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Intelligent Collaborative Optimization Method for Multi-Well Plunger Gas Lifting Process on Platform

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Abstract

The current plunger gas lift production process still relies on the traditional ‘one-to-one’ control configuration, where one controller manages a single gas well. This approach does not fulfil platform requirements for centralized, efficient, and unified coordination and management of multiple wells. To increase production, improve efficiency, and mitigate safety risks, this article offers an intelligent optimization method for a collaborative plunger gas lift in multi-objective, multi-well platforms. The method integrates mechanistic modeling and data-driven approaches to develop a collaborative model for multiple wells on the platform, accounting for inter-well pressure interference and pipeline backpressure. A particle swarm optimization algorithm is implemented to solve the model, with a composite fitness function balancing maximum daily gas production and minimum production fluctuations. A case study on the XXX Platform shows that the method enhances total gas production, reduces production fluctuations, and lowers system backpressure compared to the current operating schedule. Implemented via a localized edge computing architecture, it supports real-time scheduling, providing technical references for shale gas development.

Keywords: plunger lift; multi-well platform; multi-objective; multi-well collaboration; intelligent optimization



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1. Introduction

The target oilfield has implemented an intelligent gas production management platform (POC). However, the current gas extraction process control stays in the traditional ‘one-to-one’ isolated control mode, where individual controllers manage single wells. With increasing well intervention operations and maintenance workloads, process efficiency and cost-effectiveness face significant challenges. The primary issues include the following:

- (1) Under the current POC gas production process control mode, there are many types of on-site measure well controllers, and the failure rate of controllers is relatively high.
- (2) Frequent data packet loss is caused by network latency, leading to delayed algorithm execution.
- (3) After multi-level configuration transmission of a large amount of data, data loss and configuration errors exist.

To ensure safe, stable, and efficient wellsite operations, implementing RTU-based (localized edge computing devices) integrated process control is imperative. This approach centralizes process management while reducing implementation costs. Data processing occurs locally through edge computing, enabling real-time model computation and algorithm execution.

Integrating field production data with theoretical models to obtain calibrated parameters significantly enhances operational feasibility. Notably, the optimization of shut-in/open timing serves as the most imperative guidance for operational adjustments, directly determining the efficiency and safety of the system. However, early research is mostly based on mechanism modeling.

Subash K Kannan and Matthew Boyer [1] conducted a specific well analysis to evaluate production performance, deriving optimal shut-in/open durations through transient simulation software.

G.M. Hashmi [2] established comprehensive mechanistic assumptions, starting from the seepage mechanism, establishing the formula for the minimum casing pressure and reservoir model for well opening, laying a theoretical foundation for the design of single-well systems.

Mei Huaping [3] formulated formation pressure estimation models and wellbore liquid loading quantification models using historical well data, determining minimum casing pressure thresholds for valve operations.

Wang Xiaohui [4] analyzed historical pressure buildup curves during shut-in periods, implementing valve control strategies governed by load factor dynamics.

Wang H et al. [5] theoretically derived a universal logarithmic–linear relationship between shut-in casing pressure and duration without empirical data dependencies.

Naresh N. Nandola [6] started with the overall plunger gas lifting and used state variable modeling and the ARX model to solve the plunger lifting cycle, converting the plunger motion stage into a continuous threshold optimization problem.

Lin Peng [7] proposed an intelligent control framework for shut-in/open operations, leveraging historical production data patterns.

Liu, P. et al. [8] considered the problem of an efficient gas lift for gas well annulus packers that rely on their energy plungers. The complex gas–liquid problem is addressed within the framework of a model where the gas inflow dynamics and liquid inflow dynamics of the thought shale gas wells are weakly coupled. On this basis, and with the aid of indoor simulation experimental data, a new gas plunger lift design that takes liquid leakage into account is compiled. Finally, a dedicated software relying on this approach is drawn up and used to verify the reliability of the model by means of field examples.

Miao, S. et al. [9] established a dynamic model of the plunger lift based on the real wellbore trajectory by starting from the flow law that accounts for the four stages of movement of the plunger. The model is then tested against five example wells, and it is shown that the accuracy level is higher than 90%. The well ‘switch’, optimized based on simulations based on such a model, is tested through on-site experiments. It is demonstrated that, compared with the original switch configuration, the average production of the sample well can be increased by about 15%.

Scholars have primarily pursued two methodological approaches. The former involves deriving pressure models or liquid loading models through mechanistic analysis to establish criteria for determining shut-in and open schedules. The second utilizes historical production data combined with simulation software to calculate specific shut-in and open durations. Nevertheless, both ways present critical challenges requiring immediate resolution. Mechanistic models necessitate extensive idealized assumptions, with key parameters often measured under specific production scenarios, rendering these models non-

universal and inadequate for practical operational requirements. Meanwhile, existing data-driven methodologies exhibit limited scope and depth in guiding plunger lift operations through real-time data integration, demonstrating applicability only under constrained production conditions. The systematic integration of plunger lift mechanistic modeling frameworks with real-time data acquisition systems offers an effective solution to these persistent limitations.

Current research advancements in plunger lift well cluster operations are summarized as follows:

Compared with single-well optimization, plunger lift well cluster operations require additional considerations of multi-well pressure interference and integrated production scheduling.

Production scheduling necessitates a comprehensive evaluation of constraints, including well productivity, pipeline transport capacity, and production allocation, to develop holistic operational strategies. Current methodologies predominantly cover wellhead pressure interference rather than inter-well reservoir interactions. However, existing research on wellhead interference is limited in scope, with most studies analyzing pipeline backpressure impacts from a single-well perspective rather than investigating cluster-level dynamics. This gap highlights a critical research direction for enhancing plunger lift efficiency in well clusters: developing systematic frameworks that address multi-well interference mechanisms and enable coordinated production scheduling across entire well clusters.

In the study of well group pressure interference, Liu Mengpeng [10] investigated the impact of backpressure on individual wells through theoretical derivations of wellhead choke valve throttling, while Wang Lin proposed methods to reduce pipeline pressure by analyzing both the effects of branch line delivery pressure on gas wells and pipeline liquid loading [11].

In well cluster production scheduling, the optimization process holistically considers valve configurations, individual well operations, and pipeline status as decision variables, with production rates, pressures, and temperatures acting as constraints. This approach better addresses the downstream demand opposed to traditional plunger lift operations focused solely on well shut-in/open cycles.

In terms of scheduling optimization, E. Liu established steady-state pipeline network optimization models targeting minimal energy consumption or maximal economic benefits [12].

ENBIN LIU [13] developed transient optimization models for natural gas pipelines, considering compressor operations and terminal conditions and incorporating pressure regulation and flow restriction measures.

Md. Shaheen Shah [14] implemented nodal analysis to identify system resistances from the reservoir to separator using F.A.S.T. Virtu Well software v3.3.1.31, demonstrating production enhancement through wellhead pressure reduction.

Arnaud Hoffmann [15] formulated optimization models focusing on valve configurations, transforming MINLP problems into MILP via SOS2 piecewise linear modeling and solving them with commercial solvers.

Zheng Daoming [16] adjusted operational parameters based on casing pressure and load factors, whereas Liu Huamin [17] classified wells by productivity for customized strategies. Current methodologies exhibit limitations: excessive reliance on empirical field experience, exclusion of critical constraints (e.g., wellhead pressure-flowrate relationships, plunger velocity-pressure differentials), and lack of multi-well collaborative frameworks. Incorporating these factors to develop collaborative multi-well cluster optimization models would provide indispensable guidance for plunger lift operations.

Li Junliang et al. [18] discussed the mutual interference between the surface gathering pipelines and the oil wells and established an optimized gas distribution model for the

gas lift well group to maximize the liquid production output. According to the principle of nodal analysis, the inflow curves of each node in the well pattern were determined, so as to obtain the relationship between the gas injection volume and the liquid production output. On this basis, a genetic algorithm was utilized to solve the model. Taking a gas lift well group with six wells as an example, the reasonable total gas injection volume was determined, and then the optimized gas distribution for a single well was conducted.

WANG Q R, WANG J X, LI M W, et al. [19] focused on the main drainage gas recovery processes in the Changning block, analyzed factors influencing their application, and proposed a regime optimization method to enhance process effectiveness based on real-time monitoring and collection of shale gas well production data via an intelligent management platform. They established a shale horizontal well plunger gas lift regime optimization method by combining the plunger motion model with time series neural networks and multi-objective optimization genetic algorithms.

DU L, WANG C K. [20] systematically analyzed the principle of plunger gas lift drainage gas recovery technology, factors affecting its effectiveness, working regime optimization, and applicable conditions. Their research is significant for guiding the application of this technology and the efficient development of natural gas, particularly in addressing liquid loading issues in gas wells with weak liquid-carrying capacity.

ZHANG C, JIN D Q, LI S H, et al. [21] addressed liquid loading in low-pressure, low-yield gas wells and limitations of conventional plunger processes in Sulige Gas Field by developing a new intelligent plunger gas lift system. They enhanced control systems, optimized production regimes, and analyzed field effects to assess the system's applicability and economy, establishing a plunger gas lift process and optimization model tailored to the gas field's production traits.

The core content of the research on the production scheduling of the plunger gas lift on the platform is the research on the scheduling algorithm. Currently, in the research work on algorithms in the field of production scheduling, there are several problems: first, the existing theories are not combined with the actual situation on sites; second, the scheduling optimization algorithms are rarely applied in the field of production scheduling, especially in the application of the plunger gas lift process. Because of this, this paper conducts research on model and algorithm preparation and application, proposes a multi-objective collaborative optimization method that integrates a mechanism model and a data-driven multi-objective collaborative optimization method, solves the optimal switching system that considers inter-well pressure crosstalk, pipeline backpressure, and production stability through the particle swarm algorithm, and realizes real-time scheduling control based on localized edge computing architecture.

2. Materials and Methods

2.1. Materials

Using the XXX Platform as a case study, the oilfield operates four plunger lift wells, with specific parameters detailed in Table 1. This includes basic information of each well, fluid properties, and production parameters.

Table 1. Base data of four wells on XXX Platform.

Well ID		Well 1	Well 2	Well 3	Well 4
Formation Pressure *	MPa	10	10	10	10
Gas Productivity Index *	$10^4 \text{ m}^3/\text{d}/\text{MPa}^2$	0.01043	0.0263	0.0133	0.029
Liquid Productivity Index/WGR *	$\text{m}^3/\text{d}/\text{MPa}$	0.0761	0.2849	0.1818	0.18

Table 1. *Cont.*

Well ID		Well 1	Well 2	Well 3	Well 4
Tubing Inner Diameter	mm	50.6	50.6	50.6	50.6
Tubing Depth	m	3500	3500	3500	3500
Casing Inner Diameter	mm	114.3	114.3	114.3	114.3
Reservoir Temperature	°C	100	100	100	100
Surface Temperature	°C	15	15	15	15
Formation Water Specific Gravity	-	1.02	1.02	1.02	1.02
Gas Specific Gravity	-	0.7	0.7	0.7	0.7
Water Production	m ³ /d	0.5	1	1	1
Gas Production	10 ⁴ m ³ /d	0.928	1.525	1.063	2.265
Plunger Mass	kg	3.3	3.3	3.3	3.3
Anchor Depth(TVD)	m	3300/3250	3200/3220	3250/3280	3280/3340
Current Operating Schedule	min	Afterflow 25 min Close 60 min	Afterflow 10 min Close 55 min	Afterflow 50 min Close 65 min	Afterflow 230 min Close 60 min
Plunger Rise Time	min	150	90	90	120
Casing Pressure Before Opening	MPa	2.79	4.36	2.89	3.7
Casing Pressure Before Shut-in	MPa	2.35	3.7	2.69	3.39
Tubing Pressure Before Opening	MPa	2.48	3.62	2.53	3.63
Tubing Pressure Before Shut-in	MPa	1.4	1.28	1.22	1.83
Pipeline Delivery Pressure	MPa	1.59	1.6	1.6	1.6

*: (1) Formation pressure calculation. Depending on the real-time casing data, the bottom well flow pressure is calculated by the static column gradient method, and then the formation pressure is estimated. Formation pressure = bottom hole flow pressure by average overhead casing pressure (hydrostatic gradient method) + 10MPa (production pressure difference, based on empirical assumptions). The assumption of pressure will not affect the optimization direction of well output, and it is also consistent with the well under the current system. Therefore, it is a practical and feasible method. It has been optimized through a plunger gas lift single well and verified through on-site testing (Plunger Gas Lift Design and Optimization Software v2.2.0, Hubei, China). (2) Calculation of liquid production. The liquid production volume is calculated based on the historical gas–liquid ratio and gas production rate. (3) Calculation of the liquid production index and the gas production index. The gas production index is obtained depending on the fitting of formation pressure and bottom well flow pressure (gas production). In the same way, the liquid production index is obtained according to the formation pressure and bottom well flow pressure (liquid production).

2.2. Methods

2.2.1. Mathematical Modeling

Optimizing staggered operating cycles across plunger lift well clusters presents combinatorial complexity. For any given cluster, multiple scheduling permutations exist even when individual well schedules are attached. Each permutation yields distinct performance outcomes, with one optimal solution per configuration. Comparing these configuration-specific optima reveals the globally optimal schedule, which requires a two-layer optimization framework. This dual-layer approach substantially exceeds the complexity of conventional continuous gas allocation optimization for well clusters.

The optimization objectives (fitness calculation methods for particle swarm optimization) are defined as follows:

- (1) Objective 1—Maximize daily gas production: Calculate the cumulative gas production during 24 h or the maximum operational cycle (if exceeding 24 h), then turn it into

the equivalent daily production rate using temporal scaling. This converted value constitutes the first fitness component.

- (2) Objective 2—Stabilize production with minimized fluctuations: Determine the mean gas production rate over the operative period. Divide the period into n intervals and compute the absolute deviation between each interval's average rate and the global mean. The fitness component derives from minimizing the average deviation across all intervals: fitness component 2 = $1/(\text{average deviation}/\text{minimum observed deviation})$.
- (3) Multi-objective formulation: Implement weighted aggregation using parameter α : composite fitness = $\alpha \times (\text{total gas production}/\text{maximum achievable production}) + (1 - \alpha) \times (1/(\text{average deviation}/\text{minimum deviation}))$.

The maximum production can be calculated based on the single-well model to determine the optimal production rate for each well (without considering the interference of other wells) and then added together to obtain the total. It is possible to set a relatively large, expected output value and use the same value when calculating fitness. The larger the fitness, the better the overall coordinated optimization plan. Therefore, it is also possible to give a larger expected output value.

2.2.2. Model Establishment and Solution Method

① For a given well under a specific operational schedule, the stochastic scheduling of daily operations exhibits random initiation time windows before well opening, constrained within the periodic shut-in duration, as illustrated in Figure 1 below.

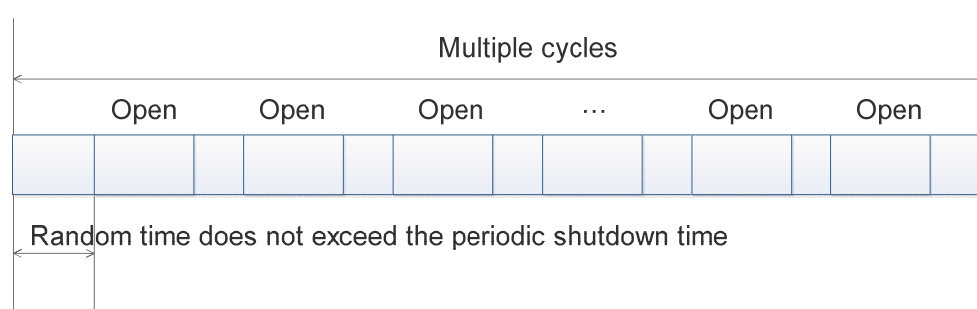


Figure 1. Production schematic of random daily scheduling for a single well.

② Multi-Well Optimization Scheduling.

Building upon the stochastic scheduling methodology for individual wells, the platform-level multi-well systems generate optimized daily scheduling configurations through randomized operational sequencing, with resultant patterns illustrated in Figure 2.

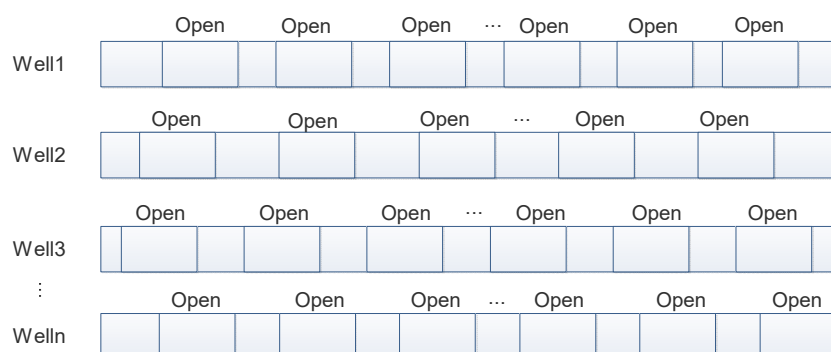


Figure 2. Stochastic multi-well scheduling configuration.

The generated platform-level multi-well optimization scheduling configurations represent individual particles within the search space, with subsequent optimization conducted via particle swarm optimization algorithm iterations following the workflow depicted in Figure 3.

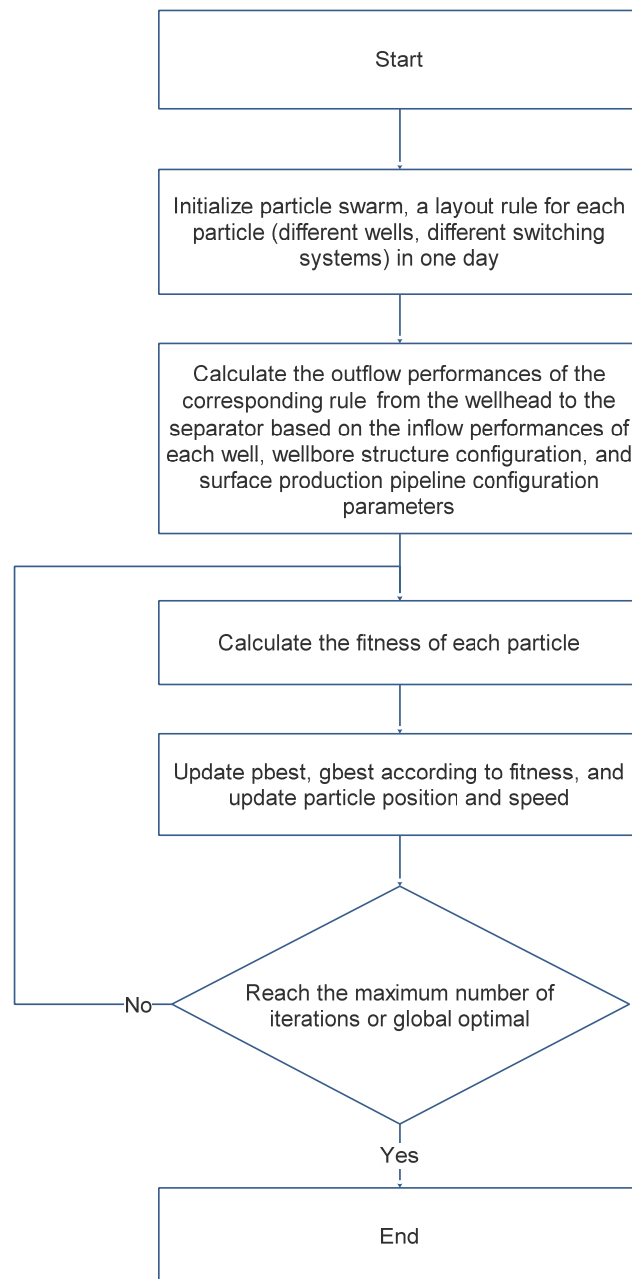


Figure 3. Particle swarm optimization framework for platform plunger lift operations.

The most critical computational component lies in determining the fitness value of each particle. The methodology for calculating particle fitness operates as follows:

For any given platform optimization scheduling scheme, each operational adjustment to individual wells constitutes a distinct platform configuration, as illustrated in Figure 4. This necessitates calculating gas and liquid production rates through the following computational process.

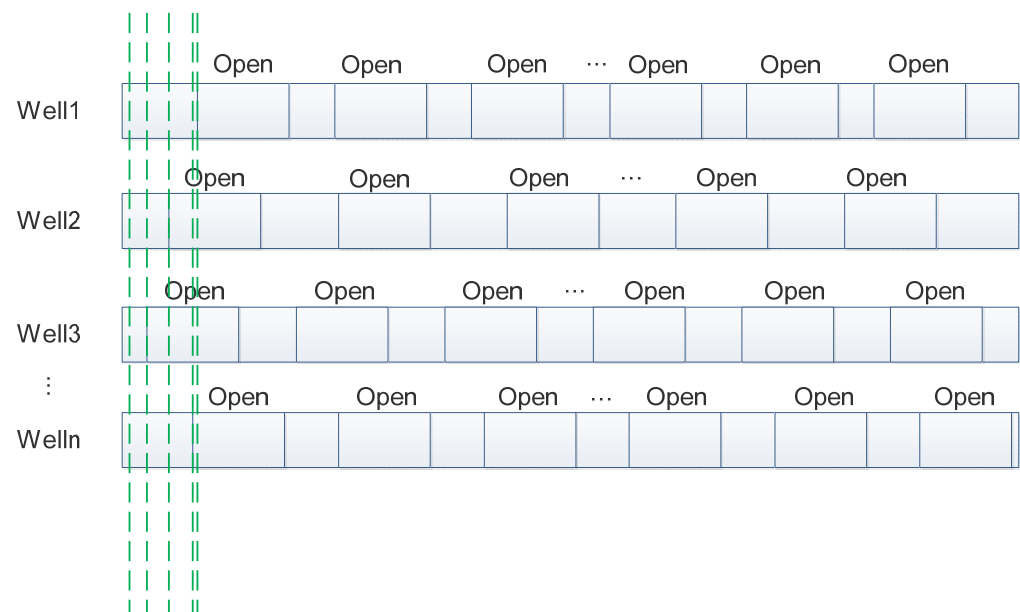


Figure 4. Platform-wide optimized scheduling solution.

Suppose there is a plunger gas lift well production system consisting of wells and one separator, as shown in Figure 5.

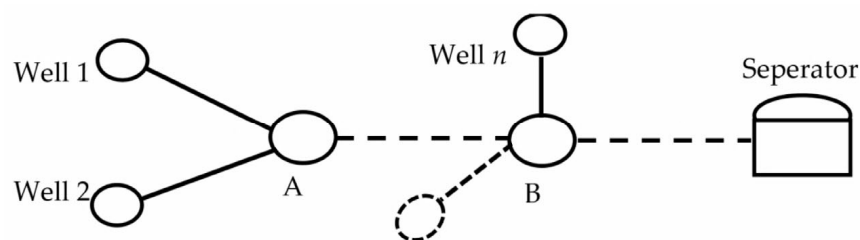


Figure 5. Plunger lift well production system configuration.

When considering surface gathering pipelines, inter-well interference exists between oil wells. The separator pressure remains constant as a boundary condition. When pressure fluctuations occur in surface gathering pipelines, they will affect the gas (oil) production rates of the wells. This influence relationship can be represented by the characteristic curves between wellhead pressure and gas (liquid) production rates under different plunger shut-in/open schedules, as shown in Figure 6. According to the principles of nodal analysis, this curve constitutes the inflow performance curve at the wellhead node during plunger lift operations.

(1) Construct inflow performance curves for each well at the wellhead node under different plunger shut-in/open schedules.

(2) For any given solution (Schedule₁, Schedule₂, ..., Schedule_n) corresponding to specific well operations, derive the wellhead inflow curves of each plunger lift well through interpolation-based methods. The fluids at Node A originate from Well 1 and Well 2, the plunger schedules of which differ in staggered timing configurations, resulting in distinct flow interactions. For Well 1, select multiple points along its inflow performance curve, calculate the pressure–flow relationships up to Node A using multiphase flow theory, and generate Well 1's nodal inflow curve relative to Node A. This process is replicated for Well 2 to establish its corresponding nodal influence curve, as demonstrated in Figure 7.

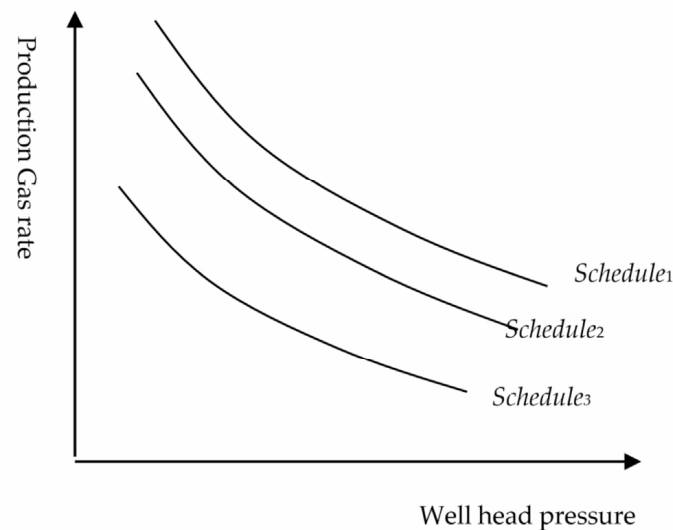


Figure 6. Wellhead inflow performance curve under open-state for the i -th plunger lift well.

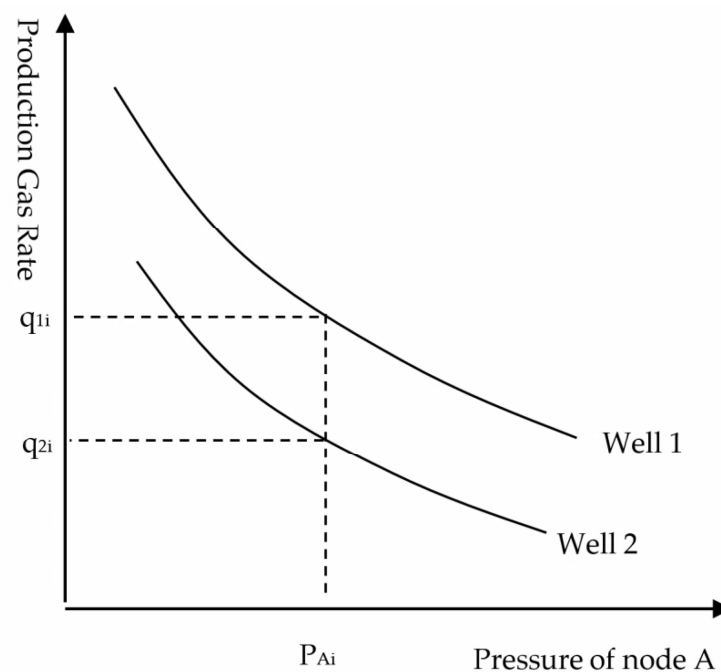


Figure 7. Nodal inflow performance curves of Well 1 and Well 2 at Node A.

(3) When the pressure at Node A is P_{Ai} , the gas (liquid) flow rates from Well 1 and Well 2 into Node A can be determined as q_{1i} and q_{2i} , respectively, based on the graphical analysis. The total gas flow rate at Node A is calculated as $q_{Ai} = q_{1i} + q_{2i}$. By iterating this process, a series of data points $(P_{A1}, q_{A1}), (P_{A2}, q_{A2}), \dots, (P_{Am}, q_{Am})$ are obtained, thereby constructing the inflow performance curve for Node A, as illustrated in Figure 8.

(4) Building upon the aforementioned methodology, inflow performance curves for all network nodes and the separator node can be systematically derived, as depicted in Figure 9. Given the predetermined separator pressure P_s , the total gas (liquid) Q is determined from the separator's inflow performance curve, which constitutes the fitness metric of the evaluated scheduling solution. This metric inherently reflects the operational variance caused by asynchronous scheduling configurations (i.e., staggered plunger cycle timing) across the well cluster.

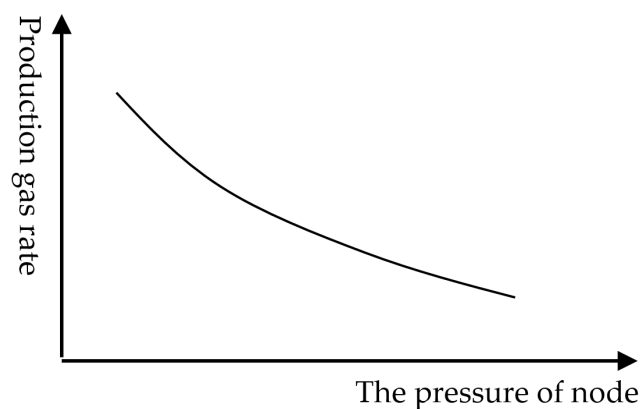


Figure 8. Composite inflow performance curve at Node A.

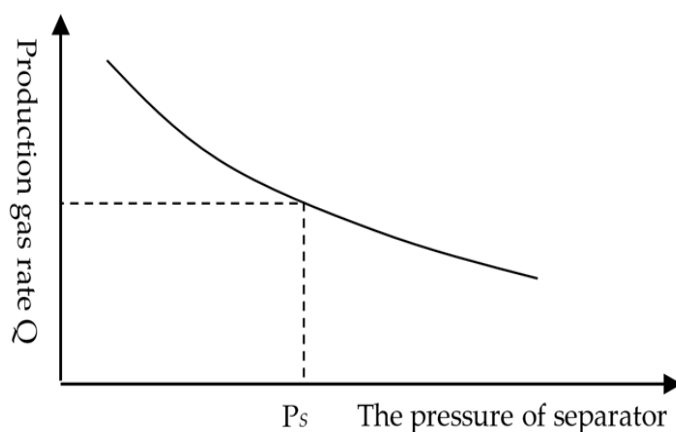


Figure 9. Separator inflow performance curve.

3. Results

3.1. Gas Production Rates Under Different Well Schedules

The single-well optimization model was applied to evaluate various operational schedules, with optimization results presented in Table 2. The data indicate limited individual optimization potential for standalone wells. Platform-level optimization involves interpolating production rates across different shut-in/open schedules and implementing coordinated scheduling to minimize backpressure while maximizing total gas production.

Table 2. Simulated production scenarios under different schedules for XXX Platform wells.

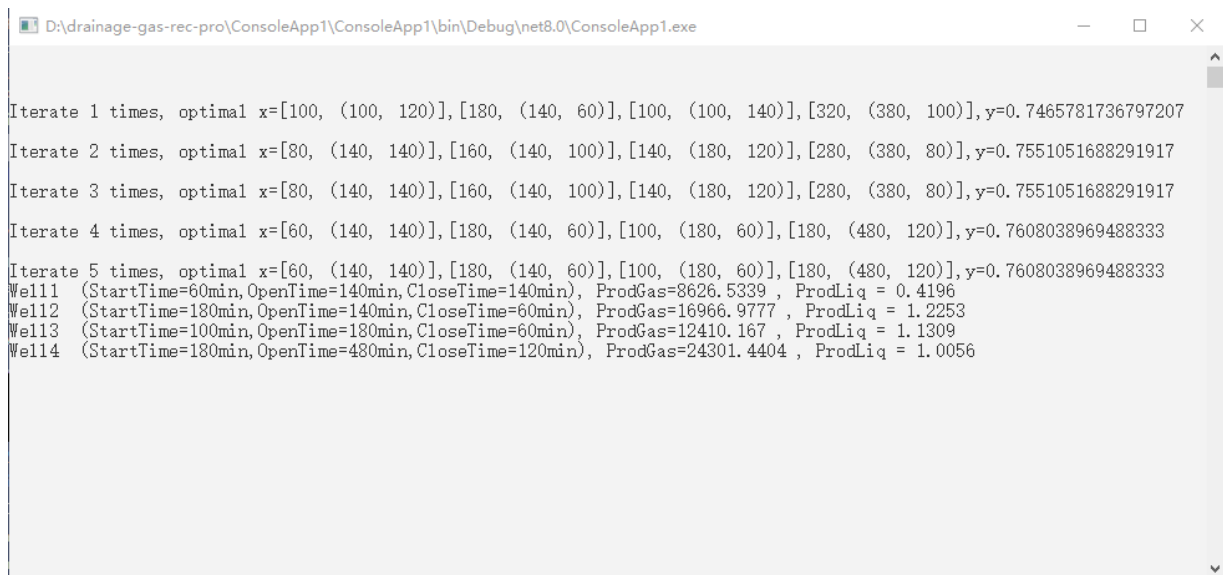
Well ID	Cycle Time (min)	Opening Duration (min)	Shut-in Duration (min)	Gas Production Rate ($10^4 \text{ m}^3/\text{d}$)	Liquid Production Rate (m^3/d)	Notes
Well 1	235	175	60	9272	0.53	Current system
	235	155	80	9355	0.53	
	235	135	100	9763	0.55	
	235	115	120	9054	0.51	
	215	155	60	9071	0.52	
	215	135	80	9175	0.52	
	215	115	100	9247	0.52	
	195	135	60	9175	0.52	
	195	115	80	9116	0.52	
	195	95	100	9004	0.51	

Table 2. Cont.

Well ID	Cycle Time (min)	Opening Duration (min)	Shut-in Duration (min)	Gas Production Rate (10 ⁴ m ³ /d)	Liquid Production Rate (m ³ /d)	Notes
Well 2	155	100	55	16761	1.2	Current system
	155	90	65	17,741	1.26	
	155	70	85	16,729	1.17	
	175	120	55	15,066	1.07	
	175	100	75	17,392	1.23	
	175	80	95	16,366	1.14	
	135	80	55	16,028	1.14	
	135	70	65	17,658	1.25	
	135	60	75	17,108	1.2	
	195	140	55	15,664	1.11	
	195	120	75	17,462	1.24	
	195	100	95	16,562	1.16	
Well 3	205	140	65	10630	1.02	Current system
	205	120	85	10,587	1.02	
	205	130	75	10,680	1.03	
	205	150	55	10,666	1.02	
	205	100	105	10,338	0.98	
	225	160	65	10,617	1.02	
	225	140	85	10,577	1.01	
	225	120	105	10,358	0.98	
	185	120	65	10,774	1.04	
	185	100	85	10,584	1.01	
	185	80	105	10,302	0.98	
	165	100	65	10,805	1.05	
	145	80	65	10,806	1.05	
	125	60	65	10,777	1.04	
	160	80	80	10,628	1.02	
Well 4	410	350	60	24200	1.09	Current system
	410	330	80	24,130	1.09	
	410	300	110	23,454	1.05	
	460	400	60	24,002	1.08	
	460	380	80	24,010	1.09	
	460	360	100	23,668	1.07	
	360	300	60	24,497	1.12	
	360	280	80	24,209	1.1	
	360	260	100	23,725	1.07	

3.2. Platform-Wide Optimization

Simulation and optimization calculations were conducted based on the established collaborative platform optimization methodology, with the optimized scheduling results shown in Figures 10 and 11. As can be seen from the figures, the results demonstrate that through scheduling optimization, well production operations can be effectively staggered in time. This approach ensures steady gas production rates across the system, significantly reduces backpressure, enhances overall production output, and achieves the predefined optimization objectives. Comparing Figures 10 and 11, it can be seen from the results of different optimization iterations that both optimization results converge towards the same value, achieving the expected effect.



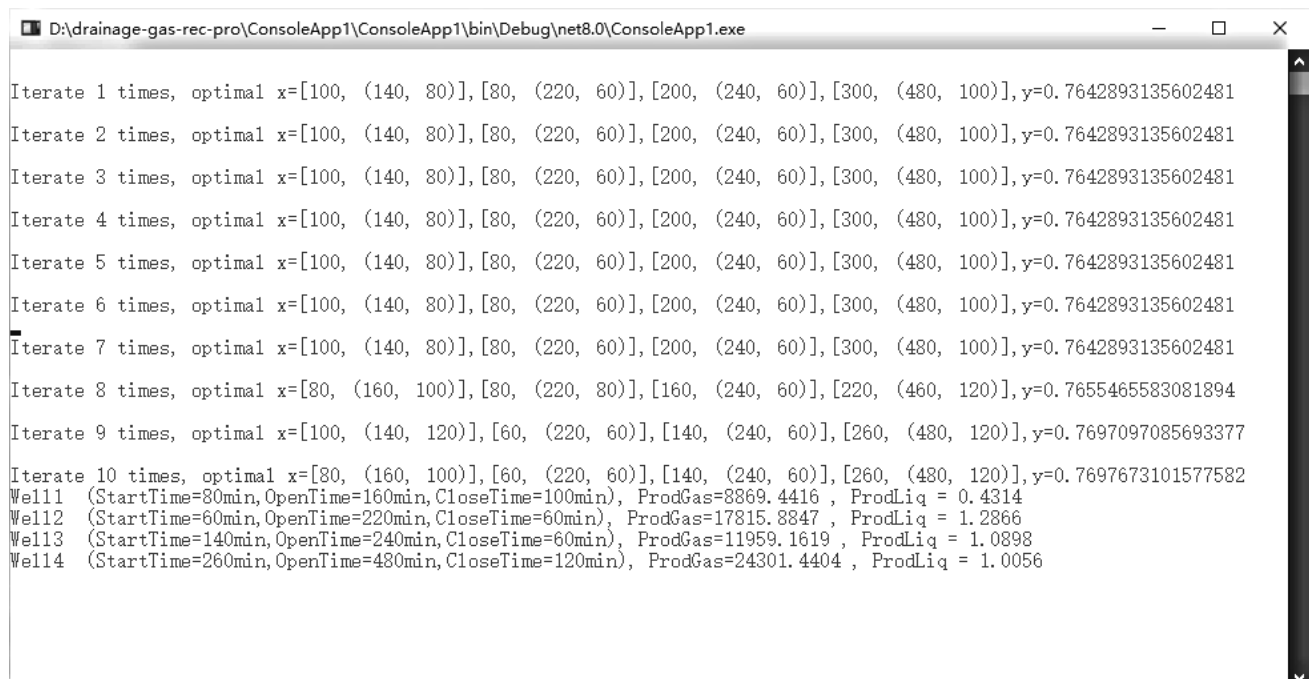
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D:\drainage-gas-rec-pro\ConsoleApp1\ConsoleApp1\bin\Debug\net8.0\ConsoleApp1.exe

Iterate 1 times, optimal x=[100, (100, 120)], [180, (140, 60)], [100, (100, 140)], [320, (380, 100)], y=0.7465781736797207
Iterate 2 times, optimal x=[80, (140, 140)], [160, (140, 100)], [140, (180, 120)], [280, (380, 80)], y=0.7551051688291917
Iterate 3 times, optimal x=[80, (140, 140)], [160, (140, 100)], [140, (180, 120)], [280, (380, 80)], y=0.7551051688291917
Iterate 4 times, optimal x=[60, (140, 140)], [180, (140, 60)], [100, (180, 60)], [180, (480, 120)], y=0.7608038969488333
Iterate 5 times, optimal x=[60, (140, 140)], [180, (140, 60)], [100, (180, 60)], [180, (480, 120)], y=0.7608038969488333
Well11 (StartTime=60min, OpenTime=140min, CloseTime=140min), ProdGas=8626.5339 , ProdLiq = 0.4196
Well12 (StartTime=180min, OpenTime=140min, CloseTime=60min), ProdGas=16966.9777 , ProdLiq = 1.2253
Well13 (StartTime=100min, OpenTime=180min, CloseTime=60min), ProdGas=12410.167 , ProdLiq = 1.1309
Well14 (StartTime=180min, OpenTime=480min, CloseTime=120min), ProdGas=24301.4404 , ProdLiq = 1.0056

```

Figure 10. Example 1 of optimized plunger lift scheduling configuration for platform operations.



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D:\drainage-gas-rec-pro\ConsoleApp1\ConsoleApp1\bin\Debug\net8.0\ConsoleApp1.exe

Iterate 1 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 2 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 3 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 4 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 5 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 6 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 7 times, optimal x=[100, (140, 80)], [80, (220, 60)], [200, (240, 60)], [300, (480, 100)], y=0.7642893135602481
Iterate 8 times, optimal x=[80, (160, 100)], [80, (220, 80)], [160, (240, 60)], [220, (460, 120)], y=0.7655465583081894
Iterate 9 times, optimal x=[100, (140, 120)], [60, (220, 60)], [140, (240, 60)], [260, (480, 120)], y=0.7697097085693377
Iterate 10 times, optimal x=[80, (160, 100)], [60, (220, 60)], [140, (240, 60)], [260, (480, 120)], y=0.7697673101577582
Well11 (StartTime=80min, OpenTime=160min, CloseTime=100min), ProdGas=8869.4416 , ProdLiq = 0.4314
Well12 (StartTime=60min, OpenTime=220min, CloseTime=60min), ProdGas=17815.8847 , ProdLiq = 1.2866
Well13 (StartTime=140min, OpenTime=240min, CloseTime=60min), ProdGas=11959.1619 , ProdLiq = 1.0898
Well14 (StartTime=260min, OpenTime=480min, CloseTime=120min), ProdGas=24301.4404 , ProdLiq = 1.0056

```

Figure 11. Example 2 of optimized plunger lift scheduling configuration for platform operations.

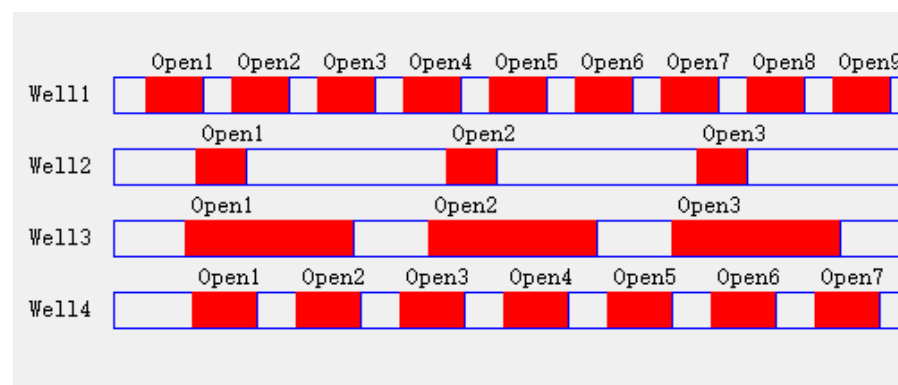
4. Discussion

Before optimization, the production of each well and the total production of the platform were calculated. During simulation correction, the production of each well (Table 2) and the total production of the platform were calculated and compared with the production of each well and the total production after optimization, as shown in Table 3. It can be seen that the total output of the platform has increased after optimization, and the production increases from $6.086 \times 10^4 \text{ m}^3/\text{d}$ to $6.231 \times 10^4 \text{ m}^3/\text{d}$; the optimization is effective. The method presented in this article is feasible, the software developed is reliable, and it can solve the optimization problem of multiple wells on the platform.

Table 3. Comparison of production results before and after optimization.

	On-Site Production of Wells (m ³ /d)	The Output of the Software Correction Simulation (m ³ /d)	Output After Optimizing the Work Schedule (m ³ /d)
Well 1	8626.53	9272	9280
Well 2	16,966.98	16,761	15,250
Well 3	12,410.17	10,630	10,630
Well 4	24,301.44	24,200	22,650
Total	62,305.12	60,863	57,810

The key to solving system optimization problems mainly lies in two aspects: (1) relying on an accurate description of the single-well model. The single-well model in this article is a well-tested mechanism model, which provides an important foundation for platform multi-well optimization; (2) the correct establishment of a multi-well optimization mathematical model, followed by the correct solution through the particle swarm optimization algorithm. By optimizing, the switch system of different wells and the staggered switch time with other wells can be obtained, and finally, the production system layout of each well is formed, as shown in Figure 12.

**Figure 12.** Optimized plunger lift scheduling configuration for platform operations.

Because each well on the platform mainly produces gas, and the total gas production of the platform is not very large, the change in gas production has little effect on the back pressure of each well. Therefore, the open and shut-in schedule between wells can be staggered to meet the requirements, and no further special instructions will be made here.

5. Conclusions

This paper proposes an intelligent collaborative optimization method for multi-well plunger lift operations on production platforms. By integrating dynamic optimization models with intelligent scheduling algorithms, the method achieves inter-well coordination and production maximization. Simulation results verify the method's feasibility, demonstrating that coordinated scheduling enables time-staggered production across platform wells. This effectively reduces backpressure, maintains stable system gas production, improves overall oilfield production efficiency, and exhibits promising potential for practical engineering applications.

This paper proposes an intelligent collaborative optimization method for multi-well plunger lift operations on production platforms.

Key outcomes include the following: (1) Quantifiable improvements in the XXX Platform case, with increased total gas production, reduced fluctuations, and lower back-

pressure, validating enhanced efficiency. (2) A novel hybrid framework merging mechanistic modeling and data-driven optimization, overcoming single-well and static model constraints. (3) Practical scalability via localized edge computing, supporting real-time scheduling critical for marine and shale gas scenarios, enabling upgrades from isolated control to platform-wide collaboration.

Future work will refine the model to include subsurface interactions and validate it in larger well clusters, expanding industrial applicability.

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Data Availability Statement: The raw/processed data required to reproduce these findings cannot be shared at this time as the data also form part of an ongoing study.

Conflicts of Interest: Authors Zhi Yang, Qingrong Wang, Yunfu Wang, and Tang Tang were employed by the PetroChina Southwest Oil and Gas Field Company. Author Chencheng Huang was employed by the Sichuan Shale Gas Exploration and Development Co., Ltd. Author Tianbao He was employed by the ShuNan Gas Mine and Southwest Oil and Gas Field Company. Author Wei Luo was employed by the company’s Key Laboratory of Drilling and Production Engineering for Oil and Gas. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Kannan, S.K.; Boyer, M.; Yuan, G.; Lu, H.; Fai-Yengo, G. Modeling and Optimization of Gas-Assisted Plunger Lift GAPL by a Transient Simulator: A Case Study of a Permian Shale Well. In Proceedings of the SPE Eastern Regional Meeting, Charleston, WV, USA, 15–17 October 2019; SPE: Richardson, TX, USA, 2019. [\[CrossRef\]](#)
2. Hashmi, G.M.; Hasan, A.R.; Kabir, C.S. Simplified Modeling of Plunger-Lift Assisted Production in Gas Wells. *J. Nat. Gas Sci. Eng.* **2018**, *52*, 454–460. [\[CrossRef\]](#)
3. Mei, H.P.; Li, K.; Hao, J.; Gao, Y.; Wang, Q. Optimization of Plunger Lift System and Intelligent Operation in Gas Fields. *Petrochem. Ind. Appl.* **2020**, *39*, 111–113.
4. Wang, X.H.; He, T.H.; Tu, L.H.; Ai, B.B.; Zhang, L.; Wang, Y.H. Optimization of Production Systems for Plunger-Lift-Assisted Gas Wells. *Inn. Mong. Petrochem. Ind.* **2019**, *45*, 55–58. [\[CrossRef\]](#)
5. Wang, H.; Wu, Z.; Tang, T.; Li, Q.; Jin, S.; Sun, Y.; Liu, H. Research on Production Pattern Optimization of Intermittent Wells. *Chem. Technol. Fuels Oils* **2021**, *57*, 133–142. [\[CrossRef\]](#)
6. Nandola, N.N.; Kaisare, N.S.; Gupta, A. Online Optimization for a Plunger Lift Process in Shale Gas Wells. *Comput. Chem. Eng.* **2018**, *108*, 89–97. [\[CrossRef\]](#)
7. Lin, P.; Bai, P.; Wang, Y.J.; Wang, Y.X.; Wang, X.; Wang, P.H. Research on Intelligent Optimization of Plunger-Lift Wells. *Inn. Mong. Petrochem. Ind.* **2021**, *47*, 46–49. [\[CrossRef\]](#)
8. Liu, P.; Chen, M.; He, Z.; Luo, W.; Miao, S. Study on a Gas Plunger Lift Model for Shale Gas Wells and Its Effective Application. *FDMP-Fluid Dyn. Mater. Process.* **2022**, *18*, 933–955. [\[CrossRef\]](#)
9. Miao, S.; Liu, X.; Feng, X.; Shi, H.; Luo, W.; Liu, P. A Dynamic Plunger Lift Model for Shale Gas Wells. *FDMP-Fluid Dyn. Mater. Process.* **2023**, *19*, 1735–1751. [\[CrossRef\]](#)
10. Liu, M.P.; Gao, X.L.; Li, D.L.; Hong, L.; Huang, S. Study on Backpressure Effects in Plunger-Lift Drainage Gas Recovery Technology. *Inn. Mong. Petrochem. Ind.* **2021**, *47*, 75–77. [\[CrossRef\]](#)
11. Wang, L.; Yang, S.Z.; Jin, J.S.; Zhang, Z.X.; Hao, S. Analysis of Intermittent Gas Production Constraints in Low-Pressure Gas Wells and Countermeasures. *Inn. Mong. Petrochem. Ind.* **2018**, *44*, 117–120. [\[CrossRef\]](#)

12. Liu, E.B.; Li, C.J.; Yang, Y. Optimal Energy Consumption Analysis of Natural Gas Pipeline. *Sci. World J.* **2014**, *2014*, 506138. [[CrossRef](#)] [[PubMed](#)]
13. Liu, E.B.; Kuang, J.C.; Peng, S.B.; Liu, Y.T. Transient Operation Optimization Technology of Gas Transmission Pipeline: A Case Study of West-East Gas Transmission Pipeline. *IEEE Access* **2019**, *7*, 112131–112141. [[CrossRef](#)]
14. Shah, S.; Khan, H.R.; Rahman, A.; Butt, S. Production Optimization in Well-6 of Habiganj Gas Field, Bangladesh: A Prospective Application of Nodal Analysis Approach. *J. Pet. Explor. Prod. Technol.* **2020**, *10*, 3557–3568. [[CrossRef](#)]
15. Hoffmann, A. Short-Term Model-Based Production Optimization for a Gas Field in North Africa. *J. Model. Optim.* **2018**, *10*, 65–80. [[CrossRef](#)]
16. Zheng, D.M.; He, S.H.; Xu, W.J.; Zhang, X.J. Intelligent Plunger-Lift Technology in Daniudi Gas Field. *Well Test.* **2020**, *29*, 19–26. [[CrossRef](#)]
17. Liu, H.M.; Li, M.; Liu, Q.P.; Zhang, L.Y. Research and Application of Plunger-Lift Technology in Fuling Shale Gas Field. *Pet. Drill. Tech.* **2020**, *48*, 102–107. [[CrossRef](#)]
18. Li, J.L.; Liao, R.Q.; Luo, W.; Han, Y. Study on Optimal Gas Distribution for Continuous Gas Lift Well Groups. *J. Pet. Gas* **2016**, *38*, 8. [[CrossRef](#)]
19. Wang, Q.R.; Wang, J.X.; Li, M.W.; Yu, F.; Cai, D.G.; Zeng, L.J. Influencing Factors and Regime Optimization Methods of Plunger Technology in Shale Gas Wells. *J. Nat. Gas Technol. Econ.* **2023**, *17*, 36–41.
20. Du, L.; Wang, C.K. Research on Plunger Gas Lift Technology for Water Drainage and Gas Production. *Liaoning Chem. Ind.* **2022**, *51*, 860–862. [[CrossRef](#)]
21. Zhang, C.; Jin, D.Q.; Li, S.H.; Zhang, J.Z. Application Research on New Plunger Gas Lift System in Sulige Gas Field. *Drill. Prod. Technol.* **2017**, *40*, 74–76+10. [[CrossRef](#)]

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