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Paper:

Intelligent Compensating Method for MPC-Based Deviation Correction with Stratum Uncertainty in Vertical Drilling Process

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With the rapid development of control technology, increasing applications are using model predictive control (MPC) for deviation correction in vertical drilling. However, the accuracy of the predictive model is affected by the uncertainty of the stratum, which results in model mismatch and a reduction in control performance. In this paper, an intelligent compensating method is proposed for MPC-based deviation correction with stratum uncertainty in a vertical drilling process to increase control accuracy. First, a trajectory extension model is introduced as the predictive model for MPC, and the uncertainty of the stratum is discussed. Then, the compensation for the MPC is acquired based on a Gaussian fitting method and hybrid bat algorithm. Finally, based on the actual drilling data, a simulation is performed to demonstrate the effectiveness of the proposed method.

Keywords: model predictive control, deviation correction control, vertical drilling, intelligent compensating method

1. Introduction

Deviation correction control performs an important role in vertical drilling processes; consequently, increasing number of scholars are conducting research on this topic [1, 2]. The ultimate goal of correction control is to ensure a straight drilling trajectory, which implies that both the inclination angle and closure distance should be corrected to zero. Consequently, the quality of the drilling trajectory is predominantly by the performance of the correction control.

Previous deviation correction control methods were primarily simple control methods based on manual experience [3]. However, they have gradually been replaced by several modern control methods, such as deviation vector control theory, attitude control method, and model-based robust control [4–6]. In recent years, there has been an increasing number of applications using model predictive control (MPC) for deviation correction in vertical drilling. To resolve the effect of control system delay in drilling systems, Bayliss et al. presented an MPC strategy with delay compensation [7]. Demirer et al. established a model predictive controller that can deal with the curvature constraints of practical drilling engineering applications [8]. Zhang et al. established a trajectory extension model to describe the vertical drilling process, and proposed a model predictive controller based on this model [9]. All these applications have shown that MPC has good control performance and can easily satisfy the practical demands of drilling engineering.

However, owing to the uncertainty of the stratum, it is difficult to establish an accurate drilling model. Poor modeling accuracy results in model mismatch in MPC as well as a deterioration in performance. The most common way to deal with this problem is compensation. Farina et al. provided an output feedback MPC to overcome a possibly unbounded additive noise by means of the Chebyshev–Cantelli inequality [10]. Tang et al. established an observer-based output feedback MPC for Takagi–Sugeno fuzzy system with bounded disturbance [11]. Hu and Ding considered the dynamic output feedback MPC for a quasilinear parameter varying model [12]. Das and Mhaskar provided a Lyapunov-based model to deal with the model mismatch of MPC [13]. These methods primarily start from observers or models to deal with model mismatch; however, they do not consider the measurement parameters themselves, which reduces their the applicability in practical applications.

A simple method for compensation is to adjust the parameters of the controller using an optimization algorithm, and this method has been widely applied in several industry applications of control engineering [14–18].

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Chang et al. used a particle swarm optimization (PSO) algorithm to optimally tune the control gains of fuzzy terminal sliding mode control for the application of uninterruptible power supply inverters [19]. Navabi et al. prevented constraint violation by determining the optimal adaptive controller parameters using an optimization algorithm [20]. Cheng et al. employed a genetic algorithm to derive optimal or near-optimal proportional-integral-derivative (PID) controller gains [21]. Although there are several works focusing on intelligent compensating methods in various industry applications, it is still not a simple and effective technique to deal with the model mismatch for MPC-based deviation correction in vertical drilling; consequently, this is the primary motivation of this paper to establish a compensation method.

In this paper, considering the uncertainty of the stratum, we aim to design an intelligent compensating method for the MPC-based deviation correction presented in [9] to increase control accuracy. First, the trajectory extension model is introduced to describe the vertical drilling process, and the problem of compensation is discussed. Then, the uncertainty of the stratum is analyzed, and the probability density distribution of the uncertainty is discussed based on the Gaussian fitting method. To simplify the design of the compensation method for the predictive controller, the hybrid bat algorithm discussed in [22] is used to acquire the compensation value. Finally, based on the raw data collected from [9], a simulation was conducted to demonstrate the effectiveness of the proposed method. The contributions of this work can be summarized as follows:

a) The uncertainty of the stratum is considered in our model, resulting in a more practical application.

b) The Gaussian fitting method is selected to acquire the probability density distribution of the uncertainty in a well section.

c) The hybrid bat algorithm is utilized to calculate the most appropriate compensation for the model predictive controller for lower implementation difficulty and higher applicability in practical applications.

The remainder of this paper is organized as follows. In Section 2, the trajectory extension model is introduced, and the problems of this study are described based on the model. In Section 3, the structure of the compensation method is presented. The uncertainty of the stratum is discussed; moreover, the Gaussian fitting method is introduced to acquire the parameters of its probability density distribution. Further, the hybrid bat algorithm is introduced to calculate the compensation for MPC. Section 4 discusses the simulation that was performed to validate the compensation method and describes the comparison performed with the MPC strategy presented in [9]. Certain conclusions are presented at the end of this paper.

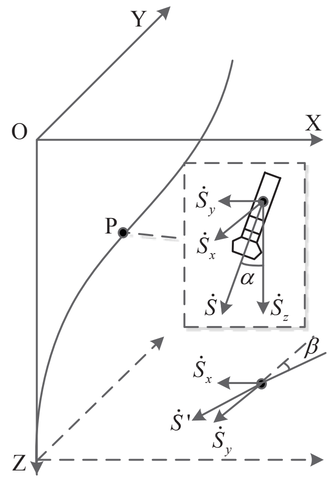

Fig. 1. Deviation correction process.

2. Trajectory Extension Model and Problem Description

This section describes the trajectory extension model presented by [9]. Then, the control problems of this paper are discussed based on this model.

2.1. Trajectory Extension Model

The schematic of the deviation correction process discussed here can be described in **Fig. 1**. The schematic shows the movement of the bottom hole assembly (BHA) and the formation of the drilling trajectory from a comprehensive perspective. To quantitatively analyze the drilling trajectory, an underground orthonormal Cartesian coordinate system is established, as shown in **Fig. 1**, where XOZ is parallel to the plane of Earth and the Y-axis moves along the North. The curve is defined as the drilling trajectory. According to [9], the trajectory extension model can be established to describe the deviation correction process as presented below.

$$\begin{cases} \tan\alpha_x = \tan\alpha\sin\beta \\ \tan\alpha_y = \tan\alpha\cos\beta \\ \dot{S}_z = \dot{S}\cos\alpha \\ \dot{S}_x = \dot{S}\tan\alpha_x \\ \dot{S}_y = \dot{S}\tan\alpha_y \\ \dot{\alpha}_x = \omega_x + \varepsilon_x = r_{BHA}\omega_{SR}\sin\tilde{\theta}_{tf} + \varepsilon_x \\ \dot{\alpha}_y = \omega_y + \varepsilon_y = r_{BHA}\omega_{SR}\cos\tilde{\theta}_{tf} + \varepsilon_y \end{cases}, \quad . \quad . \quad (1)$$

where S_x and S_y are components of the position deviation and α_x and α_y are components of the inclination angle. $\tilde{\theta}_{tf}$ and ω_{SR} are the magnetic tool face angle and steering ratio, respectively. The rated build-up rate r_{BHA} is the ideal maximum deflection capability of the BHA ideally, and $r_{BHA}\omega_{SR} \sim [0, r]$ denotes the real deflection capability provided by the BHA. Because of the existence of stratum uncertainty, there are certain uncertainty parameters in this model. The stratum uncertainty is independent of BHA, and ε_x and ε_y are utilized in this study to quantitatively describe the uncertainty.

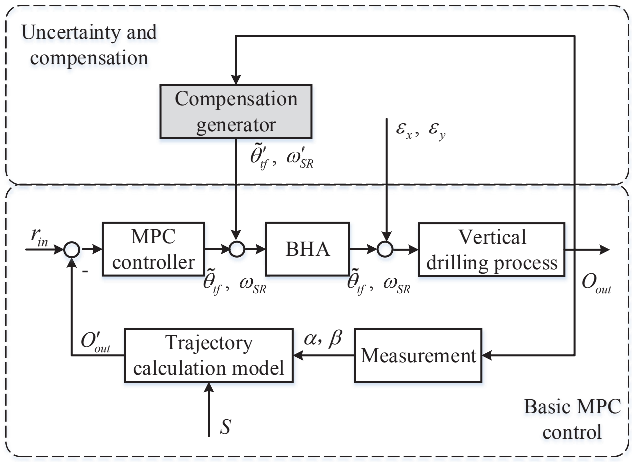

Fig. 2. Model predictive control and the compensation.

The trajectory extension model is used to describe the vertical drilling process in the form of a mathematical model; moreover, it is also an important basis for establishing the predictive model of the MPC controller in this study.

2.2. Problem Description

Deviation correction control aims to decrease the deviation of the drilling trajectory, including the position deviation components, S_x and S_y, and inclination angles, α_x and α_y, by adjusting the magnetic tool face angle $\tilde{\theta}_{tf}$ and steering ratio ω_{SR}.

In addition, because of the limited drilling conditions, there are certain constraints in practical drilling. The measurement interval is the time consumption of drilling for a certain distance according to the process requirement. In order to ensure the quality of the vertical trajectory, the inclination angle must be less than around α_{max}. Moreover, the build-up rate, $r_{BHA}\omega_{SR}$, which is provided by the BHA, should be less than its deflecting limit r_{BHA}, which is defined by the parameters of the BHA [23].

The control problem shown above was addressed using a model predictive controller in [9], and its control construction is shown as a basic MPC part in **Fig. 2**. Where r_{in} indicates the reference values of $[S_x, S_y, \alpha_x, \alpha_y]$, O_{out} indicates the trajectory parameters $[S_x, S_y, \alpha_x, \alpha_y]$, and O'_{out} represents the trajectory parameters of $[S_x, S_y, \alpha_x, \alpha_y]$ calculated using the trajectory calculation model. The vertical drilling process can be defined as the trajectory extension model; moreover, the minimum curvature method is selected as the trajectory calculation method [24].

However, as the uncertainties ε_x and ε_y are not zero, it will decrease the accuracy of the predictive model, and finally lead to model mismatch in MPC. This is a serious problem for deviation correction control, which results in difficulty in adjusting the drilling trajectory. Consequently, in this study, a compensation generator was established to determine the appropriate compensation $\tilde{\theta}'_{tf}$ and ω'_{SR} for the MPC controller to counteract the effects of model mismatch caused by the uncertainties ε_x and ε_y, which is the primary purpose of this work.

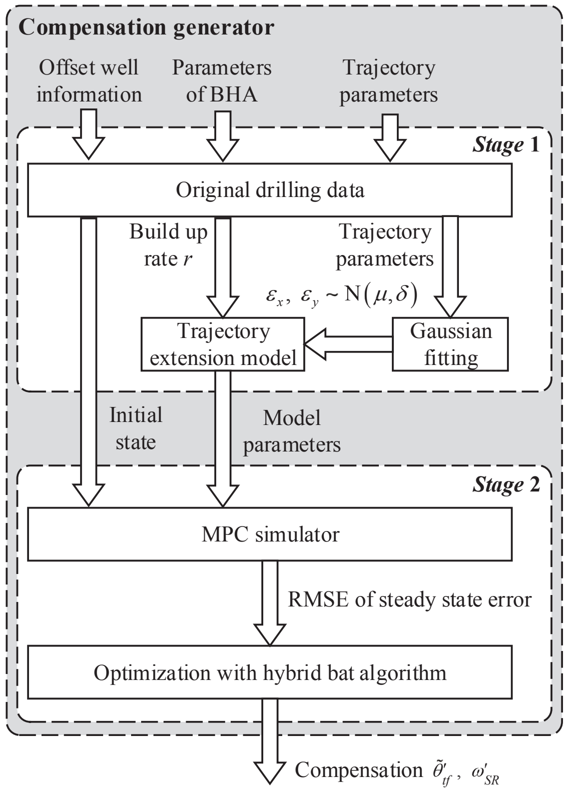

Fig. 3. Structure of the compensation generator.

3. Intelligent Compensation Method

In this section, the Gaussian fitting method is explored to calculate the parameters of the probability density distribution of the uncertainty, and the hybrid bat algorithm is utilized to acquire the compensation.

3.1. Structure of the Compensation Generator

As the parameters of the uncertainty are random variables, they are primarily defined by the characteristics of the stratum. To ensure that the compensation generator is capable of dealing with these uncertainties, it is necessary to determine the common features of these uncertainties or their probability density distributions. Subsequently, the compensation can be customized based on the information. Naturally, the compensation generator is divided into two stages: probability density distribution analysis and compensation calculation; moreover, the structure of the compensation generator is shown in **Fig. 3**.

The primary purpose of *stage* 1 is to obtain the probability density distribution of uncertainty from the trajectory parameters and determine the parameters of the trajectory extension model according to Eq. (1). The inputs of this stage are the original drilling data, including offset well information, parameters of the BHA, and trajectory parameters. Then, the fixed parameters of the trajectory extension model can be acquired, such as the length of the drill pipe and rated build-up rate of the BHA r_{BHA}. For the uncertainties ε_x and ε_y, we select the Gaussian function to describe their probability density distribution and utilize the Gaussian fitting method to acquire the parameters of the distribution. At the end of this stage, the trajectory extension model with the determined parameters can be implemented.

The primary purpose of *stage* 2 is to obtain the most appropriate compensation based on the trajectory extension model acquired from *stage* 1. To determine this compensation, an intelligent optimization algorithm is introduced. First, based on the trajectory extension model and model predictive controller in [9], an MPC simulator can be established as it can calculate the control results under different uncertainties, which follow the Gaussian distribution acquired from *stage* 1. Then, based on these control results, the hybrid bat algorithm is introduced to determine the best result by adding different compensations, and this compensation is chosen as the output of the generator.

In addition, the optimization of the compensation is not required in *stage* 2 because the probability density distribution is constant or changes slowly in a well section. The probability density distribution changes primarily when the composition of the stratum changes. This always implies that the drilling system has entered the next well section. Thus, the compensation of a well section can be fixed until the next well section.

The calculation steps are as follows:

a) Obtain the original drilling data; then, obtain the rated build-up rate of BHA r_{BHA} and set a fixed rate of penetration $\dot{S}$.

b) Obtain the probability density distributions of the uncertainties ε_x, ε_y based on trajectory parameters using the Gaussian fitting method.

c) If the drilling system enters the next well section and the probability density distribution of the uncertainty is significantly different from that of the previous well section, the hybrid bat algorithm is used to update the compensations $\tilde{\theta}'_{tf}$ and ω'_{SR}.

3.2. Probability Density Distribution of the Uncertainty

In *stage* 1, the fixed parameters of the trajectory extension model can be acquired, such as the length of the drill pipe and rated build-up rate of BHA r_{BHA}; however, the exact values of the uncertainties ε_x, ε_y cannot be determined. Therefore, the probability density function is selected to describe the distribution of ε_x or ε_y.

To acquire the probability density distribution, the characteristics of the uncertainty should initially be analyzed. We considered that the distribution of the uncertainty in a well section is constant or changes slowly as a drilling trajectory consists of several well sections. **Fig. 4** shows the

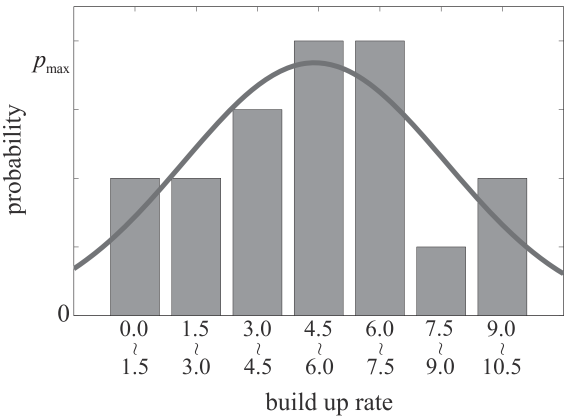

Fig. 4. Distribution of the uncertainty.

build-up rates provided by a BHA in a well section from a practical drilling site. Based on the statistical analysis performed on this data, it can be observed that the practical build-up rate is primarily within approximately 4.5 $\sim$ 7.5°/30 m, and the probability that the build-up rate is within approximately 0 $\sim$ 1.5°/30 m or 9.0 $\sim$ 10.5°/30 m is considerably smaller. This implies that the probability density distribution of the build-up rate provided by BHA is unimodal.

According to the analysis above, the Gaussian function can be used to describe the probability density distribution of the uncertainties ε_x, ε_y, and it can be written as follows:

$$\varepsilon_x, \varepsilon_y \sim a_\varepsilon e^{\frac{(r-b_\varepsilon)^2}{c_\varepsilon}} - r_{BHA}, \quad \dots\dots\dots \quad (2)$$

where r_{BHA} is the rated build-up rate of BHA which can be learned from the parameters of the BHA. r is the dogleg severity of the drilling trajectory acquired from trajectory parameters such as inclination angle and azimuth; r can reflect the build-up rate of the BHA. a_ε, b_ε, c_ε are Gaussian parameters, and it can easily be acquired from r using the Gaussian fitting method.

Finally, with ε_x, ε_y and other parameters of BHA, the trajectory extension model with the uncertainty is established, and this model is utilized to approximately describe the vertical drilling process during drilling in the selected well section.

3.3. Optimization of the Compensation

The purpose of *stage* 2 is to determine the best control results by adding compensations $\tilde{\theta}'_{tf}$ and ω'_{SR} when the probability density distribution of the uncertainty changes; moreover, the key point is optimization. The structure of the optimization is shown in **Fig. 5**.

In this optimization problem, the MPC simulator is established to define the fitness function, as the simulator consists of two parts: a trajectory extension model with uncertainty established in *stage* 1 and the model predictive controller as presented in [9]. To acquire the control result of the MPC under different uncertainties, the controller in the simulator is the same as the basic MPC. The

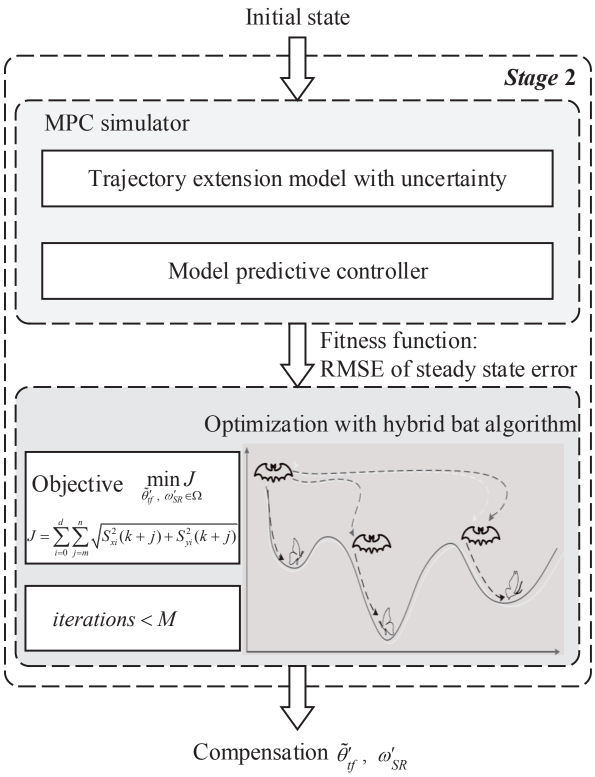

Fig. 5. Optimization of compensation.

predictive model of MPC is written as:

$$\begin{bmatrix} S_x(k+1) \\ a_x(k+1) \\ S_y(k+1) \\ a_y(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \dot{S}T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \dot{S}T \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} S_x(k) \\ a_x(k) \\ S_y(k) \\ a_y(k) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ T & 0 \\ 0 & 0 \\ 0 & T \end{bmatrix} \begin{bmatrix} \omega_x(k)+\omega'_x(k) \\ \omega_y(k)+\omega'_y(k) \end{bmatrix}, \quad (3)$$

where $\omega'_x(k)$ and $\omega'_y(k)$ are transformed from the compensations $\tilde{\theta}'_{tf}$ and ω'_{SR}. The optimization problem of MPC is as presented below:

$$\min J\left(Y(k),U(k)\right) = Y(k)^{\mathrm{T}}QY(k) + W(k)^{\mathrm{T}}RW(k)$$
$$\text{s.t.} \begin{cases} (\alpha_x(k))^2 + (\alpha_y(k))^2 \le \alpha_{\max}^2 \\ (\omega_x(k)+\omega'_x(k))^2 + (\omega_y(k)+\omega'_y(k))^2 \le r^2 \\ k = 1,\ldots,\mathrm{n} \end{cases}, \quad (4)$$

where $W(k)$ is the matrix of the incremental control signal and $Y(k)$ is the matrix of incremental state varieties. $W(k)$ and $Y(k)$ are the predictive values that can be acquired from the predictive model. $\omega_x(k)$ and $\omega_y(k)$ are the outputs of the model predictive controller.

To evaluate the performance of the compensation in a situation where the uncertainty follows the probability density distribution, d groups of ε_x and ε_y are collected randomly as all values of ε_x and ε_y follow follows the same probability density distribution. Moreover, the control results can be acquired under the uncertainties ε_x and ε_y based on the model predictive controller presented in [9] and a compensation value. Then, the fitness function is set as the root mean square error (RMSE) of the steady-state error. The RMSE will differ by adjusting the compensations $\tilde{\theta}'_{tf}$ and ω'_{SR}.

Based on the fitness function, the optimization objective can be written as follows:

$$\min_{\tilde{\theta}'_{tf},\omega'_{SR}\in\Omega} J = \sum_{i=0}^{d}\sum_{j=m}^{n}\sqrt{S_{xi}^2(k+j)+S_{yi}^2(k+j)}, \quad . \quad (5)$$

where $S_{xi}(k+j)$, $S_{yi}(k+j)$ are the position deviations at time $(k+i)$ for group i of ε_x and ε_y, m is the time when the system enters the steady-state phase, n is the duration of the simulation. J defines the compensation performance.

To solve this optimization problem, a global optimization algorithm called the hybrid bat algorithm, which is presented in [22], is used to determine the most appropriate compensation of this deviation correction process. This algorithm is used as it demonstrated successful outcomes when compared to 10 conventional algorithms, especially on unimodal functions. In addition, the end condition of the optimization is $iterations < M$, where M is a positive integer.

As the density distribution reflects the uncertainty of the entire well section, it is not necessary to update the compensation determined in *stage* 2 until the drill bit reaches the next well section. The MPC controller can use the same compensation in a single well section.

4. Simulation and Result Analysis

Based on the raw data collected from a vertical drilling site, a simulation was performed to demonstrate the effectiveness of the proposed method. Using the improved trajectory extension model to describe the vertical drilling process, the simulation was conducted to test the deviation correction capacity for the case of vertical drilling. According to [9], the parameters of the simulation are selected as follows: rate of penetration $\dot{S}$ is 30 m/h, and control cycle T is 0.3 h. For constraints, the maximum deflection capability of BHA r is 6°/30 m, which is 3°. The MPC parameters are as follows: p and c are 5, R is $\mathrm{diag}(50000, 50000)$, Q is $\mathrm{diag}(0.1, 10, 0.1, 10)$, m is 20, n is 40, and d is 50.

According to the data obtained from [9], the horizontal deviation between the actual trajectory and the reference is 8.82 m in the XOZ plane at 600 m measured depth (MD); meanwhile, the horizontal deviation is 1.51 m in the YOZ plane, inclination angle is 1.5°, and azimuth angle is 35.9°. The uncertainty of the hole well section is assumed to be $\varepsilon_x, \varepsilon_y \sim \mathrm{N}(0.54, 0.36)$. To validate the proposed method, a comparison with the MPC presented in [9] was conducted. **Fig. 6** shows the simulation results of S_x and S_y; **Fig. 7** shows the simulation results of S_{xy} and α; **Fig. 8** shows the simulation results of $\tilde{\theta}_{tf}$ and ω_{SR}.

Both these methods can correct the deviation of the

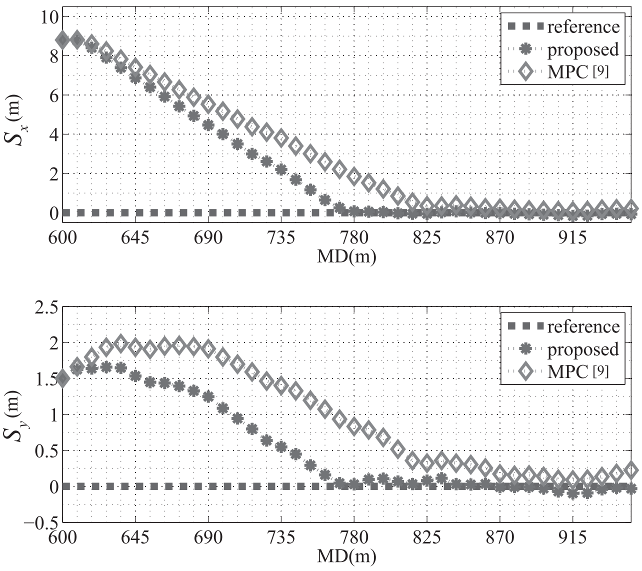

Fig. 6. Simulation results of S_x and S_y.

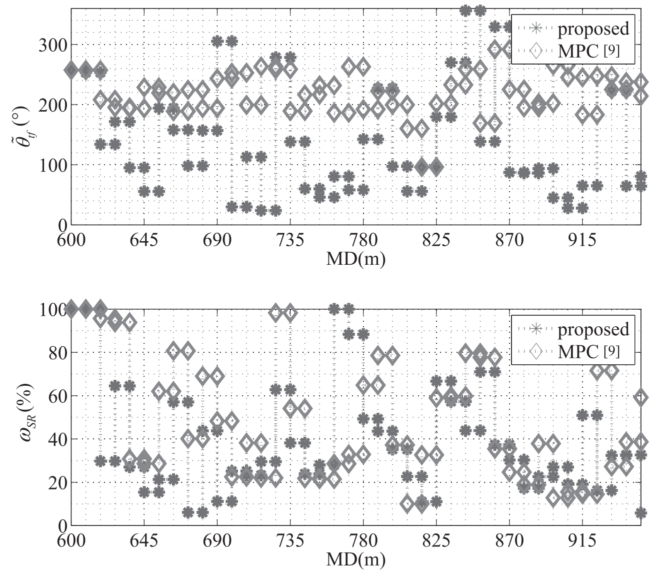

Fig. 8. Simulation results of $\tilde{\theta}_{tf}$ and ω_{SR}.

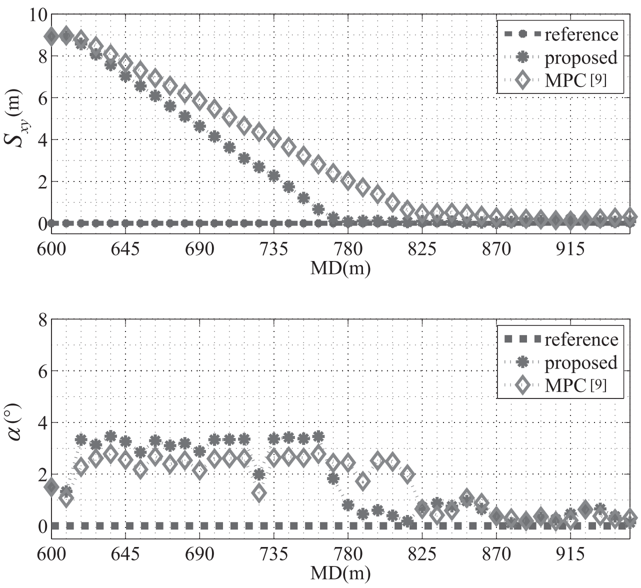

Fig. 7. Simulation results of S_xy and α.

drilling trajectory, but the results are different. It can be observed that the position deviation components S_x and S_y of the proposed method are eliminated to zero at nearly 780 m MD, as it can deal with constraints well. The position deviation components S_x and S_y of the MPC are corrected to minimal values at nearly 870 m. The RMSE of the proposed method is 0.0183 and the RMSE of the MPC is 4.6136. Therefore, the proposed method has better convergence and a smaller steady-state error than MPC.

In conclusion, the proposed method can efficiently address the problem of model mismatch for deviation correction control of vertical drilling, and has better convergence and smaller steady-state error than MPC. A two-stage compensation generator is provided, and the probability density distribution of the uncertainty from trajectory parameters is acquired, and the parameters of the trajectory extension model are determined in *stage* 1. The most appropriate compensation is acquired by the hybrid bat algorithm to achieve lower implementation difficulty and higher applicability in practical applications.

5. Conclusion

In this paper, an intelligent compensating method for the MPC-based deviation correction with the stratum uncertainty in the vertical drilling process was proposed to increase the control accuracy of MPC.

The compensation generator consists of two stages, and the probability density distribution of the uncertainty from the trajectory parameters is acquired using the Gaussian fitting method. The parameters of the trajectory extension model are determined in *stage* 1. Then, the most appropriate compensation is acquired using the hybrid bat algorithm to resolve the effect of the uncertainty of the stratum in *stage* 2.

Simulation results showed that the proposed method demonstrated better convergence and smaller steady-state error than MPC. It can efficiently address the problem of model mismatch for deviation correction control of vertical drilling and increases the accuracy of the MPC.

Acknowledgements

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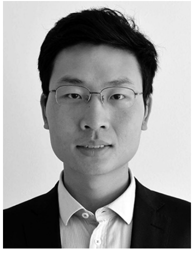

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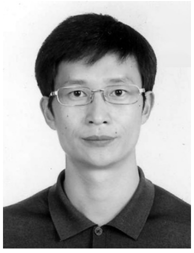

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