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Research on Low Nitrogen Combustion Strategies For Integrated Information Control and Business of Power Plants in China

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Abstract

This research examines the intelligent management strategy of the power plant's de-nitration system in order to address issues including the insufficient assessment of the intake NOx content and significant nonlinearity and inertia. To address the lag issue in the measurement of nitrogen oxide content at the intake port, a worldwide measurement calibration model is created. This model has a lower R^2 and RMSE than the single regression prediction model. The MATLAB Simulink program is used to build the de-nitration system simulation platform, and the intelligent control approach is researched. According to the simulation results, intelligent control reduces the variation in output NOx concentration by 63.7%, whereas multi-model predictive control without inlet NOx correction reduces it by 40.6%.

Keywords: Power Plant, Low Nitrogen Combustion, Optimize No_x Pollution Reduction, Artificial Intelligence, Flexible Control.

Introduction

Nitrogen oxide (NOx) emissions, primarily from coal-fired power generation, pose significant environmental and health concerns globally. Countries like Japan, Germany, the United States, and China have established stringent emission standards to combat these effects, including acid rain and respiratory health issues. China has adopted Selective Non-Catalytic Reduction (SNCR)/Selective Catalytic Reduction (SCR) technologies in power plant units to balance cost-efficiency and effectiveness. However, this transition has highlighted the need for more precise control mechanisms within these technologies. Nitrogen oxides can cause environmental pollution, endanger human health, and cause 200-300 times the greenhouse effect of other carbon dioxide, sulfur dioxide, etc., and destroy the ozone layer.(Fang, 2006)

Developing advanced control techniques for power plant units is at the core of this research, aiming to effectively manage NOx emissions. This challenge necessitates a multidimensional approach, integrating environmental science, technology, and strategic decision-making.

Statistical environmental analysis plays a crucial role in understanding emission patterns and identifying key control variables. Economically, the focus is on ensuring effective and cost-efficient emission control strategies, balancing environmental obligations with financial viability. Information technology, particularly data analytics, is essential for real-time monitoring and decision-making, enhancing the precision and adaptability of emission control strategies.

9-2 Total Energy Consumption and Its Composition

Year	Total Energy Consumption (10 000 tce)	Proportion to Total Energy Consumption (%) Coal	Petroleum	Natural Gas	Primary Electricity and Other Energy
1978	57144	70.7	22.7	3.2	3.4
1980	60275	72.2	20.7	3.1	4.0
1985	76682	75.8	17.1	2.2	4.9
1990	98703	76.2	16.6	2.1	5.1
1991	103783	76.1	17.1	2.0	4.8
1992	109170	75.7	17.5	1.9	4.9
1993	115993	74.7	18.2	1.9	5.2
1994	122737	75.0	17.4	1.9	5.7
1995	131176	74.6	17.5	1.8	6.1
1996	135192	73.5	18.7	1.8	6.0
1997	135909	71.4	20.4	1.8	6.4
1998	136184	70.9	20.8	1.8	6.5
1999	140569	70.6	21.5	2.0	5.9
2000	146964	68.5	22.0	2.2	7.3
2001	155547	68.0	21.2	2.4	8.4
2002	169577	68.5	21.0	2.3	8.2
2003	197083	70.2	20.1	2.3	7.4
2004	230281	70.2	19.9	2.3	7.6
2005	261369	72.4	17.8	2.4	7.4
2006	286467	72.4	17.5	2.7	7.4
2007	311442	72.5	17.0	3.0	7.5
2008	320611	71.5	16.7	3.4	8.4
2009	336126	71.6	16.4	3.5	8.5
2010	360648	69.2	17.4	4.0	9.4
2011	387043	70.2	16.8	4.6	8.4
2012	402138	68.5	17.0	4.8	9.7
2013	416913	67.4	17.1	5.3	10.2
2014	428334	65.8	17.3	5.6	11.3
2015	434113	63.8	18.4	5.8	12.0
2016	441492	62.2	18.7	6.1	13.0
2017	455827	60.6	18.9	6.9	13.6
2018	471925	59.0	18.9	7.6	14.5
2019	487488	57.7	19.0	8.0	15.3
2020	498314	56.9	18.8	8.4	15.9
2021	524000	56.0	18.5	8.9	16.6

9-9 Energy Consumption by Sector (2020)

Sector	Total Energy Consumption (10 000 tce)	Coal (10 000 tons)	Coke (10 000 tons)	Crude Oil (10 000 tons)	Gasoline (10 000 tons)	Kerosene (10 000 tons)	Diesel Oil (10 000 tons)	Fuel Oil (10 000 tons)	Natural Gas (100 million cu.m)	Electricity (100 million kW·h)
Total Consumption	498314	404860	[illegible]	69477	12767	3352	14283	5365	3340	77620
Agriculture, Forestry, Animal Husbandry and Fishery	9263	2254	23		257	11	1497	1	1	1422
Industry	332625	390891	48272	69477	184	9	1026	3262	2304	52353
Mining	17451	17059	199	610	14	1	377	1	185	2566
Mining and Washing of Coal	8953	15886	11	0	3	1	148	0	19	903
Extraction of Petroleum and Natural Gas	3743	72		610	6		25	0	157	463
Mining and Processing of Ferrous Metal Ores	1723	205	170		1	0	35	0	0	447
Mining and Processing of Non-Ferrous Metal Ores	1093	85	4		1	0	17	1	1	329
Mining and Processing of Nonmetal Ores	1125	540	15		1	0	48	0	3	225
Professional and Support Activities for Mining	322	63		0	3		105	0	4	35
Mining of Other Ores	481	8					0			162
Manufacturing	279651	159830	47802	68866	152	8	602	3257	1509	39853
Processing of Food from Agricultural Products	4002	1577	16		5	0	12	1	30	842
Manufacture of Foods	2149	1639	16		4	0	5	0	26	334
Manufacture of Liquor, Beverages and Refined Tea	1199	497	4		2		3	0	15	175
Manufacture of Tobacco	183	5			0		1		1	51
Manufacture of Textile	6982	592	6		3	0	4	1	31	1650
Manufacture of Textile, Wearing Apparel and Accessories	854	49			3		2	0	12	225
Manufacture of Leather, Fur, Feather and Related Products and Footwear	483	18			2		1	0	3	141
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	1007	40			1		4	0	3	284
Manufacture of Furniture	393	2			2	0	2	0	2	121
Manufacture of Paper and Paper Products	3927	3545	30	0	2		10	6	22	738
Printing and Reproduction of Recording Media	491	60			3	0	3	0	5	133
Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities	601	10			2		2	0	16	85
Processing of Petroleum, Coal and Other Fuels	35267	55519	59	65274	17	0	122	2230	147	1283
Manufacture of Raw Chemical Materials and Chemical Products	56723	23077	4289	3792	17	2	33	542	401	5781
Manufacture of Medicines	2253	736	6		3	0	4	2	20	430
Manufacture of Chemical Fibers	2365	1142	3		0	0	1	1	10	450
Manufacture of Rubber and Plastics Products	4993	280	2	0	6	0	8	2	21	1401
Manufacture of Non-metallic Mineral Products	35387	24705	1464	0	13	1	232	58	226	3930
Smelting and Pressing of Ferrous Metals	58651	39217	40336		3	0	41	0	145	6785
Smelting and Pressing of Non-ferrous Metals	25463	17138	490	0	2	0	25	8	53	7133
Manufacture of Metal Products	6385	306	589		8	0	13	1	74	1652
Manufacture of General Purpose Machinery	3987	16	412		11	1	16	0	32	1077
Manufacture of Special Purpose Machinery	1823	12		0	8	1	15	0	18	498
Manufacture of Automobiles	4073	85	12	0	14	0	16	0	29	1183
Manufacture of Railway, Ship, Aerospace and Other Transport Equipments	827	35			3	1	8	1	23	165
Manufacture of Electrical Machinery and Apparatus	3105	20	1		10	0	6	1	16	943
Manufacture of Computers, Communication and Other Electronic Equipment	5123	172			6	0	4	0	28	1671
Manufacture of Measuring Instruments and Machinery	252	2			3	0	1	0	1	77
Other Manufacture	1857	3			0	0	1		4	601
Utilization of Waste Resources	685	333	69		0	0	4	1	16	67
Repair Service of Metal Products, Machinery and Equipment	63	1			0	1	5	0	1	15
Production and Supply of Electricity, Heat, Gas and Water	35523	213202	271	0	18		47	4	611	9934
Production and Supply of Electric Power and Heat Power	32075	211123	270	0	14		45	4	576	9120
Production and Supply of Gas	1525	2057	1		2		1		34	172
Production and Supply of Water	1923	22		0	2		1	0	1	645
Construction	9320	639	4		508	11	504	41	3	1011
Transport, Storage and Post	41309	241		1	5574	3111	9532	2042	354	1751
Wholesale and Retail Trades, Hotels and Catering Services	13171	1981			273	15	198	12	62	3169
Others	28245	2571			2253	103	946	7	56	6517
Household Consumption	64380	6283	11		3718	12	580		580	11396

a) The (blank space) indicates that the figure is not large enough to be measured with the smallest unit in the table, or data are unknown or are not available.

Figure 1: Total Energy Consumption and Its Composition with the Energy Consumption by Sector

Problem Statement

In recent decades, China's industrial sector has seen remarkable growth, positioning the nation as a key player in the global economy. This rapid development, however, has brought significant environmental challenges, notably in air pollution. Among various pollutants, NOx emissions have emerged as a critical concern due to their harmful impact on air quality and public health. The thermal power sector, a cornerstone of China's industrial growth, has been a major contributor to NOx emissions. According to the China Environmental Statistical Yearbook ("China's second survey of pollution sources.," 2020), among which Coal energy NOx emissions accounted for more than 56% of the pollution, and the thermal power industry accounted for 52.66% of the total coal energy NOx emissions. Recognizing the gravity of this issue, the government has progressively tightened emission limits, with a reduction of nearly 30% in the past five years, as reported by Li Jianguo (Li Jianguo, 2019).

8-13 Main Pollutant Contents Emission in Waste Gas by Region (2022)

(10 000 tons)

Region	Sulphur Dioxide	Nitrogen Oxides	Particulate Matter
National Total	**274.78**	**972.65**	**537.60**
Beijing	0.14	8.21	0.54
Tianjin	0.85	10.72	1.28
Hebei	17.07	24.51	34.98
Shanxi	14.70	41.94	29.62
Inner Mongolia	22.48	43.35	96.12
Liaoning	16.33	80.63	27.85
Jilin	6.23	20.29	16.92
Heilongjiang	11.03	27.85	35.08
Shanghai	0.58	13.57	0.98
Jiangsu	8.86	44.34	12.58
Zhejiang	4.33	38.05	7.16
Anhui	8.55	44.58	11.73
Fujian	6.51	82.24	9.31
Jiangxi	8.75	32.42	10.97
Shandong	16.53	65.87	21.59
Henan	6.00	49.81	7.27
Hubei	9.21	28.69	13.36
Hunan	8.49	26.18	15.02
Guangdong	9.79	62.96	13.47
Guangxi	7.43	26.48	8.76
Hainan	0.43	3.83	0.93
Chongqing	5.06	15.76	5.80
Sichuan	13.58	34.97	19.21
Guizhou	14.31	22.37	11.59
Yunnan	17.31	32.01	24.81
Tibet	0.22	4.43	0.83
Shaanxi	8.11	21.02	23.14
Gansu	8.47	18.46	13.12
Qinghai	4.08	6.57	5.67
Ningxia	6.03	12.29	6.53
Xinjiang	13.33	28.25	51.37

8-14 Main Pollutant Contents Emission in Waste Gas by Main City (2022)

(ton)

City	Industrial Sulphur Dioxide Emission	Industrial Nitrogen Oxides Emission	Industrial Particulate Matter Emission	Domestic and Other Sulphur Dioxide Emission	Domestic and Other Nitrogen Oxides Emission	Domestic and Other Particulate Matter Emission
Beijing	1004	9590	2180	415	8333	2800
Tianjin	8138	24821	8189	345	3697	3743
Shijiazhuang	7826	18189	10013	3166	4101	16042
Taiyuan	8360	19351	15986	263	1264	766
Hohhot	10233	17520	6144	1082	931	5441
Shenyang	8643	16805	3584	2680	1611	6780
Changchun	14452	21838	7821	9316	5081	37353
Harbin	7172	17177	6136	26339	14837	131729
Shanghai	5535	21481	7557	220	4765	1301
Nanjing	11136	22054	19876	1	1798	165
Hangzhou	3195	13956	10768	80	387	262
Hefei	4553	9899	4594	599	1679	6081
Fuzhou	12635	28970	18922	715	700	1480
Nanchang	4932	8184	2823	215	517	473
Jinan	9458	22763	11047	4141	2390	11148
Zhengzhou	5067	10691	6628	100	1700	334
Wuhan	8725	21541	6080	9701	4134	19583
Changsha	1043	3341	2303	1387	944	3519
Guangzhou	1822	12206	4736	839	1645	2521
Nanning	2761	11700	6649	1114	610	2261
Haikou	266	188	32	0	310	28
Chongqing	41733	70029	46178	8856	6530	10910
Chengdu	3374	11201	5504	2027	5072	3549
Guiyang	11123	8436	4963	2391	374	2665
Kunming	19075	23666	22991	5936	2201	9995
Lhasa	398	1579	1730	124	76	195
Xi'an	1154	2595	802	3726	5554	11043
Lanzhou	12922	15039	5245	2165	2072	8762
Xining	26792	11793	8629	230	1162	2381
Yinchuan	7830	14366	4476	20	934	185
Urumqi	6779	14855	15441	287	2039	2077

Figure 2: Main Pollutant Contents Emission in Waste Gas by Region and main Pollutant Contents Emission in Waste Gas by Main City

In order to solve the problem of NO_X pollution to the atmosphere, the most direct and perhaps the simplest way is to reduce the total NO_X pollution emissions from power plants. Previous studies, as critiqued by Liu Hongyu (LIU Hongyu, 2021) often focus on isolated factors such as fuel properties or operational characteristics without considering the system as a whole. Others have suggested using clean energy instead of coal to reduce air pollution, which will take longer to gain acceptance. This study proposes a comprehensive approach using advanced statistical techniques, including linear regression, multivariate analysis, and time-series analysis. The linear regression model will be used to analyze data from over 10 power plant units across China, collected over the past five years. This analysis aims to establish a quantifiable link between specific operational parameters and NOx emission levels.

Our urban development will soon need to address the changes in the people's livelihood environment brought about by development, and we need to take measures and implement them as soon as possible.

China's 2030 energy and power development plan mentions that although China's energy consumption structure is gradually changing, it will vigorously develop new energy industries. But traditional coal consumption will still account for more than 60% of the share in 10 years. In order to accept more new energy and improve the flexibility of peak and frequency regulation of the power grid, the coal-fired power plant thermal generating units will operate more frequently under variable load conditions, resulting in significant changes in unit performance and management control.
The challenge of controlling NOx emissions is particularly pronounced in coal-fired power plant generation units. These units are increasingly operating under variable loads to accommodate the integration of renewable energy sources into the national grid. This

operational shift, essential for sustainable energy development, has introduced a 20% increase in operational complexity, as per the National Energy Administration's 2021 report. This complexity not only affects the performance but also the environmental compliance of these units. Ke Xiwei(KE Xiwei, 2021)highlights that the variability in operational conditions can lead to significant fluctuations in NOx emission levels, complicating the development of effective control strategies.

In order to prevent our cities from falling into the NO_X pollution problem exacerbated by complex load conditions, experts have proposed several methods. One of the most widely adopted methods is stepped off-peak pricing. Other experts suggest a passive approach to the problem of ensuring a smooth supply of power while also meeting ultra-low nitrogen emission standards. Multivariate analysis will explore how combinations of different variables influence NOx emissions, considering the complex interactions in power plant operations. Time-series analysis, utilizing a bimester-long dataset from key power plant units, will examine the impact of temporal changes in operational parameters on emission patterns. These statistical analyses will inform the development of a denitrification system model, predicting NOx emissions under various operational scenarios and providing a tool for optimizing power plant performance. If we want our cities to develop safely and reliably, we must take action on the above problems now.

At present, power plants in various regions of China basically have management methods and technical levels that adapt to local economic development.
When the model of NOx emission and its influencing factors in power plant denigration system is established. According to statistics, the demand for power plant optimization and adjustment capacity is gradually rising, and it is expected that by 2030, the social electricity provided by power supply enterprises after optimization and adjustment will account for about 90% of the total. Naturally, the optimization of NO_X pollution emissions from power plants with improved regulatory capacity is also a research hotspot: how to verify that the independent variable in this study has a positive effect on the dependent variable under the role of the regulatory variable.

In order to solve this problem, many experts are studying the optimal parameter combination with the lowest independent variable and dependent variable (NOx emission). Other experts believe that we should start from the nature of ultra-low nitrogen combustion, develop new algorithms to match it from the uncertainty and randomness of the mechanism, and achieve ultra-low NOx emission with the lowest possible cost and computing power.
the study will leverage Information Technology (IT) tools for data collection, analysis, and model development. Advanced IT solutions, such as big data analytics and machine learning algorithms, will be utilized to handle the vast amount of operational data from CFB units. This approach will ensure a more accurate and comprehensive analysis, leading to more robust and effective emission control strategies. The integration of IT will also facilitate real-time monitoring and control of NOx emissions, enhancing the responsiveness of power plant units to changing operational conditions and regulatory requirements.

Incorporating these businesses, management, and IT components will provide a holistic view of the NOx emission problem in power plant boilers. It will enable the development of solutions that are not only environmentally sound but also economically feasible and technologically advanced. This multidisciplinary approach will add significant value to the research, making its findings more relevant and applicable to a broader range of stakeholders, including industry practitioners, policymakers, and technology developers. This will also be a research hotspot for the development of ultra-low nitrogen combustion in the future.

In terms of power supply and demand: as of February 2022, the power supply and demand balance in a few provinces is tight during some peak hours of electricity consumption; In July and August, China's 21 provincial power grid load reached a new high, and the power supply situation was severe, and the national daily maximum error peak load exceeded 50 million kilowatts (China Power Industry Annual Development Report, 2023).

The dynamic balance of de-nitration system in power plant boiler is considered; each independent variable in these systems cannot be precisely controlled but only managed within a range. This range includes factors such as steady-state changes, variations in environmental emission limits, fluctuations in safety conditions, and predictive changes, as noted by (Yue, 2016). Therefore, the optimal value for each data point becomes an optimal range, which cannot achieve the best optimization of the denitrification system operating mode. This will cause obstacles to the process regulatory control of the de-nitration process and have a negative impact on NO_X pollution emissions.

In order to further solve this problem, experts have given several solutions: the most mainstream is to solve a single aspect of regulation. In my view, addressing these issues should take place at the level of policymakers and industry stakeholders, providing them with data-driven insights to develop strategies to meet increasingly stringent NOx emission standards while maintaining operational efficiency. The optimization strategies developed will not only address environmental compliance but also focus on operational efficiency and cost-effectiveness, crucial for the competitive positioning of power generation companies in the market. This includes a cost-benefit analysis of implementing the proposed denitrification strategies, assessing their financial viability and long-term sustainability for businesses. It is an urgent need to understand the changing relationship between NOx emissions and operation management.

Table 1
Development the Logo Indicates the Implementation Standards in Key Areasent of Air Pollutatnt

STEP	Standard Name (number)	Concentration Limit Requirement (mg/m^3)		
		PM	NOx	SO2
STEP1	Standardless Phase	-	-	-
STEP2	《Industrial "three wastes" discharge trial standard》 (GBJ4- 1973)	No Requirement	No Requirement	Not Involve
STEP3	《Emission standards for air pollutants from coal-fired power plants》 (GB13223- 1991)	600	No Requirement	Not Involve
STEP4	《Emission standards for air pollutants in thermal power plants》 (GB13223- 1996)	200	1200	650
STEP5	《Emission standards for air pollutants in thermal power plants》 (GB13223-2003)	50	400	450
STEP6	《Emission standards for air pollutants in thermal power plants》 (GB13223-2011)	30/20*	100/50*	100
STEP7	《Coal power energy conservation and emission reduction upgrade and action plan》 (2014-2020 年)	10/5*	35	50

Limitations
The power plants unit has more intricate internal structure and equipment, as well as a wider range of working circumstances. More study is required to determine the best operating conditions clustering to use in order to precisely monitor and adjust the NO_X content at the de-nitration intake.
This study reduced to a unified large-section processing and ignored the uneven distribution of concentration of NO_X and NH_3 in the flue gas in terms of information control of the de-nitration system. More study is still needed to determine how to accurately manage gridded ammonia injection.

Literature Review
However, through studying relevant literature both domestically and internationally, it was found that existing models for predicting NOx emission concentrations from coal-fired units, particularly in thermal power plants, primarily rely on machine learning algorithms. These algorithms continually undergo upgrades to achieve higher accuracy. Regarding data preprocessing, there is often a lack of differentiation between steady-state and non-steady-state operating conditions. The occurrence of non-steady-state conditions during unit operation is often influenced by uncontrollable factors, and analyzing the thermodynamic characteristics behind this type of data can be challenging. Therefore, analyzing the selected steady-state data holds practical significance.

In terms of modeling control for denitrification systems, the majority of domestic power plants still employ control strategies based on PID (Proportional-Integral-Derivative) control. However, with the increase in emission standards for NOx concentration and the impact of deep peak shaving, relying solely on PID control is insufficient to meet the requirements for both NOx emission reduction and ammonia escape. Scholars have introduced more advanced control concepts and methods into denitrification control.

Guangjun et al. (2016) and others designed the main and auxiliary regulators of a denitrification cascade control system using Generalized Predictive Control (GPC) and Linear Quadratic Regulation (LQR) methods, respectively. The control system includes feedforward control of the NOx generation rate and feedback control of NOx emission concentration, demonstrating practical application value. Wang Junxia (Junxia, 2020) applied Model Predictive Control (MPC) to denitrification system control and compared it with traditional PID control. The results showed that MPC could adjust ammonia injection in advance, reduce overshoot and adjustment time, outperforming traditional PID control. Xiong Weili (Xiong Weili, 2002) introduced Laguerre functions as the prediction model, establishing an adaptive predictive control method based on the Laguerre model. By updating Laguerre coefficients online, the algorithm demonstrated the ability to adapt to changes in the object's characteristics automatically. However, it did not consider possible disturbances during system operation, which could affect the accuracy of model identification.

Machine learning methods have also been used in denitrification system control. Meng Sun Xianbin (Xianbin, 2014) and others utilized Neural Network Predictive Control (NNPC) to establish a predictive and control model for nitrogen oxide emissions from power plants. However, there were significant errors in unexplored operating conditions, not covered by the model. The Radial Basis Function (RBF)-ARX non-parametric model was used to control ammonia injection in the denitrification system, but the model was only established for a few operating points, limiting its practical application (Min, 2013).

The proposal of a Radial Basis Function (RBF) neural network structure based on Generalized Growing And Pruning (GGAP-RBF) was made, but it requires initializing settings for all sampling data, and the network parameter setting process is complex (Hongyu, 2021). A hybrid structure combining Recurrent Neural Network (RNN) and RBF neural network was suggested but did not consider the impact of changing environmental temperatures on denitrification efficiency (Li Jianguo, 2019). Genetic Algorithm – Kernel Partial Least Square (GA-KPLS) was used to establish an SCR system model, but a fixed value was set for the maximum iteration times of the particle swarm, affecting optimization effectiveness (Jing, 2010).

Research on the control of SNCR (Selective Non-Catalytic Reduction) or SNCR/SCR (Selective Catalytic Reduction) combined denitrification systems is currently limited and mainly focuses on mechanism and process studies. Guangxi (Guangxi, 2004)studied the use of the main steam load line output as the feedforward of urea solution flow rate, adjusting primarily based on nitrogen oxides, and combining a Smith predictive controller with cascade feedforward control methods to achieve automatic operation of the SNCR denitrification system. However, the main steam equivalent amount as a control feedforward has a lag, cannot respond promptly under rapidly changing operating conditions, and the document does not specify the system's performance under variable operating conditions. The use of BP neural networks to establish a black-box model for the entrance and exit NOx concentrations of the denitrification system, combined with fuzzy control and model-free adaptive control algorithms, achieved SNCR denitrification system control, reducing ammonia

injection by 19.8% per 300 MW·h. However, it did not verify the control system's performance under rapidly changing operating conditions, and BP neural networks lack sufficient accuracy and robustness for time-series data modeling (Zhuzhujun, 2017).
By establishing a particle swarm algorithm for the parameters between the denitrification system reducing agent and the exit NOx concentration, (Xiujuan, 2020) proposed a cascade control strategy based on Generalized Predictive Control combined with traditional PID. The offline simulation system was used for verification, but the document did not consider the issue of denitrification system feedforward and did not conduct industrial verification.

Research Questions
Based on literature review problem statement and objectives of research, the following are the research question for this research:

1. How do key operational variables in coal-fired power plant generation units influence NOx emissions, and what is their interaction as determined by statistical analyses like linear regression and multivariate analysis?
2. What are the measurable environmental impacts of various optimization strategies on NOx emissions in power plant denitrification systems?
3. How effectively can machine learning models predict denitrification efficiency in power plant denitrification systems based on inlet NOx concentration, and what is the impact on operational cost-effectiveness?
4. How do optimization strategies affect the relationship between predicted inlet NOx concentrations and actual emissions in power plant denitrification systems, and how can this be leveraged for improved control, efficiency, and regulatory compliance using IT-driven data analytics?

Research Objectives
The primary objective of this research is to develop and study a systematic framework to enhance the control technology of the power plant denitrification system and ensure its smooth operation. the following are the research objectives:

1. To study the key operational variables influencing the NOx emissions of coal-fired power plant generating units in order to achieve the target.
2. To investigate the environmental impact of various optimization strategies on the NOx emissions of the power plant denitrification system, aiming to reduce emissions costs.
3. To develop a machine learning model based on the imported NOx concentration to predict the denitrification efficiency of the power plant denitrification system.
4. To analyze the effectiveness of system predictions to improve compliance levels for operational decisions.

Research Hypothesis
Hypothesis 1 (Stability Control - IV1)
H0: Standardization of inlet NOx concentration does not significantly affect denitrification system control effectiveness in power plant denitrification systems.
H1: Standardization of inlet NOx concentration significantly improves denitrification system control effectiveness in power plant denitrification systems.
This hypothesis examines how consistent and stable control of inlet NOx concentration affects the overall effectiveness of denitrification systems. Statistical analysis, such as variance analysis, will be employed to measure the impact of stability in controlling NOx levels.

Hypothesis 2 (Safety Control - IV2)
H0: Security of inlet NOx concentration does not significantly impact denitrification system control effectiveness in power plant denitrification systems.
H1: Security of inlet NOx concentration significantly enhances denitrification system control effectiveness in power plant denitrification systems.
Investigates the influence of safety measures in the control of inlet NOx concentration on system effectiveness. Safety parameters will be quantified and analyzed against control effectiveness using correlation analysis.

Hypothesis 3 (Precision Control - IV3)
H0: Technical Control of inlet NOx concentration does not significantly influence denitrification system control effectiveness in power plant denitrification systems.
H1: Technical Control of inlet NOx concentration significantly influences denitrification system control effectiveness in power plant denitrification systems.
Focuses on the role of precision in controlling NOx emissions. Precision variables will be statistically tested for their impact on denitrification effectiveness, using methods like linear regression.

Hypothesis 4 (Timeliness Control - IV4)
H0: Operational Control of inlet NOx concentration does not significantly affect denitrification system control effectiveness in power plant denitrification systems.
H1: Operational Control of inlet NOx concentration significantly improves denitrification system control effectiveness in power plant denitrification systems.
Explores the effect of timely adjustments in NOx concentration control on system effectiveness. Time-series analysis may be used to understand the dynamics of this relationship.

Research Methodology
Quantitative Study: the current research the quantitative technique was chosen for this research since the data collection and analysis were in numerical format.
Statistical Study: multivariate regression and stochastic programming.
Simulation Study: Architecture: Describe the specific type of neural network used (e.g., feedforward, convolutional, recurrent). Detail the number of layers, types of layers (hidden, dropout, normalization), and activation functions used in each layer.
Hyperparameters: Document the selection of learning rate, batch size, and number of epochs. Explain the rationale behind these choices based on preliminary experiments or literature.
Training Process: Describe the dataset splitting (training, validation, testing), including the proportions. Explain any data augmentation techniques used to enhance the model's ability to generalize.
Validation and Testing: Outline how the model's performance is evaluated, including the metrics used (e.g., accuracy, mean squared error, F1-score). Discuss cross-validation techniques if used.
Experimental Study: Implementation Details: Provide a detailed description of the Synchronous Perturbation Stochastic Approximation (SPSA) algorithm, including the calculation of the gradient estimate using simultaneous perturbation. Mention the specific choice of the gain sequences (a[k], c[k]) and their impact on convergence.

Algorithm Parameters: Justify the choice of parameters, such as the perturbation amplitude and the step size. Discuss how these parameters were tuned and their effect on the optimization process.
Convergence Criteria: Explain how you determine when the algorithm has converged to a solution. This might include setting a maximum number of iterations or a threshold for the change in the objective function.

Sample Size
In scientific research, especially in studies involving large populations, selecting an appropriate sample size is critical. It ensures that the findings of the study are statistically significant and can be generalized to the entire population. One of the methodologies to determine the sample size is Yamane's formula, an approach that balances precision and practicality.
Yamane (1967) introduced a simplified formula to calculate sample sizes, particularly useful when dealing with large populations. The formula is predicated on the principles of statistical theory and provides a balance between accuracy and efficiency. It is particularly effective when researchers are dealing with vast datasets or populations and need to ascertain a representative sample size that can yield reliable and generalizable results.

$$n=\frac{N}{1+Ne^2}$$

Where:
N is the total population size.
n is the sample size.
e is the level of precision or margin of error.
This formula assumes a 95% confidence level and a 50% proportion (i.e., $P=0.5$), which often represents the most conservative scenario in terms of sample size requirement.
Since I will be working with a dataset that simulates a population of 1 million (i.e., $N=1{,}000{,}000$). To determine a statistically significant sample size with a confidence level of 95% and a standard error of 5% (i.e., $e=0.05$), Yamane's formula can be applied:

$$n=\frac{1{,}000{,}000}{1+1{,}000{,}000\times(0.05)^2}\approx 400$$

This sample size ensures that the study's findings are statistically reliable and can be generalized to the entire population with a high degree of confidence. It is particularly relevant in studies where surveying the entire population is impractical, costly, or time-consuming. Researchers in fields like social sciences, market research, and environmental studies frequently rely on this method to draw meaningful conclusions from large datasets.

Pilot Study
Multivariate Regression Model
Overview
A multivariate regression model is used to explore the relationship between multiple independent variables and a single dependent variable. It's particularly useful in cases where several factors are believed to influence the outcome.
Mathematical Formulation:

The general form of the multivariate regression model is:

$$Y=\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k+\epsilon$$

Where:
Y is the dependent variable (in this case, the effectiveness of denitrification system control in power plant denitrification systems).
$X_1, X_2, \ldots, X_k$ are the independent variables (e.g., stability control, safety control, etc.).
β_0 is the intercept, representing the expected value of Y when all independent variables are zero.
$\beta_1, \beta_2, \ldots, \beta_k$ are the regression coefficients, indicating the expected change in Y for a one-unit change in the respective independent variable, holding other variables constant.
ϵ is the error term, accounting for the variation in Y not explained by the model.

Model Building Steps
Data Collection and Preparation: Gather data on the independent variables (control mechanisms) and the dependent variable (system control effectiveness). This includes preprocessing steps like handling missing values, encoding categorical variables, and standardizing/normalizing the data.
1. Variable Selection: Decide which independent variables to include in the model. This could be based on theoretical considerations or exploratory data analysis.
2. Model Estimation: Use statistical software to estimate the regression coefficients. This typically involves solving the normal equations or using optimization techniques like gradient descent.
3. Model Evaluation: Assess the model's performance through metrics like R-squared, adjusted R-squared, F-statistic, and p-values for each coefficient. Check for assumptions like linearity, homoscedasticity, multicollinearity, and normality of residuals.
4. Interpretation: Interpret the coefficients, understanding how each control mechanism affects the effectiveness of the denitrification system. A significant positive coefficient suggests a favorable impact, while a negative coefficient suggests the opposite.

Diagnostic Checking
Perform diagnostic tests to check for potential issues in the model, such as outliers, leverage points, or influential observations Application to Hypotheses:
This model allows testing each hypothesis by examining the significance and impact of the corresponding control mechanism's coefficient (β_i).
For instance, a significant positive coefficient for the stability control variable would support Hypothesis $1(\mathrm{H}1)$, indicating that stability control significantly improves control effectiveness.
Example Formula for Hypothesis Testing

For Hypothesis 1, the formula might look like

$$Y=\beta_0+\beta_1 \times \text{ Standardization }+\beta_2 \times \text{ OtherVariable } 1+\cdots+\epsilon$$

Where Standardization is the independent variable of interest for Hypothesis 1, and the significance of β_1 will be assessed to validate the hypothesis.
By applying this comprehensive multivariate regression approach, you can effectively analyze the impact of various control mechanisms on the effectiveness of denitrification systems in power plants.

Stochastic Optimization

Stochastic optimization models incorporate randomness directly into the model, either in the objective function, the constraints, or both. They are designed to find an optimal solution under uncertainty.

Mathematical Formulation

Basic Formulation

•A general stochastic optimization problem can be formulated as: $\min_{x \in X} \mathbb{E}[f(x, \omega)]$

Where:

•X is the feasible region for x.

•ω represents the random variables or stochastic elements.

•$f(x, \omega)$ is the stochastic objective function.

•$\mathbb{E}$ denotes the expected value over the distribution of ω.

Incorporating Constraints

•Stochastic constraints can be added to the model:

$$g(x, \omega) \leq 0$$

•Where $g(x, \omega)$ represents stochastic constraints. These could include operational limits that vary randomly.

Chance Constraints

•A common approach in stochastic optimization is to use chance constraints, which ensure that the constraints are satisfied with a certain probability:

$$P(g(x, \omega) \leq 0) \geq \alpha$$

•Where P represents the probability, and α is a predefined threshold (e.g., 0.95), indicating that the constraints should be satisfied with at least 95% probability.

Objective Function Examples

•In the context of power plant denitrification systems, the objective function might aim to minimize operational costs or emissions under uncertainty:

$$\min_{x} \mathbb{E}[\text{Cost } (x, \omega)]$$

•Or maximize system efficiency: $\max_{x} \mathbb{E}[\text{Efficiency } (x, \omega)]$

Solution Methods

•Solving stochastic optimization problems often involves simulation-based methods like Stochastic Gradient Descent (SGD) or Monte Carlo simulations.

•SGD updates the decision variables based on the gradient of the objective function with respect to x, considering the random nature of ω :

$$x_{n+1} = x_n - \eta_n \nabla f(x_n, \omega_n)$$

•Where η_n is the learning rate at iteration n, and $\nabla f(x_n, \omega_n)$ is the gradient of the objective function with respect to x_n under the realization ω_n of the stochastic process.

Application To Power Plant Denitrification Systems
•In the context of your hypotheses about power plant denitrification systems, a stochastic optimization model can be utilized to:
•Optimize control strategies (e.g., stability, safety, precision) under varying operational conditions.
•Incorporate the randomness in parameters like inlet NOx concentration, coal quality, and airflow rates.
•Use historical data to estimate the probability distributions of these random parameters.
This model allows for more robust decision-making by considering the inherent uncertainties in the power plant process, leading to strategies that are more likely to maintain effectiveness even under fluctuating conditions.

Data Analysis Plan
Data Collection Methodologies
• Linear Interpolation Method/Moving Average Filter Method/K-Means Method: Utilize these methods to collect and process data from sources like the International Energy Agency (IEA), Environmental Protection Agency (EPA), and industry-specific databases that track emissions, operational efficiency, and technological advancements in power plant units.
• MATLAB Version 2018a/Simulink: Apply these tools to analyze time-series data from power plant operations, focusing on NOx emissions, fuel usage, and system stability indicators.

Industrial Software Analysis
• Reliability Test/Monitor/Regression/Correlations/Forecast: Leverage these tools to analyze data from sources like the CHN Department of Energy or independent research bodies that monitor power plant performance and environmental compliance.

Table 2
Analysis Design

Procedure	Research Problem	Thought Design	Research Design
First Step	How can the dynamic and quick fluctuations in inflow NOx in the de-nitration system be efficiently controlled in the presence of frequent load changes	The global model of inlet NOx concentration measurement correction is established	1.The key characteristics of the modified model are analyzed 2. Pure time delay analysis between key features 3.Super-parameter determination method of spiking neural network 4. Study on the division method of typical working conditions of power plant 5.Study on correction model of NOx measurement at denitrification inlet based on clustering of typical working conditions of power plant
Second Step	The non-linear characteristics of the de-nitration system are strong, and the outlet NOx concentration is measured.	The intelligent control strategy combining inlet measurement correction model and multi-model predictive control is studied.	1.Study on nonlinear model of de-nitration 2.Study on the influence of inlet concentration correction on control quality 3.Research on the influence of control quantity constraints on control effect 4.Control system simulation research
Fourth Step	Production environment application, requirements Lu	Industrial Information Validation	1.Field experiment object and system deployment 2.Key parameters on-site debugging 3.The effect and economic analysis after optimal control

Data Analysis

Type of Data

Secondary data: The actual experimental operation data of power PI system database.(Plant Information, PI).("China Power Industry Annual Development Report 2023," 2023)

Data Source Description: Provide specifics about the Power PI system database, including the type of data it stores (e.g., sensor readings, operational parameters), the time frame of the collected data, and the geographical location of the power plants.

Data Limitations and Biases: Discuss any potential biases in the data, such as those introduced by sensor inaccuracies or missing data points. Explain how these biases were addressed in the study.

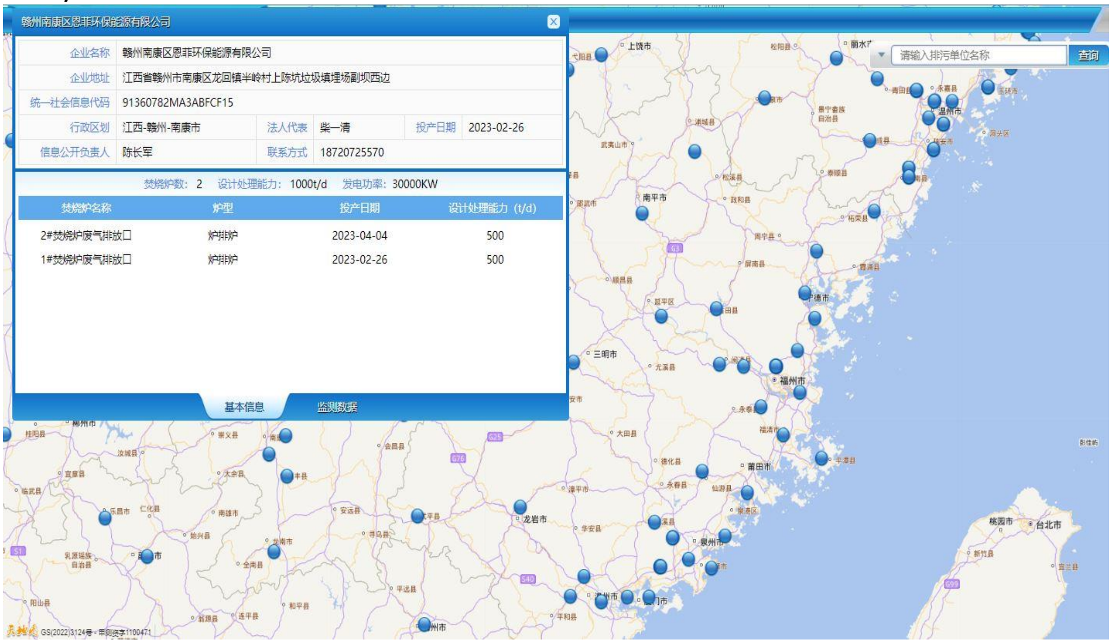

Figure 3: Power plant operation data collection

Data Preprocessing

Filtering Method: Elaborate on the moving average filter, including the mathematical formula used and the rationale behind the choice of a 5-sample interval window(Cekik & Uysal, 2020).

Anomalous Data Processing: Describe the methods used to identify and handle outliers or anomalous data points. This may include statistical methods or heuristic criteria.

Data Sampling and Standardization

Sampling Methodology: Justify the decision to use 1,000,000 data sets for validation, including how this sample size is representative of the typical operating conditions(Fan et al., 2019).

Standardization Process: Detail the calculation of the mean value and standard deviation for each feature. Explain how this standardization impacts the training of the neural network, particularly in terms of weight updates.

Feature Selection and Analysis

Selection Criteria for Indices: Define the process for selecting the primary and secondary indices, such as coal feed types and air volumes. Discuss the importance of these features in relation to inlet NOx concentration.

Mutual Information Analysis: Provide a more detailed explanation of how mutual information is calculated and interpreted in the context of this study. Include the mathematical formula and its implementation.

Correlation Analysis

Statistical Methods: Describe the specific statistical methods used for analyzing the correlation between input and output features. This could include Pearson correlation, Spearman rank correlation, or other relevant methods.

Interpretation of Results: Discuss how the results of the correlation analysis influenced the model design and feature selection.

Table 3

Correlation Analysis Between Input Feature And Output Feature(Yue, 2016)

Primary Index	Secondary Index	Unit
Coal feed	Lignite	t/h
	Anthracite	t/h
	Bituminous coal	t/h
	Meager coal	t/h
Air volume	Primary air volume	m^3/h
	Secondary air volume	m^3/h
CFB temperature	<845	℃
	845-935	℃
	>935	℃
O_2%	<1.9	%
	1.9-3.31	%
	>3.31	%

Addressing Sensor Data Distortion

-Linear Interpolation Approach: Explain in detail how the linear interpolation is applied to the distorted data. Include the formula used and how it corrects for delays or distortions.

-Impact on Data Quality: Discuss the effectiveness of this approach in improving data accuracy and how it contributes to the overall reliability of the model's predictions.

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Map of thermal power plants in China

Finding and Conclusion

This article begins by analyzing the thermodynamic characteristics of the power plant denitrification system and the typical denitrification control from the perspectives of system theory and control theory. It addresses factors affecting NOx emissions, such as distortion, large system inertia, and strong non-linear characteristics. Utilizing a quantitative identification method, suitable operational data for each system is selected from actual production sites. Intelligent control strategies based on input correction and predictive control are constructed. The paper provides quantitative results for the large inertia of the combustion system, enabling ammonia control under different loads and conditions, reducing outlet NOx fluctuations, lowering the risk of low-temperature corrosion in downstream equipment, optimizing comprehensive control quality, and enhancing the standardization, operational management, technical operability, and safety of joint denitrification operation. This work serves as a reference for optimizing the efficiency of power plant combustion systems and low-nitrogen systems.

Recommendation

With the development of Chinese society, there will be a lot of power enterprises facing the problem of temporary shortage and storage of power supply, which is not good for the environment. It is necessary to further integrate power grid management, from regional networking to the interconnection of some provinces to the construction of the data platform of the national power system, to realize the digital coverage of the whole network step by step, optimize the management and allocation of resources.

To recommend power enterprises should address the impact of more complex electricity demand from industrial enterprises and civil use on the NO_X emission environment. They should optimize the coupled power supply strategy and enhance the intelligent management strategy of power plant de-nitration systems. This will ensure the smooth operation of the system under the influence of standardization, safety, technical operation, and operational management factors, ultimately achieving the emission reduction target.

Acknowledgement
The researchers would like to thank all power company managers who generously shared valuable insights and experiences for this study. The candid views of the respondents help to reveal the problem of NO_X environmental pollution after future changes in electricity supply. Their contributions enrich the knowledge of researchers and will undoubtedly benefit policy makers and managers, including governments and enterprises, in addressing the challenges and opportunities of global energy and environment for production and life.

References

Cekik, R., & Uysal, A. K. (2020). A novel filter feature selection method using rough set for short text data. *Expert Systems with Applications*, *160*, 113691. https://doi.org/https://doi.org/10.1016/j.eswa.2020.113691

China's second survey of pollution sources (2020). *Environmental protection*, *48*(18), 8-10.

China Power Industry Annual Development Report 2023. (2023, 2023-07-12). *China Electric Power News*, 003.

Fan, Y., Cui, X., Han, H., & Lu, H. (2019). Chiller fault diagnosis with field sensors using the technology of imbalanced data. *Applied Thermal Engineering*, *159*, 113933. https://doi.org/https://doi.org/10.1016/j.applthermaleng.2019.113933

Fang, L. (2006). The impact of nitrogen oxides in the atmosphere on the ecological environment. *Journal of Qinghai Normal University (Natural Science Edition)*(03), 87-89. https://doi.org/10.16229/j.cnki.issn1001-7542.2006.03.029

Guangjun., C. (2016). De-nitration retrofit scheme of domestic 300 MW circulating fluidized bed boiler. *Automation application*(01), 6-7+9.

Guangxi, Y. (2004). Development and Application of Circulating Fluidized Bed Technology (II). *Energy saving and environmental protection*(01), 11-12.

Jing., G. (2010). *The application of SNCR / SCR combined denitrification technology in 410t / h power station boiler.* [Master's thesis, North China Electric Power University].

KE Xiwei, Z. M., YANG Hairui, LYU Junfu, GUO Xuemao, LI Jun, HE Huibao. (2021). Research Progress on NOx Generation and Emission Characteristics of Circulating Fluidized Bed Boilers. *41*(08), 2757-2771.

Li Jianguo, Z. F., Sun Xueli. (2019). Current situation and challenges of air pollution prevention and control in China's thermal power plants. The 18th Chinese Academic Conference on Electric Precipitation, Nanjing, Jiangsu, China.

LIU Hongyu, S. X. (2021). Analysis of Influencing Factors of NOx in Circulating Fluidized Bed Boilers. (12), 143-144.

Min, H. (2013). *Study on SNCR and SCR Denitrification Coupled with Deep Low Nitrogen Combustion of Large Power Plant Boiler* [Doctoral dissertation, Zhejiang University].

Sun Xianbin, S. Z., Jin wangsen. (2014). Research on ultra-low emission technology of circulating fluidized bed boiler. *China Power*, *47*(01), 142-145.

Wang Junxia, L. M., & Jing Hong. (2020). Analysis and Suggestions on Nitrogen Oxide Emission Control in China. *Environmental protection*, *48*(18), 24-27. https://doi.org/10.14026/j.cnki.0253-9705.2020.18.004

Xiong Weili, H. W., &Zhang Guobin. (2002). The harm and prevention of nitrogen oxides (NOx) in thermal power plants. *Hunan Electric Power*(01), 61-62+52.