Data-Driven Threat Intelligence for Energy and Critical Asset Management

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Abstract

Advanced cyber and physical threats are increasingly becoming a target of energy systems and critical infrastructure assets, which are threatening the continuity of its operations, safety and economic stability. Threat intelligence based on data (DTI) has become an essential method of detecting, threatening and preventing these threats on the spot. DTI will allow detecting the anomalies beforehand, assessing risks in advance, and making decisions by combining various sources of data, including industrial control systems (ICS) and SCADA networks with IoT sensors and external threat feeds. Machine learning and artificial intelligence are used as advanced analytics to identify vulnerabilities in time and provide automated response tactics. Despite the data quality, system interoperability, and privacy issues, the DTI implementation can improve the situational awareness, resilience, and protection of key assets within the energy environment, despite the challenges. This paper underscores the need to be systematic in terms of the data-driven approach to threat intelligence and the need to constantly adapt to changing threats.

Keywords: Data-driven threat intelligence, energy infrastructure, critical asset management, cybersecurity, industrial control systems, machine learning, predictive analytics, threat mitigation.

1. Introduction

Advanced data-driven strategies have increasingly become the key to the security and reliability of the energy system as well as other critical infrastructure assets. There is a growing interconnection of modern energy and industrial systems with Internet of Things (IoT) devices, smart sensors, and cyber-physical systems, which produce large amounts of operational and security-related data (Zohuri et al., 2022; Balali et al., 2020). Although these developments have allowed making the processes more efficient and operationally insightful, they have also introduced a broader attack surface, predisposing critical assets to cyber and physical attacks.

The data-driven threat intelligence (DTI) offers a methodical way to detect, analyze, and alleviate a threat by using the ongoing gathering and assessment of different datasets (Qamar et al., 2017; Alwaheidi and Islam, 2022). With the help of big data analytics, machine learning, and predictive modeling, organizations will be able to use raw operational and security data to generate actionable intelligence and proactively defend against known and newly identified threats (Moradi et al., 2019; Moustafa et al., 2018).

In the energy sector, DTI is instrumental for managing renewable and conventional energy assets, optimizing performance, and safeguarding critical operations from cyber-physical attacks (Oyekan & Enyejo, 2023; Zhou et al., 2016). Moreover, the integration of threat intelligence into energy management systems enhances situational awareness and supports decision-making processes, ensuring that operators can respond rapidly to anomalies and potential security breaches (Karagiannis et al., 2021; Althobaiti et al., 2021).

Overall, the convergence of data-driven analytics and threat intelligence represents a transformative approach for energy and critical asset management, offering the dual benefits of operational efficiency and enhanced security. This approach not only addresses current vulnerabilities but also anticipates future challenges in an increasingly complex and interconnected infrastructure landscape.

2. Threat Landscape in Energy and Critical Assets

The energy sector and critical infrastructure are increasingly reliant on digital technologies, including IoT devices, SCADA systems, and cloud platforms. While this connectivity enhances operational efficiency, it also introduces significant cyber and physical vulnerabilities (Qamar et al., 2017; Zohuri et al., 2022). Threats in these environments are often complex, targeting both the information technology (IT) and operational technology (OT) layers, which are tightly integrated in modern energy systems (Karagiannis et al., 2021; Alwaheidi & Islam, 2022).

Key threat categories include cyber-attacks, physical sabotage, insider threats, and systemic risks arising from interdependent networks. Attackers exploit vulnerabilities in smart grids, renewable energy assets, and industrial control systems to disrupt operations, cause financial loss, or compromise safety (Balali et al., 2020; Oyekan & Enyejo, 2023). Data-driven threat intelligence frameworks help organizations detect, analyze, and mitigate such threats, but challenges remain due to the heterogeneity and scale of data sources (Moradi et al., 2019; Moustafa et al., 2018).

Modern energy systems also face evolving threats due to the integration of renewable energy sources and distributed generation. These systems increase the attack surface and require sophisticated threat intelligence solutions to monitor dynamic operational environments (Oyekan

& Enyejo, 2023; Zhou et al., 2016). A data-driven approach allows operators to identify anomalous behaviors in real-time, anticipate emerging threats, and strengthen asset resilience.

The following table 1 summarizes the major threats to energy and critical assets, along with their potential impacts and examples:

Threat Category	Description	Potential Impact	Examples
Cyber Attacks	Unauthorized access, malware, ransomware, and phishing targeting IT/OT systems	Operational disruption, data theft, financial loss	Stuxnet-like attacks, ransomware on power grids (Qamar et al., 2017)
Insider Threats	Malicious or negligent actions by employees or contractors	Sabotage, theft of sensitive data, compliance issues	Unauthorized configuration changes, data leaks (Alwaheidi & Islam, 2022)
IoT/Smart Device Exploits	Exploiting vulnerabilities in connected sensors, meters, and actuators	System manipulation, inaccurate readings	Energy theft, grid manipulation (Althobaiti et al., 2021; Zohuri et al., 2022)
Physical Attacks	Vandalism, sabotage, or natural disasters affecting physical infrastructure	Service disruption, safety hazards	Substation destruction, pipeline attacks (Karagiannis et al., 2021)
Systemic/Interdependency Risks	Cascading failures due to interconnected systems and supply chains	Widespread outages, operational instability	Blackouts triggered by upstream failures (Moradi et al., 2019)
Data Integrity Threats	Manipulation of sensor or operational data	Incorrect decision-making, inefficiency	False SCADA readings, manipulated analytics (Moustafa et al., 2018)

3. Data-Driven Threat Intelligence (DTI) Concepts

Data-Driven Threat Intelligence (DTI) is an approach that leverages the collection, analysis, and interpretation of large volumes of data to identify, predict, and mitigate threats against energy and critical infrastructure assets. Unlike traditional threat intelligence, which often relies on manual reporting or reactive measures, DTI emphasizes **automation, analytics, and predictive insights** to strengthen security and operational resilience (Qamar et al., 2017; Alwaheidi & Islam, 2022).

DTI typically integrates data from multiple sources, including IT networks, operational technology (OT) systems, IoT devices, and external threat feeds, providing a **holistic view of asset vulnerabilities and emerging threats** (Zohuri et al., 2022; Karagiannis et al., 2021). The approach allows energy operators to not only detect anomalies in real time but also **prioritize risks based on asset criticality and potential impact** (Moradi et al., 2019; Balali et al., 2020).

Key Components of DTI

Table 2: The core components of DTI can be summarized in the following table:

Component	Description	Relevance to Energy & Critical Assets
Data Sources	IT/OT logs, SCADA/ICS systems, IoT sensors, threat intelligence feeds	Provides a comprehensive foundation for monitoring both cyber and physical threats (Zohuri et al., 2022; Oyekan & Enyejo, 2023)
Data Integration & Storage	Centralized or distributed repositories; includes cloud, edge, and hybrid storage solutions	Enables seamless analysis and historical trend assessment (Alwaheidi & Islam, 2022)
Analytics & Machine Learning	Anomaly detection, predictive modeling, clustering, correlation analysis	Identifies emerging threats, predicts potential attacks, and reduces false positives (Moustafa et al., 2018; Moradi et al., 2019)
Threat Prioritization	Scoring and ranking threats based on likelihood, impact, and asset criticality	Focuses response efforts on the most significant risks (Karagiannis et al., 2021)
Visualization & Reporting	Dashboards, alerts, and reports for operators and decision-makers	Enhances situational awareness and supports timely response (Zhou et al., 2016)

Information Sharing	Sharing threat intelligence with other organizations, CERTs, and industry consortia	Improves collective security and resilience across energy networks (Qamar et al., 2017)

Principles of DTI for Energy Systems

1. **Proactive Defense:** Using predictive analytics to anticipate threats before they impact assets (Moustafa et al., 2018).
2. **Integration of Cyber and Physical Data:** Combining IT network data with operational sensor data for a complete threat view (Karagiannis et al., 2021).
3. **Continuous Monitoring and Adaptation:** Systems continuously ingest and analyze data, allowing adaptive responses to evolving threats (Zohuri et al., 2022; Althobaiti et al., 2021).
4. **Actionable Insights:** DTI transforms raw data into practical intelligence that informs decision-making, incident response, and resource allocation (Balali et al., 2020; Oyekan & Enyejo, 2023).

DTI thus provides a data-centric foundation for securing energy infrastructure and other critical assets, improving not only threat detection but also operational efficiency and resilience (Qamar et al., 2017; Zhou et al., 2016).

4. Analytics and Threat Detection

Data-driven analytics play a critical role in detecting, understanding, and mitigating threats to energy and critical infrastructure assets. By leveraging large volumes of heterogeneous data from IT and OT systems, organizations can transition from reactive security to proactive threat intelligence (Qamar et al., 2017; Alwaheidi & Islam, 2022).

4.1. Role of Data Analytics in Threat Detection

Data analytics enables the identification of patterns, anomalies, and potential attack vectors that may compromise critical assets. In the energy sector, data collected from SCADA, IoT sensors, smart meters, and industrial control systems can be analyzed to detect both cyber and physical threats in near real-time (Zohuri et al., 2022; Oyekan & Enyejo, 2023). Big data frameworks facilitate the processing of high-velocity data streams, allowing for predictive threat modeling and enhanced situational awareness (Moradi et al., 2019; Balali et al., 2020).

4.2. Machine Learning and AI for Threat Detection

Machine learning (ML) and artificial intelligence (AI) techniques are increasingly applied to detect anomalies and predict attacks before they occur. Supervised learning models can classify known threats, while unsupervised models uncover previously unseen attack patterns (Moustafa

et al., 2018). Deep learning approaches have been utilized to monitor energy asset behavior, distinguishing between normal operational variations and suspicious activities that may indicate cyber intrusions or operational sabotage (Zhou et al., 2016; Karagiannis et al., 2021).

4.3. Predictive Analytics and Threat Prioritization

Predictive analytics allows operators to assess the likelihood and potential impact of threats, enabling prioritized responses to critical risks. Techniques such as time-series analysis, clustering, and correlation of multi-source data streams improve accuracy in identifying vulnerabilities and potential attack paths (Althobaiti et al., 2021; Balali et al., 2020). This approach not only enhances security but also ensures operational continuity and resilience of energy infrastructure.

4.4. Visualization for Situational Awareness

Effective threat detection requires actionable insights presented through intuitive visualization dashboards. Visual analytics allow operators to monitor network traffic, asset performance, and anomaly alerts simultaneously, facilitating rapid response to potential threats (Zohuri et al., 2022; Alwaheidi & Islam, 2022).

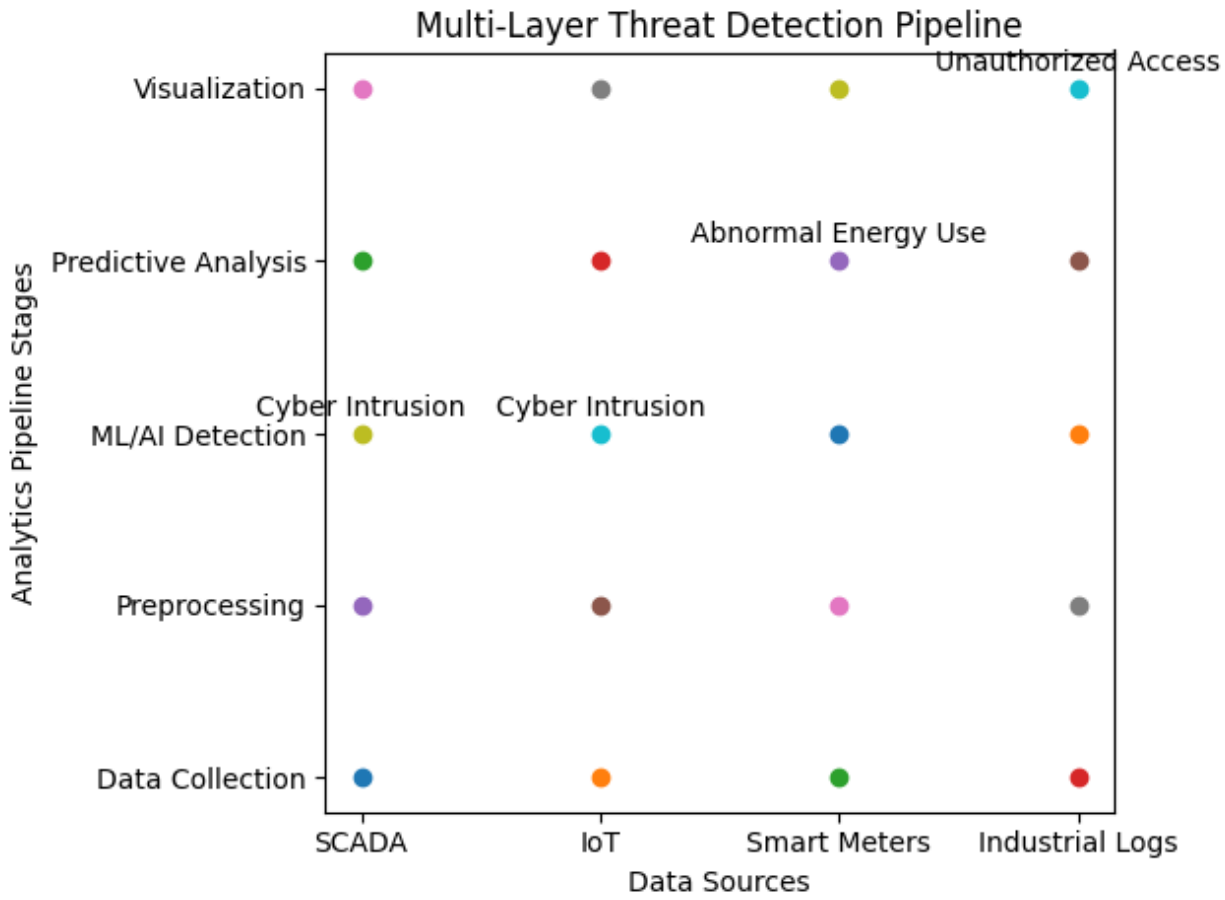

Fig 1: This visualization concisely demonstrates how heterogeneous industrial data streams are transformed through layered analytics into actionable threat intelligence, supporting real-time monitoring, predictive risk assessment, and informed security decision-making.

By integrating AI, machine learning, and real-time visualization, analytics-driven threat detection significantly strengthens the security posture of energy systems and other critical infrastructure (Qamar et al., 2017; Oyekan & Enyejo, 2023; Moustafa et al., 2018).

5. Risk Assessment and Prioritization

Risk assessment and prioritization form the analytical core of data-driven threat intelligence for energy systems and other critical assets. This stage translates raw threat data and detected anomalies into actionable security decisions by systematically identifying which assets are most at risk, the severity of potential impacts, and the urgency of mitigation actions.

5.1 Asset Criticality Identification

Energy and critical infrastructure environments consist of heterogeneous assets such as generation units, transmission networks, substations, SCADA servers, IoT sensors, and cloud-based analytics platforms. Data-driven approaches first classify assets based on their operational importance, interdependencies, and potential cascading effects in the event of compromise. Asset criticality is often quantified using operational, safety, financial, and regulatory impact metrics derived from historical operational data and system models (Balali et al., 2020; Zhou et al., 2016).

5.2 Threat and Vulnerability Correlation

Threat intelligence feeds, system logs, network traffic, and IoT telemetry are correlated to identify exposure points where known or emerging threats intersect with system vulnerabilities. Machine learning and analytics techniques enable continuous assessment of attack likelihood by learning patterns from past incidents and near-miss events (Qamar et al., 2017; Moustafa et al., 2018). In cyber-physical energy systems, this correlation extends beyond IT assets to include physical process vulnerabilities, such as manipulation of sensor data or control signals (Moradi et al., 2019; Karagiannis et al., 2021).

5.3 Risk Scoring and Prioritization

Data-driven risk scoring combines three core elements: likelihood of attack, vulnerability severity, and potential impact. Advanced analytics and AI models dynamically update these scores as new data becomes available, enabling adaptive prioritization rather than static risk registers (Alwaheidi & Islam, 2022). For energy infrastructures, impact assessment explicitly considers service disruption, safety hazards, energy theft, and loss of public trust (Althobaiti et al., 2021; Zohuri et al., 2022).

5.4 Decision Support for Mitigation Planning

Prioritized risk outputs support decision-making by guiding resource allocation toward the most critical threats and assets. This ensures that limited cybersecurity budgets and operational resources are focused where they yield the highest risk reduction. In renewable and smart energy systems, data-driven prioritization also supports performance optimization by aligning security investments with asset reliability and efficiency goals (Oyekan & Enyejo, 2023).

Table 3: Data-Driven Risk Assessment Framework for Energy and Critical Assets

Assessment Dimension	Description	Data Sources	Analytical Methods	Outcome

Asset Criticality	Importance of asset to operations, safety, and compliance	Asset registries, operational logs	Dependency analysis, impact modeling	Criticality ranking
Threat Likelihood	Probability of threat occurrence	Threat intelligence feeds, network traffic	Machine learning, pattern recognition	Likelihood score
Vulnerability Severity	Weakness level of asset or system	Vulnerability scans, configuration data	CVSS-based analytics, anomaly detection	Severity score
Impact Assessment	Consequences of successful attack	Historical incidents, simulation data	Scenario analysis, predictive modeling	Impact score
Composite Risk Score	Aggregated risk level per asset	Combined analytical outputs	Weighted risk models, AI-driven scoring	Risk prioritization
Mitigation Priority	Urgency and order of response actions	Risk scores, resource constraints	Decision-support analytics	Actionable mitigation plan

Data-driven risk assessment and prioritization enable a continuous, evidence-based understanding of security posture across energy and critical asset environments. By integrating cyber, physical, and operational data, organizations can move from reactive defenses to proactive, intelligence-led risk management that strengthens resilience against evolving threats (Qamar et al., 2017; Karagiannis et al., 2021; Zohuri et al., 2022).

6. Challenges and Limitations

Despite its strategic value, implementing data-driven threat intelligence (DTI) for energy systems and critical asset management faces several technical, organizational, and operational challenges. These limitations can constrain effectiveness if not properly addressed.

6.1 Data Quality, Volume, and Heterogeneity

Energy infrastructures generate massive volumes of heterogeneous data from SCADA systems, IoT devices, smart meters, and enterprise platforms. Inconsistent data formats, missing values, and noisy sensor readings reduce the reliability of analytics-driven threat detection (Qamar et al., 2017; Moradi et al., 2019). Poor data quality directly affects model accuracy and increases false positives.

6.2 Integration of Legacy and Modern Systems

Many critical assets operate on legacy industrial control systems that were not designed for continuous data sharing or advanced analytics. Integrating these systems with cloud-based or AI-driven threat intelligence platforms introduces interoperability and latency challenges (Balali et al., 2020; Karagiannis et al., 2021).

6.3 Scalability and Real-Time Processing Constraints

Real-time threat intelligence requires scalable data pipelines capable of handling high-velocity streams. Computational overhead, limited edge-processing capabilities, and bandwidth constraints can delay threat detection and response, particularly in geographically distributed energy networks (Zhou et al., 2016; Zohuri et al., 2022).

6.4 Model Robustness and Adaptability

Machine learning models used for anomaly detection and prediction are vulnerable to concept drift, adversarial manipulation, and limited generalization across different asset types. Static models may fail to detect evolving attack patterns, reducing long-term effectiveness (Moustafa et al., 2018; Alwaheidi & Islam, 2022).

6.5 Privacy, Security, and Data Governance

Threat intelligence systems often rely on sensitive operational and consumption data. Ensuring data confidentiality, regulatory compliance, and secure information sharing across stakeholders remains a critical challenge, especially in cloud-enabled environments (Qamar et al., 2017; Alwaheidi & Islam, 2022).

6.6 Organizational and Skills Limitations

Effective DTI deployment requires cross-domain expertise spanning cybersecurity, data science, and operational technology. Shortages of skilled personnel and insufficient coordination between IT and OT teams can limit adoption and operational impact (Oyekan & Enyejo, 2023).

Table 4. Key Challenges and Implications of Data-Driven Threat Intelligence in Energy and Critical Asset Management

Challenge Category	Description	Implications for Asset Management	Key References
Data Quality & Variety	Noisy, incomplete, and heterogeneous data from multiple sources	Reduced detection accuracy, higher false alarms	Qamar et al. (2017); Moradi et al. (2019)
Legacy System Integration	Limited compatibility between old ICS and modern analytics platforms	Increased integration cost and delayed deployment	Balali et al. (2020); Karagiannis et al. (2021)
Scalability & Latency	High data velocity and processing demands	Delayed threat response and reduced situational awareness	Zhou et al. (2016); Zohuri et al. (2022)
Model Adaptability	Concept drift and evolving attack strategies	Degraded long-term detection performance	Moustafa et al. (2018); Alwaheidi & Islam (2022)
Privacy & Governance	Sensitive operational and consumer data exposure	Regulatory risk and limited data sharing	Qamar et al. (2017); Alwaheidi & Islam (2022)
Human & Organizational Factors	Skills gaps and weak IT–OT collaboration	Inefficient use of threat intelligence insights	Oyekan & Enyejo (2023)

Overall, while data-driven threat intelligence significantly enhances the protection of energy systems and critical assets, addressing these challenges is essential to ensure reliability, scalability, and sustained security performance across complex cyber-physical environments.

Conclusion

Threat intelligence is a vital part of the protection of energy systems and assets of critical infrastructure that rely on data. Organizations can become proactive in detecting, evaluating, and preventing threats as they happen by using advanced analytics, machine learning, and AI to minimize operational risks and increase system resilience (Qamar et al., 2017; Zohuri et al., 2022). By combining the data of various sources, such as IoT devices, SCADA systems, and the cloud, it will be possible to gain a holistic view of possible vulnerabilities and attack vectors (Alwaheidi and Islam, 2022; Karagiannis et al., 2021).

Data-based methods also make it easier to have optimized asset management and performance, especially in renewable and intelligent energy systems, by converting giant amounts of operational data into actionable knowledge (Balali et al., 2020; Oyekan and Enyejo, 2023; Moradi et al., 2019). In addition, predictive threat modeling and continuous monitoring enable organizations to react quickly to anomalies and cyber-physical threats and reduce the possible damage of essential services (Moustafa et al., 2018; Zhou et al., 2016).

Nevertheless, the issues of data quality, legacy-modern system interoperability, and sophisticated attack types, including energy theft in smart grids, persist (Althobaiti et al., 2021). To overcome such issues, there is a need to integrate complex analytics, cross-industrial cooperation, and dynamic defense systems to guarantee the safety and stability of the energy industry and critical infrastructure.

To recap it all, the connection between threat intelligence that is data-driven and situational awareness makes digital-physical security practices more crucial, and this aspect should be enhanced through sustained innovation (Qamar et al., 2017; Zohuri et al., 2022; Alwaheidi and Islam, 2022).

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