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AI-BASED CRITICAL INFRASTRUCTURE MONITORING AND INCIDENT ANALYSIS IN SMART CITIES

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ABSTRACT

As urbanization accelerates globally, the development of smart cities has become imperative to address the increasing complexity of urban challenges. Critical infrastructure, such as transportation systems, energy grids, and water supply networks, plays a pivotal role in ensuring the seamless functioning of urban environments. This article presents a comprehensive framework for integrating Artificial Intelligence in monitoring and analysing critical infrastructure within smart cities. The proposed system employs advanced sensor networks, Internet of Things devices, and data analytics to gather real-time information from the city's critical infrastructure components. Machine Learning algorithms are then applied to process and analyze the collected data, enabling the system to identify patterns, anomalies, and potential vulnerabilities. The integration of artificial intelligence facilitates predictive maintenance, early detection of faults, and optimization of resource allocation, contributing to the overall resilience and efficiency of urban infrastructures.

KEY WORDS

smart city, critical infrastructure, monitoring, anomaly detection, AI

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INTRODUCTION

Critical infrastructure is a broad term comprising assets, systems, and networks vital for a well-functioning society. It encompasses different areas such as energy, chemical, transportation, water, wastewater, communications, financial, healthcare, emergency, food, agriculture, government, and information technology. These sectors are closely connected. Hence, a disruption can compromise homeland security [1].

Classically Rinaldi et al. identify, understand and analyse critical infrastructure interdependences [2]. They explore the framework of the challenges and complexities of interdependency, as shown in Figure 1.

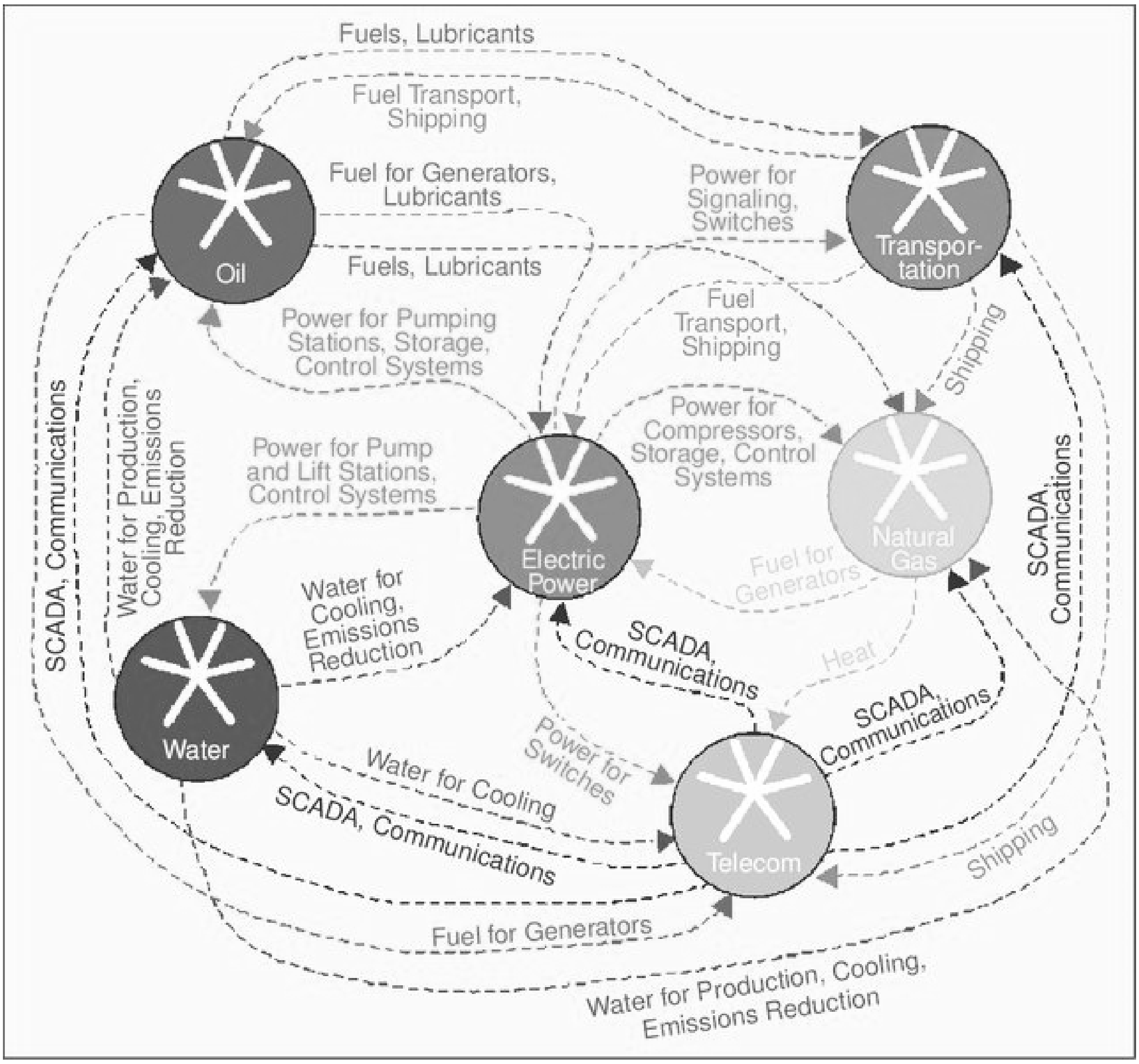

Figure 1. Infrastructure interdependencies [2].

In a smart city, advanced technology, including digital and data-driven solutions, is implemented to benefit the population. It requires various aspects such as information and communication technology usage in different sectors such as education, health, transportation, solid waste management, urban planning, automation and service control, government transparency, and more. Critical infrastructure improvement in terms of sustainability, resilience, and safety is a critical concern in smart city development [3].

Artificial Intelligence (AI) is decisive in smart cities and critical infrastructure [4]. It facilitates process automation, decision-making, forecasting, and optimization via big data analysis.

Hence, critical infrastructure monitoring for incident analysis using AI enhances resilience and efficiency in smart cities. The present work provides a detailed outline of AI monitoring, anomaly detection, prediction, and incident analysis in smart cities. Moreover, it provides relevant applications and recommendations concerning AI deployment within critical infrastructures

ANALYSIS OF CRITICAL INFRASTRUCTURE IN SMART CITIES

Which systems are critical in a smart city? In his work, Zlatogor presents the analytical model of the critical infrastructure of future smart cities. This research identifies 15 entities and 42 bi-directional relations such as Smart Transportation System, Smart Delivery System, Smart Energy System, Smart Health and Sport System, Smart Education, Smart Garbage Handling System, Smart Entertainments, Smart Governance, Smart Water Supply System, Smart Food Supply System, Smart Financial System, Smart Buildings, Transformed Citizens, Smart Working CritilyEnvironment, Transformed Biotope [5].

In contrast Tokody et al. discussed the six main pillars of a smart city, for example Smart economy, Smart Government, Smart People, Smart Living, Smart Mobility, and Smart environment. The pillars of the smart city can be compared to critical infrastructure sectors [6].

The European critical infrastructure sectors were first defined by Directive 2008/114/EC Annex I. It defines only the Energy and Transport sectors. After that Directive (EU) 2016/1148 listed additional sectors, such as the Banking, Financial market infrastructure, Health sector, Drinking water supply and distribution, and Digital Infrastructure [7, 8].

We can conclude that these categorizations show significant overlap. Nevertheless, the critical infrastructure of smart cities will have to be protected.

REAL-TIME MONITORING

Among critical infrastructure protection tools, real-time monitoring is an emerging area that was examined in the present study. During the analysis of data sources, two main groups were defined: the first is data from the monitored part of the critical infrastructure, and the second group is data from the critical infrastructure monitoring system. The critical infrastructure monitoring system can be part of another critical infrastructure, typically energy and data networks. Some data sources in the smart city subsystems were also identified, such as: public and private data network, public and isolated energy network, water network, transportation network, and the weather monitoring system. AI-driven sensors are used to continuously monitor systems to track critical infrastructure components such as energy grids, transportation systems, and communication networks in real-time.

Real-time monitoring of critical infrastructure in smart cities is vital to ensure the efficient operation, safety, and resilience of urban environments. Leveraging advanced technologies like sensors, Internet of Things (IoT) devices, and data analytics enables continuous surveillance and instant response to potential issues. A comprehensive network of sensors and IoT devices across critical infrastructure components, including transportation systems, energy grids, water supply networks, and communication systems, must be deployed into the monitoring system. Good monitoring must connect and integrate different data sources into the network. Additionally, it relies on sensors measuring various parameters such as temperature, humidity, pressure, traffic flow, structural integrity, and other relevant metrics. Data from diverse sources, including sensors, surveillance cameras, satellite imagery, and public databases, can be integrated to create a unified and real-time dataset.

Furthermore, the following aspects are essential for real-time monitoring:

- data aggregation platforms to collect, process, and normalize information from different sources facilitate a seamless analysis [9, 10],
- implementing real-time analytics tools and algorithms to process incoming data instantaneously [11, 12],
- continuous supervision of anomalies, patterns, and deviations from standard operating conditions to identify potential issues or threats [13-15],
- integrating machine learning models for predictive maintenance, leveraging historical data and real-time inputs to forecast potential failures or maintenance needs [16],
- proactively scheduling maintenance activities based on the predictions to minimize downtime and enhance infrastructure reliability [17],
- implementing AI-driven algorithms for automated incident detection to recognize real-time abnormal patterns or potential threats [18, 19],
- integrating incident management systems to trigger immediate responses, notifications, and alerts to relevant authorities [20],
- creating user-friendly dashboards that visually represent the critical infrastructure's real-time status [21],
- graphical displays such as maps and charts ease data interpretation, allowing city officials to make informed decisions quickly [21],
- designing a scalable monitoring system permits easy integration of new sensors or infrastructure components as the city evolves [21],
- flexibility to adapt to infrastructure or technology changes ensures an effective monitoring system over time [22],
- real-time monitoring of smart city critical infrastructure enhances overall situational awareness, facilitates rapid response to incidents, and contributes to long-term sustainability and resilience in urban environments [22].

This approach enables cities to address challenges proactively, minimize disruptions, and optimize the performance of essential services.

ANOMALY DETECTION

Filtering out operational disruptions is of great importance to maintaining the complex infrastructure operation of the smart city. AI algorithms analyze data streams to identify anomalies or irregularities in the functioning of infrastructure elements. It enables early detection of potential issues or security threats. AI-based anomaly detection is crucial to ensure the security, reliability, and efficiency of critical infrastructure in smart cities [13]. Leveraging artificial intelligence, particularly machine learning algorithms, enables automatic real-time identification of abnormal patterns or deviations from expected behavior [14, 15]. An overview of how AI-based anomaly detection can be implemented in the context of smart city critical infrastructure is presented further in the text.

The first tool is data collection and preprocessing. Data is gathered from multiple sources, including sensors, IoT devices, surveillance cameras, and other relevant sources within the critical infrastructure. Data preprocessing is required to check missing values, normalize scales, and ensure compatibility for input into machine learning models.

The next step in the system's design is function design. At this stage, relevant characteristics indicating the normal operation of the system are identified and extracted from the collected data. Feature engineering may involve transforming or combining raw data to improve the performance of anomaly detection algorithms.

For anomaly detection unsupervised machine learning models are utilized. The Isolation Forests model is effective for detecting outliers in high-dimensional datasets. Neural network-based models are capable of learning the underlying patterns and identifying anomalies. The One-Class Support Vector Machine is suitable for detecting outliers in a dataset with predominantly normal instances.

First, the most suitable model for the task is selected from the options. Then the training of the model follows. The chosen machine learning model is trained using historical data representing normal operating conditions. The model learns to identify patterns and features that characterize normal behavior within the critical infrastructure.

The trained model is deployed to analyze incoming data in real time. The model flags instances that deviate significantly from the learned normal patterns as potential anomalies.

It is possible to parameterize the AI and set appropriate thresholds for the anomaly scores to control the sensitivity of the detection system. It also generates alerts or notifications when abnormalities exceed pre-defined thresholds, enabling immediate investigation and response.

The created model must be constantly adjusted to reality. That means adapting the anomaly detection model to evolving conditions by continuous learning. The model must be periodically updated using new data to account for permanent changes in the infrastructure or in the environment.

If the anomaly detection systems are integrated into incident response mechanisms, it will facilitate immediate actions when anomalies are detected.

In summary, by incorporating AI-based anomaly detection into the critical infrastructure monitoring of smart cities, these cities can enhance their ability to detect and respond to abnormal events in real-time. This proactive approach contributes to the overall resilience and security of smart cities, ensuring the uninterrupted functioning of essential services and minimizing the impact of potential threats.

PREDICTIVE ANALYTICS

By analyzing historical data and patterns, machine learning models predict potential failures or incidents. Hence, it allows predictive maintenance and minimizes downtime. AI-based predictive analysis in smart cities involves leveraging artificial intelligence to forecast future trends, events, and conditions within urban environments. By analyzing historical data, current information, and various contextual factors, predictive analysis can offer valuable insights for decision-making, resource optimization, and proactive planning [16].

What are the key elements of AI-based predictive analytics for smart cities? The following system structure is recommended.

The key element of forecasting is the data collection and integration process. Data may be aggregated and integrated from various sources, including sensors, IoT devices, social media, weather forecasts and historical records. A comprehensive dataset can be created covering a significant period of time, which records relevant information on various aspects of the city, such as transport, energy consumption, public services and environmental conditions.

In this case, it is also important to identify the key features and variables that influence the results to be predicted during feature design.

There is a variety of machine learning models for predictive analysis to choose from. Time Series Models are suitable for forecasting trends and patterns over time. Regression Models are useful for predicting numerical values. Classification Models are applied when predicting categorical outcomes. These models also have to be trained, using historical data, allowing them to learn patterns, relationships, and dependencies. During the training process, the models are fine-tuned to ensure accuracy and reliability in making predictions.

After that, these models can be used for Real-time Prediction, to analyze incoming data in real-time and generate predictions.

With the help of some analyses, a predictive analysis can be performed to predict the maintenance needs of critical infrastructure elements. Scheduled maintenance can assist in activities based on predicted failure probabilities, minimizing downtime and extending the life of the infrastructure.

The main feature of the system is the feedback mechanism with continuous improvement, that is a feedback loop that evaluates the accuracy of the forecast against the actual results.

AI-based predictive analysis in smart cities gives a foresight to urban planners, administrators, and decision-makers, enabling them to proactively address challenges, allocate resources efficiently, and create more resilient and sustainable urban environments, for example, in the area of Traffic and Transportation Optimization, Energy Consumption Forecasting, Resource Allocation and Urban Planning.

INCIDENT ANALYTICS

In case of an incident, AI analyzes the data to understand the root cause, severity, and potential impact on other interconnected systems, facilitating a quicker and more targeted response. AI-based incident analysis in smart cities involves utilizing artificial intelligence to process and interpret data in real-time [18]. It aims to identify and understand various incidents or anomalies within the urban environment [19]. This approach enables quicker responses to emergencies, enhances public safety, and optimizes resource allocation.

AI-based incident analysis is based on data integration and data collection. Data is collected from diverse sources, including sensors, surveillance cameras, social media, emergency services, and other relevant sources. Data integration is carried out to create a unified and comprehensive dataset that provides a holistic view of the urban environment.

The large volumes of collected and preprocessed information can be processed in real-time utilizing AI algorithms.

Machine learning models can be used for incident detection and classification. These are trained models which use historical data to recognize patterns and anomalies associated with different types of incidents. In addition to recognition, the classification of events is an important task, such as traffic accidents, public disturbances, natural disasters, etc. For the analysis of emergency calls natural language processing techniques and text-based incident classification can be used.

CONCLUSION

AI integration into critical infrastructure monitoring and anomaly detection, as well as predictive incident analysis in smart cities can significantly improve their ability to respond to challenges, enhance public safety, and achieve a more sustainable and resilient urban environment. The present article examined how to use AI to create a safer smart city, and what steps can be taken to integrate AI in the critical infrastructure of a smart city.

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