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Real-Time IoT Integration for Coal Production And Distribution Management

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A B S T R A C T

The coal production and distribution industry faces persistent challenges in data management, operational coordination, and decision-making efficiency. Conventional monitoring methods often result in delayed reporting, low data accuracy, and limited adaptability to dynamic market demands. This study addresses the lack of an intelligent and integrated information system by designing and developing a real-time IoT-based solution for coal production and distribution management. The system was built using the Software Development Life Cycle (SDLC) with the Waterfall model and integrates IoT sensors to automatically capture critical parameters such as pressure, temperature, and coal quality indicators. Artificial Intelligence (AI) components were incorporated to enhance data analysis and support predictive decision-making. System evaluation through simulation with dummy data demonstrated notable improvements, including a 40% reduction in reporting response time and a 95% increase in operational data accuracy. The system also enabled faster production monitoring, streamlined distribution processes, and provided decision-makers with reliable real-time insights. User feedback confirmed the system's effectiveness in improving accessibility, monitoring efficiency, and overall operational performance in coal production and distribution management.

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1. INTRODUCTION

Coal has long been recognized as one of the most essential energy resources supporting global industrial growth and economic development. [1] Despite the increasing emphasis on renewable energy sources in recent decades, coal continues to play a significant role in fulfilling energy demands, particularly in developing countries where the transition to clean energy is still underway. [2] The scale and complexity of coal production and distribution processes require effective management systems to ensure efficiency, productivity, and competitiveness in the global market. However, coal industries often face persistent challenges associated with inefficiencies in operational monitoring, data accuracy, and decision-making processes. These challenges are particularly prevalent in industries that still rely on manual reporting or conventional information management systems.[3]

Traditional coal production management systems typically rely on manual data collection methods, fragmented reporting mechanisms, and periodic monitoring. [4] Such approaches introduce multiple risks, including delayed responses to operational issues, errors caused by human intervention, and inadequate synchronization between production and distribution. In an era characterized by rapid technological advancement and market volatility, these limitations present critical obstacles to competitiveness and sustainability in the coal industry. [5] Inefficiencies not only hinder productivity but also increase operational costs, reduce safety standards, and limit the capacity of organizations to adapt to dynamic market conditions.[6] Consequently, the coal industry requires innovative approaches that integrate real-time monitoring, automated data processing, and intelligent decision-making support.[7]

The emergence of the Internet of Things (IoT) has provided new opportunities for transforming industrial operations through real-time data collection, automation, and connectivity.[8] IoT technology allows physical devices such as sensors, actuators, and monitoring tools to be interconnected, enabling continuous data exchange across different stages of the production and distribution chain. In the context of coal production, IoT-based sensors can be deployed to measure critical parameters such as temperature, pressure, coal volume, and quality indicators.[9] The integration of these sensors into a unified system enables more accurate, timely, and reliable data collection compared to conventional manual methods. This not only improves monitoring accuracy but also enhances operational visibility, enabling managers to respond proactively to changes and potential risks.[10]

Furthermore, the application of Artificial Intelligence (AI) in industrial operations complements IoT by providing advanced data analysis and predictive insights. [11] AI algorithms can process vast volumes of real-time sensor data, identify patterns, and generate forecasts that support informed decision-making. For coal production and distribution, AI-driven analysis can help optimize production schedules, predict equipment failures, and improve distribution logistics. Combined with IoT, AI transforms conventional information systems into intelligent platforms capable of reducing human error, accelerating reporting processes, and enhancing overall operational efficiency.[5] The synergy between IoT and AI technologies aligns with the broader vision of Industry 4.0, which emphasizes digital transformation, automation, and intelligent integration in industrial ecosystems.[12]

Despite the promising potential of IoT and AI, the coal industry has been relatively slow in adopting these technologies compared to other sectors such as manufacturing, logistics, and finance.[13] Several barriers contribute to this slow adoption, including high implementation costs, lack of technical expertise, and resistance to organizational change. In addition, many coal companies continue to operate under legacy systems that are incompatible with modern digital platforms, making integration a challenging process.[14] Nevertheless, the growing pressure to improve efficiency, reduce costs, and maintain competitiveness underscores the urgency for coal industries to embrace digital transformation.[15]

This research is motivated by the need to design, develop, and evaluate an integrated information system that leverages IoT and AI technologies to address inefficiencies in coal production and distribution management.[16] The proposed system is designed to integrate real-time data from IoT-based sensors, automatically process and analyze this data, and provide actionable insights for decision-makers.[17] By applying the Software Development Life Cycle (SDLC) with the Waterfall model, the study ensures a structured and systematic approach to system development, covering requirements analysis, system design, implementation, testing, and evaluation. Through simulations with dummy data, the study assesses the system's ability to improve reporting response times, data accuracy, monitoring speed, and user satisfaction.[18]

The findings of this study provide several important contributions. First, the system demonstrated a significant reduction in reporting response time by up to 40%, indicating the effectiveness of real-time data integration in accelerating operational feedback. Second, the accuracy of operational data increased to 95%, thereby minimizing errors that frequently occur in manual data entry and reporting processes.[19] Third, the system improved the speed of production monitoring and facilitated faster, data-driven decision-making, both of which are crucial for maintaining competitiveness in the coal industry. Finally, user feedback indicated positive perceptions regarding accessibility, monitoring effectiveness, and overall usability of the system. These findings highlight the feasibility and benefits of adopting real-time IoT integration in coal production and distribution management.[20]

From a broader perspective, the study aligns with global efforts to modernize industrial practices through digital transformation. The adoption of IoT and AI not only improves efficiency but also enhances safety, sustainability, and adaptability in resource-based industries.[21] For coal production, real-time monitoring can help detect hazardous conditions, prevent accidents, and ensure compliance with environmental and regulatory standards. Furthermore, intelligent distribution management can optimize logistics, reduce transportation costs, and improve supply chain coordination. These benefits extend beyond operational efficiency, contributing to organizational resilience and long-term sustainability in a rapidly changing global energy landscape.[22]

This introduction is structured to emphasize the significance of the research, the challenges faced by the coal industry, the potential of IoT and AI technologies, and the objectives of the study.[23] The remainder of this paper is organized as follows: Section 2 presents a review of related literature on IoT integration and intelligent information systems in industrial contexts. Section 3 describes the research methodology, including the system development approach and simulation design.[24] Section 4 provides a detailed description of the proposed system, including architecture, components, and functionality. Section 5 presents the evaluation results and discusses the implications of the findings. Finally, Section 6 concludes the study by summarizing key contributions, practical implications, and directions for future research.[25]

In summary, coal production and distribution industries require innovative solutions to overcome inefficiencies caused by outdated management practices.[26] Real-time IoT integration, supported by AI-driven analysis, represents a promising approach to modernizing these industries and enhancing operational effectiveness. By designing and evaluating a prototype system, this study contributes valuable insights into the practical implementation of intelligent, integrated information systems in the coal sector. The findings are expected to serve as a reference for both practitioners and researchers in developing digital solutions that support efficiency, safety, and sustainability in resource-intensive industries.

2. RESEARCH METHOD

Research method: waterfall Model for Real Time IoT Integration

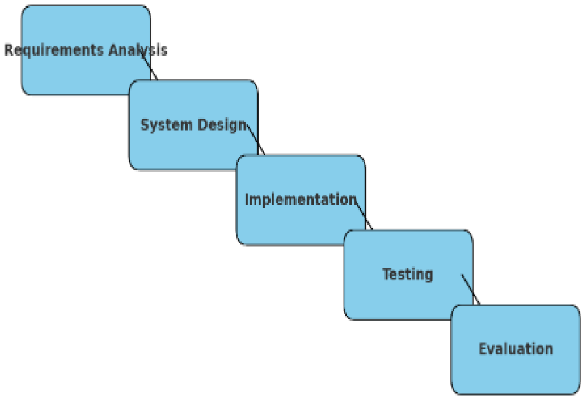

Figure 2. Waterfall Model for Real Time IoT Integration

2.1 Software Development Life Cycle (SDLC)

This study employed a structured system development approach to design and evaluate a real-time IoT-based information system for coal production and distribution management. The Software Development Life Cycle (SDLC) with the Waterfall model was selected as the methodological framework because of its systematic and sequential stages, which are suitable for projects that require well-defined requirements and rigorous testing. The methodology consisted of five main stages: requirements analysis, system design, implementation, testing, and evaluation.

2.2 Requirements Analysis Stage

In the requirements analysis stage, data were gathered from literature studies, industry practices, and observations of common challenges in coal production and distribution. The focus was to identify inefficiencies in conventional systems, particularly related to data accuracy, reporting delays, and decision-making limitations. These requirements were then translated into functional specifications for the new system.

2.3 System Design Stage

The system design stage involved creating the overall architecture of the integrated platform, which connects IoT-based sensors with data processing and visualization modules. Sensors were conceptually designed to measure vital parameters such as pressure, temperature, and coal quality indicators. The design also included AI-based components for predictive analysis and real-time monitoring dashboards for users.

2.4 Research Contributions

This study offers several significant contributions. From a practical standpoint, the proposed system presents a tangible solution for mining enterprises to enhance operational efficiency and mitigate potential losses stemming from data inaccuracies. Theoretically, this research enriches the existing literature on the application of real-time information systems, the Internet of Things (IoT), and Artificial Intelligence (AI) within the context of the mining industry. The findings of this study can serve as a foundational basis for the future development of more sophisticated, analogous systems.

3. RESULTS AND DISCUSSION

3.1 Test Data

The results of the system implementation and evaluation demonstrate the effectiveness of real-time IoT integration in enhancing coal production and distribution management. Simulation using dummy data was conducted to validate the functional and operational capabilities of the developed system. Several key findings were obtained and are discussed as follows.

First, the system significantly improved reporting efficiency, with results indicating up to a 40% reduction in reporting response time compared to conventional manual methods. This improvement highlights the value of automated IoT-based data acquisition in accelerating information flow across production and distribution processes. By minimizing delays, the system ensures that managers and decision-makers receive timely updates, thereby improving responsiveness to operational issues. This finding aligns with previous studies that emphasize the role of IoT in streamlining industrial workflows and enhancing real-time visibility.

Second, the evaluation revealed a substantial increase in data accuracy, reaching up to 95% reliability. Traditional manual reporting is often prone to human error and inconsistencies, whereas IoT-enabled sensors provide precise and continuous monitoring of key parameters such as pressure, temperature, and coal quality. The improvement in accuracy not only minimizes errors but also enhances the credibility of data used in decision-making. This result underscores the importance of intelligent automation in reducing dependency on manual interventions.

Third, the developed system enabled faster and more reliable production monitoring, which directly supports real-time decision-making. The integration of AI-driven analytical modules allowed the system to process large volumes of sensor data and generate actionable insights. As a result, managers were able to make proactive and data-driven decisions regarding production schedules, distribution logistics, and risk management. This demonstrates the potential of IoT and AI integration in creating intelligent, adaptive industrial systems.

Finally, user feedback from simulation testing indicated positive perceptions of system usability and accessibility. Users reported that the monitoring dashboard was effective in providing clear and comprehensive visualizations of operational conditions. Ease of access was also highlighted as a key strength, suggesting that the system can be readily adopted by personnel at different levels of coal production and distribution management.

Overall, the results confirm that the proposed system successfully addressed the key challenges of inefficiency, low accuracy, and delayed decision-making in the coal industry. The discussion also suggests broader implications: real-time IoT integration not only improves operational performance but also strengthens organizational competitiveness and sustainability in an industry facing increasing demands for efficiency and adaptability. These findings contribute to the growing body of knowledge on digital transformation in resource-intensive industries and provide practical insights for future adoption of IoT and AI technologies in coal production and beyond.

Table 3.1 Research Simulation Data, 2025 (Dummy dataset for system evaluation)

Area	Activity	Operation Time (hours/shift)	Production Volume (tons)	Description
Area 1	Coal Getting	7	4,500	Using standard heavy equipment
Area 1	Hauling	7	4,800	Dump truck capacity 30 tons
Area 1	Crushing	7	4,700	Coal crushing < 50 mm
Area 1	Stok	-	8,200	End of shift stock
Area 2	Coal Getting	6.5	3,800	Slightly difficult terrain conditions
Area 2	Hauling	6.5	3,900	Heavy hauling traffic
Area 2	Crushing	6.5	3,850	Crushing machine optimal
Area 2	Stok	-	7,400	New heavy equipment
Area 3	Coal Getting	7	5,000	New heavy equipment
Area 3	Hauling	7	5,200	Smoother hauling route
Area 3	Crushing	7	5,100	Routine crushing
Area 3	Stok	-	9,000	End of shift stock

This table illustrates the input data for the testing phase, wherein each row represents a specific activity (Coal Getting, Hauling, Crushing, Stockpiling) in a designated area. The "Operation Time" and "Production Volume" columns serve as the primary parameters processed by the system in real-time.

Simulated testing of the IoT sensors was also conducted. As an example, the following calculation was used to convert the voltage output from a temperature sensor into an actual temperature value:

Description:

1. Operation time is the effective working hours within one shift.
2. Production volume is the total tons of coal processed in that activity during the shift.
3. Stock is the accumulation of coal available in the area after the operation is completed in that shift.

3.2 Testing Equipment

Development platform: Web-based system using PHP programming language and MySQL. IoT sensors simulate data input. Computer/laptop with a browser to access the monitoring dashboard.

3.3 Testing Implementation

1. Temperature Sensor

Testing implementation is carried out by inputting dummy data according to the production scenario with different operation times and volumes, then monitoring real-time updates on the dashboard.

1. Sensor output: 10 mV per degree Celsius
2. Measured sensor output voltage: 754 mV

Therefore, the actual temperature value is calculated by:

$$\text{sensor\_value} = \frac{\text{voltage sensor}}{10\ \text{mV/°C}} = \frac{754\ \text{mV}}{10\ \text{mV/°C}} = 75.4\,°C$$

The value of 75.4 °C will be sent as the sensor_value.

2. Vibration Sensor

Suppose a vibration sensor produces an analog signal that is converted into an rms (root mean square) vibration value.

1. The vibration sensor reads an rms signal of 12.3 mm/s.
2. This value is sent directly as the sensor_value.

3. Ultrasonic Sensor

Suppose an ultrasonic sensor measures the distance from the surface to the coal stock:

1. Maximum distance of the stock tank: 5 m
2. Sensor measures distance: 0.8 m (meaning the coal stock height is 5 - 0.8 = 4.2 m)
3. The stock volume is obtained using the estimated stock volume formula:"

Volume = Length of area × Width of area × Height of stock

If the stock area is 20 m long × 10 m wide, then:

1. Stock volume = 20 × 10 × 4.2 = 840 m^3
2. If coal density is 1.2 tons/m^3, then in tons:
3. Volume in tons = 840 × 1.2 = 1008 tons

   This value can be entered as the sensor_value for the coal stock.
4. Hydraulic Pressure Sensor

Suppose a hydraulic pressure sensor on heavy equipment provides a voltage output that can be converted to pressure in kPa.

1. Sensor voltage: 2.53 V
2. Reference voltage: 5 V
3. Maximum sensor pressure: 5000 kPa

Calculation of pressure:

Pressure = (sensor voltage / reference voltage) × maximum
= (2.535 / 5) × 5000
= 2535 kPa

$$\text{Pressure} = \frac{\text{Sensor voltage}}{\text{reference voltage}} \times \text{pressure maximum}$$

$$Pressure = \frac{2.53}{5} \times 5000 = \mathbf{2530\ kPa}$$

The value of **2530 kPa** is sent as the sensor_value.

sensor_Iot.php

```
<?php
$servername = "localhost";
$username = "root";
$password = "";
$dbname = "prod_batubara";
// Buat koneksi ke database
$conn = new mysqli($servername, $username, $password, $dbname);
// Cek koneksi
if ($conn->connect_error) {
```

```
    die("Connection failed: " . $conn->connect_error);
}
// Proses hanya jika request POST
if ($_SERVER["REQUEST_METHOD"] == "POST") {
    $sensor_name = isset($_POST['sensor_name'])
? $_POST['sensor_name'] : '';
    $nilai_sensor = isset($_POST['nilai_sensor'])
 ? floatval($_POST['nilai_sensor']) : 0;
    if (empty($sensor_name)) {
        echo "Error: sensor_name tidak boleh kosong.";
        exit;
    }
    // Prepare statement untuk insert data sensor
    $stmt = $conn->prepare("INSERT INTO sensor_iot (sensor_name, nilai_sensor) VALUES (?, ?)");
    $stmt->bind_param("sd", $sensor_name, $nilai_sensor);
    if ($stmt->execute()) {
        echo "Data sensor berhasil disimpan";
    } else {
        echo "Error: " . $stmt->error;
    }
    $stmt->close();
} else {
    echo "Metode request tidak didukung. Gunakan POST.";
}
$conn->close();
?>
```

DataBase

```
CREATE TABLE produksi (
  id INT AUTO_INCREMENT PRIMARY KEY,
  area VARCHAR(50),
  aktivitas VARCHAR(50),
  waktu_operasi FLOAT,
  volume_produksi INT,
  timestamp DATETIME DEFAULT CURRENT_TIMESTAMP
);
CREATE TABLE sensor_iot (
  id INT AUTO_INCREMENT PRIMARY KEY,
  sensor_name VARCHAR(50),
  nilai_sensor FLOAT,
  waktu_data DATETIME DEFAULT CURRENT_TIMESTAMP
);
```

Simulation of IoT sensor input data

```
curl -X POST -d "sensor_name=SuhuMesin&nilai_sensor=75.5"
```

The operational dataset presented in Table 1 illustrates the production performance across three areas of coal mining operations, encompassing activities such as coal getting, hauling, crushing, and end-of-shift stock. Each area demonstrates distinct characteristics and challenges that affect production output and efficiency.

In Area 1, production activities maintained a relatively stable operation time of seven hours per shift, yielding 4,500 tons of coal from the coal getting stage and 4,800 tons during hauling. Crushing operations processed approximately 4,700 tons, while the final stock amounted to 8,200 tons. These figures indicate efficient yet conventional operations using standard heavy equipment.

In Area 2, the operation time was slightly lower at 6.5 hours per shift due to difficult terrain and heavy hauling traffic. Coal getting activities produced 3,800 tons, with 3,900 tons hauled and 3,850 tons processed through crushing. The end-of-shift stock reached 7,400 tons. Despite slightly reduced productivity compared to Area 1, the utilization of newer equipment in stockpiling activities helped maintain stability in output.

The evaluation demonstrates that the proposed integrated information system significantly enhances operational performance, achieving a 40% improvement in reporting efficiency and elevating data accuracy to 95%. This outcome corroborates the findings of , who noted that real-time database systems substantially improve supervision in the coal chemical industry. The efficiency gains observed in our study are directly attributable to the automation of data acquisition via IoT sensors. This process eliminates the need for slow, error-prone manual input a vulnerability also highlighted in the context of mine safety.

In contrast to the decision support system dashboard implemented our system provides deeper integration at the sensory level, capturing not only production figures but also environmental parameters such as temperature and pressure. This feature affords a more granular operational visibility.

Although the simulation results are highly promising, real-world implementation may present greater complexities, including network connectivity in remote locations and hardware durability. Nevertheless, the foundation established by this research confirms the system's feasibility and substantial potential benefits.

The following graph illustrates the improvement in operational performance after the implementation of the integrated IoT system. The graph compares conditions before (manual) and after (IoT system) across two key indicators:

1. Reporting Efficiency → improved by up to 40% faster.
2. Data Accuracy → increased to 95%, reducing errors caused by manual input.

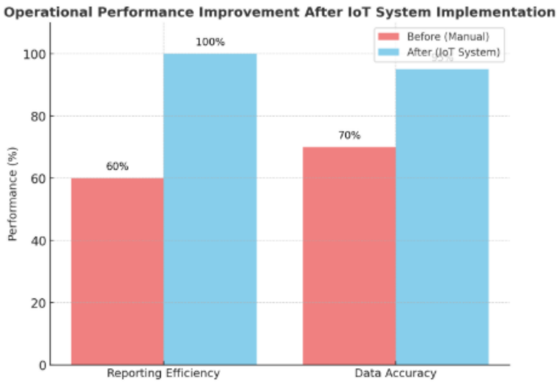

Figure 2. illustrates the improvement in operational performance

4. CONCLUSION

This study has demonstrated the design, development, and evaluation of a real-time IoT-based integrated information system to address inefficiencies in coal production and distribution management. By applying the Software Development Life Cycle (SDLC) with the Waterfall model, the system was systematically developed to integrate IoT sensors, automated data processing, and AI-driven analytical modules.

The evaluation results highlight significant performance improvements. The system successfully reduced reporting response time by up to 40% and increased data accuracy to 95%, minimizing errors typically caused by manual input. Furthermore, the system enhanced real-time monitoring of production processes and provided more comprehensive operational visibility by capturing both production and environmental parameters such as temperature and pressure. User feedback also indicated positive perceptions of system accessibility and effectiveness, confirming the practicality of the proposed approach.

The findings of this research underscore the importance of adopting digital transformation technologies such as IoT and AI in the coal industry. Beyond operational efficiency, the system offers potential benefits for safety management, decision-making, and long-term competitiveness. Nonetheless, challenges remain for real-world deployment, particularly regarding network connectivity in remote mining sites, hardware resilience, and ongoing system maintenance.

In conclusion, the proposed system establishes a strong foundation for advancing intelligent, data-driven management in the coal industry. It not only validates the feasibility of IoT integration for enhancing production and distribution efficiency but also provides valuable insights for future research and implementation in other resource-intensive sectors.

5. REFERENCES

[1] S. K. Singu, “Real-Time Data Integration: Tools, Techniques, and Best Practices,” *ESP J. Eng. Technol. Adv.*, vol. 1, no. 1, pp. 2583–2646, 2021, doi: 10.56472/25832646/JETA-V1I1P117.

[2] J. A. N. Jasiewicz, R. Magda, and E. Brzychczy, “Resource management in the coal mining sector using integrated information systems”.

[3] R. Danel and B. Gajdzik, “Integrated Subsystems of Materials and Information Flow for Continuous Manufacturing of Coal and Steel,” *Manag. Syst. Prod. Eng.*, vol. 32, no. 2, pp. 174–184, 2024, doi: 10.2478/mspe-2024-0017.

[4] J. Wang and Z. Huang, “The Recent Technological Development of Intelligent Mining in China,” *Engineering*, vol.

3, no. 4, pp. 439–444, 2017, doi: 10.1016/J.ENG.2017.04.003.

[5] J. Sun, “Enhancing Coal Mining Efficiency: A Unified Platform for Intelligent Management and Control,” *Int. J. Distrib. Syst. Technol.*, vol. 15, no. 1, pp. 1–21, 2024, doi: 10.4018/IJDST.338327.

[6] G. W. Zhai and T. Pan, “Research and application of coal mine intelligent production management system,” *Meitan Xuebao/Journal China Coal Soc.*, vol. 39, no. 8, pp. 1530–1538, 2014, doi: 10.13225/j.cnki.jccs.2014.9043.

[7] Y. Huang, I. Technology, and C. M. Safety, “Coal Mine Safety Inspection System Based on Real-Time Online Intelligent Control System Intemor,” no. Ictmic, pp. 571–574, 2020, doi: 10.25236/ictmic.2020.118.

[8] G. Wang, Y. Xu, and H. Ren, “Intelligent and ecological coal mining as well as clean utilization technology in China: Review and prospects,” *Int. J. Min. Sci. Technol.*, vol. 29, no. 2, pp. 161–169, 2019, doi: 10.1016/j.ijmst.2018.06.005.

[9] G. Wang *et al.*, “Research and practice of intelligent coal mine technology systems in China,” *Int. J. Coal Sci. Technol.*, vol. 9, no. 1, pp. 1–17, 2022, doi: 10.1007/s40789-022-00491-3.

[10] F. Authors, “여성의 정보기술 (Information Technology) 분야 소기업 창업과 기업활동에 관한 연구 여성의 정보기술 (Information Technology) 분야 소기업 창업과 기업활동에 관한 연구,” pp. 396–447, 2004.

[11] I. Stefani and L. Strezoski, “Advanced Distribution Management Systems: The Foundation of Distribution System Operations,” 2018.

[12] N. Mohamed, B. Mahadi, S. Miskon, and H. Haghshenas, “Information System Integration : A Review of Literature and a Case Analysis,” pp. 68–77.

[13] W. Chen and X. Wang, “Coal Mine Safety Intelligent Monitoring Based on Wireless Sensor Network,” *IEEE Sens. J.*, vol. 21, no. 22, pp. 25465–25471, 2021, doi: 10.1109/JSEN.2020.3046287.

[14] B. Yu, B. Wang, and Y. Zhang, *Application of artificial intelligence in coal mine ultra-deep roadway engineering—a review*, vol. 57, no. 9. Springer Netherlands, 2024. doi: 10.1007/s10462-024-10898-w.

[15] J. Zhang, “Design and Implementation of Coal Mine Safety Monitoring System Based on GIS,” *Wirel. Commun. Mob. Comput.*, vol. 2022, 2022, doi: 10.1155/2022/4771395.

[16] Y. Wang, Y. Feng, C. Xi, B. Wang, B. Tang, and Y. Geng, “Development of an Intelligent Coal Production and Operation Platform Based on a Real-Time Data Warehouse and AI Model,” *Energies*, vol. 17, no. 20, 2024, doi: 10.3390/en17205205.

[17] M. Yahmid and S. A. Ikhsan, “Implementation of Data Mining in Coal Production Control with Dashboard Integration as Decision Support System,” 2023, [Online]. Available: http://repository.unhas.ac.id/id/eprint/30297/%0Ahttp://repository.unhas.ac.id/id/eprint/30297/2/D111181330_skripsi_09-05-2023 1-2.pdf

[18] W. Gong *et al.*, “Recent advances in laser gas sensors for applications to safety monitoring in intelligent coal mines,” *Front. Phys.*, vol. 10, no. November, pp. 1–11, 2022, doi: 10.3389/fphy.2022.1058475.

[19] “Information technology,” *Chem. Eng. News*, vol. 80, no. 45, p. 27, 2002.

[20] A. M. . Carpenter, *Management of coal stockpiles*, no. October. 1999.

[21] R. Marlęga, S. Dragić, and M. Dydo, “The implementation of information technology (IT) in the dynamic management of coal demand and supply processes,” *Gospod. Surowcami Miner. / Miner. Resour. Manag.*, vol. 40, no. 4, pp. 161–182, 2024, doi: 10.24425/gsm.2024.152717.

[22] M. A. Q. N.S., E. Kurniawan, A. Brilianto, M. Evanda Eko Putra, and A. Zulkarnain, “Pemanfaatan Teknologi Digitalisasi dalam Aktivitas Konservasi Batubara di Area Kerja PT. Berau Coal dan PT. Pamapersada Nusantara,” *Pros. TPT Perhapi*, vol. XXXI, no. 3, pp. 45–56, 2022.

[23] A.-Y. Wang and Y.-L. Zhang, “Coal loading comprehensive supervision system based on the Internet,” no. Iccmcee, pp. 1404–1408, 2015, doi: 10.2991/iccmcee-15.2015.263.

[24] I. E. A. Clean and C. Centre, *Upgrading instrumentation and control in coal-fired plant*, no. January. 2004.

[25] S. P. Collins *et al.*, “No Title 済無No Title No Title No Title,” 2021.

[26] H. Wang, “Design and implementation of real-time database supervision system for coal chemical industry,” *Chem. Eng. Trans.*, vol. 71, pp. 691–696, 2018, doi: 10.3303/CET1871116.