test process to assess the drilling performance of a specified set of target set points [58]. The set points are identified by a research method whose development was based on earlier work in the application of real-time MSE display. Field testing results that were presented are generally favorable and indicate a practical and flexible potential for autonomous drilling optimization without drilling knowledge which is promising in a range of cost-effective applications.

Elshafei, Khamis and Al-Majed (2015) presented a unified approach for real-time drilling optimization of the drilling parameters and directional steering, which combined the conventional drilling parameters as well as the directional steering control [39]. The proposed objective function compromised between trajectory tracking accuracy, drilling effort, and drilling time. The optimization problem was solved subject to operations limits and constraints using constraint optimization techniques.

Yashodhan et al. (2016) launched an Artificial Neural Network drilling parameter optimization system to provide the rig-site operator real time data analysis to help in decision making in order to increase the operating efficiency, increase the ROP, maximize the bit lifetime, and decrease the total cost [59]. The operating parameters such as WOB, and RPM can be selected depend on the provided data. The proposed system save much more money via reducing the drilling days.

Jiang and Samuel (2016) presented a combination of two optimization techniques, the Artificial Neural Network and the Ant Colony optimization, to simultaneously predict the ROP [60]. The inputs to the Neural Network are the depth, WOB, RPM, the mud flow rate, and the gamma ray, where the ROP is considered as the output. The Ant Colony algorithm is used to optimize the ROP. The results showed the how the Neural Network succeed to calculate the ROP without prescribed models.

CHAPTER 3

SYSTEM DYNAMICS

The location of the BHA of any directional steering system including the RSS is defined by its position and orientation Figure 3-1. Where the position can be expressed with respect to the body fixed frame which is attached to the BHA at point **B**, or the earth (inertia) fixed frame considered as the starting point of drilling at the surface at point **E**. The orientation of the BHA is defined by the three Euler angels, namely, roll, pitch, and yaw angles. Symbolized as $\phi, \theta, and\ \psi$, respectively, where the roll angle is aligned with the direction of drilling.

The body axes at any point in the space can be transformed to the earth axes using the transformation matrix R.

$$R = \begin{bmatrix} c\psi\, s\theta & c\psi\, c\theta\, s\phi - s\psi\, c\phi & c\psi\, s\theta\, c\phi + s\psi\, s\phi \\ s\psi\, c\theta & s\psi\, s\theta\, s\phi + c\psi\, c\phi & s\psi\, s\theta\, c\phi - c\psi\, s\phi \\ -s\theta & c\theta\, s\phi & c\theta\, c\phi \end{bmatrix} \tag{3-1}$$

Where $s\psi$ and $c\psi$ denote $\sin(\psi)$ and $\cos(\psi)$ respectively. If there is interest only in the direction of the wellbore, the roll angle can be ignored and the transformation matrix is simplified to,

$$R = \begin{bmatrix} c\psi\ s\theta & -s\psi & c\psi\ s\theta \\ s\psi\ c\theta & c\psi & s\psi\ s\theta \\ -s\theta & 0 & c\theta \end{bmatrix} \tag{3-2}$$

The location of any point with respect to the earth axes can be formulated as,

$$P_{XYZ} = \begin{bmatrix} X_E(t) \\ Y_E(t) \\ Z_E(t) \end{bmatrix} = R \, . \, P_{UVW} \tag{3-3}$$

Where X_E, Y_E, and Z_E are the location of any point with respect to the earth axes, and P_{UVW} is the location of any point with respect to the body axes.

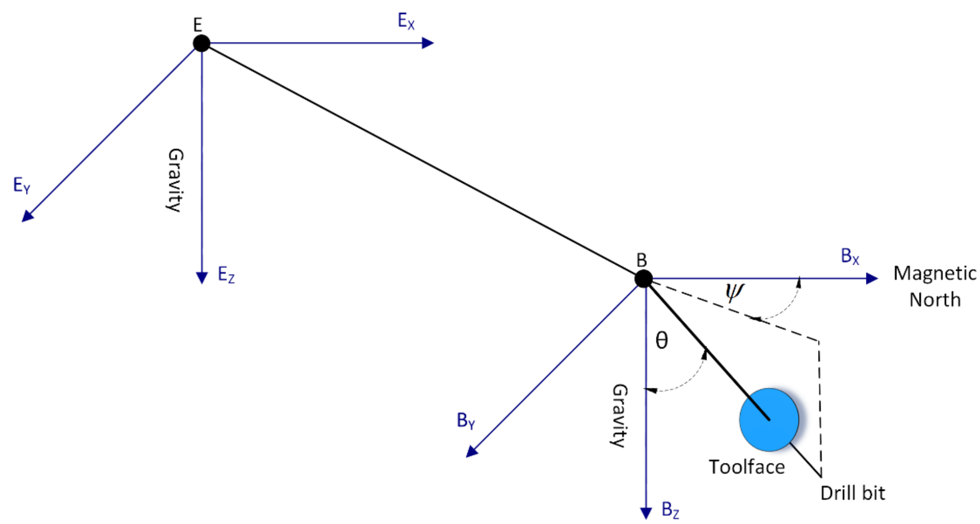

Figure 3-1 Earth and Body frames

Wellbore trajectory

The desired well trajectory is given as a table of points (k) indexed by the measured depth. Each point (P_T) is represented by the desired measured depth (w_b), North (X_E), East (Y_E), True Vertical Depth (Z_E), inclination angle (θ), and azimuth (Ψ).

$$P_T(k) = [w_b(k) \, , \, X_E(k) \, , \, Y_E(k) \, , \, Z_E(k) \, , \, \theta(k) \, , \, \psi(k)] \tag{3-4}$$

3.1 Rotary Steerable System

Rotary drilling is described as a system in which the BHA is connected to a rotatable drill string driven from the drilling platform at the surface. The RSS is an evolution in DD technology that overcomes the disadvantages in steerable motors and in conventional rotary assemblies. To begin a change in the well trajectory the actuator introduces a deflection from the centerline of the hole, this mode is known as the steering mode Figure 3-2 [61]. RSSs permit the drill string to continuously rotate while the drill bit steer its direction. Consequently, they generally provide better ROP than the conventional steerable motor assemblies.

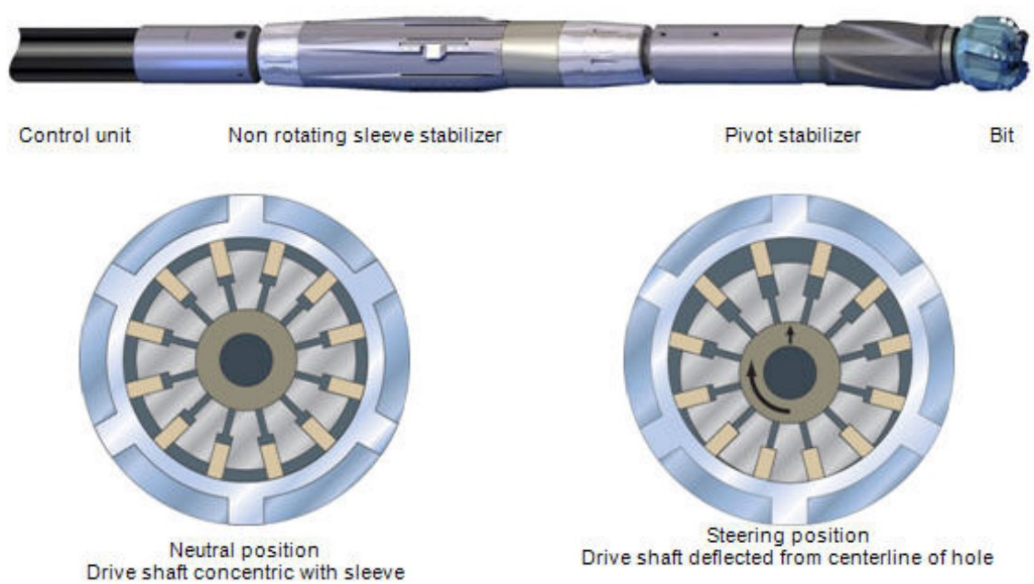

Figure 3-2 Modes of Rotary Steerable System

The RSS consists of three points of contact Figure 3-3. First of all is the drill bit, which is the contact part with the formulation, then the steering actuator located at L_1 from the bit. This actuator eccentrically deflects the centreline of the drill string away from the centreline of the hole by a controllable amount ecc in a given plane. The third point is the stabilizer which is located at a distance L_2 from the actuator. The stabilizer, actuator, and control unit are placed in a non-rotating sleeve [62].

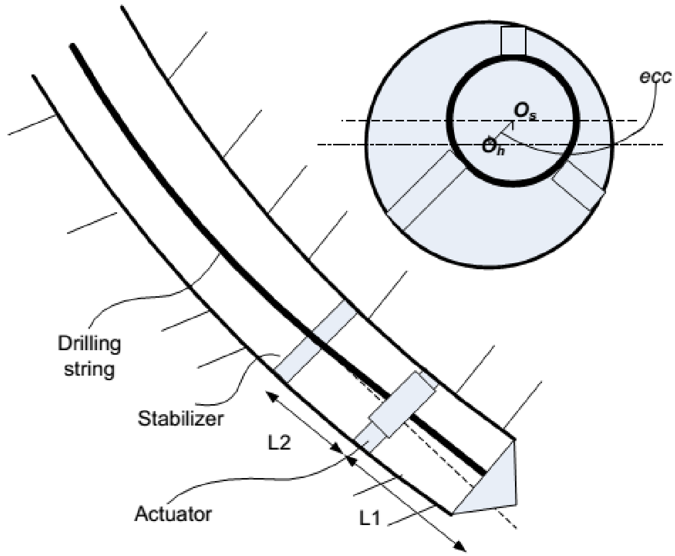

Figure 3-3 Rotary Steerable System structure

3.1.1 RSS equations

Let us assume now at the stabilizer location the BHA axis is aligned with the bore hole centreline. If the drill bit is currently at measured depth $w_b(t)$ then the stabilizer position is at $[w_b(t) - L_1 - L_2]$ and the actuator position is at location $[w_b(t) - L_1]$. If the actuator creates an eccentricity between the drill string and the hole (ecc), measured with respect to the BHA axes, two eccentricity components will be generated eccu and eccv in the body coordinates U_b and V_b, respectively. Then using the small angles approximation, the derivative of angles with respect to time are given by,

$$\dot{\theta} = K_1 .eccu \tag{3-5}$$

$$\dot{\psi} = K_2 .eccv \tag{3-6}$$

Where K_1 and K_2 depend on the rock properties. The deviation angles of the drill bit from the stabilizer are given by

$$\delta\theta = \Delta T.\dot{\theta} = \Delta T.\ K_1 .eccu \tag{3-7}$$

$$\delta\psi = \Delta T.\dot{\psi} = \Delta T.\ K_2 .eccv \tag{3-8}$$

Where ΔT is the time step. The predicted drill position with respect to the body axis is formulated as,

$$\Delta\hat{w}_b(t+1) = \hat{w}_b(t+1) - w_b(t) \tag{3-9}$$

$$\Delta\hat{u}_b(t+1) = \delta\theta.[L_1 + L_2 + \Delta w_b(t+1)] = \Delta T.\ K_1 .eccu(t).[L_1 + L_2 + \Delta\hat{w}_b(t+1)] \tag{3-10}$$

$$\Delta\hat{v}_b(t+1) = \delta\psi.[L_1 + L_2 + \Delta w_b(t+1)] = \Delta T.\ K_2 .eccv(t).[L_1 + L_2 + \Delta\hat{w}_b(t+1)] \tag{3-11}$$

The predicted drill position with respect to the inertia axis is formulated as,

$$\hat{P}_E(t+1) = P_E(t) + R.\begin{bmatrix} \Delta\hat{u}_b(t+1) \\ \Delta\hat{v}_b(t+1) \\ \Delta\hat{w}_b(t+1) \end{bmatrix} \tag{3-12}$$

Where $P_E(t)$ is the current position of the BHA.

The values of K_1 and K_2 change continuously due to the change of the rock properties and rock specific energy. So, K_1 and K_2 can be calculated adaptively at each time step based on previous well data as,

$$P_E^d(t) = P_E(t-1) + R.\begin{bmatrix} \Delta\hat{u}_d(t) \\ \Delta\hat{v}_d(t) \\ \Delta\hat{w}_d(t) \end{bmatrix} \quad (3\text{-}13)$$

Where $[\Delta\hat{u}_d \quad \Delta\hat{v}_d \quad \Delta\hat{w}_d]^T$ is the predicted drill position with respect to the body axis which drives the BHA from the current drill position with respect to the inertia axis $P_E(t-1)$ to the desired drill position with respect to the inertia axis $P_E^d(t)$ after time step t. That yields,

$$\begin{bmatrix} \Delta\hat{u}_d(t) \\ \Delta\hat{v}_d(t) \\ \Delta\hat{w}_d(t) \end{bmatrix} = R^{-1}.\left[P_E^d(t) - P_E(t-1)\right] \quad (3\text{-}14)$$

The actual drill position with respect to the inertia axis $P_E(t)$ after applying the new control inputs that yield the actual drill position with respect to the body axis $[\Delta\hat{u} \quad \Delta\hat{v} \quad \Delta\hat{w}]^T$ can be represented as,

$$P_E(t) = P_E(t-1) + R\cdot\begin{bmatrix} \Delta\hat{u}(t) \\ \Delta\hat{v}(t) \\ \Delta\hat{w}(t) \end{bmatrix} \quad (3\text{-}15)$$

So, the error between the desired drill position with respect to the inertia axis $P_E^d(t)$ and the actual drill position with respect to the inertia axis $P_E(t)$ can be calculated as,

$$Error = P_E^d(t) - P_E(t) = R\cdot\begin{bmatrix} \Delta\hat{u}_d(t) - \Delta\hat{u}(t) \\ \Delta\hat{v}_d(t) - \Delta\hat{v}(t) \\ \Delta\hat{w}_d(t) - \Delta\hat{w}(t) \end{bmatrix} \quad (3\text{-}16)$$

The value of this error converges to zero as,

$$\begin{bmatrix} \Delta\hat{u}_d(t) - \Delta\hat{u}(t) \\ \Delta\hat{v}_d(t) - \Delta\hat{v}(t) \\ \Delta\hat{w}_d(t) - \Delta\hat{w}(t) \end{bmatrix} \cong 0 \tag{3-17}$$

So, the new values of K_1 and K_2 which satisfy the previous condition are formulated as,

$$\hat{K}_1(t+1) = \frac{\hat{K}_1(t).eccu(t)\cdot\left[L_1 + L_2 + \Delta\hat{w}(t)\right]}{eccu_d(t).\left[L_1 + L_2 + \Delta\hat{w}_d(t)\right]} \tag{3-18}$$

$$\hat{K}_2(t+1) = \frac{\hat{K}_2(t).eccv(t)\cdot\left[L_1 + L_2 + \Delta\hat{w}(t)\right]}{eccv_d(t)\cdot\left[L_1 + L_2 + \Delta\hat{w}_d(t)\right]} \tag{3-19}$$

These new values can be used for the next control step.

3.1.2 Drilling power balance equation

Nonlinear model for the drilling operation was developed using energy balance equation, where Rock Specific Energy (RSE), the amount of work required to crush a unit volume of the rock, is used to calculate the minimum power required for a given ROP.

$$T\cdot\omega + WOB\cdot\dot{w}_b = \dot{w}_b\cdot A_h\cdot E_{rs} \tag{3-20}$$

Where T is the motor toque, ω is the angular velocity of the rotary disk, $(T.\ \omega)$ represents the mechanical motor power, $\dot{w}_b$ is the ROP in m/sec, ($WOB\cdot\dot{w}_b$) represents the power delivered by the weight on bit, A_h is the area of borehole, E_{rs} is the RSE, and ($\dot{w}_b\cdot A_h$) represents the volume rate of the crushed rocks.

By estimating the value of RSE, the value of ROP of the next time step can be predicted as follows,

$$\hat{\dot{w}}_b(t+1) = f(T, \omega, WOB) \cong \frac{T(t) \cdot \omega(t)}{A_h \cdot \hat{E}_{rs}(t) - WOB(t)} \tag{3-21}$$

The values of the predicted measured depth and the predicted E_{rs} can be calculated as follows,

$$\hat{w}_b(t+1) = w_b(t) + \Delta T \cdot \dot{w}_b(t+1) \tag{3-22}$$

$$\hat{E}_{rs}(t) = \frac{T(t-1) \cdot \omega(t-1) + \hat{\dot{w}}_b(t) \cdot WOB(t-1)}{A_h \cdot \hat{\dot{w}}_b(t)} \tag{3-23}$$

3.2 Stick-Slip Oscillations

In particular, a BHA which has a rotary steerable system essentially acts as a series of rotating cylindrical spring mass systems with variable support points. These support points can be typically stabilizers or extended blades [63]. The natural frequencies of these spring mass systems can create a variety of damaging vibrations during operation. Stick Slip oscillations represent the enormous amplitude torsional oscillation of the drill string in drilling wells [28]. Stick-slip occurs when there is an increased torque demand from the bit to achieve penetration that cannot be met by the drilling motor power section, causing bit rotation to slow or stop Figure 2-4.

By optimizing the WOB and rpm, the lateral vibrations (Stick-Slip oscillations) can be decreased to reduce the probability of drill bit stall and equipment failure [27].

In 2015, Tang et al., presented an equation of motion for the drill bit roll angle (θ_B) subjected to the WOB and the rotary disk speed (ω) as shown in Figure 3-5 [64].

$$J\ddot{\theta}_B + c\dot{\theta}_B + K_D(\theta_B - \omega.\Delta T) + \mu_K \cdot WOB \cdot \overline{R}_B = 0 \tag{3-24}$$

Where J is the bit moment of inertia, c is the damping coefficient, K_D is the stiffness of the drillstring, μ_k is the kinetic friction coefficient, t is the time, L_p is the length of drill pipe, and $\overline{R}_B$ is the equivalent radius of the drill bit which is a function of the actual radius of the drill bit (R_B).

$$\overline{R}_B = \frac{2}{3} R_B \tag{3-25}$$

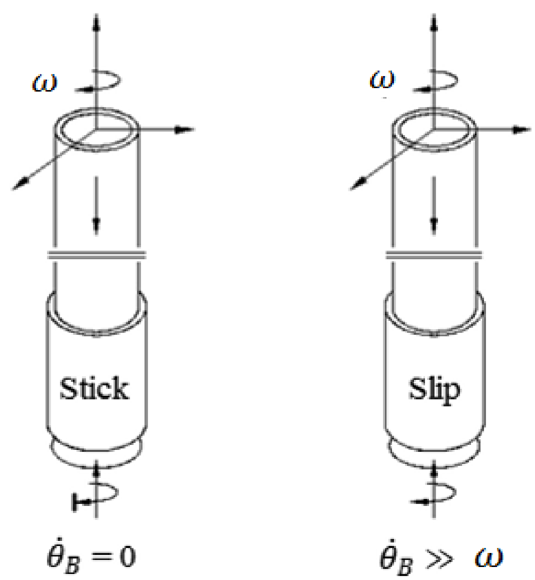

Figure 3-4 Stick-Slip oscillation mechanism

Put $X = [x_1 \quad x_2 \quad x_3] = [\theta_B \quad \dot{\theta}_B \quad \omega \cdot \Delta T]$ (3-26)

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} x_2 \\ -a_1 x_2 - b_1 (x_1 - x_3) - c_1 \mu_k \cdot WOB \cdot \overline{R}_B \\ \omega \end{bmatrix} \quad (3\text{-}27)$$

Where:

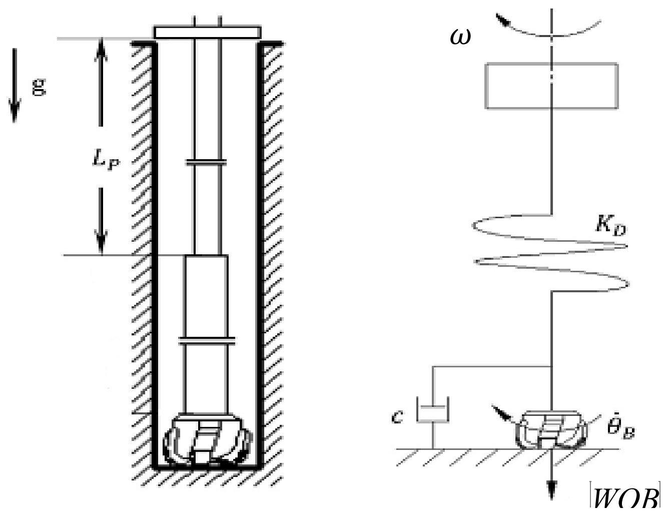

Figure 3-5 Stick-Slip model

$$a_1 = \frac{c}{J} \quad , \quad b_1 = \frac{K_D}{J} \quad , \quad c_1 = \frac{1}{J} \quad (3\text{-}28)$$

The initial values of the bit roll angle and bit roll angular velocity are calculated as

$$\theta_{B0} = \frac{\mu_s \cdot WOB \cdot \overline{R}_B}{K_D} \quad and \quad \dot{\theta}_{B0} = 0 \quad (3\text{-}29)$$

3.3 Bit wear

Bourgoyne et al. investigated an earlier composite equation for the tooth wear based on the combination of the relationships of the factors affecting tooth wear [5]. Where WOB, tooth geometry, and RPM are included as main factors affecting tooth wear.

The instantaneous rate of tooth wear is formulated as,

$$\frac{dh}{dt}=\frac{1}{\tau_H}\cdot\left(\frac{\omega}{60}\right)^{H_1}\cdot\left[\frac{\left(\frac{WOB}{d_b}\right)_m-4}{\left(\frac{WOB}{d_b}\right)_m-\left(\frac{WOB}{d_b}\right)}\right]\cdot\left(\frac{1+H_2/2}{1+H_2/h}\right) \tag{3-30}$$

Where:

h: the fractional tooth height that has been worn away.

WOB: the weight on bit, (1000 Ibf units).

τ_H: the formation abrasiveness constant, (hours).

H_1, H_2, WOB/d_b: constants related to the bit geometry.

d_b: the bit diameter.

The predicted fractional tooth height that has been worn away is given by,

$$\hat{h}(t+1)=h(t)+\Delta T\cdot\frac{dh(t)}{dt} \tag{3-31}$$

3.4 High DOF RSS

Adding more DOF's to the RSS, makes the drilling path more smooth and decreases the error between the trajectory and the actual path. The RSS dynamics consists of four points of contact Figure 3-6 and Figure 3-7. There are two steering actuators, actuator 1 is located at L_1 from the bit, and actuator 2 is located at a distance L_2 from the actuator 1. The stabilizer is located at a distance L_3 from actuator 2. The stabilizer, actuators, and control unit are placed in a non-rotating sleeve.

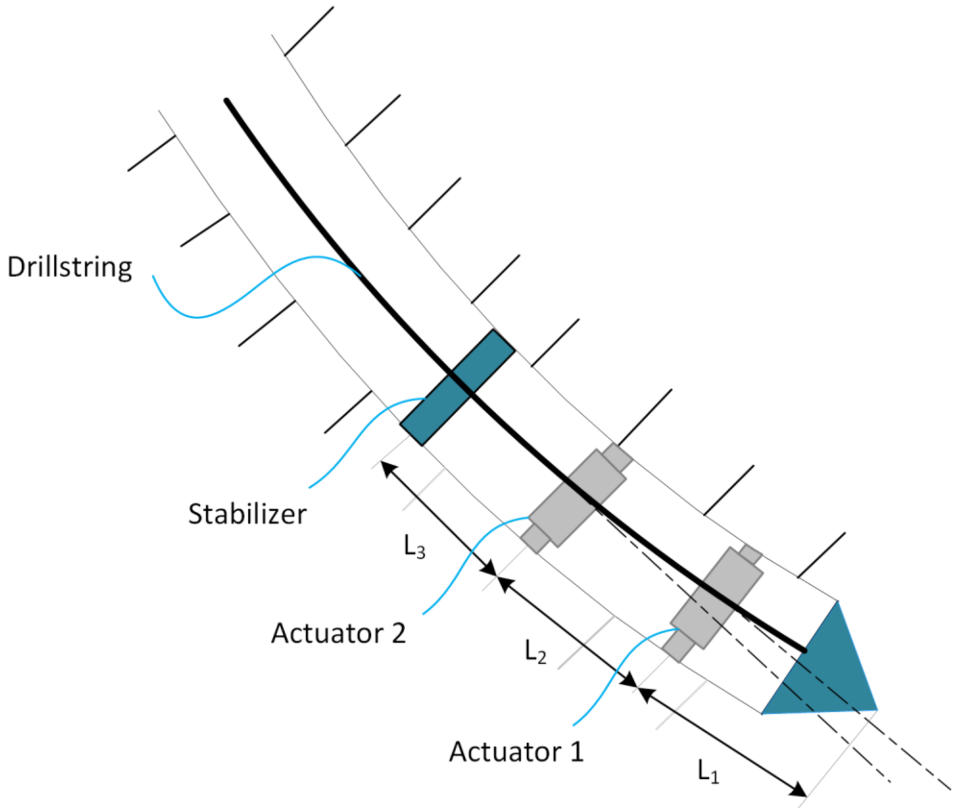

Figure 3-6 High DOF Rotary Steerable System

If both actuators create eccentricities between the drill string and the hole (ecc_1 and ecc_2), measured with respect to the BHA axes, four eccentricity components will be generated. $eccu_1$, and $eccu_2$ in the body coordinate U_b. $eccv_1$, and $eccv_2$ in the body coordinate V_b. Using the small angles approximation, the derivative of angles with respect to time are given by,

$$\dot{\theta} = K_1 \cdot eccu_1 \qquad (3\text{-}32)$$

$$\dot{\psi} = K_2 \cdot eccv_1 \qquad (3\text{-}33)$$

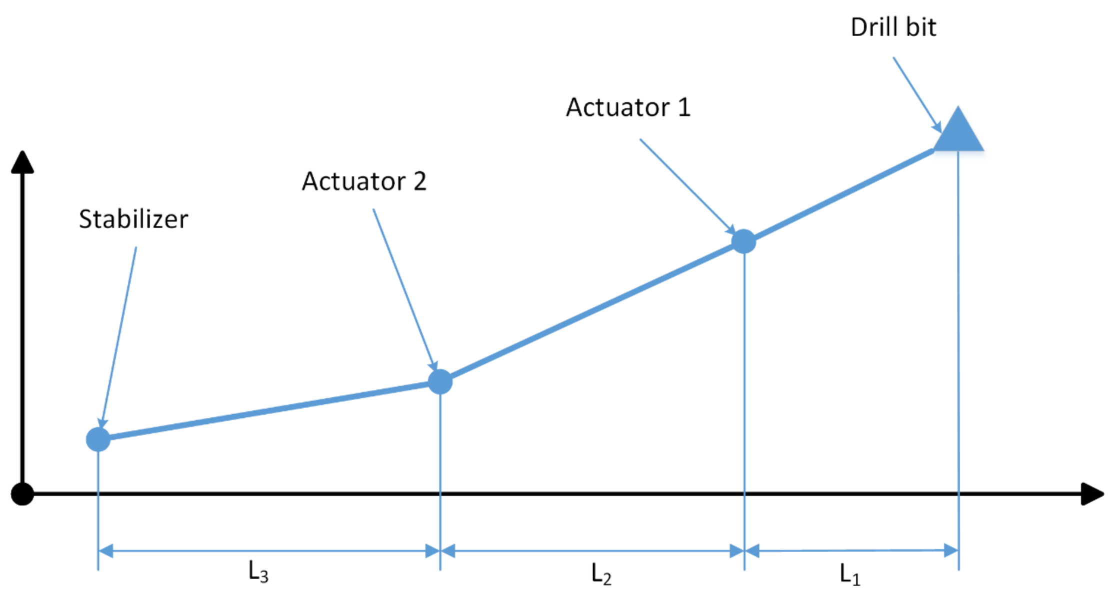

Figure 3-7 Structure of High DOF Rotary Steerable System

The deviation angles of the drill bit from the stabilizer are given by

$$\delta\theta = \Delta T \cdot \dot{\theta} = \Delta T \cdot K_1 \cdot eccu_1 \tag{3-34}$$

$$\delta\psi = \Delta T \cdot \dot{\psi} = \Delta T \cdot K_2 \cdot eccv_1 \tag{3-35}$$

The predicted drill position with respect to the body axis is formulated as,

$$\Delta\hat{w}_b(t+1) = \hat{w}_b(t+1) - w_b(t) \tag{3-36}$$

$$\begin{aligned}\Delta\hat{u}_b(t+1) &= \delta\theta \cdot [L_1 + L_2 + L_3 + \Delta w_b(t+1)] + eccu_2(t) \\ &= \Delta T \cdot K_1 . eccu_1(t) \cdot [L_1 + L_2 + L_3 + \Delta\hat{w}_b(t+1)] + eccu_2(t)\end{aligned} \tag{3-37}$$

$$\begin{aligned}\Delta\hat{v}_b(t+1) &= \delta\psi \cdot [L_1 + L_2 + L_3 + \Delta w_b(t+1)] + eccv_2(t) \\ &= \Delta T \cdot K_2 . eccv_1(t) \cdot [L_1 + L_2 + L_3 + \Delta\hat{w}_b(t+1)] + eccv_2(t)\end{aligned} \tag{3-38}$$

The new values of K_1 and K_2 are formulated as,

$$\hat{K}_1(t+1) = \frac{\hat{K}_1(t) \cdot eccu_1(t) \cdot \left[L_1 + L_2 + L_3 + \Delta\hat{w}(t)\right]}{eccu_{1d}(t) \cdot \left[L_1 + L_2 + L_3 + \Delta\hat{w}_d(t)\right]} \quad (3\text{-}39)$$

$$\hat{K}_2(t+1) = \frac{\hat{K}_2(t) \cdot eccv_1(t) \cdot \left[L_1 + L_2 + L_3 + \Delta\hat{w}(t)\right]}{eccv_{1d}(t) \cdot \left[L_1 + L_2 + L_3 + \Delta\hat{w}_d(t)\right]} \quad (3\text{-}40)$$

These new values can be used for the next control step.

3.5 Quad-rotor directional drilling

Conventional directional drilling techniques use deflectors to drive the drill bit laterally through the borehole such as whipstocking [18]. Otherwise, a bent joint can be inserted in the drill-string, i.e., bent subs [16]. It can also propel pressurized drill mud via a nozzle in the drilling process to drive the bit laterally as side jetting [19]. The whipstocking technique demands a sequence of independent processes such as pilot holes punching, reaming of the pilot hole, then remove the deflector. Therefore, the process is costly and needs much more time. The technique of bent subs requires expensive actuators in order to produce lateral forces on the drill bit. The use of side jetting technique is not suitable for all fields such as hard rock earth because the hard rock will not be eroded by the conventional mud pressure. In addition, this technique uses special drill bits to introduce offset holes by the pressurized drill mud.

The invention reported in [1] discloses a drilling apparatus with four drilling motors. The proposed apparatus eliminates the need for the current complicated techniques, and provides simple and intuitive technique for precise drilling of the desired hole bore trajectory. The rate of rocks removal can be precisely controlled by controlling the angular speed of every motor individually. Consequently, the direction of advancement of the drilling head is properly controlled.

A directional steering mechanism equipped with 4 rotors, as shown in Figure 3-8, is driving 4 independent cones assemblies. Each rotor speed can be regulated individually, creating a precisely control for the rate of removing rocks by each cone in addition to the progression direction of the drill head. The drilling head assembly is settled at the end of the drillstring, which contains an inner tube for conveying the drilling fluid. The use of four motors in coordination with other classical drilling variables permits precise control of the drilling direction and optimization of ROP [1].

Sensors that are spatially displaced from the drill bit are used to measure the angular orientation of drillstring. This measurement inferentially gives the local inclination (i.e. pitch angle) of the borehole. The sensors also indicate the azimuthal direction of the borehole, i.e., the horizontal angular distance from North direction to a point of interest projected on the same plane. Both the azimuthal direction and local inclination are transmitted to a controller, which could be positioned in the drillstring, surface rig, or remote location. This controller takes these measurements as a feedback to identify the current position and shape of the borehole then compare it to the desired borehole trajectory to calculate the steady state error. The controller then computes and transmits a steering direction correction to the DD mechanism [7].

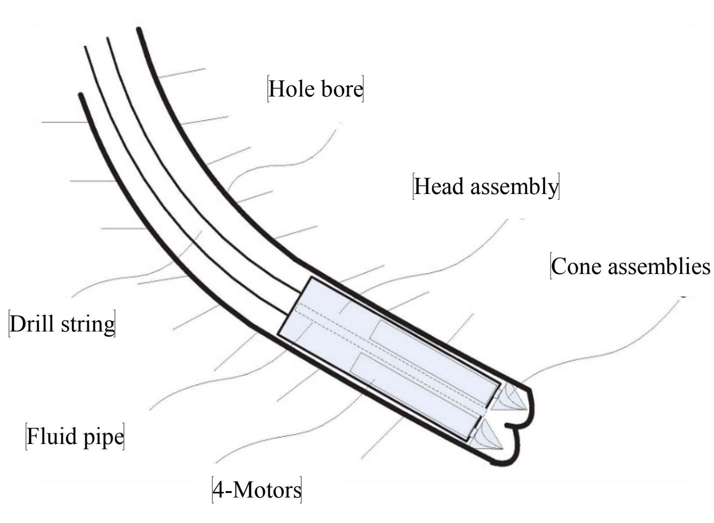

Figure 3-8 Drilling head assembly

The four drill cones are positioned symmetrically with respect to three body axes. The drill bit resolves the motor torque into two main components; a drag torque (T_D) on a plane orthogonal to the bit axis, and a lift force (F_L), which pushes removed rocks up along the spiral groves of the drilling bit.

The most commonly used approach for optimization of the actual rotary drilling operation is the MSE. MSE principle is illustrated as the amount of work desired to crush a certain volume of the rocks. It can be used as an optimization tool during drilling operations where any change in drilling efficiency can be detected in order to enhance instantaneous ROP by optimizing the drilling parameters [57].

The transformation of the inputs is defined as follows:

$$u_1 = F_{L_1} + F_{L_2} + F_{L_3} + F_{L_4} + FoB \tag{3-41}$$

$$u_2 = F_{L_2} - F_{L_4} \tag{3-42}$$

$$u_3 = F_{L_1} - F_{L_3} \tag{3-43}$$

$$u_4 = T_{D_1} - T_{D_2} + T_{D_3} - T_{D_4} \tag{3-44}$$

Where:

u_i is the input control action; i=1 , 2 , 3 or 4.

F_{Li} is the motor lift force; i=1 , 2 , 3 or 4.

T_{Di} is the motor drag torque; i=1 , 2 , 3 or 4.

FOB stands for Force on Bit, which is a quantitative part used to represent axial force amount placed on the assembly of drill bit. This force directly acts on the center axis of a system. Therefore, it is treated as an additional term of input variable u_1 and usually used to enhance the ROP.

Breaking rocks demands the drag torque (T_D) of the actuator to be higher than the lift force (F_L). However, higher values of F_L are required to develop steering and ROP. The F_L and T_D are related to the input torque of the motor (T_m) and the motor angular speed (ω) by the following expressions,

$$F_{L_i} = \alpha_1 T_m = b \cdot \omega^2 \tag{3-45}$$

$$T_{D_i} = \alpha_2 T_m = d \cdot \omega^2 \tag{3-46}$$

Where α_1 and α_2 depend on the geometry of drill bit, b is the thrust factor that depends on the geometry of drill bit and the density of mud, and d is the drag factor that depends on the drill bit geometry, rock density, and rock specific energy.

The orientation of the 4-motor drill bit system is defined by the three Euler angles, namely, roll, pitch, and yaw angles. The proposed dynamic model of the DSS can be represented by the following four nonlinear differential equations:

$$\ddot{w} = \frac{1}{m}(u_1 - F_{fw}) - g\cos\theta \tag{3-47}$$

$$\ddot{\psi} = \dot{\theta}\dot{\phi}\left(\frac{I_y - I_z}{I_x}\right) - \frac{I_r}{I_x}\dot{\theta}G_u + \frac{L_b u_2}{I_x} \tag{3-48}$$

$$\ddot{\theta} = \dot{\phi}\,\dot{\psi}\left(\frac{I_z - I_x}{I_y}\right) + \frac{I_r}{I_y}\dot{\psi}G_u + \frac{L_b u_3}{I_y} \tag{3-49}$$

$$\ddot{\phi} = \dot{\theta}\,\dot{\psi}\left(\frac{I_x - I_y}{I_z}\right) + \frac{L_b u_4}{I_z} - T_{fw,\psi} \tag{3-50}$$

Where:

w: measured depth.

ϕ , θ, and ψ: roll , pitch, and yaw angels.

m: mass of the DSS.

I_x , I_y, and I_z: inertia of the DSS.

I_r: inertia of the drill bit.

g: gravitational acceleration.

F_{fw}: the friction force.

$T_{fw,\psi}$: the friction torque.

G_u gyroscopic torque coefficient.

T_{fw}, $T_{fw,\psi}$, and G_u can be expressed as,

$$F_{fw} = \mu m g (\sin\theta \cos\phi + \sin\theta \sin\phi) \tag{3-51}$$

$$T_{fw,\psi} = \mu m g \cos\theta (\sin\theta \cos\phi + \sin\theta \sin\phi) \tag{3-52}$$

$$G_u = \omega_1 - \omega_2 + \omega_3 - \omega_4 \tag{3-53}$$

where μ is the friction coefficient (0.25 ~ 0.4). Equations (3.41) : (3.44) can be rewritten as:

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b & b & b & b \\ 0 & b & 0 & -b \\ b & 0 & -b & 0 \\ d & -d & d & -d \end{bmatrix} \begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_4^2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \cdot FoB \tag{3-54}$$

That yields,

$$\begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_4^2 \end{bmatrix} = \begin{bmatrix} b & b & b & b \\ 0 & b & 0 & -b \\ b & 0 & -b & 0 \\ d & -d & d & -d \end{bmatrix}^{-1} \times \left[\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} - \begin{bmatrix} FoB \\ 0 \\ 0 \\ 0 \end{bmatrix} \right] \quad (3\text{-}55)$$

The body axes at any point in the space can be transformed to the earth axes using the transformation matrix R.

$$R = \begin{bmatrix} c\psi\, c\theta\, c\phi - s\psi\, s\phi & -c\psi\, c\theta\, s\phi - s\psi\, c\phi & c\psi\, s\theta \\ s\psi\, c\theta\, c\phi + c\psi\, s\phi & -s\psi\, c\theta\, s\phi + c\psi\, c\phi & s\psi\, s\theta \\ -s\theta\, c\phi & s\theta\, s\phi & c\theta \end{bmatrix} \quad (3\text{-}56)$$

Where $s\psi$ and $c\psi$ denote $\sin(\psi)$ and $\cos(\psi)$, respectively. The location of any point with respect to the earth axes can be formulated as

$$\begin{bmatrix} X_E(t) \\ Y_E(t) \\ Z_E(t) \end{bmatrix} = \begin{bmatrix} X_E(t-1) \\ Y_E(t-1) \\ Z_E(t-1) \end{bmatrix} + R \cdot \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \cdot \Delta w(t) \quad (3\text{-}57)$$

Where X_E, Y_E, and Z_E are the location of any point with respect to the earth axes. The Δw is the change of measured depth and can be calculated as:

$$\Delta w(t) = w(t) - w(t-1) \quad (3\text{-}58)$$

Generally, the model structure is illustrated in Figure 3-9.

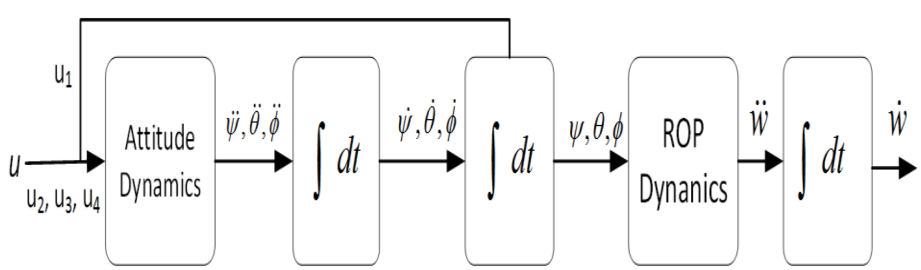

Figure 3-9 Structure of a DSS Model

CHAPTER 4

DESIGN OF CONTROL AND OPTIMIZATION ALGORITHM

The purpose of this chapter is to illustrate an integrated approach for optimization of the drilling parameters and directional steering control of a both RSS and quad-rotor directional steering systems presented in the previous chapter.

4.1 Control and optimization techniques

There are different control and optimization techniques which can be used to control and optimize the drilling process. The selection of each technique depends on the system behavior (as the nature of system dynamics, inputs, outputs, and states) and the optimization criteria. These techniques include,

4.1.1 Optimal Control

Optimal control theory is a mathematical optimization method for deriving control algorithms. It is playing an increasingly important role in the design of modern systems. Optimal control can be used for the maximization of the return form, or the minimization of the cost of, the operation of physical, social, and economical process. In order to evaluate the performance of a system, the designer should develop a performance function which describes the objectives required from the controller. Then the optimal controller is used to minimize (or maximize) this performance measure [65].

Optimal control is to find optimal ways to control a dynamic system. Some systems cannot be controlled using classical control system design because, classical design is a trial-and-error process, classical design is to determine the parameters of an “acceptable” system, and essentially restricted to single input single-output LTI systems. But optimal control is based on state-space description of systems and applicable to control problems involving multi-input multi-output systems and time-varying situations, can be applied to linear and nonlinear systems, and provides strong analytical tools. Applications of optimal control include, engineering system design, study of biology, management science, and economics [66].

In order to solve nonlinear optimal control problems, numerical methods should be employed because analytical methods are not applicable. “fmincon” is a numerical Matlab function which can be used to find the minimum of constrained nonlinear multivariable function specified by,

$$\min_{x} f(x) \, such\ that \begin{cases} c(x) \le 0 \\ ceq(x) = 0 \\ A \cdot x \le b \\ Aeq \cdot x = beq \\ lb \le x \le ub \end{cases} \tag{4-1}$$

Where, *b* and *beq* are vectors, *A* and *Aeq* are matrices, *c(x)* and *ceq(x)* are functions that return vectors, and *f(x)* is a function that returns a scalar. *f(x), c(x),* and *ceq(x)* can be nonlinear functions. *x*, *lb*, and *ub* can be passed as vectors or matrices. The solution of variable *x* is found by,

$$x = fmincon\ (fun, x_0, A, b, Aeq, beq, lb, ub, nonlcon, options) \tag{4-2}$$

Where:

x_0: is the initial condition.

Aeq and *beq*: are the linear equalities constraints.

lb and *ub*: are the lower and upper bound of the variable x.

nonlcon: defines the nonlinear inequalities *c(x)* or equalities *ceq(x).*

options: to specify some other properties to the function as, set the Display option to 'iter' to observe the fmincon solution process. Also, use the 'sqp' algorithm, which is sometimes faster or more accurate than the default 'interior-point' algorithm.

4.1.2 Adaptive Control

Adaptive control is the control method used by a controller that can modify its behavior in response to changes in the dynamics of the process and the character of the disturbances. Adaptive control is formally defined in 1961 as, "An adaptive system is any physical system that has been designed with an adaptive viewpoint" [67]. Adaptive control is different from robust control in that it does not need a priori information about the bounds on these uncertain or time-varying parameters.

An adaptive controller is a controller with adjustable parameters and mechanism for adjusting the parameters. Its main objective is to maintain consistent performance of a system in the presence of uncertainty and variations in plant parameters. The controller becomes nonlinear because of the parameter adjustment mechanism. An adaptive control system can be thought of as having two loops Figure 4-1. One loop is a normal feedback with the process and the controller. The other loop is the parameter adjustment loop. The parameter adjustment loop is often slower than the normal feedback loop.

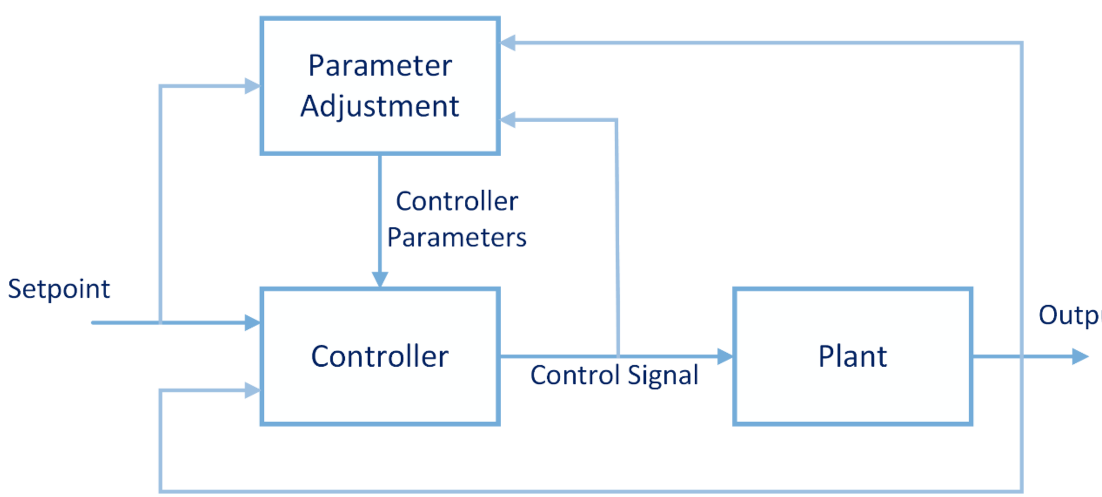

Figure 4-1 Block diagram of an adaptive system

Adaptive control is an important tool for controlling some mechanisms that give rise to variations in process dynamics, such as,

1. Nonlinear actuator, a very common source of variations is that actuator, like valves, have a nonlinear characteristic. This may create difficulties to the feedback controller.
2. Flow and speed variations, systems with flows through pipes and tanks are common in process control. The flows are often closely to the production rate. Process dynamics thus change when the production rate changes, and a controller that is well tuned for one production rate will not necessarily work well for other rates.
3. Flight control, the dynamics of an airplane change significantly with speed, altitude, angle of attack, and so on. Control systems such as autopilots and stability augmentations system were used early. These systems were based on linear feedback with constant coefficients. This worked well when speeds and altitudes were low, but difficulties were encountered with increasing speed and altitude.
4. Drilling process, till now there is no an accurate mathematical model which can describe the drilling process. The dynamics of the drilling system change significantly with depth, temperature, pressure, and rock strength. So, traditional feedback controllers are not suitable for this kind of systems to avoid any failure in the system due to vibrations or missing the trajectory.
5. There are many other practical problems of a similar type in which there are significant variations in the disturbance characteristics. Having a controller that can adapt to changing disturbance patterns is particularly important when there is limited control authority or dead time in the process dynamics.

4.1.3 Feedback Linearization

Feedback linearization is an approach to nonlinear control design which has attracted a great deal of research interest in recent years. The core idea of this technique is to transform the dynamics of a nonlinear system into a (partly or fully) equivalent linear one, so that linear control techniques can be applied [68]. This approach totally differs from conventional linearization techniques as (Jacobian linearization) in that feedback linearization is performed by exact state transformations and feedback, rather than by linear approximations of the system dynamics.

Obviously, it is not expectable to be able to cancel nonlinearities in every nonlinear system. The system has to have a certain structure that allows us to implement such cancellation [69]. The ability to use feedback signals to transform a nonlinear state equation into a controllable linear one by cancelling the system nonlinearities requires the nonlinear state equation to have the structure

$$\dot{x} = Ax + B\gamma(x) \cdot \left[u - \alpha(x)\right] \tag{4-3}$$

Where:

A is a *nxn* matrix, *n* is the number of system states.

B is a *nxp* matrix, *p* is the number of inputs.

The pair *(A, B)* is controllable.

The matrix $\gamma(x)$ is nonsingular.

The given system can be linearized using the state feedback.

$$u = \alpha(x) + \gamma^{-1}(x) \cdot v \tag{4-4}$$

That yields,

$$\dot{x} = Ax + Bv \tag{4-5}$$

Where v is the virtual input. In order to stabilize the system, the virtual input can be replaced by $v = -Kx$ such that $A - BK$ is Hurwitz. The overall state feedback control which stabilize the nonlinear system is

$$u = \alpha(x) + \gamma^{-1}(x) \cdot Kx \tag{4-6}$$

Feedback linearization has been used successfully to tackle some practical control problems. These include the control of helicopters, industrial robots, high performance aircraft, and biomedical devices [68].

4.1.4 Evolutionary Programming

Over past few decades, there was an increasing interest in techniques inspired by the physical processes and biological behavior [70]–[74]. It was demonstrated by many researchers that these algorithms are proper for solving complicated computational problems. These include dynamic optimization [75], pattern recognition [76], controller design [77]–[79], and image processing [80]-[81].

Those algorithms are widely used in various applications with impressive success such as,

4.1.4.1. Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization technique that based on adjusting the amount of change of each particle at each iteration [82]. The value of each particle is compared to its previous best solution and the global best solution to compute the value of error. The amount of change is calculated based on the value of error and how far it is from the best solution as shown in Figure 4-2. PSO has been used in a wide variety of applications such as system design, classification, multi-objective optimization, pattern recognition, signal processing, robotic applications, games, decision making, and identification [83].

The general steps of the particle swarm optimization algorithm can be summarized as:

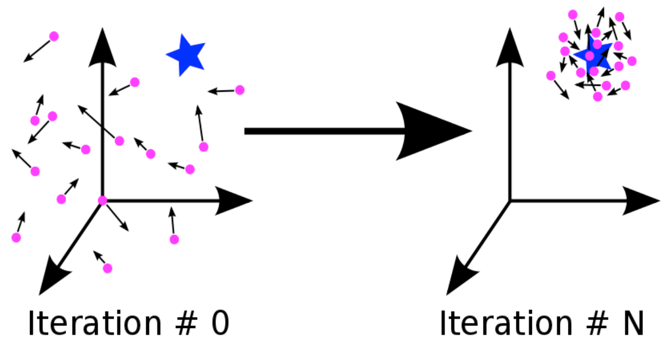

Figure 4-2 PSO algorithm

Step 1 (Initialization): Initiate the iteration counter with t=0 then create arbitrarily n particles, $\{X_j(0), j=1, 2, \ldots, n\}$, where $X_j(0)=[x_{j,1}(0), x_{j,2}(0), \ldots, x_{j,m}(0)]$. $x_{j,d}(0)$ is created randomly by selecting a value within the d^{th}, $\{d=1, 2, \ldots, m\}$ optimized parameter range $[x_d^{min}, x_d^{max}]$ using uniform distribution. The initial velocity for each particle is generated arbitrarily within the d^{th} optimized parameter range $[-v_d^{max}, v_d^{max}]$. The maximum velocity in the d^{th} dimension is characterized by the range of the d^{th} optimized parameter and given by (4-7).

The fitness of each particle is evaluated using the cost function, then search for the individual best (the best fitness value of each particle at the current position compared to previous positions, at t=0 the individual best for each particle equals its initial value) and the global best (the best fitness value of the population).

$$v_d^{max} = \frac{p*(x_d^{max} - x_d^{min})}{2} \quad , p \text{ is a predefined percentage.} \tag{4-7}$$

Step 2 (Iteration updating): Update the iteration counter t=t+1.

Step 3 (inertia weight updating): The inertia weight (w_i) is initialized at t=0 and will be decreasing with iterations to control the impact of previous velocities on the current velocity, $w_i(t+1)=\alpha.w_i(t)$ where α is a decrement constant smaller than but close to 1.

Step 4 (Velocity updating): Update the velocity of each j^{th} agent in the d^{th} dimension based on the global best ($x^{**}_{j,d}(t)$) and individual best ($x^{*}_{j,d}(t)$) using the given equation:

$$v_{j,d}(t+1) = w_i(t+1)v_{j,d}(t) + c_1 r_1 (x^{*}_{j,d}(t) - x_{j,d}(t)) - c_2 r_2 (x^{**}_{j,d}(t) - x_{j,d}(t)) \quad (4\text{-}8)$$

where c_1 and c_2 are positive constants, r_1 and r_2 are uniformly distributed random numbers in [0,1].

Step 5 (Position updating): Update the position of each j^{th} agent in the d^{th} dimension based on the updated velocity using the given equation:

$$x_{j,d}(t+1) = x_{j,d}(t) + v_{j,d}(t+1) \quad (4\text{-}9)$$

Step 6 (fitness updating): Update the values of fitness then search for the new individual best and global best.

Step 7 (Stopping criteria): If the pre-specified number of generations or any other stopping criteria is reached then stop, else go back to step 2.

The flowchart of PSO is shown in Figure 4-3 [84].

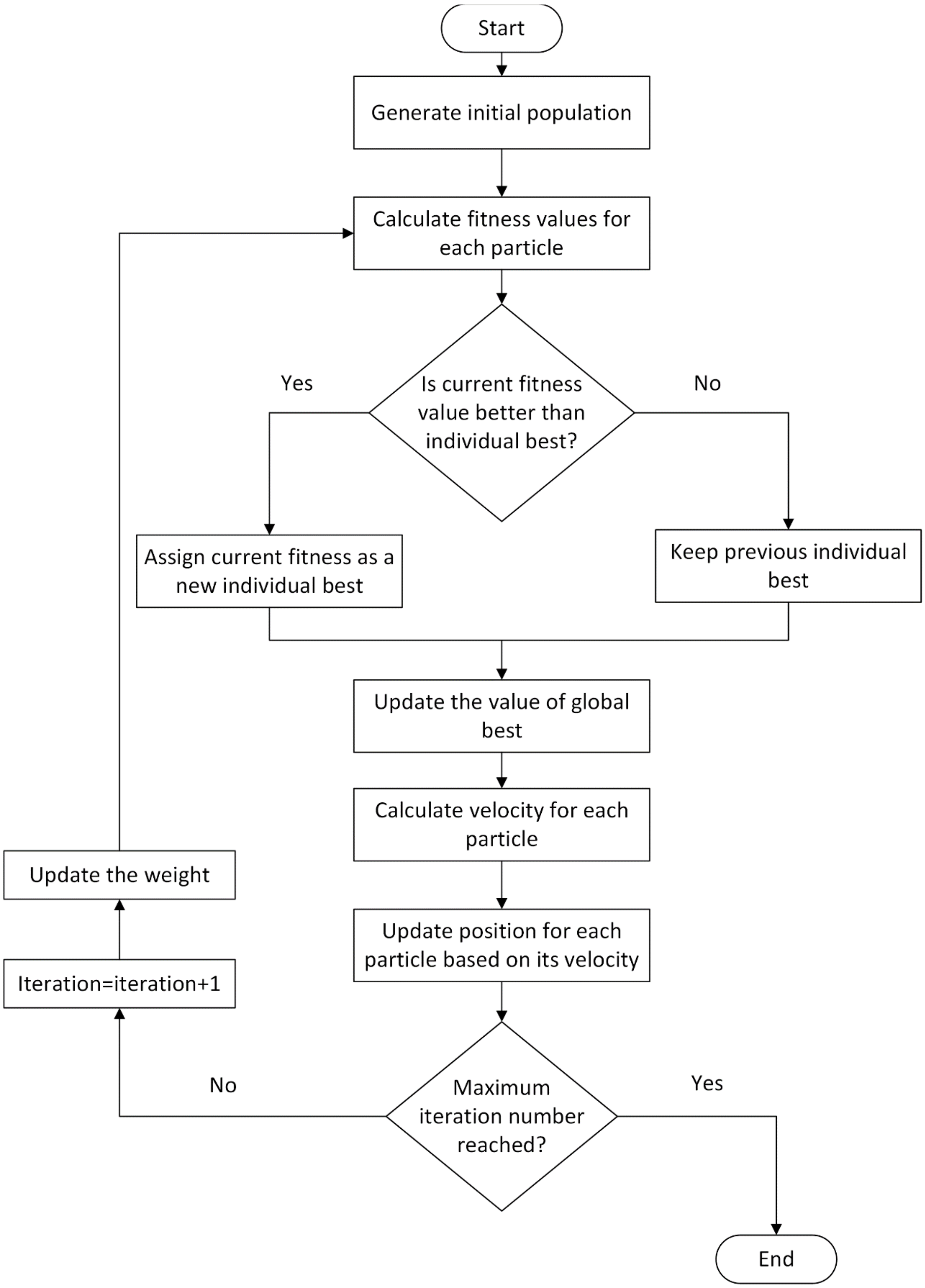

Figure 4-3 PSO flowchart

4.1.4.2. Gravitational Search Optimization

Gravitational search algorithm (GSA) for solving the optimization problems has been recently presented [85]. It was reported that the GSA is able to provide more precise, efficient and robust solution for a number of optimization problems. GSA was exercised in different disciplines such as minimizing losses in power systems [86], controller design for optimum tuning of PI-fuzzy controllers [87], network routing [88], wireless sensor networks [89], software design [90], optimum design of antennas [91], renewable micro-grids [92], and PD-fuzzy controller for MIMO systems [93]. An experimental comparative study has been developed between GSA, central force optimization, particle swarm optimization, and real genetic algorithm [94]. It was reported that the results acquired by GSA in most cases are much better compared to other optimization techniques.

Due to its potential, GSA has been hybridized with other evolutionary algorithms and soft computing techniques and the results were impressive such as Fuzzy logic-based adaptive GSA for optimal tuning of fuzzy-controlled servo systems [95], feature subset selection in machine learning [96], hybrid PSO–GSA algorithm to improve the power system stability [97], and hybrid GSA-CSA algorithm conducted based on eight benchmark functions including both unimodal and multimodal types [98].

Gravitation is defined in physics as the trend of two masses to move towards each other as shown in Figure 4-4. M_1, M_2, M_3, and M_4 are four masses with different weights. Also, F_{12}, F_{13}, and F_{14} are the gravitational forces applied from M_1 towards M_2, M_3, and M_4 respectively. F_1 is the equivalent attraction force of F_{12}, F_{13}, and F_{14}. Here, a_1 is the generated acceleration of M_1. In the gravitational law of Newton, each mass (body) attracts the other masses with a force, which is called the gravitational force [99]. This force is directly proportional to the product of their masses (M_1 and M_2) and inversely proportional to the square of the distance R between them.

The gravitational force, F, is expressed as:

$$F = G\frac{M_1 M_2}{R^2} \tag{4-10}$$

G is the gravitational constant.

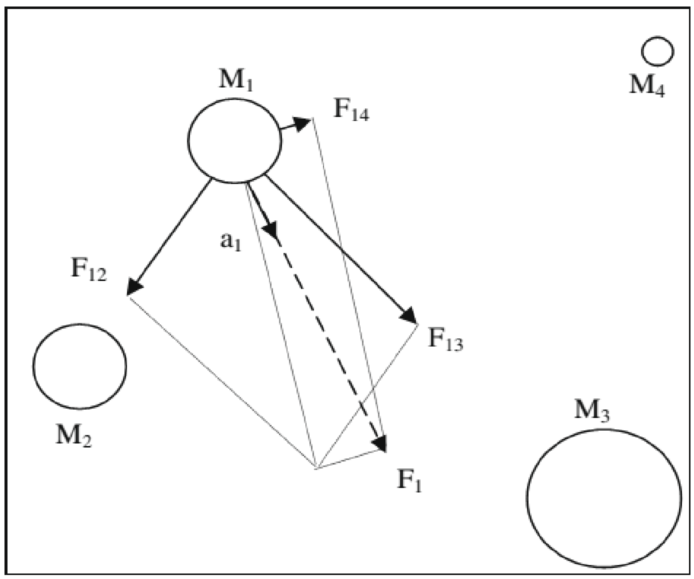

Figure 4-4 The acceleration and the resultant force for each mass

The general steps of the gravitational search algorithm can be summarized as,

Step 1 (Initialization): Initialize the iteration counter with t=0 then create arbitrarily n agents, $\{X_j(0), j=1, 2, \ldots, n\}$, where $X_j(0)=[x_{j,1}(0), x_{j,2}(0), \ldots, x_{j,m}(0)]$ where m is the number of the optimized parameters. $x_{j,d}(0)$ is created randomly by selecting a value within the d^{th} optimized parameter range $[x_d^{min}, x_d^{max}]$ using uniform distribution. Evaluate the fitness using the cost function then calculate the best and worst values.

Step 2 (Iteration updating): Update the iteration counter t=t+1.

Step 3 (gravitational constant updating): The gravitational constant (G) is initialized at t=0 and decreased with iterations to improve the exploration accuracy, $G(t)=f(G_0,t)$ where G_0 is the initial value. The value of G is expressed as:

$$G(t) = G_0 \times e^{-\alpha(t/t_{\max})} \tag{4-11}$$

where t_{max} is the maximum number of iterations and α is a positive integer.

Step 4 (Acceleration updating): Using the law of motion, the acceleration of the agent j at iteration t is calculated according to the below equations:

$$a_{j,d}(t) = \frac{F_{j,d}(t)}{M_{jj}(t)} \tag{4-12}$$

$$F_{j,d}(t) = \sum_{k=1, k\neq j}^{n} rand_k \, F_{jk,d}(t) \tag{4-13}$$

where M_{jj} is the inertial mass of j^{th} agent and $F_{j,d}$ is the total force acting on agent j in dimension d, $rand_k$ is a random number in the interval [0,1], and F_{jk} is the force acting on agent (mass) j from mass k. Those forces are multiplied by a random number to give a stochastic characteristic to the algorithm. F_{jk} in the d^{th} dimension can be calculated as follows.

$$F_{jk,d}(t) = G(t)\frac{M_{pj}(t) \times M_{ak}}{R_{jk}(t) + \varepsilon}\left(x_{k,d}(t) - x_{j,d}(t)\right) \tag{4-14}$$

where M_{ak} is the active gravitational mass for agent k, M_{pj} is the passive gravitational mass for agent j, $G(t)$ is the gravitational constant at iteration t, ε is a small constant, and $R_{jk}(t)$ is the Euclidian distance between two agents *j* and *k* at iteration *t*. Those parameters can be calculated as follows,

$$R_{jk}(t) = \left\| X_j(t), X_k(t) \right\|_2 \tag{4-15}$$

$$M_{aj} = M_{pk} = M_{jj} = M_j, \quad j = 1,2,..,n \tag{4-16}$$

$$m_j(t) = \frac{fit_j(t) - worst(t)}{best(t) - worst(t)} \tag{4-17}$$

$$M_j(t) = \frac{m_j(t)}{\sum_{j=1}^{n} m_k(t)} \tag{4-18}$$

Step 5 (Velocity updating): Update the velocity of the j^{th} agent in the d^{th} dimension depending on the updated acceleration using the below equation:

$$v_{j,d}(t+1) = rand_j \times v_{j,d}(t) + a_{j,d}(t) \tag{4-19}$$

Step 6 (Position updating): Update the position of the j^{th} agent in the d^{th} dimension according to the updated velocity as follows:

$$x_{j,d}(t+1) = x_{j,d}(t) + v_{j,d}(t+1) \tag{4-20}$$

Step 7 (fitness updating): Calculate the fitness of the updated parameters then search for the new best and worst values.

Step 8 (Stopping criteria): If the pre-specified number of generations or any other stopping criteria is reached then stop, else go back to step 2.

The flowchart of GSA is shown in Figure 4-5,

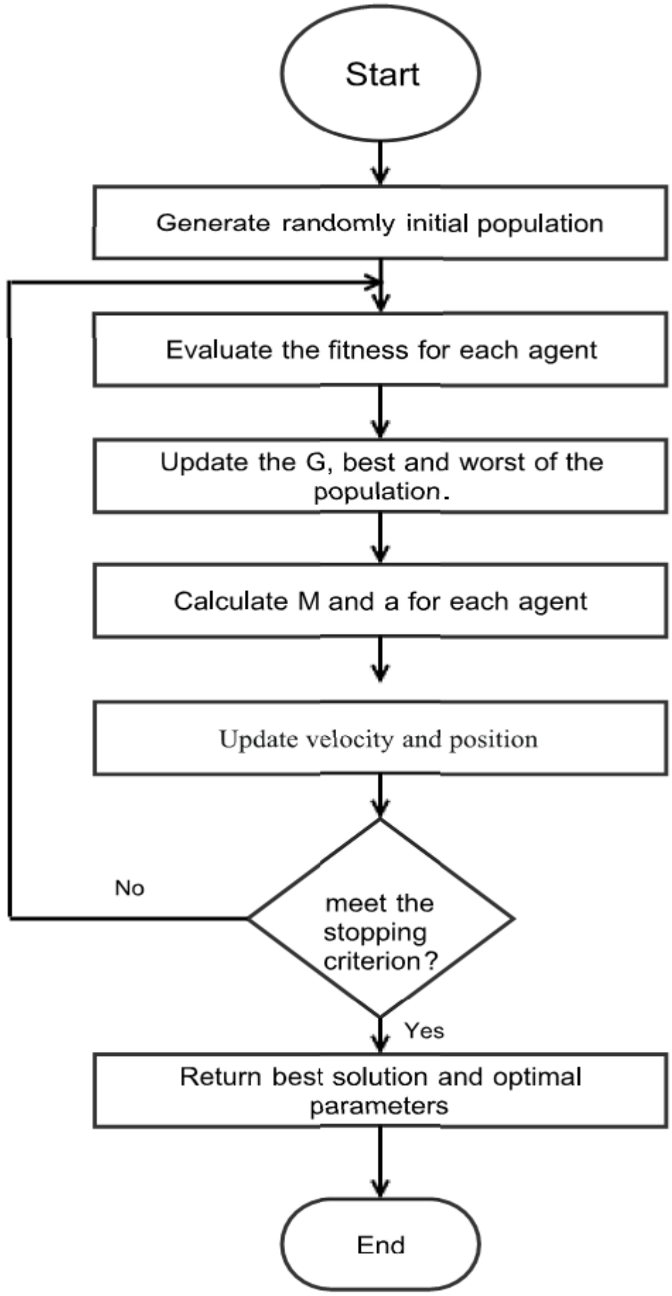

Figure 4-5 Gravitational Search Algorithm

4.2 Online control and Optimization of RSS

This work provides an integrated approach for the control of the RSS with unknown formation friction and rock strength using real time MWD data as a feedback. The work presents an adaptive control scheme for real time optimization of drilling parameters, trajectory tracking, and drilling efforts. A mathematical model is implemented for this intent using real-field data gathered via advanced well monitoring systems and data recorders. This model forecasts the ROP of any drilling well as a function of available parameters. An adaptive controller illustrated in Figure 4-1 has been used to adjust the system parameters K_1, and K_2 calculated in Equation (3-18) and Equation (3-19) and the value of rock specific energy Equation (3-23). The control algorithm finds the optimal control inputs going to the system including torque, rpm, weight-on-bit, and the steering actuators commands to calculate the predicted ROP Equation (3-21) and predicted BHA position Equation (3-9) to Equation (3-12).

a. Drilling Optimization

The optimal control values are obtained by minimizing an objective function, which compromises between trajectory tracking accuracy, drilling effort, and ROP. The optimization problem is solved subject to operations limits and constraints using constraint optimization techniques.

$$J = (\hat{P}_E(t+1) - P_E^d(t+1))^T \Gamma_1 (\hat{P}_E(t+1) - P_E^d(t+1)) + U^T \Gamma_2 U \quad (4\text{-}21)$$

Where:

$\hat{P}_E$: The predicted location of the BHA.

P_E^d : The desired location of the BHA.

$P_E = [X_E(t) , Y_E(t) , Z_E(t)]$, The position of BHA with respect to the inertia frame.

U: The input vector.

Γ_1: A positive semi-definite weight matrix for the error between the predicted and measured locations.

Γ_2: A positive semi-definite weight matrix for the input.

At each time step, the desired location of the BHA is known (point c) as shown in Figure 4-6, and it is required to find the values of optimal control inputs to move the BHA from the current location (point a) to the desired one. Where the state vector of the system (*X*) and the input vector (U) are defined as,

$$X(t) = [t_{total} , w_b , X_E , Y_E , Z_E , \theta , \psi , \dot{w}_b , \hat{E}_{rs}] \qquad (4\text{-}22)$$

$$U = [T , \omega , WOB , \frac{1}{\Delta md} , eccu , eccv] \qquad (4\text{-}23)$$

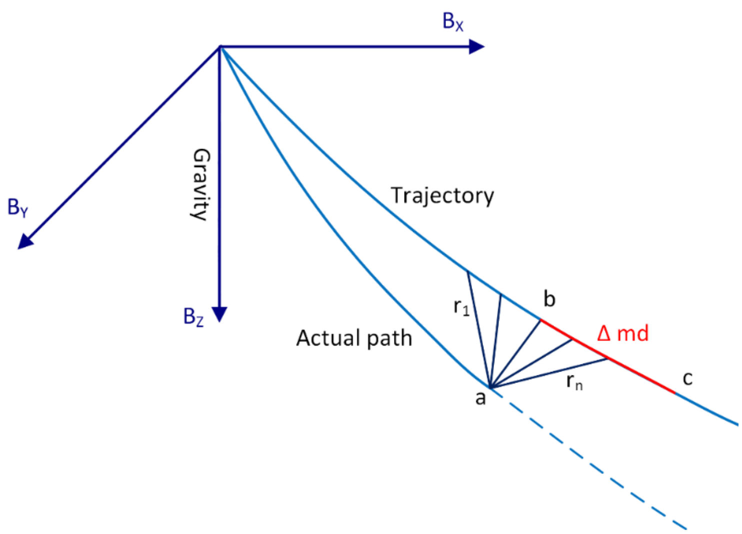

Figure 4-6 Projection of the BHA on the trajectory

In order to maximize the ROP, the value of change in measured depth (Δ md) has to be maximized too. So, it is included in the control input vector, but, at the same time should not affect the accuracy of tracking. To improve the tracking accuracy, the current position of the BHA (point a) has to be projected on the trajectory to find the closest point (point b). From Figure 4-6, point b represents the shortest distance (r) between the current position of BHA (point a) and the trajectory at each time step. Where the value of r can be calculated as,

$$r = \sqrt{(X_E(t) - X_E^d(t))^2 + (Y_E(t) - Y_E^d(t))^2 + (Z_E(t) - Z_E^d(t))^2} \tag{4-24}$$

4.3 Control of RSS with stick-slip and bit wear

The optimal control values are obtained by minimizing an objective function, which compromises between trajectory tracking accuracy, drilling effort, ROP, Stick-Slip oscillations, and bit wear. The optimization problem is solved subject to operations limits and constraints using constraint optimization techniques.

$$J_1 = (\hat{P}_E(t+1) - P_E^d(t+1))^T \Gamma_1 (\hat{P}_E(t+1) - P_E^d(t+1)) + U^T \Gamma_2 U + (\omega - \dot{\theta}_B)^2 \Gamma_3 + h^2 \Gamma_4 \tag{4-25}$$

Where:

$\hat{P}_E$: The predicted location of the BHA.

P_E^d : The desired location of the BHA.

$$P_E = [X_E(t), Y_E(t), Z_E(t)]$$

$X_E(t), Y_E(t), Z_E(t)$: The position of BHA with respect to the inertia frame.

U: The input vector.

$\dot{\theta}_B$: The measured roll angular velocity of the drill bit.

h: The fractional tooth height that has been worn away.

Γ_1: A positive semi-definite weight matrix to reduce the error between the predicted and measured locations.

Γ_2: A positive semi-definite weight matrix for the input.

Γ_3: A weight value to reduce the stick slip oscillation.

Γ_4: A weight value to reduce the bit wear.

At each time step, the desired location of the BHA is known (point c) as shown in Figure 4-6, and it is required to find the values of optimal control inputs to move the BHA from the current location (point a) to the desired one. Where the state vector of the system (X) and the input vector (U) are defined as,

$$X(t) = [t_{total}, w_b, X_E, Y_E, Z_E, \theta, \psi, \dot{w}_b, \hat{E}_{rs}] \tag{4-26}$$

$$U = [T, \Delta\dot{\omega}, WOB, \frac{1}{\Delta md}, eccu, eccv] \tag{4-27}$$

The value of RPM is always varied to optimize the ROP and the Stick-Slip oscillation. So, the rate of change of the RPM should be limited and optimized to avoid any sudden change with the change of the formation characteristics. On the other hand, the more penalties on the rate of change of the RPM, the Stick-Slip oscillations will be increased due to the limitation on the RPM. The new value of the RPM can be calculated as,

$$\text{Rate of change of RPM } (\Delta\dot{\omega}) = \frac{\omega(t+1) - \omega(t)}{\Delta T} \tag{4-28}$$

$$\omega(t+1) = \Delta\dot{\omega} \cdot \Delta T + \omega(t) \tag{4-29}$$

a. Identification of Stick-Slip Oscillation model parameters

The parameters of the stick-slip oscillation model change continuously with the hole length accordingly J, K_D, c, and μ_k in Equation (3-24) should be identified at each time step using an optimization technique to improve the dynamic model accuracy as shown in Figure 4-7.

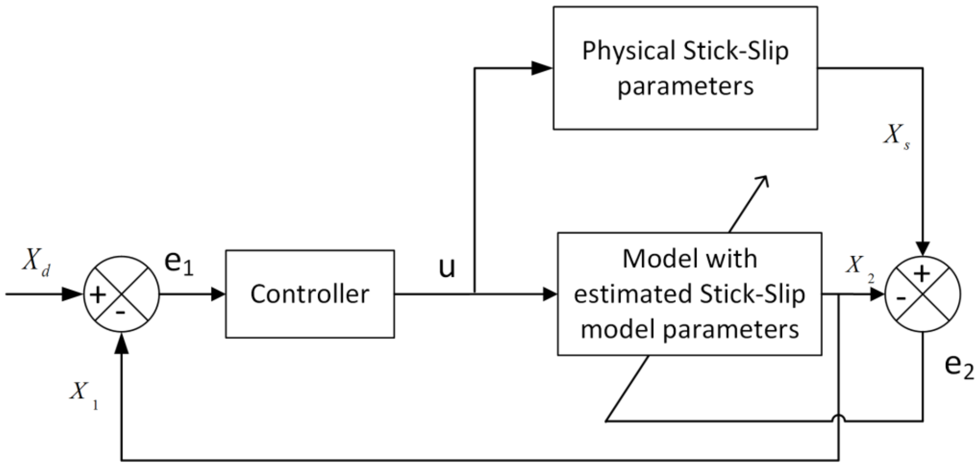

Figure 4-7 Overall control strategy of the RSS

Where e_1 is the error between the desired well trajectory X_d and the model states X_1 which is used in optimization of trajectory tracking, and e_2 is the error between the actual states coming from the well (simulator) Xs and the model states X_2 which is used in optimization of stick-slip oscillation model parameters.

$$e_1(t) = X_d(t) - X_1(t) \tag{4-30}$$

$$e_2(t) = X_s(t) - X_2(t) \tag{4-31}$$

The estimation accuracy of stick-slip oscillation model parameters depends on the minimization of e_2. So, the objective function for estimating these parameters is formulated as,

$$J_2 = \tfrac{1}{2}\ [(X(t) - X_s(t))^T\ Q\ (X(t) - X_s(t))\ ] \tag{4-32}$$

Where X_s is the simulator states vector, and X is the model states vector as given in the following equations.

$$X_d = [X_E{}^d \quad Y_E{}^d \quad Z_E{}^d] \tag{4-33}$$

$$X_s = [\theta_{B,s} \quad \dot{\theta}_{B,s} \quad \varphi_s.t] \tag{4-34}$$

$$X_2 = [\theta_B \quad \dot{\theta}_B \quad \varphi.t] \tag{4-35}$$

b. Optimization Problems

For the given two optimization problems, the input vector represents the optimized variables to minimize the first objective function and can be formulated as,

$$\underset{U}{Minimize} \quad J_1$$

$$\text{Subject to} \quad L_{bound} \leq U \leq U_{bound} \tag{4-36}$$

parameters of the stick-slip oscillation model represent the optimized variables of the second minimization problem in order to minimize the second objective function and can be formulated as,

$$\underset{J, K_D, c, and\ \mu_K}{Minimize} \quad J_2$$

$$\text{Subject to} \quad L_{bound} \leq J, K_D, c, and\ \mu_K \leq U_{bound} \tag{4-37}$$

4.4 Control of high DOF RSS

The optimal control values are obtained by minimizing an objective function, which compromises between trajectory tracking accuracy, drilling effort, and ROP. The optimization problem is solved subject to operations limits and constraints using constraint optimization techniques. The objective function proposed in Equation (4-21) is also used but with change in the input vector (U) which is defined as,

$$U = [T, \omega, WOB, \frac{1}{\Delta md}, eccu_1, eccv_1, eccu_2, eccv_2] \tag{4-38}$$

4.5 Gravitational search optimization of Quad-rotor directional drilling

The control strategy consists of two control actions. The first step is to linearize the highly nonlinear dynamics of the system using feedback linearization as a nonlinear control approach. The second step is to optimize the controller design. In this regard, the gravitational search algorithm is developed and employed, which is an optimization methodology that inspired by the law of gravity and interactions among masses.

a. Feedback Linearization

The system model presented in Equation (3-47) to Equation (3-50) is highly nonlinear and its complexity is significant. This model can be represented as,

$$\dot{x} = f(x,u,t) \tag{4-39}$$

by considering the state variables as:

$$\begin{aligned} X &= [w\,,\ \psi\,,\ \theta\,,\ \phi\,,\ \dot{w}\,,\ \dot{\psi}\,,\ \dot{\theta}\,,\dot{\phi}] \\ &= [x_1\,,\ x_2\,,\ x_3\,,\ x_4\,,\ x_5\,,\ x_6\,,\ x_7\,,\ x_8] \end{aligned} \tag{4-40}$$

The final state space equation for the DSS can be written as:

$$\dot{X}(t)=\begin{bmatrix} x_5 \\ x_6 \\ x_7 \\ x_8 \\ -g\cos x_3-\frac{1}{m}F_{fw}+\frac{1}{m}u_1 \\ x_7x_8\left(\frac{I_y-I_z}{I_x}\right)-\frac{I_r}{I_x}x_7G_u+\frac{L_b}{I_x}u_2 \\ x_6x_8\left(\frac{I_z-I_x}{I_y}\right)+\frac{I_r}{I_y}x_6G_u+\frac{L_b}{I_y}u_3 \\ x_6x_7\left(\frac{I_x-I_y}{I_z}\right)-T_{fw,\psi}+\frac{L_b}{I_z}u_4 \end{bmatrix} \quad (4\text{-}41)$$

It can be remarked from the system model equations that the system is fully actuated and has minimum phase dynamics. The system dynamics can be linearized with respect to the control u using:

$$u_1=m(g\cos x_3+\frac{1}{m}F_{fw}+v_1) \quad (4\text{-}42)$$

$$u_2=\frac{I_x}{L_b}\left(\frac{I_r}{I_x}x_7\,G_u-x_7x_8\,\frac{I_y-I_z}{I_x}+v_2\right) \quad (4\text{-}43)$$

$$u_3=\frac{I_y}{L_b}\left(-\frac{I_r}{I_y}x_6\,G_u-x_6x_8\,\frac{I_z-I_x}{I_y}+v_3\right) \quad (4\text{-}44)$$

$$u_4=\frac{I_z}{L_b}\left(T_{fw,\psi}-x_6x_7\,\frac{I_x-I_y}{I_z}+v_4\right) \quad (4\text{-}45)$$

where v_i, i=1,2,3,4 is the new control signals that help to implement the desired operation.

$$v_i=K_i\cdot(x_a-x_d)\ ;\ i=1,2,3,\text{ and }4 \quad (4\text{-}46)$$

K is the feedback gain, x_a is the actual value of a variable and x_d is its desired value. The feedback loop depends on the MWD. These drilling apparatuses continuously and automatically provide real-time reading of drilling parameters such as the orientation and the location of the BHA and then send acquired data to the main computer in order to display, record, print, and provide the control action [4].

The controllability canonical form for the linearized model can be rewritten as,

$$\dot{X} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix} \quad (4\text{-}47)$$

The cost (objective) function J_1 for tracking a predefined trajectory is formulated as:

$$J_1 = \tfrac{1}{2}[(X_1(k+1) - X_d(k+1))^T Q(X_1(k+1) - X_d(k+1)) + V(k)^T RV(k)] \quad (4\text{-}48)$$

Where X_d is the desired well trajectory vector, X_1 is the model states vector, V is the vector of new control inputs, k is the distance step, and Q & R are weighting matrices.

$$X_1 = \begin{bmatrix} w & \psi & \theta \end{bmatrix}^T \quad (4\text{-}49)$$

$$X_d = \begin{bmatrix} w_d & \psi_d & \theta_d \end{bmatrix}^T \quad (4\text{-}50)$$

$$V = \begin{bmatrix} v_1 & v_2 & v_3 & v_4 \end{bmatrix}^T \quad (4\text{-}51)$$

The objective of the optimization techniques is to select the proper feedback gains *K*s to optimize the control input signals that leads the system to satisfy the physical restrictions in addition to maximize (or minimize) some performance criterion [65].

In aerial vehicles applications the values of thrust factor *b* and drag factor *d* presented in Equation (3-45) and Equation (3-46) may be considered as constants [100]. However, in oilfield drilling, these factors change continuously as going deeper. Therefore, *b* and *d* have to be optimized at each iteration using an optimization technique to improve the dynamic model accuracy as shown in Figure 4-8.

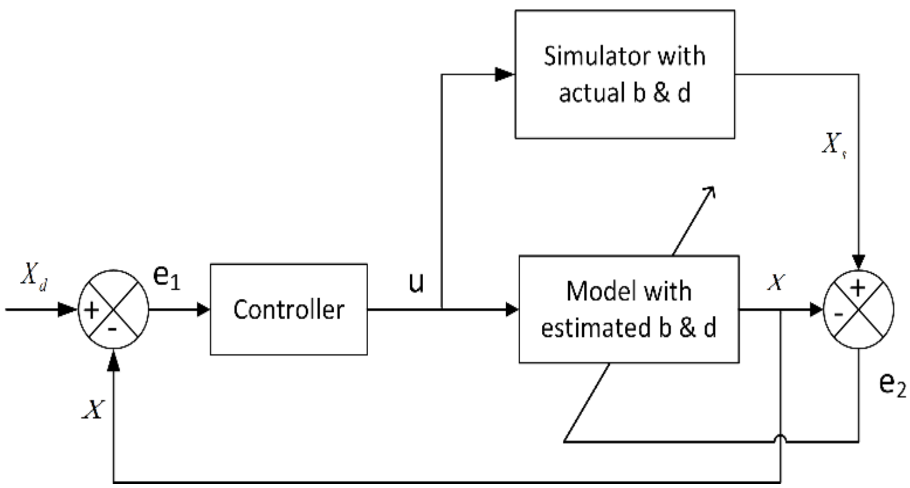

Figure 4-8 Overall control strategy of the quad-rotor DSS

Where e_1 and e_2 are defined as,

$$e_1 = X_d - X \tag{4-52}$$

$$e_2 = X_s - X \tag{4-53}$$

It is worth mentioning that e_1 is used for optimizing the feedback gains while e_2 is used for optimizing the thrust and drag factors.

The estimation accuracy of factors b and d depends on the minimization of e_2. So, the objective function for estimating b and d is formulated as

$$J_2 = \tfrac{1}{2}\left[(X(k) - X_s(k))^T \; Q \, (X(k) - X_s(k))\right] \tag{4-54}$$

where X is the model states vector and X_s is the simulator states vector that can be defined as follows,

$$X_s = [w_s \; , \; \psi_s \; , \; \theta_s \; , \; \phi_s \; , \; \dot{w}_s \; , \; \dot{\psi}_s \; , \; \dot{\theta}_s \; , \dot{\phi}_s] \tag{4-55}$$

b. Gravitational Search Algorithm

Since the optimization problem formulated has a high dimensional search domain, the conventional optimization techniques have limited capability as the search domain grows exponentially with the size of the problem [94]. So, it is necessary to use an evolutionary programming technique.

The proposed control system begins with linearizing the nonlinear dynamic system using the system inputs to facilitate the tracking problem. Then, the controller gains should be optimized to improve the system response using GSA. Finally, to make the control system act adaptively to overcome any changes in the operation conditions or parameters, the GSA is applied to estimate the actual values of the system parameters b and d based on obtained data from previous iterations. The flowchart of the overall control algorithm of the quad-rotor DSS is shown in Figure 4-9.

For the given two minimization problems, the feedback gains represent the agents to minimize the first objective function (fitness) and can be formulated as,

$$\underset{Ks}{Minimize} \quad J_1 \tag{4-56}$$

Subject to $\quad 0 \le K_i \le 5 \;\; , \;\; i = 1,\ldots,8$

Factors b & d represent the agents of the second minimization problem in order to minimize the second objective function (fitness) and can be formulated as,

$$\underset{b,d}{Minimize} \quad J_2 \tag{4-57}$$

Subject to $\quad 1 \le b, d \le 100$

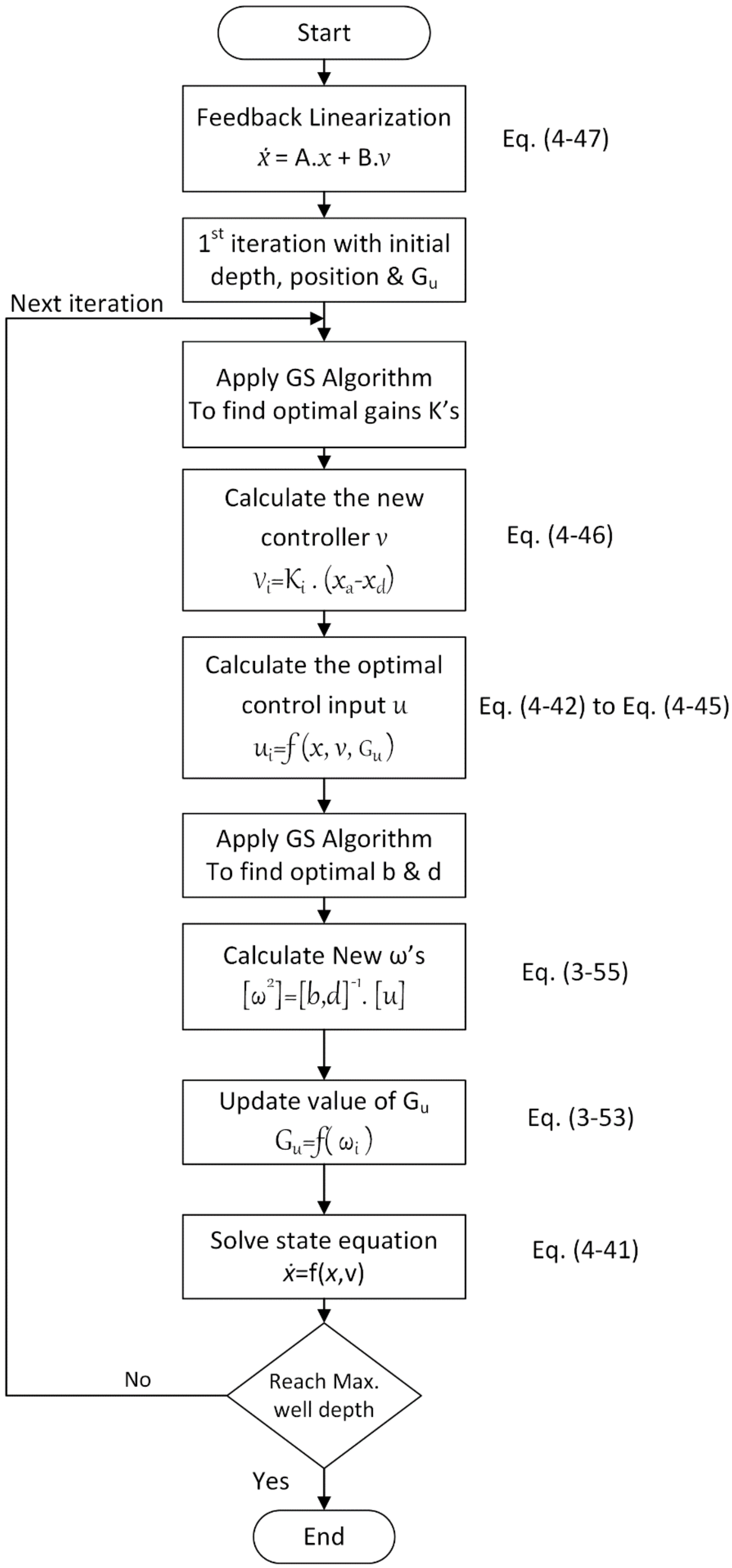

Figure 4-9 Overall control algorithm of the quad-rotor DSS

CHAPTER 5

RESULTS AND CONCLUSION

5.1 Online control and optimization of RSS

The proposed control approach was evaluated using real well trajectory. An iterative simulation has been implemented to validate the RSS model using Matlab. The simulation results presented several compromising scenarios between well drilling time, and tracking accuracy. The on-line adaptive tuning of the model and control parameters showed excellent ability to accommodate the changes in the formation properties. The BHA starts from zero North, East, and TVD, with initial inclination and azimuth equal to 30 and 230.78, respectively. The manipulated variables used in the objective function proposed in Equation (4-21) are subjected to some constraints as given in Table 5-1, These values are set by the drill engineer based on his experience with the system and the well. The well maximum measured depth is 1318 meter.

Table 5-1 Upper and lower limits for the manipulated variables

Parameter	Lower	Upper	Unit
Torque	50	1500	Nm
RPM	5	240	Rev/min
WOB	200	5000	kg
Δ md	0.1	3	m

Figure 5-1 shows the trajectory tracking, where the root mean square error (RMSE) of the Euclidian distance between the desired trajectory and the actual path, and the maximum value are given in Table 5-2 for three different scenarios. More penalties are added to the second and third scenarios through weighting the variable (Δ md) to increase the ROP, so that, the drilling time is decreased. On the other hand, the tracking accuracy is decreased. By tuning the weight matrix of the input vector (Γ_2) introduced in Equation (4-21), the drilling operator can compromise between drilling time and tracking accuracy. Figure 5-2 shows the value of mean square error for the three scenarios.

The measured depth development for the first and third scenario are presented in Figure 5-3. It is shown that the ROP for the third scenario is greater than the first one due to the penalty on the change of measured depth accomplishing the objective function.

The value of rock specific energy during the drilling process is illustrated in Figure 5-4.

Table 5-2 Data analysis for the three drilling process scenarios

	RMSE (m)	Max. Error (m)	Time (hr)
Scenario 1	0.4	0.47	44.98
Scenario 2	0.53	1.56	25.7167
Scenario 3	0.57	1.74	21.5

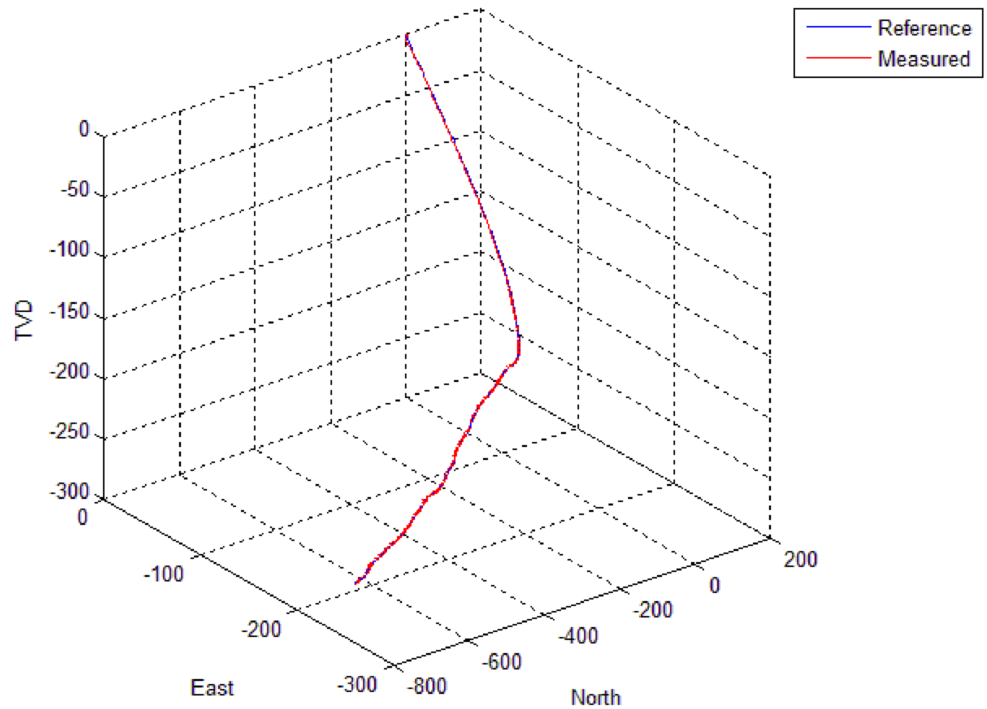

Figure 5-1 3D view of the trajectory tracking

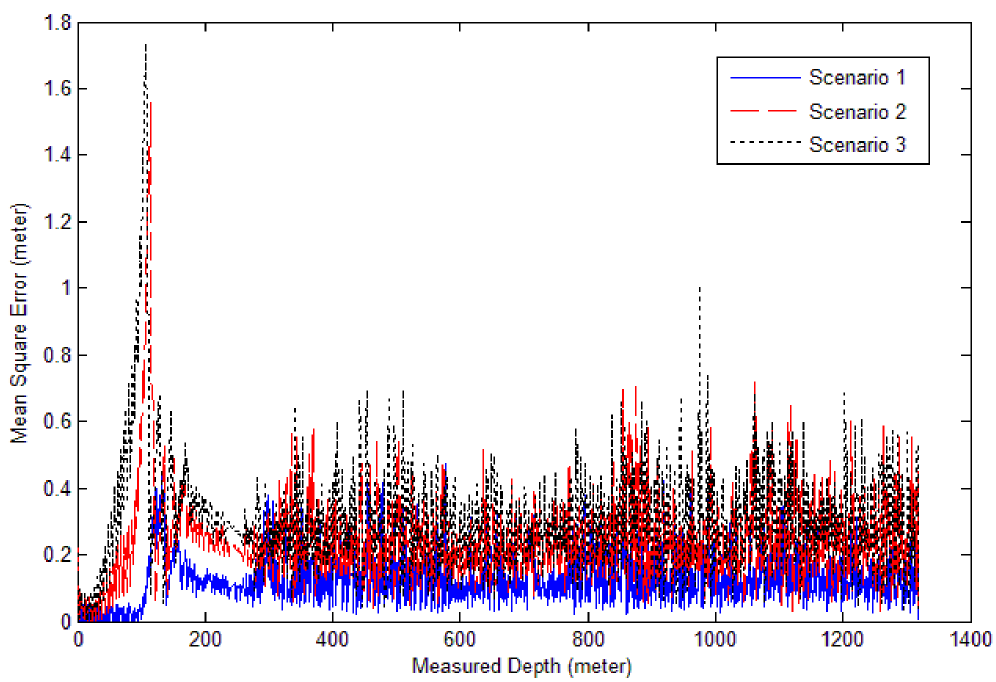

Figure 5-2 Mean Square Error for the three scenarios

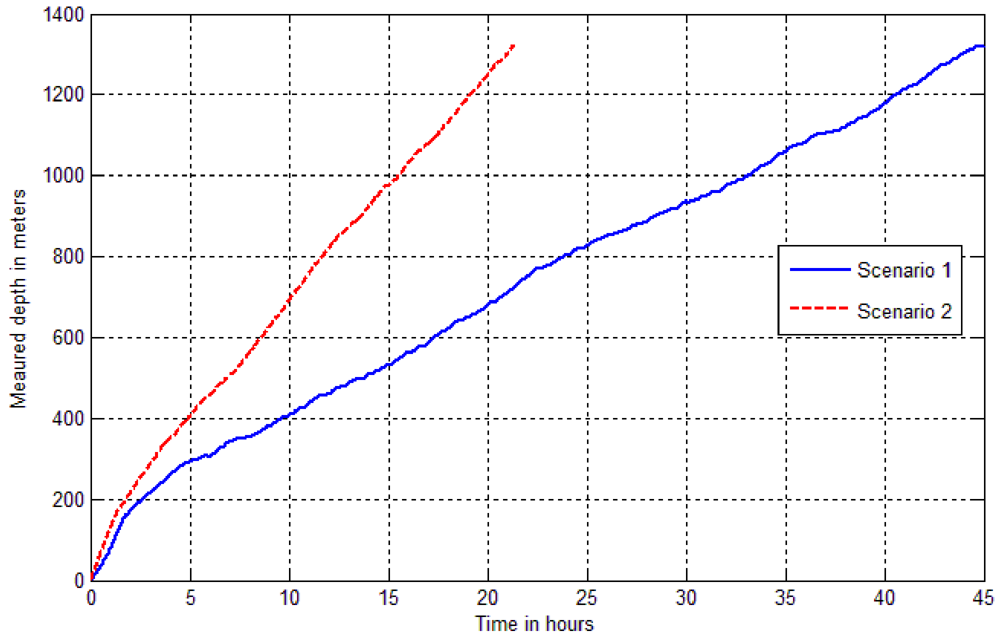

Figure 5-3 Measured Depth of scenario 1 and scenario 2

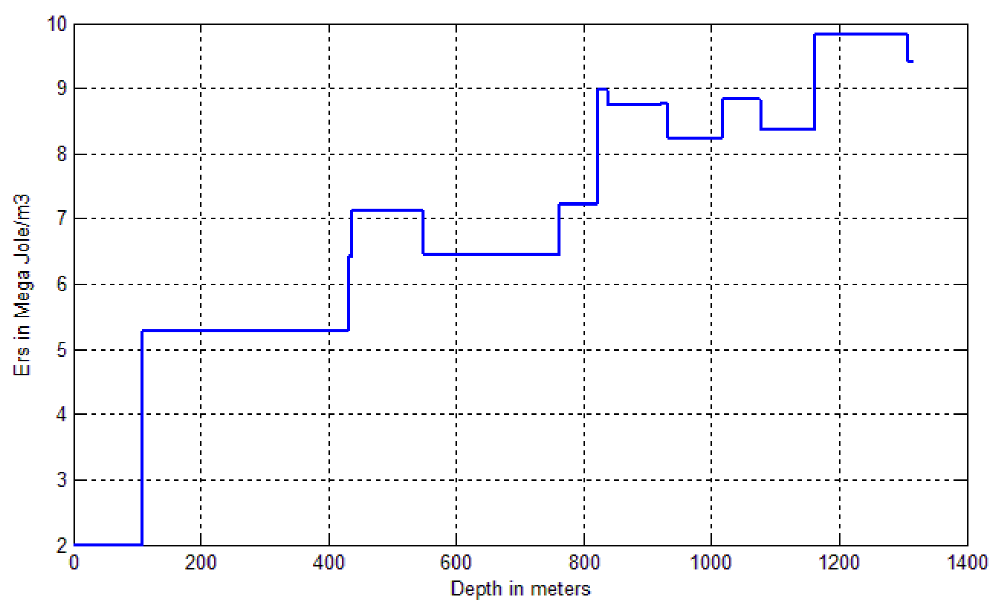

Figure 5-4 Rock Specific Energy

5.2 Control of RSS with stick-slip and bit wear

An iterative simulation has been implemented to validate the proposed optimization algorithm. The proposed model for RSS is simulated using Matlab. The manipulated variables used in the objective function proposed in Equation (4-25) are subjected to some constraints as given in Table 5-1. The parameters for the PSO are given in Table 5-3. Results reflect the efficiency of the proposed algorithm. Figure 5-5 shows the trajectory tracking, where the root mean square value of the Euclidian distance between the desired trajectory and the actual path is 0.35 meters and the maximum Euclidian distance is 0.71 meters. The total elapsed time is 30.15 hours. The drilling process can be quickened by tuning the weight matrix Γ_2, but this will change the trajectory tracking accuracy. So, the driller engineer has to compromise between accuracy and time depend on the nature of well formation, characteristics, and cost of drilling.

Figure 5-6 illustrates the value of measured depth during the process, since the well depth is 1318. The value of change of measured depth at each time step is also controlled using the weight matrix in the objective function.

Figure 5-7 and Figure 5-8 represent the bit roll angular velocity of the drill bit and the rotary disk angular velocity, respectively, without optimizing the rate of change of RPM. Both values are fluctuating around 120 rpm in order to maintain the difference between both of them close to zero rad/s. The RPM value is changing rapidly to overcome the occurrence of stick-slip oscillations. By optimizing the rate of change of RPM, the rate of change becomes more realistic to avoid sudden changes in the rotary disk angular velocity as shown in Figure 5-9. On the other hand, Figure 5-10 shows the reverse influence comparing to the previous case. Where the value of the bit roll angular velocity changes rapidly due to the limitations on the rate of change of RPM.

The error between the bit roll angle and the estimated model of stick-slip is given in Figure 5-11. The root mean square value is 0.05 rad, with maximum value 0.454 rad.

The rate of bit wear can be controlled by tuning the weights of rpm and WOB in the objective function. The rate of bit wear in two different modes, small weights and large weights has been tested. The rate of bit wear is 32.2% per 1 km in mode 1, but the rate becomes 28.6% per 1 km by adding more penalties on the rpm and the process time. Depend on the properties of rocks and the drilling process, the drill engineer can tune the weight matrix to keep the drill bit for longer time or to finish the drilling process more quickly.

To evaluate the robustness and performance of the proposed PSO for estimating the stick-slip model parameters, the algorithm has been tested several times with different settings and initial populations. The change of initial population, constant α, and the percentage p may lead to some changes in the fitness value at certain iteration. Figure 5-12 shows the value of fitness function versus iterations for 6 different cases as given in Table 5-4, respectively. The minimum fitness value for each experiment is almost zero. The robustness of this algorithm is confirmed from the closeness of these fitness values. The estimation of stick-slip model parameters is not affected by the parameter setting of PSO.

Table 5-3 Parameters setting for PSO

	Parameter				
	w_i	α	P	# *Pop.*	# *iter.*
Setting	0.5	0.95	0.2	50	50

Table 5-4 Fitness values for six cases

Cases	Parameter		
	# Pop.	*P*	*α*
case 1	50	0.2	0.95
case 2	100	0.2	0.95
case 3	50	0.2	0.90
case 4	50	0.2	0.85
case 5	50	0.3	0.95
case 6	50	0.4	0.95

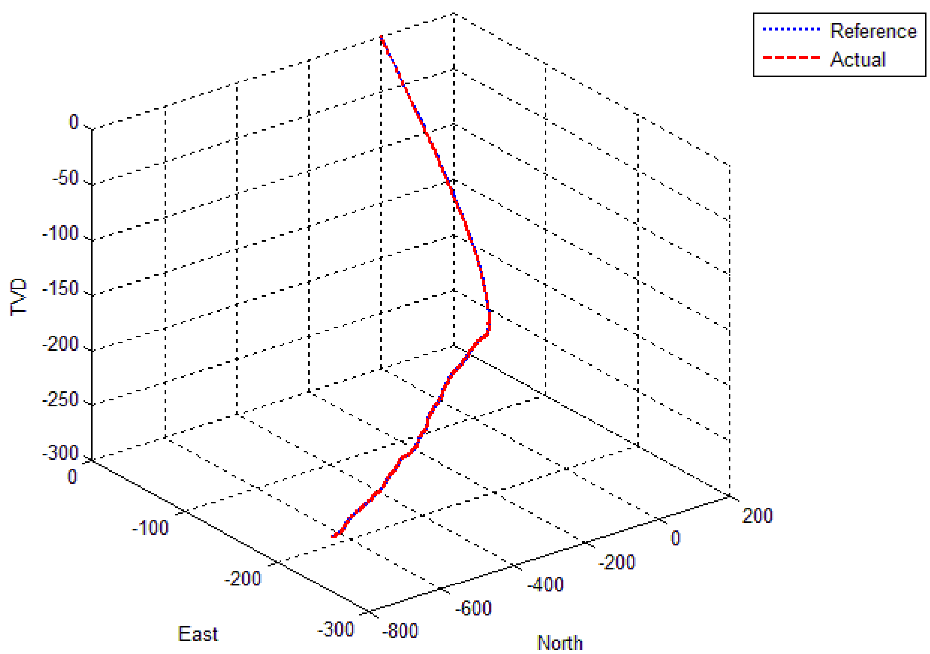

Figure 5-5 3D view of the trajectory tracking

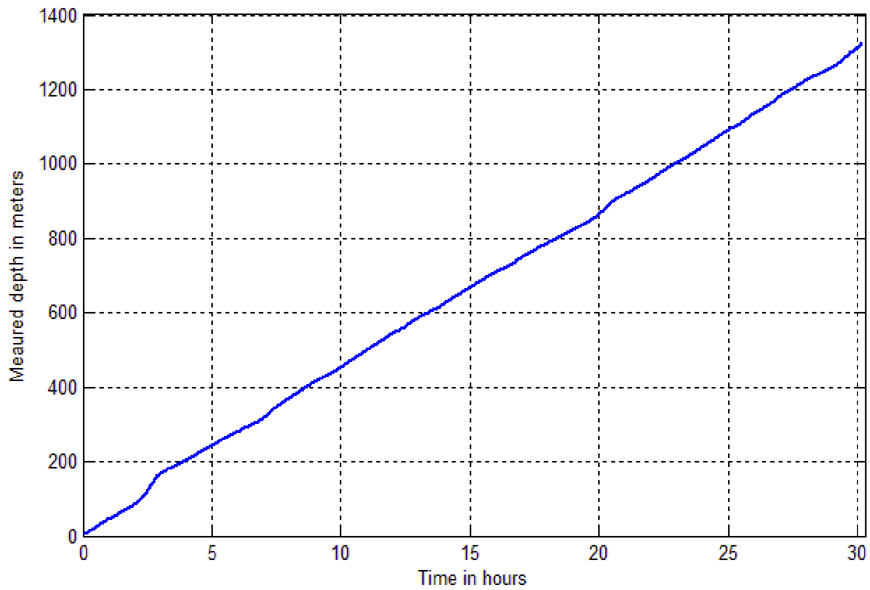

Figure 5-6 Measured Depth

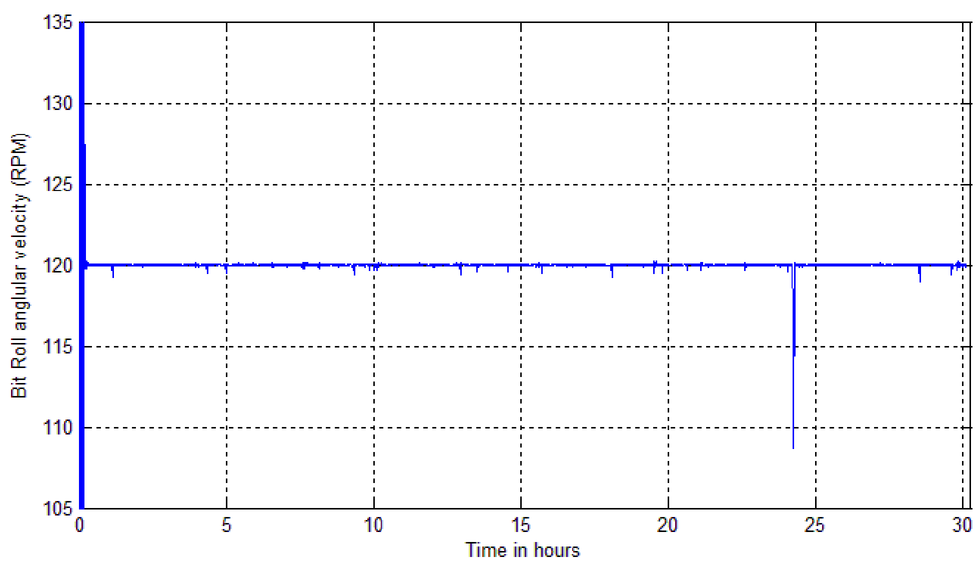

Figure 5-7 Bit roll angular velocity – without optimizing the rate of change of RPM

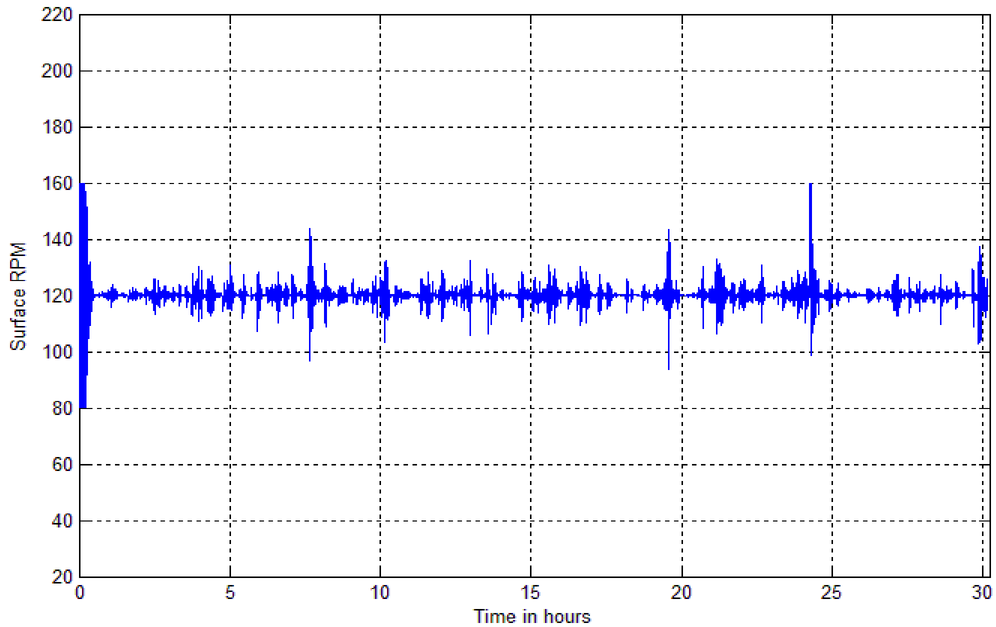

Figure 5-8 Input RPM – without optimizing the rate of change of RPM

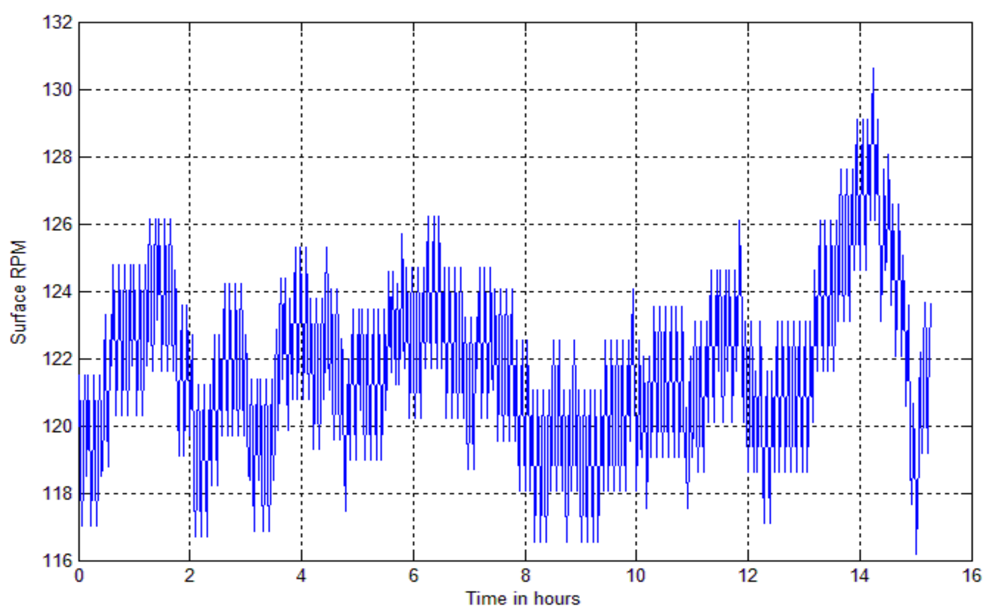

Figure 5-9 Input RPM – with optimizing the rate of change of RPM

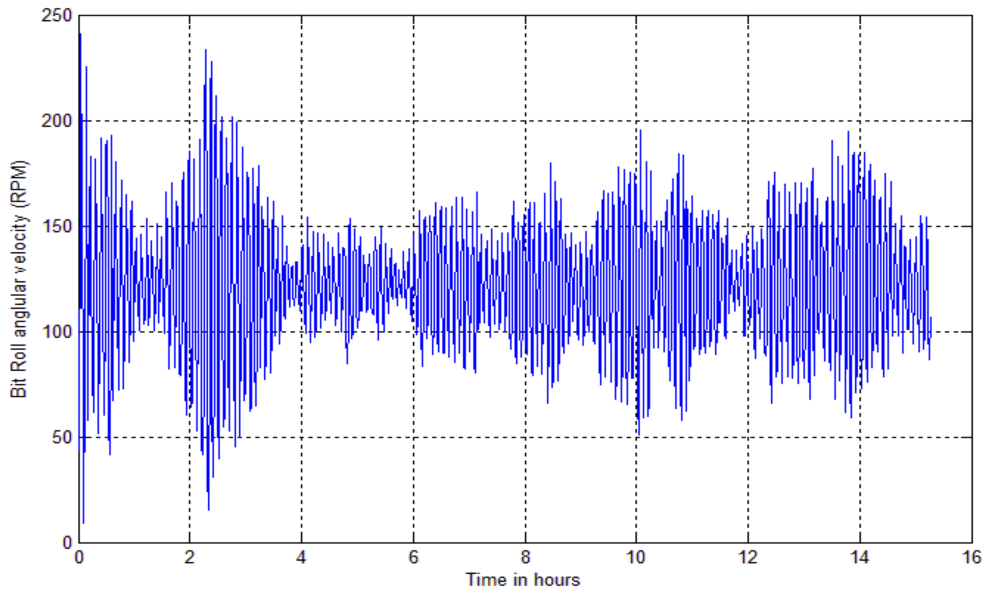

Figure 5-10 Bit roll angular velocity – with optimizing the rate of change of RPM

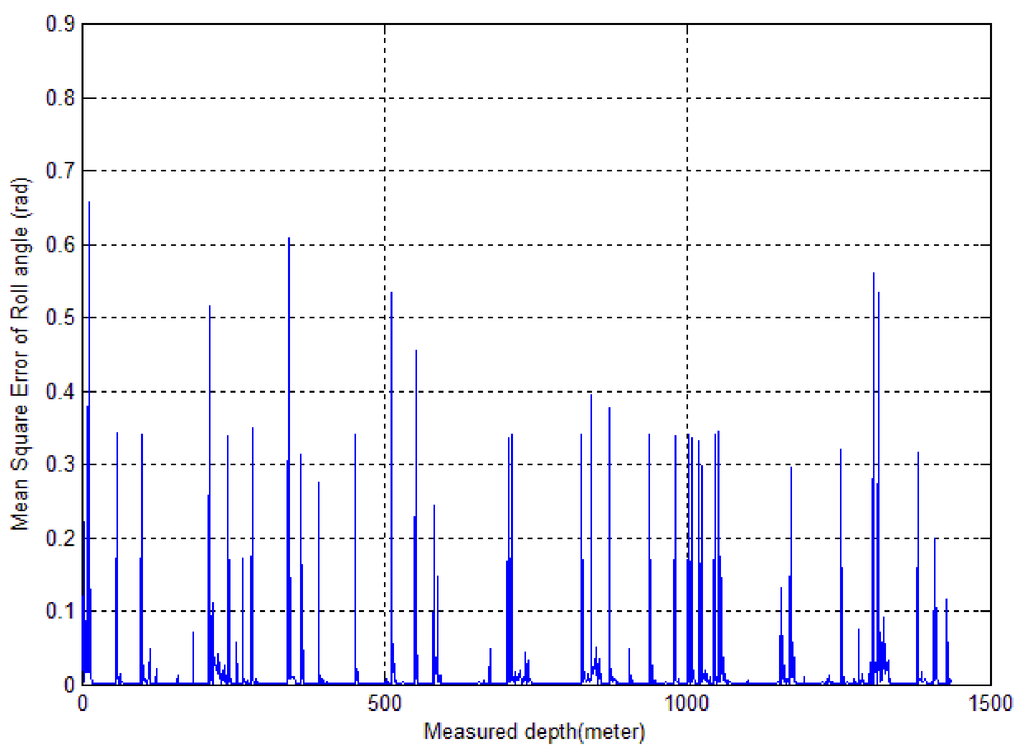

Figure 5-11 Mean Square Error between actual and model bit roll angle

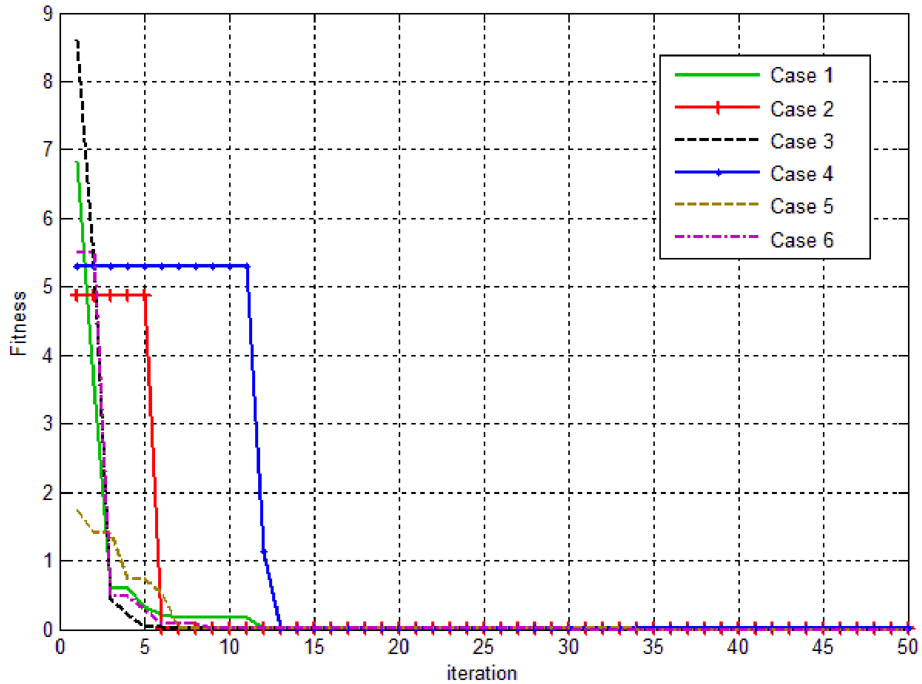

Figure 5-12 Fitness values for the different six cases

5.3 Control of high DOF RSS

The proposed control approach was evaluated using same real well trajectory for the previous RSS and same conditions. An iterative simulation has been implemented to validate the high DOF RSS model. The simulation results given in Table 5-5 show the advantage of adding more degrees of freedom to the RSS model where the root mean square error (RMSE) of the Euclidian distance between the desired trajectory and the actual path, and the maximum value are lower than the previous RSS. Using high DOF RSS dynamics make the trajectory smoother. Comparison between the second scenario for the High DOF RSS and previous RSS is shown in Figure 5-13.

Table 5-5 Data analysis for the three drilling process scenarios of High DOF RSS

	RMSE (m)	Max. Error (m)
Scenario 1	0.326	0.587
Scenario 2	0.488	1.51
Scenario 3	0.547	1.49

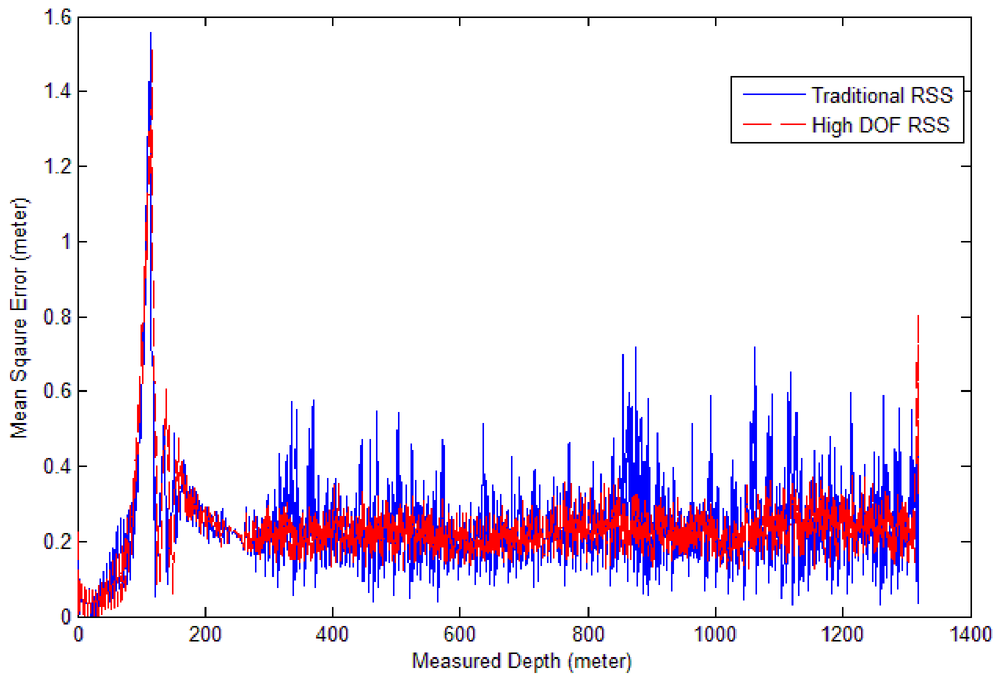

Figure 5-13 Comparison of Mean Square Error

5.4 Gravitational search optimization of Quad-rotor directional drilling

An iterative simulation mechanism has been implemented to validate the proposed optimization approach with feedback linearization controller. The proposed model for DSS is simulated using Matlab with the given parameters of Table 5-6. An ODE function has been used to solve the linearized system dynamics in Equation (4-47) at each iteration with given initial conditions from previous iteration. The GSA has been applied at each iteration to find the optimal gains values in Equation (4-46) to optimize the control input action proposed in Equation (4-42) to Equation (4-45) in order to improve the system behavior and minimize the error from the preplanned trajectory, in addition, the GSA has been used again with previous system data to estimate the exact values of system parameter *b* and *d*. The parameters for the GSA are given in Table 5-7.

GSA optimization technique is proposed to optimize the control inputs of the four rotors and overcomes shortcomings of Linear Quadratic Regulator (LQR) which is done in previous work. In LQR technique the weight matrices Q and R are set by trial and error which gives narrow range for weighting the objective function, in contrast, GSA is more robust and can self-search for optimal solutions for any given objective function with different weights. The proposed controller design approach is applicable to wide range of oilfields with unknown formation friction and rock strength as it adaptively estimates the optimal system parameters.

The optimization algorithm has been applied for two different well trajectories from the Middle East with zero initial X_E, Y_E, and Z_E. The following simulation results were obtained for the measured depth as shown in Figure 5-14 and Figure 5-17. A 3D plot of the trajectory tracking is presented in Figure 5-15 and Figure 5-18. The mean square error between simulator and model states is illustrated in Figure 5-16 and Figure 5-19.

Table 5-6 DSS dynamic parameters

Parameter	Value	Unit
g	9.81	m/s^2
m	200	kg
L_b	0.55	m
$I_x = I_y$	60	Kg/m^2
I_z	25	Kg/m^2
I_r	0.83	Kg/m^2
μ	0.3	-

Table 5-7 Parameters setting for GSA

Parameter	α	ε	G_0	# Pop.	# iter.
Setting	7	0.00001	100	50	100

It can be seen that the value of the measured depth is identical to the trajectory of both wells as shown in Figure 5-14 and Figure 5-17.

In Figure 5-15 and Figure 5-18, values of North, East, and TVD represent the earth coordinates and can be calculated using Equation (3-57). The root mean square values of the Euclidian distance between the desired trajectory and the actual path of well-1 and well-2 using the proposed optimized gravitational search algorithm based control strategy are 3.32 meters and 1.99 meters, respectively. While, the root mean square error values of well-1 and well-2 using LQR are 4.19 meters and 2.82 meters, respectively. It can be concluded that the proposed GSA-based control strategy reduces the trajectory error by 20.8% and

29.4% for well-1 and well-2, respectively compared to LQR [1]. The obtained results clearly confirm the high performance and superiority of the proposed GSA control strategy. The reults also demonstrate the robustness and effectiveness of the proposed control strategy over a wide range of operating conditions.

The value of mean square error represented in Figure 5-16 and Figure 5-19 measures the accuracy of estimation for the values of thrust factor b and drag factor d. These figures show the difference between the simulator states including real values of b and d and the model states with the estimated values. The root mean square value of well-1 is 0.0091 and the maximum value is 0.105 due to a suddenly change in the formation. Additionally, the root mean square value of well-2 is 0.0016 and the maximum value is 0.06.

In order to demonstrate the robustness and evaluate its performance, the developed GSA approach for optimal controller design proposed in Equation (4-56) has been executed several times with different settings and initial populations. The response of the fitness function minimization versus iterations with different parameters settings is shown in Figure 5-20. The fitness value is gradually decreasing to a suitable value which is reflected on the output performance. Table 5-8 presents the five cases with different initial gravitational constant value G_0 and the constant α. It can be seen that the best and worst cases have a fitness funcion of 26.38 and 27.04, respectively with an average of 26.76. The closeness of these values confirms the robustness of the developed GSA with repect to its setting and initialization.

Table 5-8 Fitness values for five cases

	G_0	α	Fitness Min
case 1	100	7	26.9
case 2	90	7	26.85
case 3	80	7	27.04
case 3	100	6	26.67
case 4	100	8	26.38

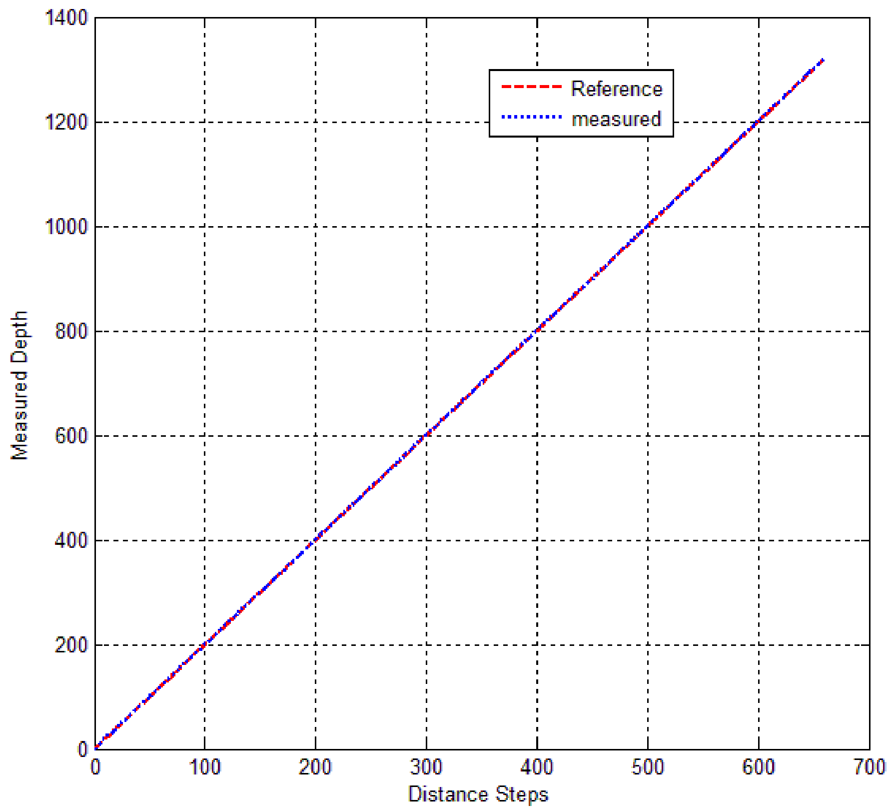

Figure 5-14 The response of measured depth of well-1

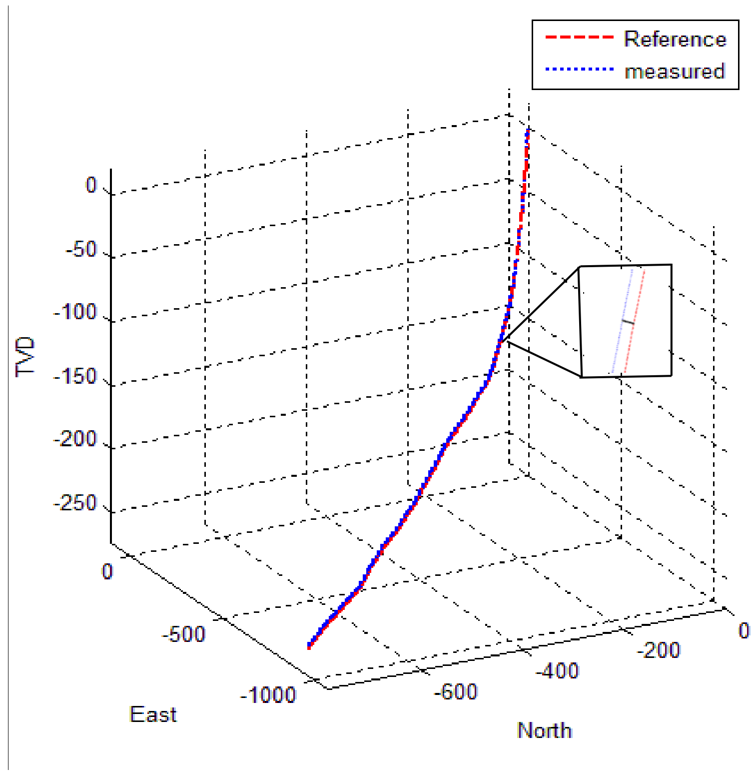

Figure 5-15 3D plot of the trajectory tracking of well-1

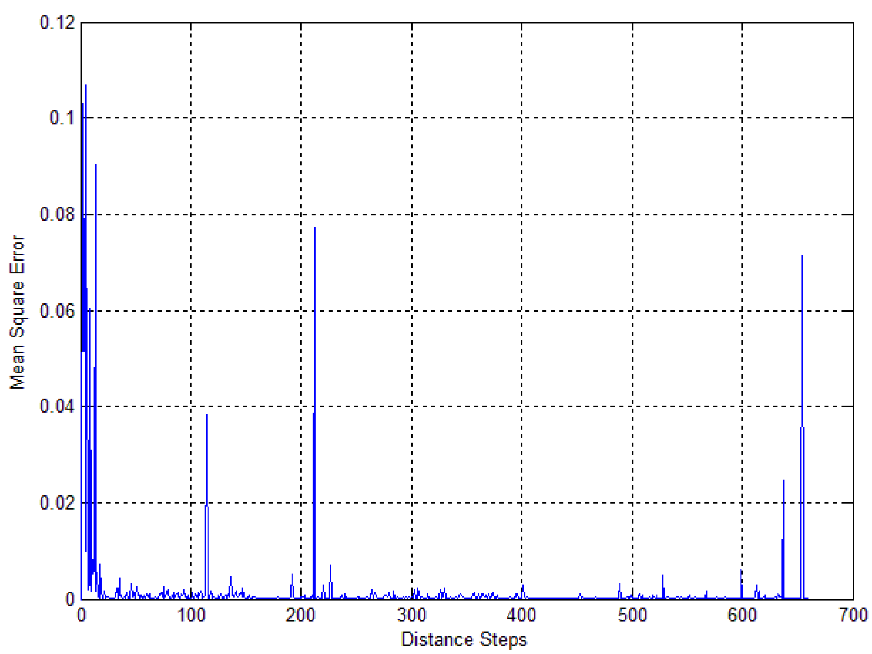

Figure 5-16 Mean Square Error between simulator and model states of well-1

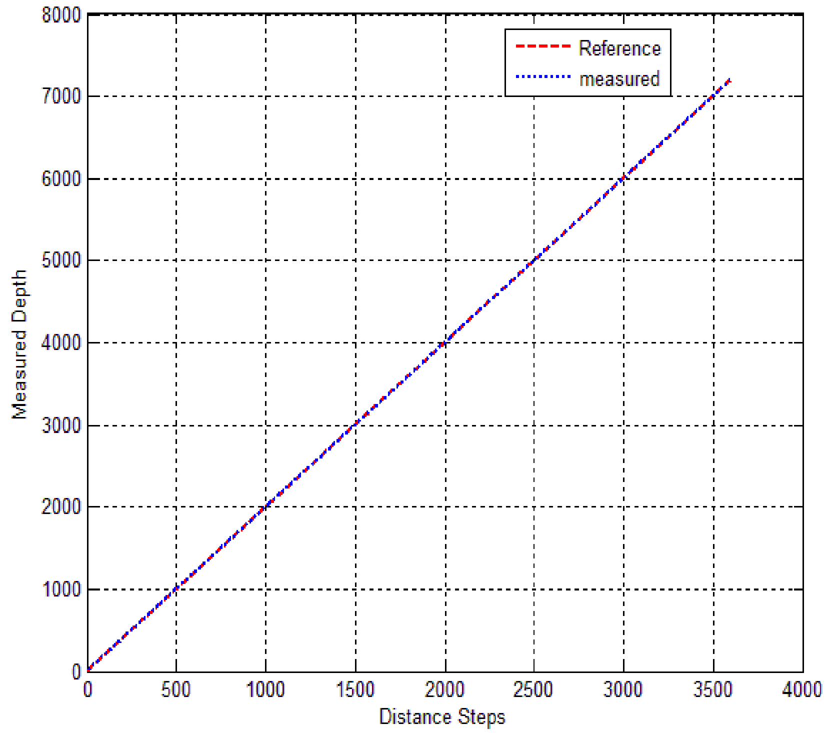

Figure 5-17 The response of measured depth of well-2

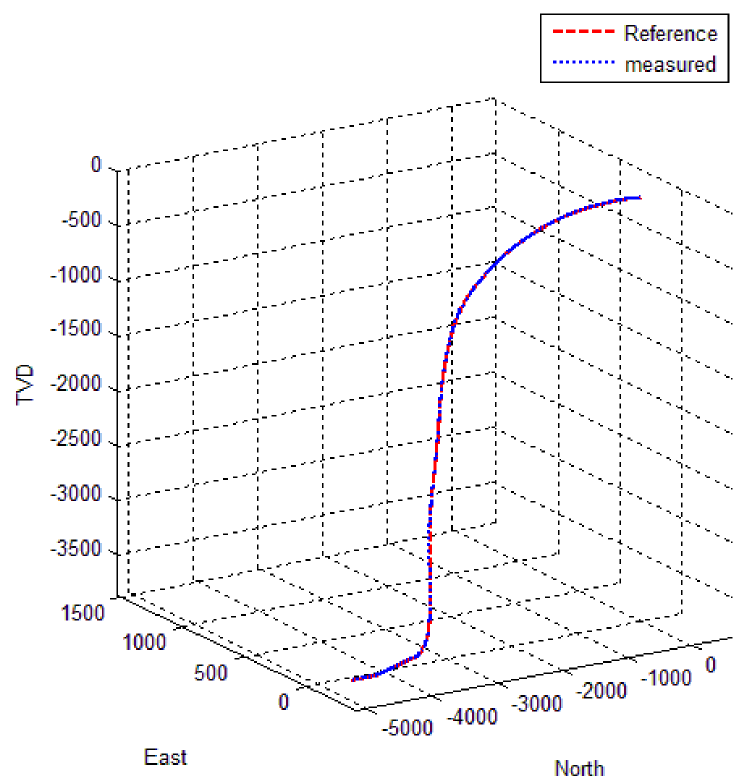

Figure 5-18 3D plot of the trajectory tracking of well-2

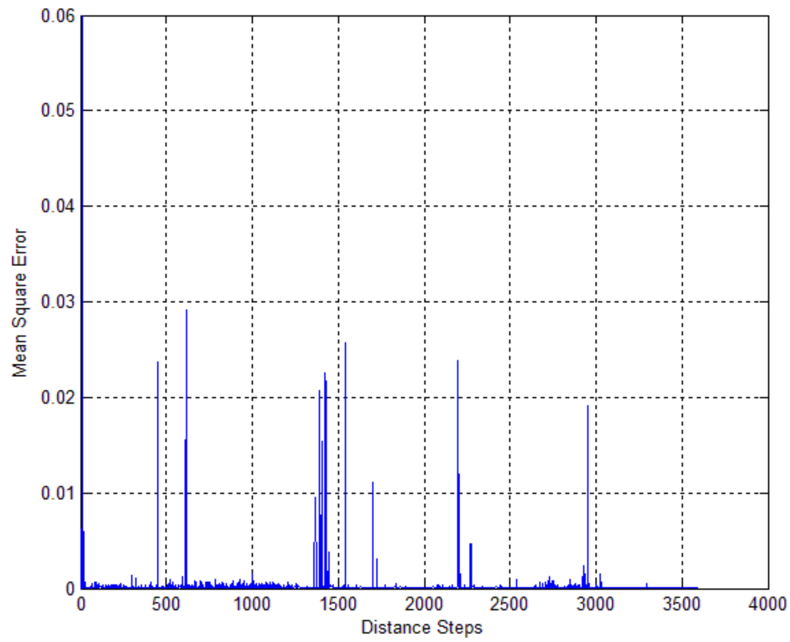

Figure 5-19 Mean Square Error between simulator and model states of well-2

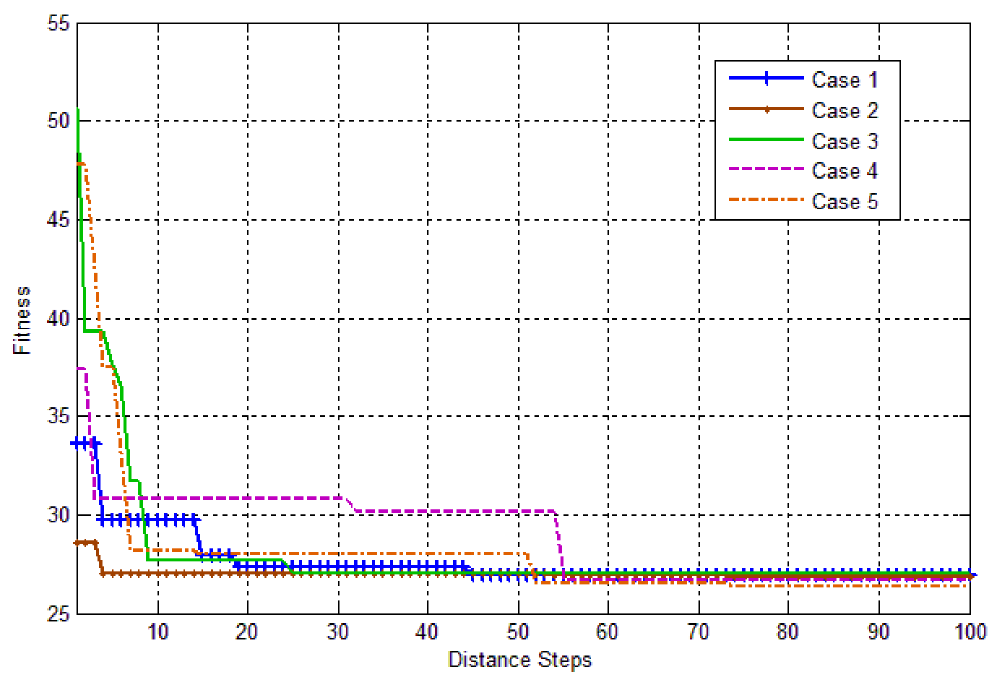

Figure 5-20 Fitness function minimization with GSA with different parameter settings

CHAPTER 6

CONCLUSION

An integrated approach for the control of the Rotary Steerable System is investigated where an adaptive control scheme for real time optimization of the drilling process was used to optimize drilling parameters, trajectory tracking, stick-slip oscillations, bit wear, and drilling efforts. Different drilling process scenarios have been implemented to show the realization and robustness of the proposed technique where the drilling operator can easily tune the weight matrix of the input vector in the objective function to optimize the drilling time and trajectory tracking. The response of the RSS can be improved by adding more degrees of freedom to the system dynamics. Results showed excellent ability to accommodate the changes in the formation properties.

In addition, a new control strategy for the quadrotor directional steering system is proposed and implemented. The controller design has been formulated as an optimization problem. The gravitational search algorithm has been developed and implemented to search for the optimal gains of the feedback linearization controller and estimate system parameters *b,* and *d* to enhance the tracking capability. The effectiveness of the proposed controller has been evaluated using two different wells in this study. The results show an improved response for two wells considered with the proposed optimized GSA based control strategy compared to LQR. The accuracy of estimation for the system parameters has been verified. In addition, the robustness of the proposed design approach has been confirmed. The proposed controller can be applied in wide range of oilfields with unknown formation friction and rock strenth.

6.1 Recommendations

1. Online control of high degree of freedom rotary steerable system with flexible shaft in order to increase the radius of curvature and minimize the tracking error.
2. Apply the proposed control algorithms with taking into consideration the time delay of the MWD signals from the downhole to the surface.
3. Use the quaternions to rotate the location of any point from body space to inertia space instead of using the rotation matrix of Euler's angels to avoid singularities in the rotation matrix and rounding errors, and to consume less computations. Quaternions form a four-dimensional vector space instead of a 3x3 matrix.

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