

## Hybrid AI-assisted multi-criteria optimization of horizontal well trajectories under representative Caspian offshore conditions

Y.Y. Shmoncheva<sup>1, 2\*</sup>, S.D. Abbaszade<sup>2</sup>

<sup>1</sup> Scientific Research Institute “Geotechnological Problems of Oil, Gas and Chemistry”, 227 Dilara Aliyeva Avenue, Baku, AZ1010, Azerbaijan

<sup>2</sup> Azerbaijan State Oil and Industry University, 20 Azadlig Avenue, Baku, AZ1010, Azerbaijan

**Abstract.** A hybrid artificial-intelligence workflow is proposed for multi-criteria optimization of a horizontal well trajectory and its drilling set-points under representative Caspian offshore conditions. The method combines a physics-based trajectory generator, engineering indicators for dogleg severity, mechanical specific energy, drilling time, effective target contact and screening-level operational risk, an extremely randomized trees surrogate, and a weighted composite-objective search. A transparent synthetic case with a target true vertical depth of 3200 m, a landing departure of 2200 m, a 20 m productive interval and a 3° reservoir dip was evaluated. The surrogate was trained on 10,000 Latin-hypercube designs and used to screen 180,000 additional combinations within predefined engineering bounds. For the independent test set, the coefficient of determination for the penalized composite objective was  $R^2 = 0.996$  and the mean absolute error was 0.104 objective units. Relative to the conventional reference design, the verified optimized solution reduced measured depth by 1.1%, maximum dogleg severity by 32.0%, mechanical specific energy by 20.9%, estimated drilling time by 26.0% and the integrated screening risk index by 16.6%. Predicted rate of penetration increased by 33.7%, while effective in-zone contact increased by 57.5%. The results are illustrative outputs of a reproducible synthetic model rather than disclosed field-performance data. The workflow is intended as an engineering decision-support layer that screens feasible alternatives and updates recommendations from MWD/LWD information while retaining expert control.

**Keywords:** artificial intelligence; horizontal well; well trajectory; geosteering; multi-criteria optimization; drilling optimization.

Corresponding author. Tel.: +994 50 394 03 18

E-mail address: [yelena.shmoncheva@asoiu.edu.az](mailto:yelena.shmoncheva@asoiu.edu.az)

**1. Introduction.** Horizontal wells increase reservoir contact, improve drainage of laterally heterogeneous intervals and allow offshore accumulations to be developed from a limited number of platform slots. Their benefit depends directly on trajectory quality. A geometrically short path may still be unacceptable if it produces excessive dogleg severity, high mechanical loading, poor hole cleaning or insufficient target exposure. Conversely, an overly conservative path may increase measured depth, drilling time and cost without improving useful reservoir contact [1, 2].

Trajectory planning is therefore a multi-criteria engineering problem. The planned path must reach the geological target, remain inside a defined drilling corridor, satisfy the maximum dogleg-severity limit and provide acceptable mechanical and hydraulic operating conditions. Within the reservoir, the lateral must follow the local dip and be updated when MWD/LWD information changes the interpreted formation boundary. Figure 1 presents the principal well architectures used as planning context; the numerical study reported here is restricted to a single horizontal well.

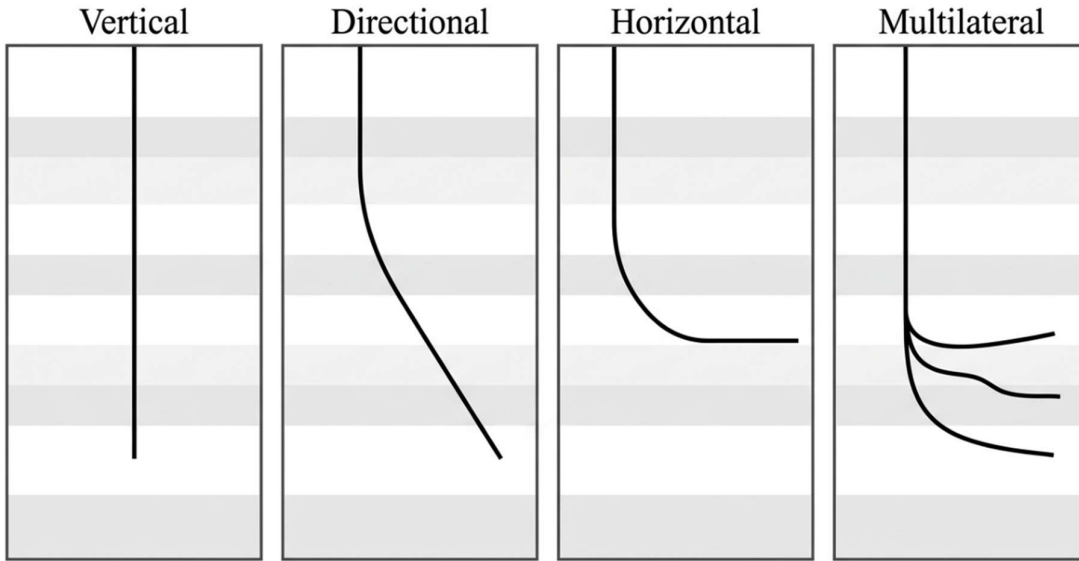


Figure 1. Representative well architectures considered during trajectory planning

Classical trajectory design relies on deterministic survey calculations, engineering constraints and the experience of the directional-drilling team. The minimum-curvature method remains the standard basis for survey reconstruction [2], while mechanical specific energy (MSE) is widely used to relate drilling inputs to rock-removal efficiency [3, 4]. Optimization methods have also been applied to trajectory length, torque, drag, buckling and operational risk [5, 6]. Their repeated application becomes computationally expensive when a large number of geological and operating combinations must be screened.

Artificial intelligence can reduce this computational burden by learning a surrogate of the engineering model inside a predefined design space. Data-driven planners have been used to adapt trajectories to reservoir geometry [7], and real-time AI-assisted geosteering has been investigated using LWD information [8]. Deep reinforcement learning and automated horizon interpretation have further extended trajectory-control research [9–14]. Nevertheless, an AI recommendation is acceptable only when it satisfies explicit engineering constraints and can be checked by the drilling team.

The objective of this study is to develop a transparent surrogate-assisted workflow for optimizing a horizontal well trajectory and drilling set-points under representative Caspian offshore conditions. The case is deliberately synthetic and fully methodological: it does not disclose or reproduce operating data from a specific field. The emphasis is on numerical consistency, constraint handling and human-in-the-loop implementation.

**2. Methodological part.** The workflow integrates trajectory geometry, operating-parameter selection, target contact and screening-level risk assessment in one closed optimization cycle. Geological and geomechanical information defines the target and exclusion zones; trajectory and BHA limits define constructability; historical and real-time drilling data define the operating envelope; the AI surrogate evaluates candidate combinations; and all shortlisted solutions are recalculated with the original engineering model before a recommendation is issued.

### Hybrid AI-assisted trajectory optimization workflow

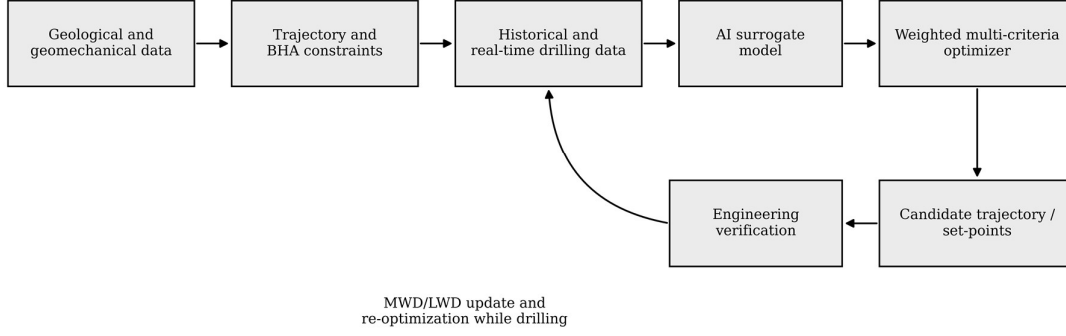


Figure 2. Hybrid AI-assisted trajectory optimization workflow

### Trajectory representation and engineering constraints

The well path is represented by a smooth three-dimensional centerline. The build-and-land section is controlled by two engineering lengths,  $L_1$  and  $L_2$ , measured along the initial and terminal tangents of the parametric trajectory. For numerical reconstruction and plotting, the calculated survey-control stations are connected by shape-preserving cubic interpolation, which prevents oscillation and preserves monotonic depth increase. The reservoir section is described by lateral inclination, azimuth correction and lateral length. The eight decision variables are  $L_1$ ,  $L_2$ , lateral inclination, lateral length, weight on bit (WOB), rotary speed, flow rate and azimuth correction.

Dogleg severity was calculated between adjacent survey stations from the minimum-curvature relationship:

$$DLS = \frac{30}{\Delta MD} \cos^{-1}[\cos I_1 \cos I_2 + \sin I_1 \sin I_2 \cos(A_2 - A_1)] \quad (1)$$

where  $I_1$  and  $I_2$  are the inclinations at two adjacent stations,  $A_1$  and  $A_2$  are their azimuths, and  $\Delta MD$  is the measured-depth interval. The factor 30 scales the dogleg angle to degrees per 30 m; the inverse-cosine result is expressed in degrees. Survey stations were evaluated at 30 m measured-depth intervals. The hard constraint was  $DLS \leq 3^\circ/30 \text{ m}$ .

The target centerline was defined by a true vertical depth of 3200 m at a horizontal departure of 2200 m and a reservoir dip of  $3^\circ$  downward in the preferred drainage direction. The target window had a total thickness of 20 m. The target-contact coefficient was defined as  $C_t = L_{in}/L_{lat}$ , where  $L_{in}$  is the lateral length located inside the target window and  $L_{lat}$  is the nominal lateral length. Two elliptical exclusion zones represented a gas-prone interval and a mechanically weak interval. For zone  $j$ , normalized clearance was defined as  $c_j = d_j/r_j$ , where  $d_j$  is the minimum trajectory-to-zone distance in the normalized ellipse metric and  $r_j$  is the corresponding boundary value. Feasible solutions required  $c_j > 1$ .

### Mechanical efficiency and synthetic operating response

Mechanical specific energy was calculated in SI units as:

$$MSE = \frac{WOB}{A_b} + \frac{2\pi NT}{A_b v} \quad (2)$$

where  $A_b$  is the bit area,  $N$  is rotary speed in revolutions per second,  $T$  is bit torque and  $v$  is rate of penetration in metres per second. A bit diameter of 0.216 m was used. Before substitution,  $N = \text{RPM}/60$  and  $v = \text{ROP}/3600$ . Before substitution, WOB was converted from kN to N and torque from kN·m to N·m. For the synthetic case, bit torque was generated by  $T = 1.9484 +$

$0.010581(\text{WOB} - 90) + 0.003(\text{RPM} - 100) + 0.15\text{DLS}$ , with  $T$  in  $\text{kN}\cdot\text{m}$ ,  $\text{WOB}$  in  $\text{kN}$  and  $\text{DLS}$  in degrees/30 m.

The ROP response was intentionally defined as a bounded synthetic surface rather than a field-calibrated correlation. The normalized variables were  $w = (\text{WOB} - 90)/55$ ,  $n = (\text{RPM} - 100)/60$ ,  $q = (Q - 28.5)/6$ ,  $d = \text{DLS}/3$ ,  $a = |\Delta A|/5$  and  $p_c = \max(c_j^{-2})$ . The illustrative ROP model was:

$$\text{ROP} = 15.17 + 7.44w + 4n + 4q - 3w^2 - 2n^2 - 2d^2 - 1.5a^2 - 2p_c c \quad (3)$$

where ROP is in m/h. The negative quadratic terms prevent unlimited improvement when WOB or RPM is increased. The model is used only to compare candidates inside the bounds of Table 1 and must not be interpreted as a transferable field ROP correlation.

The operational screening index combined a hole-cleaning component and a stability/trajectory component:

$$R = 0.60R_{hc} + 0.40R_{st} \quad (4)$$

The hole-cleaning component  $R_{hc}$  was obtained by min–max normalization over the generated candidate set of  $(\text{ROP}/Q)(1 + 2\sin^2 I)$ . The stability/trajectory component  $R_{st}$  was the min–max normalized value of  $(\text{DLS}/\text{DLS}_{lim})^2 + (\Delta A/A_{max})^2 + (1 - C_t)^2 + \max(c_j^{-2})$ . Both components therefore lie between 0 and 1. The index is a comparative screening measure and does not replace a detailed hydraulics, wellbore-stability or anti-collision calculation.

### AI surrogate and weighted multi-criteria search

A database of 10,000 candidate designs was generated by Latin hypercube sampling within the engineering bounds in Table 1. Each candidate was evaluated with the exact synthetic geometry and operating model. An extremely randomized trees ensemble with 400 trees, a minimum leaf size of 2 and a fixed random seed of 42 was trained to predict the penalized composite objective from the eight decision variables. Eighty percent of the cases were used for training and 20% for testing. The surrogate was used only for interpolation inside the predefined bounds.

For every minimized quantity  $x$ , the normalized component was

$$f_x = \frac{x - x_{min}}{x_{max} - x_{min}}$$

using the minimum and maximum values of the 10,000-case design database. Target-contact loss was represented by  $1 - C_t$ . The composite objective was:

$$J = 0.11f_{MD} + 0.14f_{DLS} + 0.16f_{MSE} + 0.15f_t + 0.22f_R + 0.22(1 - C_t) + P \quad (5)$$

The penalty was

$$P = 10 \left[ \max \left( 0, \frac{\text{DLS}}{\text{DLS}_{lim}} - 1 \right)^2 + \sum_j \max(0, 1 - c_j)^2 + \max(0, C_{min}^2 - C_t) + \max \left( 0, \frac{|\Delta A|}{A_{max}} - 1 \right)^2 \right]$$

The minimum target-contact coefficient was  $C_{min} = 0.50$  and  $A_{max} = 5^\circ$ . The weights sum to 1.00 and are listed in Table 2.

The trained surrogate screened 180,000 additional combinations. The 120 candidates with the lowest predicted objective values were recalculated with the exact model, and the best verified candidate was refined by differential evolution in a narrow neighbourhood. This two-stage procedure prevents the optimizer from exploiting local surrogate errors and ensures that the reported solution satisfies the original model.

**3. Results and discussion.** The surrogate reproduced the nonlinear penalized objective with high accuracy inside the sampled design space. For the independent test set,  $R^2 = 0.996$  and  $\text{MAE} = 0.104$  objective units. Figure 3 compares predicted and exact values. The largest deviations

occurred for strongly penalized infeasible cases, whereas the feasible low-objective region controlling the engineering decision remained close to the one-to-one line.

Table 1

| Parameter                                  | Range or value | Role in the model           |
|--------------------------------------------|----------------|-----------------------------|
| Target true vertical depth, m              | 3200           | Landing depth               |
| Horizontal departure to landing, m         | 2200           | Geometric target            |
| Productive interval thickness, m           | 20             | Target window               |
| Reservoir dip, degrees                     | 3              | Preferred lateral direction |
| Bit diameter, m                            | 0.216          | MSE calculation             |
| First control length $L_1$ , m             | 950–2100       | Build-section shape         |
| Second control length $L_2$ , m            | 650–1500       | Landing smoothness          |
| Lateral inclination, degrees from vertical | 85.5–89.5      | Target tracking             |
| Lateral length, m                          | 1200–1500      | Reservoir contact           |
| WOB, kN                                    | 90–145         | Drilling load               |
| Rotary speed, rpm                          | 100–160        | Rotational input            |
| Flow rate, L/s                             | 28.5–34.5      | Screening hydraulics        |
| Azimuth correction, degrees                | –5 to +5       | Drainage direction          |
| Maximum DLS, degrees/30 m                  | 3.0            | Hard constraint             |
| Minimum normalized clearance               | 1.0            | Hard constraint             |

Table 2

| Objective component        | Weight | Optimization direction |
|----------------------------|--------|------------------------|
| Measured depth             | 0.11   | Minimize               |
| Maximum dogleg severity    | 0.14   | Minimize               |
| Mechanical specific energy | 0.16   | Minimize               |
| Estimated drilling time    | 0.15   | Minimize               |
| Integrated screening risk  | 0.22   | Minimize               |
| Target-contact loss        | 0.22   | Minimize               |

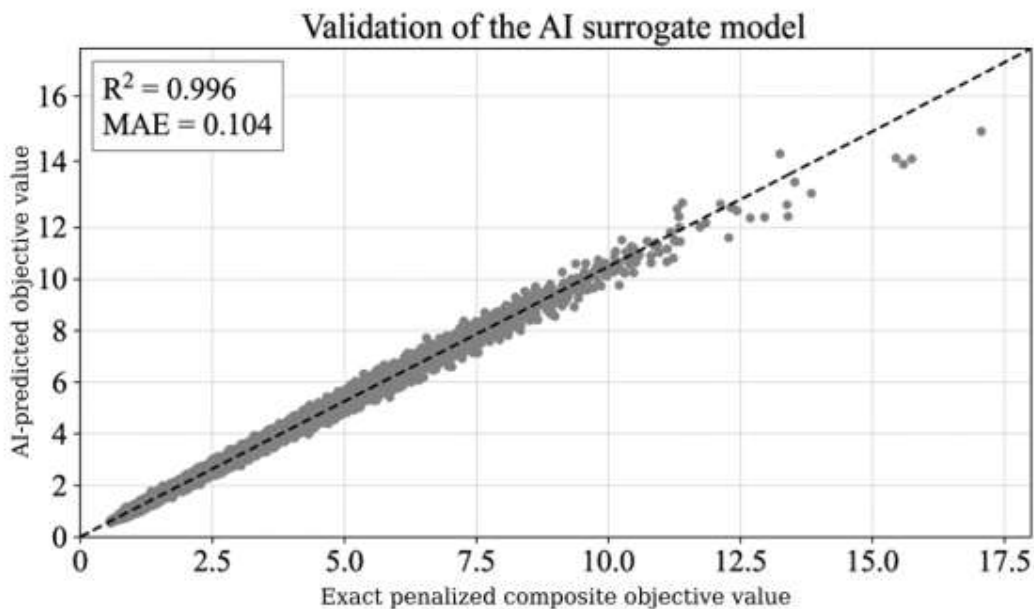


Figure 3. Validation of the AI surrogate against exact penalized composite-objective calculations.

### Optimized trajectory and drilling parameters

The conventional reference design used  $L_1 = 1350$  m,  $L_2 = 1250$  m, a lateral inclination of  $87.75^\circ$  from vertical, a lateral length of 1350 m, WOB = 108 kN, rotary speed = 118 rpm, flow rate = 30.0 L/s and an azimuth correction of  $3.0^\circ$ . The verified optimized design used  $L_1 = 1680$  m,  $L_2 = 980$  m, a lateral inclination of  $87.00^\circ$  from vertical, a lateral length of 1200 m, WOB = 143.1 kN, rotary speed = 110.0 rpm, flow rate = 34.5 L/s and an azimuth correction of  $0.2^\circ$ .

The geometric effect is shown in Fig. 4. The conventional trajectory passed closer to both exclusion zones and followed a  $2.25^\circ$  downward lateral, whereas the optimized trajectory followed the  $3^\circ$  target centerline. The conventional path therefore remained inside the 20 m target window for approximately 762 m before leaving through the upper boundary. The optimized 1200 m lateral remained inside the target for its full displayed length. Figure 4 is a vertical-section reconstruction from the verified survey-control stations.

Table 3

| Decision variable                          | Conventional design | AI-optimized design |
|--------------------------------------------|---------------------|---------------------|
| First control length $L_1$ , m             | 1350                | 1680                |
| Second control length $L_2$ , m            | 1250                | 980                 |
| Lateral inclination, degrees from vertical | 87.75               | 87.00               |
| Lateral length, m                          | 1350                | 1200                |
| WOB, kN                                    | 108.0               | 143.1               |
| Rotary speed, rpm                          | 118                 | 110                 |
| Flow rate, L/s                             | 30.0                | 34.5                |
| Azimuth correction, degrees                | 3.0                 | 0.2                 |

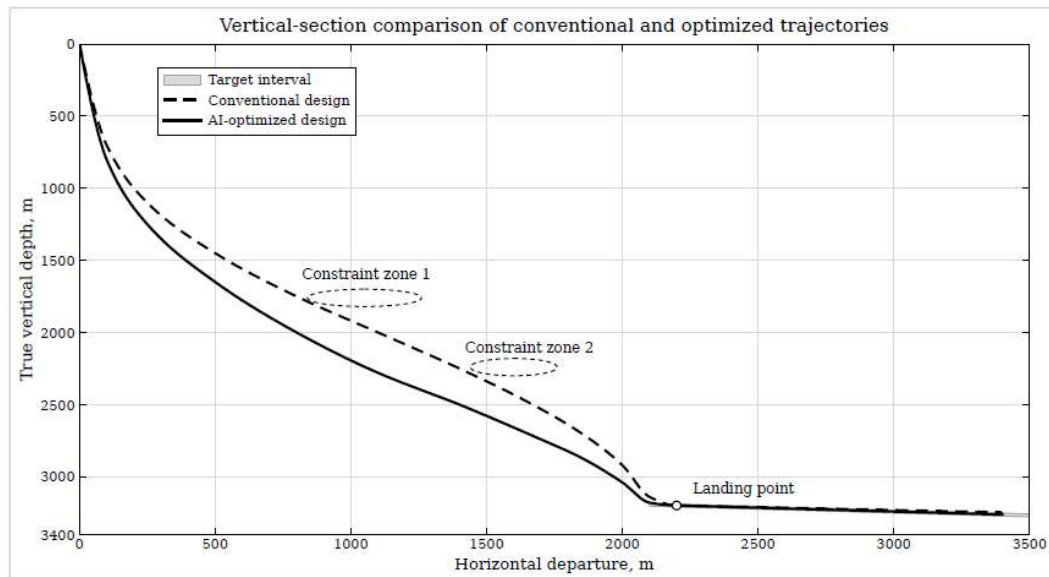


Fig. 4. Vertical-section comparison of the conventional and AI-optimized trajectories.

The maximum dogleg severity decreased from 1.28 to  $0.87^\circ/30$  m, while measured depth decreased by 1.1%. The main geometric gain was therefore improved smoothness and target placement rather than unrealistic shortening of the well. Effective target contact increased from 762 to 1200 m even though the nominal lateral length decreased by 11.1%.

Table 4

| Indicator                       | Conventional design | AI-optimized design | Relative change, % |
|---------------------------------|---------------------|---------------------|--------------------|
| Measured depth, m               | 5557                | 5497                | -1.1               |
| Maximum DLS, degrees/30 m       | 1.28                | 0.87                | -32.0              |
| Target exposure, %              | 56.4                | 100.0               | +77.3              |
| Effective target contact, m     | 762                 | 1200                | +57.5              |
| Predicted ROP, m/h              | 17.8                | 23.8                | +33.7              |
| Synthetic bit torque, kN·m      | 2.38                | 2.67                | +12.2              |
| MSE, MPa                        | 165.6               | 130.9               | -20.9              |
| Estimated drilling time, h      | 311.5               | 230.5               | -26.0              |
| Integrated screening risk index | 0.313               | 0.261               | -16.6              |

The optimized operating point increased the synthetic ROP from 17.8 to 23.8 m/h. Although WOB increased, the combined effect of a smoother path, moderate rotary speed, higher flow rate and lower proximity penalty reduced MSE from 165.6 to 130.9 MPa. Estimated drilling time decreased by 81.0 h. Within the screening model, the higher flow rate and lower trajectory severity also reduced the normalized hole-cleaning and stability components of the integrated risk index.

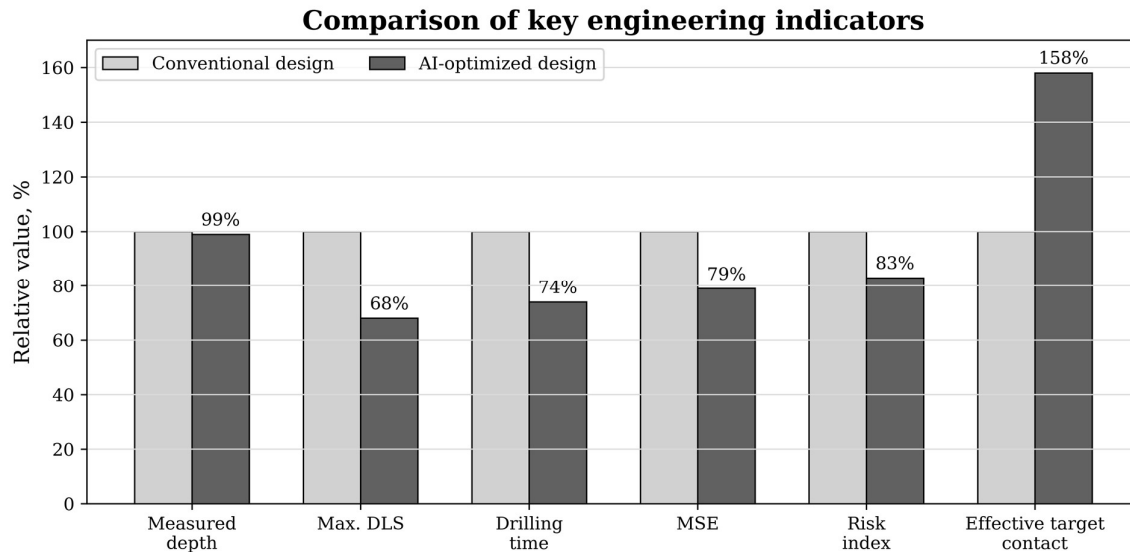


Figure 5. Relative comparison of selected engineering indicators. The conventional design is 100%; values below 100% indicate reductions in length, severity, time, energy or risk, whereas the value above 100% indicates increased effective target contact

### Engineering interpretation and real-time application

Three practical implications follow. First, trajectory and drilling-parameter optimization should not be separated: a smoother path permits more efficient operating set-points without violating the DLS constraint. Second, reservoir placement should be evaluated by effective in-zone length rather than nominal lateral length alone. Third, the surrogate should operate in a closed loop. After each survey or LWD interpretation update, the remaining design space can be regenerated from the current bit position and revised formation boundary.

For field use, the workflow should operate in advisory mode. It should return a small set of feasible candidates together with predicted gains, active constraints and sensitivity to uncertain

inputs. The directional driller and geosteering team would then accept, modify or reject the recommendation. This human-in-the-loop arrangement preserves engineering responsibility.

The study has explicit limitations. It is a synthetic methodological verification and does not use a complete dynamic torque-and-drag model, transient hydraulics, drillstring vibration, probabilistic geological uncertainty or a field-calibrated ROP correlation. The integrated risk index is a screening indicator and must not replace detailed hole-cleaning, wellbore-stability or anti-collision analyses. Before deployment, the trajectory generator, torque and ROP responses, target uncertainty and surrogate must be recalibrated using offset-well and real-time data for the relevant formation, BHA and mud system.

**4. Conclusions.** A hybrid AI-assisted multi-criteria workflow for horizontal well trajectory optimization has been developed and tested on a transparent representative Caspian offshore synthetic scenario. The main conclusions are as follows:

1. The combination of an explicit engineering model, an Extra Trees surrogate and exact recalculation of shortlisted candidates provides a transparent method for screening large trajectory and operating-parameter design spaces while retaining hard DLS, clearance, azimuth and target-contact constraints.

2. The surrogate predicted the penalized composite objective with  $R^2 = 0.996$  and  $MAE = 0.104$  objective units on the independent synthetic test set; this measures reproduction of the internal engineering model and is not a field-accuracy claim.

3. Relative to the conventional design, the verified optimized solution reduced maximum dogleg severity by 32.0%, estimated drilling time by 26.0%, MSE by 20.9% and the integrated screening risk index by 16.6%, while the synthetic ROP increased by 33.7%.

4. Effective target contact increased from 762 to 1200 m, or by 57.5%, despite a shorter nominal lateral. This confirms that in-zone placement is a more informative criterion than drilled lateral length alone.

5. The appropriate implementation is an advisory closed-loop system that updates candidate trajectories and drilling set-points from MWD/LWD information while leaving the final operational decision with drilling and geosteering specialists.

#### **Conflict of interest.**

The authors declare that they have no conflict of interest in relation to this research.

#### **References**

1. Mitchell, R.F., Miska, S.Z. *Fundamentals of Drilling Engineering*. Richardson, Texas: Society of Petroleum Engineers, 2011. 696 p.
2. Sawaryn, S.J., Thorogood, J.L. A compendium of directional calculations based on the minimum curvature method // *SPE Drilling & Completion*. 2005. Vol. 20, No. 1. P. 24–36. DOI: 10.2118/84246-PA.
3. Teale, R. The concept of specific energy in rock drilling // *International Journal of Rock Mechanics and Mining Sciences*. 1965. Vol. 2, No. 1. P. 57–73.
4. Dupriest, F.E., Koederitz, W.L. Maximizing drill rates with real-time surveillance of mechanical specific energy // *SPE/IADC Drilling Conference*. Amsterdam, 2005. SPE-92194-MS. DOI: 10.2118/92194-MS.
5. Jeong, J., Lim, C., Park, B.-C., Bae, J., Shin, S.-c. Multi-objective optimization of drilling trajectory considering buckling risk // *Applied Sciences*. 2022. Vol. 12. Art. 1829. DOI: 10.3390/app12041829.
6. Yavari, H., Qajar, J., Aadnoy, B.S., Khosravanian, R. Selection of optimal well trajectory using multi-objective genetic algorithm and TOPSIS method // *Arabian Journal for Science and Engineering*. 2023. Vol. 48. P. 16831–16855. DOI: 10.1007/s13369-023-08149-1.

7. Kristoffersen, B.S., Bellout, M.C., Silva, T.L., Berg, C.F. An automatic well planner for complex well trajectories // *Mathematical Geosciences*. 2021. Vol. 53. P. 1881–1905. DOI: 10.1007/s11004-021-09953-x.
8. Peshkov, G., Pavlov, M., Katterbauer, K., Al Shehri, A. Real-time AI geosteering for horizontal well trajectory optimization // *SPE Annual Caspian Technical Conference*. Baku, 2023. SPE-217527-MS.
9. Yu, Y., Chen, W., Liu, Q., Chau, M., Vesselinov, V., Meehan, R. Training an automated directional drilling agent with deep reinforcement learning in a simulated environment // *SPE/IADC International Drilling Conference and Exhibition*. Virtual, 2021. SPE-204105-MS. DOI: 10.2118/204105-MS.
10. Huang, X., Luu, T.P., Furlong, T., Bomidi, J. Deep reinforcement learning for automatic drilling optimization using an integrated reward function // *IADC/SPE International Drilling Conference and Exhibition*. Galveston, 2024. SPE-217733-MS.
11. Gu, H., Wu, Y., Li, X., Hou, Z. Research on wellbore trajectory optimization and drilling control based on the TD3 algorithm // *Applied Sciences*. 2025. Vol. 15. Art. 7258. DOI: 10.3390/app15137258.
12. Zhu, D., Xu, Q., Wang, F., Chen, D., Ye, Z., Zhou, H., Zhang, K. A target-aware well path control method based on transfer reinforcement learning // *SPE Journal*. 2024. Vol. 29, No. 4. P. 1730–1741. DOI: 10.2118/218409-PA.
13. D'Angelo, J., Zhao, Z., Zhang, Y., Ashok, P., Chen, D., van Oort, E. Real-time automated geosteering interpretation combining log interpretation and 3D horizon tracking // *Geosciences*. 2024. Vol. 14. Art. 71. DOI: 10.3390/geosciences14030071.
14. Brantson, E.T., Adu-Awuku, J., Asase, W., Akoto, Obeng S.D., Kwakye-Tannor, M.B., Nuamah, J.A., et al. Optimization of well trajectory with machine learning algorithms for geosteering directional drilling // *Journal of Geophysics and Engineering*. 2025. Vol. 22, No. 5. P. 1245–1265. DOI: 10.1093/jge/gxaf055.
15. Wiktorski, E., Kuznetsov, A., Sui, D. ROP optimization and modeling in directional drilling process // *SPE Bergen One Day Seminar*. Bergen, 2017. SPE-185909-MS. DOI: 10.2118/185909-MS.
16. Wallace, S.P., Hegde, C.M., Gray, K.E. A system for real-time drilling performance optimization and automation based on statistical learning methods // *SPE Middle East Intelligent Oil and Gas Conference and Exhibition*. Abu Dhabi, 2015. SPE-176804-MS. DOI: 10.2118/176804-MS.
17. Huang, M., Zhou, K., Wang, L., Zhou, J. Application of long short-term memory network for wellbore trajectory prediction // *Petroleum Science and Technology*. 2024. Vol. 42, No. 22. P. 3185–3204. DOI: 10.1080/10916466.2023.2193608.
18. Vishnumolakala, N., Kesireddy, V., Dey, S., Gildin, E., Losoya, E.Z. Optimizing well trajectory navigation and advanced geo-steering using deep-reinforcement learning // *SPE Annual Technical Conference and Exhibition*. San Antonio, Texas, 2023. SPE-215011-MS. DOI: 10.2118/215011-MS.