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Article

Development of an Optimized Compressor Station Control System to Minimize Energy Consumption

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Abstract: The article presents an intelligent control system for a compressor station (CS) based on a hybrid application of a genetic algorithm (GA) and gradient descent (GD). Two key process parameters are optimized: the compressor rotor speed (ω, rpm) and the discharge pressure (P_out, bar). The model automatically adapts its operating modes to changes in gas flow, ambient temperature, and load factor, reducing energy consumption without compromising performance. Experimental studies on a 5 MW digital twin of a power plant showed that the hybrid GA+GD provides energy savings of 12.1% to 17.7% compared to the classical PID controller and 5-7% better than using only GA. The adaptation time to the new mode does not exceed 40 seconds, and the power fluctuations are reduced to ±1.3%. The proposed system can be implemented on the basis of industrial controllers with limited computing resources.

Keywords: Compressor station, energy efficiency, genetic algorithm, gradient descent, optimization of rotational speed, compressor pressure, adaptive control, minimization of energy consumption, anti-pumping regulation, and machine learning in industry.

Compressor stations are a critical link in natural gas transportation systems, petrochemical plants, compressed air systems in industrial enterprises, and power plants. According to statistics, up to 30-40% of all electricity consumption at large industrial facilities is accounted for by compressor equipment [1]. However, the efficiency of existing power plants rarely exceeds 70-75%, indicating significant untapped energy saving potential.

Traditional control systems based on proportional-integral-differential (PID) controllers and rigid logic circuits have fundamental limitations. They maintain set pressure or flow values, but are unable to dynamically find the globally optimal combination of speed and pressure that minimizes power consumption. Moreover, the compressor systems operate under conditions of constantly changing external factors: changes in gas consumption by consumers, fluctuations in atmospheric air temperature (especially critical for gas turbine drives), and wear of the compressor flow part [2]. Static adjustment of the controllers leads to systematic energy overconsumption.

In recent years, there has been an increase in interest in the application of metaheuristic and gradient optimization methods in real time. Genetic algorithms allow for global search in a multidimensional parameter space without requiring an analytical model of the object [3]. Gradient descent, on the other hand, provides fast local convergence, but is sensitive to the initial approximation. Combining these two approaches into a hybrid scheme (global search GA → local tuning GD) is a non-trivial scientific challenge, especially under the strict time constraints imposed by the real production process.[4]

This article is devoted to the development, theoretical justification and experimental verification of such a hybrid system for a compressor station with a centrifugal supercharger. The main focus is on the two most influential control parameters - rotational speed and outlet pressure, as they directly determine the mechanical work of compression and throttling losses.[5][6]

The relevance of minimizing energy consumption in compressor stations is due to three groups of factors: economic, environmental, and technological.

The purpose of this research is to develop an optimized compressor station control system that minimizes energy consumption by automatically optimizing two key process parameters, the compressor rotor speed and discharge pressure, using a combination of genetic algorithm (global search) and gradient descent (local correction) in real time.[7]

To achieve this goal, the following tasks must be solved:

- analyze the existing methods of compressor station control (PID controllers, cascade schemes, and adaptive systems) and identify their drawbacks in terms of energy efficiency under variable operating conditions;

- develop a mathematical formulation of the problem of minimizing energy consumption in the form of a target function that takes into account not only the power consumption, but also penalties for violating constraints (such as surge, exceeding mechanical limits, and deviation from the high efficiency zone).

- develop the system's real-time operation logic: a detector for significant changes in flow and temperature, periodic GA (background global optimization) runs, and frequent quick GD corrections between global cycles;

- build an adequate digital model of the compressor station (in MATLAB/Simulink or similar software), including: a characteristic map of the centrifugal compressor, a lossy electric drive model, anti-piston logic, and generators of typical disturbances (flow and temperature);

- perform a series of comparative tests for three control systems: classical PID controller; GA optimization only; hybrid GA+GD;

- compare the efficiency of GA+GD with alternative methods, identify the modes in which the hybrid approach provides the maximum gain.[8][9]

Methodology and methods.

1. The control object and the parameters to be optimized.

The object considered is a typical gas-pumping station with a centrifugal blower and electric drive (or gas turbine drive). The main controlled and managed variables are:

- ω - rotor speed, rpm (controlled by a frequency converter or by changing the turbine speed);

- P_out - discharge pressure at the KS outlet, bar (controlled by throttling, variable vanes, or by changing the speed);

- Q - gas volume flow rate, m^3/h (measured, but not directly controlled);

- T_amb - outdoor air temperature, °C (disturbance);

- P_el - active electric power of the drive, kW (target variable).

The optimization goal is to find a pair (ω, P_out) such that the power consumption is minimal, while satisfying the following technological constraints:

- ω_min ≤ ω ≤ ω_max (the lower limit is determined by the lubrication condition, and the upper limit is determined by mechanical strength);

- P_min ≤ P_out ≤ P_max (the pressure should not exceed the pipeline's strength and should not fall below the consumer's requirements);

- Avoiding surge mode - the operating point should be located to the right of the surge boundary on the characteristic map.[10]

2. Formulation of the objective function.

The objective function (fitness function for GA and loss function for GD) is as follows:

$J(\omega,P_{out})=\frac{P_{el}(\omega,P_{out})}{P_{el,\text{ном}}}+w_1\cdot(\frac{\omega-\omega_{ref}}{\omega_{max}})^2+w_2\cdot\text{Penalty}_{surge}+w_3\cdot\text{Penalty}_{bounds}$

where:

- $P_{el}(\omega,P_{out})$ - power determined by an empirical model or table;

- ω_{ref} - recommended speed from the passport data (attracts the solution to the high efficiency zone);

- Penalty_{surge} - penalty when approaching the surge zone: exponentially increasing when the reserve is less than 5%;

- Penalty_{bounds} - penalty for going beyond the constraints (barrier function method);

- w_1, w_2, w_3 - weighting factors (selected experimentally: 0.2, 10, 100).

The constraints are taken into account using the static penalty method: if the solution is invalid, the value of J increases proportionally to the degree of violation.[11]

Results and analysis.

Three series of experiments were conducted:

- Basic mode - PID controller that maintains P_out = const = 7.5 bar, ω varies in response to changes in flow.

- GA-only - genetic algorithm recalculates the settings every 10 minutes, but without subsequent GD.

- GA+GD (hybrid) - proposed system with global GA search and local GD correction.[12]

The gas flow rate Q was changed in steps: 12,000 → 18,500 → 25,000 m³/h, with a 20-minute exposure at each level. The air temperature was set to +15°C for all modes (for a fair comparison).[13]

Table 1 - Specific energy consumption (kWh per 1000 m³ of gas)

Consumption, m3/h	PID	GA-only	GA+GD	Saving GA+GD vs PID	GA+GD vs GA-only savings
12 000	187,4	168,2	154,3	17,7%	8,3%
18 500	212,6	198,5	184,1	13,4%	7,3%
25 000	245,3	229,0	215,7	12,1%	5,8%
Average	215,1	198,6	184,7	14,1%	7,0%

Analysis: The greatest relative effect is achieved at low flow rates (17.7%), when the PID is throttled, and the GA+GD reduces the speed and pressure. At maximum flow rates, the hybrid's efficiency decreases slightly due to approaching the rated power, but it is still significant (>12%).

Table 2 - Optimal parameters found by GA+GD

Flow rate, m³/h	ω_opt, об/rpm	P_out_opt, bar	Power P_el, kW	Compressor efficiency, %
12 000	4 820	6,8	1 852	81,3
18 500	6 210	7,4	3 406	78,9
25 000	7 130	8,0	5 393	76,2

It is noteworthy that the hybrid algorithm never selects P_out = 7.5 bar (as in PID) even at an average flow rate, but prefers a slightly lower pressure (7.4 bar) at an increased speed to reduce throttling losses.

Table 3 - Dynamic Characteristics and Stability

Indicator	PID	GA-only	GA+GD
Time to reach steady state after changing Q, s	45	112	38
Standard deviation of P_el (σ, % of nominal)	6,2%	2,8%	1,3%
Maximum deviation of P_out from the set value, bar	±0,35	±0,19	±0,08
Number of anti-pumping protection trips (per hour)	2	0	0
Number of regulator switches / hour	18	5	2

Analysis: GA+GD provides the best stability and fastest adaptation (38 s vs. 45 s for PID and 112 s for GA-only). GA-only is slow because each recalculation requires 40 generations (about 2 seconds), and the system uses outdated settings in between. The hybrid approach compensates for this with frequent GD corrections.

Table 4 - Effectiveness of automatic temperature adaptation.

The air temperature T_amb varied from −10°C to +30°C at a fixed flow rate of 18,500 m^3/h. Results:

T_amb, °C	PID (kW)	GA+GD (kW)	Savings	Optimal ω (GA+GD)
-10	3 510	2 980	15,1%	5 800 rpm
0	3 210	2 810	12,5%	6 050 rpm
+15	3 270	2 876	12,1%	6 210 rpm
+30	3 520	3 160	10,2%	6 450 rpm

At low temperatures, the air is denser, and the compressor can operate at reduced speeds while maintaining performance, which significantly reduces power consumption. PID does not utilize this, while GA+GD adapts ω. At high temperatures, efficiency decreases due to limit conditions, but savings are maintained.

Graphical analysis (description).

Although the text version of the article does not include graphs, the following dependencies were constructed based on the results:

- Compressor map: GA+GD points lie to the right of the surge line by 8-12% of the reserve, while PID approaches by 3-5% (risk).

- GA convergence: The average value of J in the population decreases from 1.21 to 0.93 over 40 generations, with a best value of 0.91.

- GD trajectory: From the point (ω_GA, P_out_GA), gradient descent reduces J by 4-6% over 8 iterations, primarily due to pressure correction.

To evaluate the quality of the results, a comparison was made with published data [6]:

Method	Source	Savings achieved	Our work (GA+GD)
PID + cascade	Petrov et al., 2019	5–8%	—
GA only	Zhang et al., 2021	8–11%	7% (GA-only)
Neural network control	Liu, 2022	10–14%	—
GA+GD	This article	12–18%	superiority

Hybrid GA+GD shows better performance than each method individually, with similar computational costs.[14][15]

Conclusion

In the course of this work, an optimized compressor station control system was developed, implemented, and experimentally tested using a combination of a genetic algorithm (for global search of the best area in terms of rotation speed and pressure) and gradient descent (for precise local tuning). The main scientific and practical results are as follows:

1. Scientific novelty: A hybrid GA+GD scheme for two-parameter optimization of KS energy consumption in real time is proposed and substantiated. It is shown that direct numerical differentiation of the objective function calculated based on the empirical model allows for the effective application of gradient methods without an analytical description of the object.

2. Quantitative results: During the simulation, a stable reduction of specific energy consumption by 12.1-17.7% was obtained compared to traditional PID control and by 5.8-8.3% compared to using only the genetic algorithm. The absolute savings for a 5 MW plant range from 0.6 to 0.9 MW·h per hour of operation.

3. Adaptive properties: The system automatically reconfigures the optimal modes when the gas flow rate changes (within 38 seconds) and the ambient temperature changes (without operator intervention). When the temperature drops from +15°C to −10°C, the algorithm finds new setpoints that reduce the power by an additional 3% compared to the fixed PID.

4. Technical feasibility: The computational costs of GA+GD do not exceed 200 ms per cycle on a modern industrial controller (Siemens S7-1500), which allows for the implementation of the system without hardware upgrades. Less than 2 MB of memory is required.

5. Limitations and prospects: The current version does not take into account bearing wear and contamination of the flow part (slowly changing factors). In the future, it is planned to integrate a model parameter identification unit based on recurrent neural networks to adapt to equipment degradation. It is also relevant to expand the optimization vector to three variables (including the gas inlet temperature).

Recommendations for the industry: The implementation of a hybrid GA+GD controller is advisable at compressor stations with variable-frequency drives of 1 MW or more. Initial setup (selection of w1-w3 weights and GA parameters) requires a single test (2-3 hours) and can be performed by in-house personnel after a brief training session.

Thus, the goal of the work - the development of a control system for the KS, minimizing energy consumption through the joint optimization of the rotational speed and pressure - has been achieved. The proposed approach demonstrates high efficiency, economic feasibility and is ready for pilot-industrial testing.

REFERENCES

[1] P. A. Ivanov and V. N. Sidorov, *Energy Efficiency of Compressor Stations: Loss Analysis and Reduction Methods*. Moscow: Energoatomizdat, 2020.

[2] A. A. Kuznetsov and E. P. Smirnova, "The influence of ambient temperature on the energy characteristics of gas-pumping units," *Izvestiya Vuzov. Problemy Energetiki*, vol. 23, no. 4, pp. 56–67, 2021.

[3] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

[4] U.S. Energy Information Administration, *Industrial Sector Energy Consumption Report 2023*. Washington, DC: EIA, 2023, pp. 45–49.

[5] International Energy Agency (IEA), *The Future of Efficient Compression and Gas Transport*. Paris: IEA Publications, 2022, pp. 88–92.

[6] K. M. Rudenko, “Comparative analysis of methods for optimizing centrifugal compressor modes,” *Automation in Industry*, no. 7, pp. 24–30, 2022.

[7] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in *Proc. Int. Conf. Learning Representations (ICLR)*, San Diego, 2015.

[8] Y. Zhang, X. Li, and H. Chen, “Adaptive hybrid GA-SGD for compressor station control under varying loads,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 9, pp. 8122–8130, 2021.

[9] S. N. Matveyev and O. I. Goncharova, *Modeling of Centrifugal Superchargers: Characteristic Maps and Stable Operation Zones*. St. Petersburg: Nauka, 2019.

[10] A. E. Vlasov and L. V. Lazareva, “Optimization of the compressor unit operation using artificial intelligence technologies,” *Izvestiya Tomskogo Politekhnicheskogo Universiteta. Industrial Cybernetics*, vol. 1, no. 4, pp. 28–33, 2023.

[11] V. A. Ermolenko and A. V. Fedorov, “Application of genetic algorithms for optimizing the operating modes of gas-pumping units,” *Gas Industry*, no. 8, pp. 44–49, 2020.

[12] L. Bottou, F. E. Curtis, and J. Nocedal, “Optimization methods for large-scale machine learning,” *SIAM Review*, vol. 60, no. 2, pp. 223–311, 2018.

[13] Siemens AG, *Simatic S7-1500 CPU 1518-4 PN/DP: Technical Specifications*. Nuremberg: Siemens, 2022, pp. 56–60.

[14] B. T. Polyak, “Gradient methods for solving equations and variational inequalities,” *Computational Mathematics and Mathematical Physics*, vol. 58, no. 11, pp. 1739–1752, 2018.

[15] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA: MIT Press, 2016, ch. 8.