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Chapter 7: IoT Data Integration and Edge-to-Cloud Intelligence

7.1. Introduction

The vast scale at which the Internet of Things (IoT) is deployed generates an unprecedented volume of data, from tiny sensor readings in chips hosted in remote or hostile environments to high-resolution images helping to pilot long-haul aircraft. This information deluge captured from even the most remote deployed sensors creates opportunities for companies and governments to enhance services and enable new implementations. Solutions range widely in type and spatial/temporal density, and consequently differing data integration trajectories are required. A closer investigation of these trajectories reveals similarities that can be articulated within a consistent framework.

Realizing the full potential of the IoT requires integrating data from vast-scale and diverse sources, which spans sources deployed in remote environments configured merely as sensors (e.g. smart dust) to groups of phones in smart cities. The goal is to enact security and privacy controls, remove background noise and dry runs, enhance quality via data fusion or bleeding-edge AI techniques (e.g. YOLO for image processing), and utilize services exposed within clouds. Extracting maximum business value requires not just data integration, but also edge-to-cloud intelligence, which places edge control, response time, response reliability, trust, and actor involvement into the optimization mix. Together, these concepts weave a holistic theory of IoT data integration and edge-to-cloud intelligence.

7.1.1. Background and Significance

The exponential growth of connected devices makes integrating their data into business processes a multidisciplinary challenge. Designing a framework for seamless data integration involves addressing data models, protocol incompatibilities, ingestion and

streaming architectures, computing assets, and governance controls. The study reviews the state of the art, synthesizes the primary components of data integration, and highlights the interdependencies among these aspects. Three research questions drive the investigation. First, how should the hardware, software, and procedural architecture for integrating IoT data into IoT-decision-making be designed? Second, how should the data generated by IoT devices be prepared and made available in the necessary regions for intelligent decision-making? Third, what are the core requirements for successfully integrating IoT data into IoT decision-making? The investigation centers on the specific use case of data integration for edge-to-cloud intelligence.

The tremendous increase in the number of IoT devices deployed across many domains and the rapid development of edge-cloud computing architecture promise vast amounts of valuable, readily available real-time data for intelligent decision-making. Several application domains, including industrial IoT, smart cities, healthcare, and environmental monitoring, leverage the benefits of a large sensor network connected to a physical world for monitoring, control, and optimization. Researchers and practitioners have harnessed these developments for implementing predictive maintenance, fault detection, data-driven process optimization, and other applications. Most of these applications define a centralized architecture, focusing exclusively on the required machine learning models and ignore the data preparation portion of the system.

Equation 1: Data Fusion at Edge Nodes

This represents how multiple sensor inputs are integrated at an edge device:

$$Dedge = \sum i = 1nwi \cdot SiD_{edge} = \sum_{i=1}^{n} w_i \cdot S_i Dedge = \sum i = 1nwi \cdot Si$$

Where:

- DedgeD_{edge}Dedge: Aggregated data at the edge
- SiS_iSi: Sensor data from device iii
- wiw_iwi: Weight (importance/reliability of each sensor)
- nnn: Number of sensors

7.1.2. Research design

The research design employs a conceptual framework supported by a systematic review of the body of work related to IoT data integration and intelligence. The scope of the investigation is wide-ranging, embracing not only the porous boundary conditions between cloud and edge but also the many sub-components required to support high-

quality data-driven innovation. Sources of volume and velocity deserve particular attention because, as the sheer scale of the IoT makes proliferation of cloud datacentres and other resources impractical, local decisions must be made that are often strongly influenced by the time constraints of edge analytics and the ability to combine information from many locations for more reliable inferencing. The need to populate sepulchral data lakes with vast quantities of data invites the implementation of streaming pipelines whose location-agnostic nature may undermine quality.

Typically, existing systematic reviews provide valuable insights into sub-areas of the disciplines of interest. It is difficult, however, to find authoritative resources that take a more comprehensive view, and any that do often descend into a collection of lists. Here, the intention is to not only capture the state of the art but also provide lucid perspectives at each resolution of the hierarchy. The focus is therefore given to the most salient aspects of data integration, architectural design, and edge-to-cloud intelligence, from supporting data models and formats through to security considerations. The review filters-out content from adoption studies and engineering-focused publications, as these concerns are well covered elsewhere and least contribute to knowledge beyond existing implementation capabilities.

7.1.3. Scope and Objective

The scope of this research encompasses Information Technology-related consideration and design-focus areas that affect the integration of different tiers in a generic IoT deployment. Candidate considerations under these headings are proposed. Research focuses on determining how integrated with others, deployment- and operational-related dimensions of IoT data may be independently optimized to yield the greatest overall Data Value without significant Data Risk, and without requiring Data Risk assessment at high total-investment cost.

The objectives are to clarify how the discrimination of IoT Data perimeter/geometry, evaluation of Data Value, and control of Data Risk may be separated to enable pragmatic Data Governance. The eventual aim is to reduce risks inherent in design-involving practical deployment-related aspects of IoT Data Value creation, realisation, and protection. The work therefore proposes a characterization of IoT end-to-end settings, and analyses of where and why security anchors—covering confidentiality, integrity, and (trusted) availability—are most needed.

7.2. Foundations of IoT Data Integration

Data integration in the context of the Internet of Things enables assimilating packets of information from heterogeneous sources and making them consumable by data-centric applications, such as advanced analytics and Artificial Intelligence (AI) or Machine Learning (ML) models, typically hosted on cloud platforms. Fulfilling the prerequisite of ingesting data from the diverse IoT ecosystem is paramount for any form of data-driven optimization or prediction. Such a data ingest pipeline comprises elements that prepare data to counter the high velocity of data generation from IoT sources, mitigate data quality issues, and infuse it into a back-end data repository of choice to be collected, processed, combined, and analyzed for higher-level insights. Supporting the growing types of edge sources requires broader data format and communication protocols acceptance, which may be achieved by evaluation over an integration layer centralized on design-time and runtime aspects.

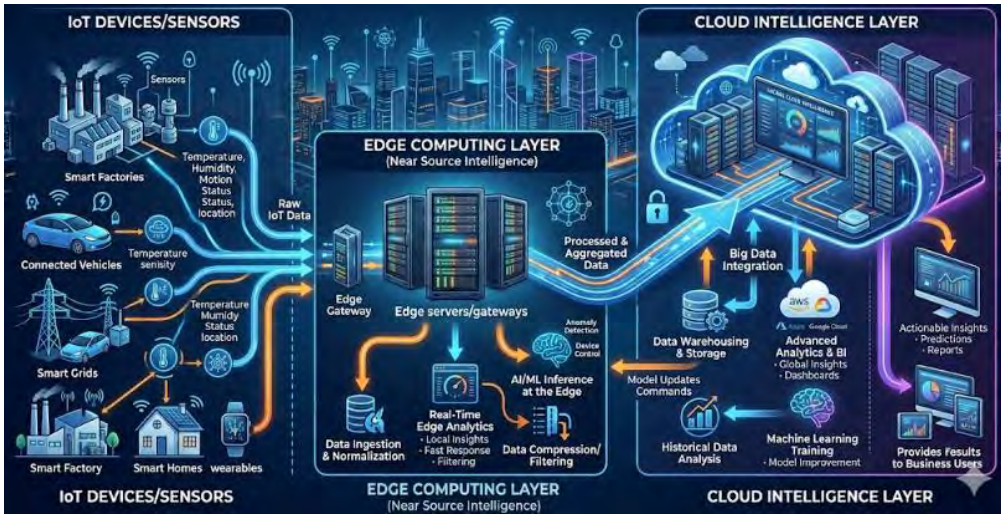

Fig 7.1: IoT Data Integration and Edge-to-Cloud Intelligence

Data modeling is an indispensable layer of such systems since it defines the glossary with formal descriptions of data present in a specific domain, building the preliminary foundation for semantic integration. The digital ontological concept expands the idea of a data model to encompass the logical representation with defined terms semantically annotated. Semantics, expressed using Semantic Web languages, drives automatic mappings between different digital representations of the same data. The lack of a mapping between two representations at design time should not prevent any expressions of data of one representation from being used together with data of another. At runtime, the integration layer can leverage hashing techniques to dynamically detect the variables in the received data and match them with the semantics description that corresponds to that specific data packet.

7.2.1. Data Models and Semantics

Selecting suitable data models is vital for ensuring that the information stored within IoT systems is meaningful. Available data models range from predefined structure types, such as those found in relational databases, to highly flexible formats, such as JSON documents, or model definitions that allow for the definition of practically any shape, like RDF. Regardless of the used data storage technology or format, the precise definition of the information prevention is crucial for knowledge extraction and operational intelligence in data integration processes. Either data schemas—in the case of relational databases and fixed-tables NoSQL storages—or data modeling definition languages, such as JSON schema, Avro schema, Protocol Buffers, and RDF schemas/Ontologies, must reflect the information components in demand and must be utilized consistently across the applications potentially written by independent developers.

Data semantics must also be determined to allow answers to complex queries emerging from distinct applications at the same time. One approach for achieving formal semantics is based on the use of ontologies defined by the Web Ontology Language (OWL). A more flexible ontology is defined by RDF-Schema, allowing for the organization of data into vocabularies that declare classes, subclasses, properties, sub-properties, and domains and ranges of properties. In this case, the mapping of the data into tuples of a graph, as the underlying storage model of RDF data is a Directed Acyclic Graph, follows a simple rule. The preservations of the Semantic Web's architecture through the definition of RDF ontologies aiming at supporting the integration of data generated by independent developers introduces a big advantage for the use of IoT data: ontology-based queries enable data fusion from different sources and their analysis in a broader context.

Identifying the relevant data models and their semantics is only a first step toward a usable IoT Data infrastructure. Chatper 7.2 continues by investigating the majority of data models, ontologies, semantics, and mapping strategies required by the different IoT subsystems.

7.2.2. Protocols and Interoperability

IoT comprises devices built and programmed by vendors for specific use cases. These include sensors, actuators, control elements, gateways, and management platforms. A standard protocol offers functionally compatible message exchanges using a common syntax and semantics. Interoperability standards aim to facilitate exchange and sharing of data between devices. Therefore, devices from different vendors must use the same protocol. Though such standards may exist at the application layer for specific protocols,

no universal standard exists to allow all vendor devices to work together. Even many security and other data-rich protocols cannot support all vendor needs.

Furthermore, such standards may not cover impending requirements like high-frequency streaming data. Fundamentally open and interoperable by publicly building incompatible rich data structures addressed by existing protocols with message format extensibility are flexible enough to meet the present, past, and future needs of any IoT data sharing and transfer, while providing all the advantages and functionality of Cloud Computing. Any IoT protocol designed with a rich message format base will take care of future requirements through message extensions. This will enable adaptation, enhancement, and increment of either message format or message structure without changing the protocol core. Such wide compatibility flexibility will tremendously reduce the burden of any implementing vendor.

7.2.3. Data Ingestion and Streaming

Ingesting and processing IoT data at high velocity and volume is a challenging task, particularly when considering data diversity and quality aspects. As users increasingly move from vertical to horizontal data analysis and pursue market trends such as edge computing or data lakes, the demand for real-time processing increases, and specialized streaming architectures become necessary. Architectural components traditionally designed for batch processing—or heuristically designed to bridge a gap between batch and real-time processing—are insufficient supports since they can incur unacceptable processing latencies in real-time applications. Fast buffering and dissatisfaction with data quality, often ignored by practitioners who inadvertently enter the world of streaming data management, warrant a careful analysis. Data quality concerns can best be addressed by managing data quality from its inception. In many environments, the actual quality achieved is at least as important as the quality deemed acceptable.

Ingestion pipelines capture sporadically arriving data items generated by producers. Their length can be determined in a straightforward manner through queuing theory. Buffering delays associated with such sporadic arrivals can be unacceptably large. On the other side of the equation, buffering within a stream processing engine introduces data velocity and/or volume increases into the system. Example architectures, dedicated to data ingestion or ingestion coupled with fast buffering, are presented.

7.3. Edge Computing for Intelligence

Edge Computing for Intelligence

Edge computing moves data processing and intelligence from the cloud closer to where data is generated, enabling faster decision-making and reduced bandwidth costs. Data analytics workloads typically follow a hierarchy from the edge to the cloud, with three main categories: batch-oriented tasks requiring significant computing resources, streaming tasks needing real-time processing but not interactive response times, and real-time tasks demanding instantaneous responses. Edge computing, a new tier in the cloud continuum, addresses the first two categories and is particularly advantageous for Internet-of-Things (IoT) applications generating immense data volumes.

Operations at the edge vary by location, type of device, and use case. From simple event detection to complex machine learning algorithms, local analytics play an important role in determining what data reaches the cloud. Data transmission should be optimized so only mission-critical information is sent, thereby reducing network strain and latency. In heterogeneous IoT ecosystems combining devices with different capabilities, limited computation performance and energy resources at the edge create a trust gap for decision-making, especially in safety-critical applications. New workflow paradigms are emerging for distributed intelligent system execution, including static edge collaboration, dynamic cloud–edge association, and cloud offloading with partial computation at the cloud.An edge ML model is trained and periodically updated in the cloud and deployed in the edge devices in a more reduced footprint and inferences can be made in a more real-time and reliable manner. Local classifiers or prediction engines can act in conjunction with a larger cloud model providing higher level prediction, risk and threat analysis, and decision.

Equation 2: Edge-to-Cloud Offloading Decision

This equation determines whether data should be processed locally or sent to the cloud:

$$O = Lc + TcLe + TeO = \frac{L_c + T_c}{L_e + T_e} O = Le + TeLc + Tc$$

Where:

- OOO: Offloading factor
- Lc,LeL_c, L_eLc,Le: Latency (cloud vs edge)
- Tc,TeT_c, T_eTc,Te: Processing time (cloud vs edge)

7.3.1. Edge Architectures and Processing Paradigms

The architecture of edge nodes, the hierarchy at which data processing occurs, and the compute paradigm that determines data processing modes and patterns all influence the design of IoT integration. Several types of architectures can be deployed within edge

nodes. Processing hierarchies can be pipeline or arbitrary for streaming data. Data can be processed in batch, streaming, or real-time modes or through a mixed approach, depending on latency and freshness requirements. Some edge nodes are deployed in a centralized manner, working as local servers or aggregators with stronger compute power, while others are distributed and share the processing load.

Processing at the edge can be categorized into local analytics, edge machine learning, and decision making. Local analytics play a significant role in addressing issues of explosion in volume and velocity of the incoming data streams and performing real-time operations based on low-level data streaming from connected devices, such as data cleansing or filtering and data compression.

7.3.2. Local Analytics and Real-Time Decision Making

As edge devices become smarter with advanced computation and storage capabilities, some local knowledge-based analytics can considerably ease the communication burden on the edge-cloud infrastructure. The latency-sensitive IoT applications that allow local decision making, with the help of machine learning can be deployed to edge nodes to minimize round-trip delays. The ML models can either be trained directly on the edge with small-batch learning, or on the cloud with model inference pushed down to the edge. In either case, a key requirement is to assure a reliable, low-latency inference response from the edge, because even momentary failures may lead to adverse consequences. Reliability is affected by multiple parameters, including the criticality of the inference task, the business impact of a delay in decision making, and the trustworthiness of the detected inference outcome.

The decision-making executed within the edge devices can be further optimized by introducing a coordinated execution workflow that distributes the decision making across multiple decision-making-enabled devices deployed in the vicinity. By introducing a workflow-level view of the decision-making task, the reliability can be improved not only by detecting possible failures in the direct inference at a single device but also by properly designing data-sharing and coordination mechanisms among neighboring devices, thus enabling round-trip decisions with a higher reliability in a timely manner.

7.3.3. Resource Constraints, Security, and Privacy at the Edge

Resource constraints at the edge relative to the cloud influence four interrelated aspects of security, privacy, and trust. First, the limited processing power, memory, and energy at edge endpoints necessitate lightweight or specialized security controls that can reduce

the additional resource costs they impose. Edge devices further assume primary responsibility for data collection and filtering, thus establishing the security of the raw data stream. Edge access control provides an additional boundary of trust around endpoints that supply sensitive data. By preventing unauthorized access during this phase, the risk of traffic interception or malicious data/uploads is removed, thereby minimizing downstream concerns.

Data transmission is the phase at which risk can be most effectively mitigated. It is the only stage in the system where data can be intercepted or altered. Privacy issues are typically associated with cloud services, but social acceptance rests on more than security strength. Users want to know how their data are being processed. Edge-based computation enables privacy by limiting the sensitive information actually sent to the cloud for aggregation or higher-level analysis. Credential-based authentication functions are well understood and easily implemented. Secure multiparty computation and differential privacy are additional approaches that avoid data exposure at the cost of greater complexity and resource consumption. Trust and privacy concerns are greatest for detections and inferences based on video or audio feeds, perhaps explaining the industry preference to avoid processing human-sensitive data on the edge whenever possible.

7.4. Cloud-Based Intelligence and Data Management

Traditional Information and Communications Technologies offer a wealth of cloud computing capabilities. Public clouds or hybrid clouds along with operational data lakes provide the necessary infrastructure and platform to process vast volumes of historical data. The advanced analytics and machine learning techniques on these scalable computers have enhanced applicability and performance. Scope, nature, and lifecycle of the deployment decide the effectiveness of cloud-based intelligence. Organizations leveraging cloud for Machine Learning or integrating with

external cloud-hosted Machine Learning services must account for feasibility and governance aspects.

Unlike the edge server resources are elastic, pay-per-use, and not bound by latency and bandwidth constraints. Models can be built on historical data, governancede ficiencies can be compensated, freshness factor tolerated, and latency can be periphery controlled. Dedicated cloud service models like SaaS, PaaS, and FaaS utilize the layered data lake concept for logical grouping. Backend API-based integration reduce effort overhead and build time. The advanced algorithms, high external data merger possibilities, and multiplicity of models enhance prediction quality. Run passive models on core and activate on abnormal SSD based data flow-volume. But data residency regulation, third-

party risk, and governance issues are often neglected. Organizations must not treat these as side bread and butter model, rather treat these like the costly meal. Building a hybrid cloud strategy brings in multi-layered governance and flexibility for data placement.

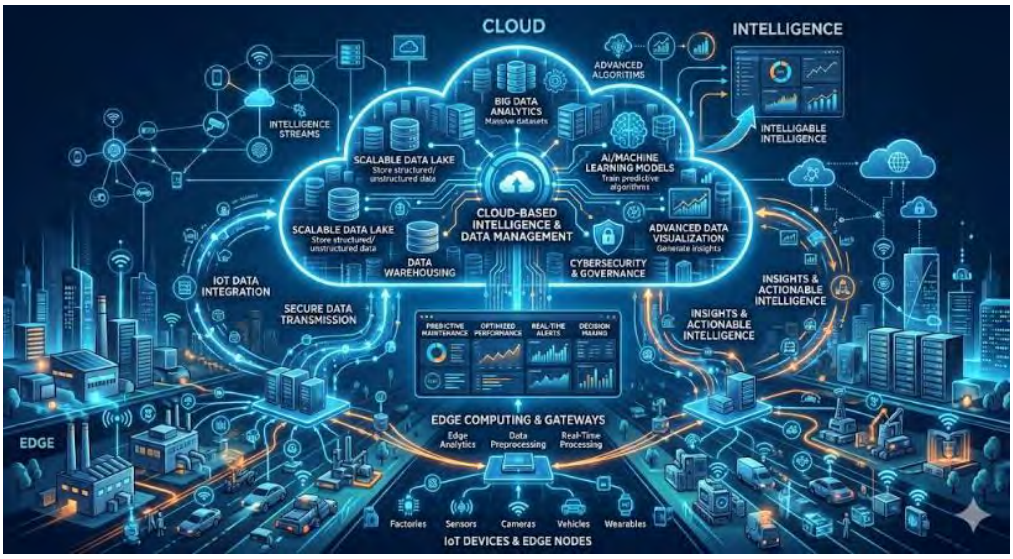

Fig 7.2: Cloud-Based Intelligence and Data Management

7.4.1. Cloud Platforms, Data Lakes, and Compute Farms

Variants of cloud platforms characterized by data lakes and compute farms address huge data velocity and volume requirements. Such cloud farms also make it easier and economical to run advanced analytics, including AI/ML techniques. They support the entire lifecycle, from model training to operational deployment. The design of cloud farms is different for different requirements, combining techniques from performance and cost governance. Performance-oriented clouds, e.g. Microsoft Azure, support both native modules and 3rd-party market apps, thus providing easy-to-access high-performance AI/ML modules. Clouds deployed primarily on cost governance principles hide the details of the underlying complex systems (e.g. Hadoop) through user-friendly API, open-source modules, and commons, thereby enabling customers to focus on data innovation and not on infrastructure. Hybrid (mainly edge-cloud) and multi-cloud deployment strategies introduce further data placement and orchestration complexities.

Cloud platforms executing analytics algorithms on aggregate data have arrived late in the game, yet are now set to conquer the market. The reason for their late entry has been their fairly limited data resource, which pre-empted serious large AI development. However, with Industrial IoT/Digital Twin enabling enterprise-wide omnipresent sensor/actuator networks, these clouds have suddenly become ideal for such resource-

hungry large AI, ML-based predictive maintenance digital twins, and more generally, digital transformation with sensor network-based data-driven optimization. The service requirements are different from the other types. Cost is no longer the primary consideration; latency, throughput, and data consistency have become key factors.

7.4.2. Advanced Analytics, AI, and Machine Learning on the Cloud

Data analytics and artificial intelligence research has relied heavily on significantly large data collections. The data is generally acquired from multiple sources through several data preparation processes and is performed using a variety of computing tools at a very high scale. Cloud computing provides on-demand access to a shared pool of configurable computing resources, and this demand scaling elasticity allows cloud resources to handle large-scale data analytics very effectively. The compute layer of nearly all cloud platforms can scale elastically, but only a few cloud-distributed data lake architecture can scale elastically. The analytics carried out on the acquired data can be at layers ranging from simple business-intelligence reporting and dashboarding, to predictive analytics, to advanced analytics like text image and video analytics and understanding, to machine-learning-based systems, Artificial Intelligence (AI)-augmented systems. The research of AI and machine learning can also be service-oriented and is often based on an as-a-Service service model.

Many analytics tasks can be performed using service functions being directly provided by the cloud service provider. The service model can considered being that of SaaS and the cloud service user need not bother with model training and deployment lifecycle operations, with the exception of providing data access. Nevertheless, advanced analytics, AI, and ML techniques can often be equivalent to carrying out typical cloud adversarial machine-learning operations. The necessary cloud capabilities, such as the aforementioned scaling capabilities, will be formally considered in the design well, and beyond scaling, the proper governance management of the services are of primary importance with respect to AI, ML, and analytics tasks.

7.4.3. Data Governance, Lineage, and Compliance

Policies and procedures for data quality control and governance must be implemented at the data lake level. Data governance issues include data security, policy enforcement, privacy, and compliance with standards such as GDPR and HIPAA. Data owners, typically the data-acquiring organization, apply data usage policies to the collected data. Sensors, camera feeds, and other data can access and share data based on the data security policy of the data lake. Data controls need to be implemented to ensure that sensitive data (e.g., personally identifiable information) is not leaked into untrusted

hands. Data encryption (with appropriate keys), masking, and anonymization techniques are typically applied to the data before being stored in the cloud. A data lineage solution enables organizations to conduct audits, identify the origins of the collected data, meet data-related compliance regulatory requirements, and understand how the quality of data has been impacted over time by assessing the processes that the data has been through. Data provenance or lineage outlines the history of detailed events that a data set has gone through since its creation and across handoffs in the data life cycle. Informed auditability and meeting data-related compliance regulatory requirements depend on detailed tracking and monitoring of data assets across pipelines.

7.5. Edge-to-Cloud Integration Strategies

Designing an edge and cloud integration strategy presents several architectural considerations, including data placement, cross-tier orchestration, and synchronization. By studying existing edge–cloud implementations and their deployment strategies, a supportive checklist can be derived to guide the design of future applications.

Edge and cloud tiers of the overall architecture may belong to the same administrative domain or, alternatively, be deployed in a hybrid or multicloud manner. The former is simpler, generally preferred, and typically dominates existing use cases and solutions. Seamless orchestration is facilitated when both tiers reside within the same cloud. Nevertheless, certain application or business constraints induce a multicloud design—such as compelling storage prices at different cloud vendors, individual user preferences to keep selected data within a specific cloud, or government restrictions to avoid the cross-border flow of sensitive information. Contrarily, a hybrid architecture involves coordination among clouds owned by distinct organizations.A third approach combines the two strategies, searching for an appropriate set of tradeoffs minimizing the total cost related to the two major types of injected errors: the anonymization error of sensitive attributes and the distortion error introduced either by the first or the last protection. Security-aware privacy-preserving data processing focuses instead on another aspect of the problem. To achieve accurate prediction of a sensitive attribute, a cloud trusted by the data owner receives a perturbed version of the data set containing the remaining attributes. The cloud needs to ensure that it performs the correct computation on the received perturbed data.

Equation 3: End-to-End Intelligence Score

This represents overall system intelligence combining edge and cloud contributions:

$$Itotal = \alpha Iedge + (1-\alpha)IcloudI_{total} = \alpha I_{edge} + (1-\alpha)I_{cloud}Itotal = \alpha Iedge + (1-\alpha)Icloud$$

Where:

- ItotalI_{total}Itotal: Overall intelligence
- IedgeI_{edge}Iedge: Intelligence from edge analytics
- IcloudI_{cloud}Icloud: Intelligence from cloud analytics
- alpha\\alphaalpha: Weight factor (0 to 1, prioritizing edge vs cloud)

7.5.1. Hybrid and Multi-Cloud Architectures

Multiple cloud providers often offer tailored solutions, optimizing costs and performance for specific workloads. When organizations adopt a best-of-breed cloud strategy, distinct security zones emerge. These typically include security-focused cloud services (e.g., Darktrace), hands-off multi-cloud, or industry-cloud implementations providing matching governance, performance, latency, compliance, or other mission-relevant criteria.

Cloud computing generally fosters simplicity, where data and workloads can be liquid and thus move to the right cloud at any given moment. As clouds can be orchestrated without bottlenecks, a burstable mode can follow an on-premise basis. Services such as Google BigQuery support the Common Storage Engine, enabling federated queries spanning GCS and Cloudera, Snowflake, or Amazon data lakes without data movement. This architecture's added flexibility allows for joint projects with external partners while addressing compliance at innovation speed. However, a multi-cloud approach is less straightforward when sensitive information is managed or when high throughput needs to be expected.

7.5.2. Data Synchronization, Consistency, and orchestration

The operations in Edge networks usually follow modes suitable for time-bound analytical use cases where data is integrated and fused persistently. However, an interactive request-response model along with other push-pull mechanisms can distribute small amounts of data from different edge networks. When using Cloud Computing, data from different sources can easily be orchestrated and centralized in a temporal-data lake, fully enabling an in-depth understanding of reality. In these cases, Edge and Cloud can be integrated through a Data Synchronization mechanism that guarantees consistency among edges and with the Cloud when the synchronization happens. Latency and bandwidth become critical metrics when considering the Data Synchronization between the Edge and the Cloud. Fault tolerance also should be considered, mainly for Cloud systems that are scaling continuously. A load in a Cloud

environment may be present one instant and not in another one. However, such a variation should not reflect in the Edge operations.

The Cloud infrastructure has its own Data Consistency mechanism based on redundancy and, therefore, it has to be different in order to improve efficiency by considering different Data Consistency at Cloud level, such as Eventual Consistency. Security, Trust, and Privacy are important additional aspects. Data generated at the Edge can be considered as more sensible than at the Cloud for pure privacy reasons, but not only for that. In some applications, data are encrypted at the source, not only to become unreadable but also to ensure that only one entity may decrypt it. In other cases, data sources may even produce false data for some entities. So, Secrecy, Trust, and Privacy have to be considered and, due to that, risks mitigated at every point of interaction between two entities or the Edge and the Cloud.

7.5.3. Security, Trust, and Privacy across Tiers

Security, trust, and privacy concerns permeate all three IoT data integration layers, knowing the type of control exerted on an integrated data set helps select the best protection mechanisms. A first-order risk analysis enables the identification of major vulnerability exposure, which drives the specification of access control policies. A second-order analysis quantifies privacy loss due to data de-identification, providing a statistical background against which to compare privacy policies affecting either edge or cloud operators.

Privacy-aware design explores how functional requirements of a monitoring solution influence the end-users' privacy. The sex protection can be conducted either by modifying the monitoring solution prior to implementation or by employing anonymization techniques to protect sensitive attributes.

7.6. Use Cases and Reference Architectures

Industrial IoT empowers predictive maintenance solutions, which prevent unplanned downtime and high repair costs by leveraging data-driven processes targeting machine failures. Different predictive maintenance use cases rely on analytical capabilities for detecting sensor drifts or failures, anticipating remaining useful life, predicting machine failure, or enabling health assessments. Yet predictive maintenance cannot solve all equipment problems; data models are siloed and specialized, infrequently reused in other business functions or applications. Reference architectures, which allow testing of business initiatives and applications early in the design cycle, can therefore help

systematically select and compose use-case-enabling analytical capabilities and decision-making models from business function models.

Data-driven optimization provides another advanced Industrial IoT use case. The solution connects with data lakes from combined solutions or other systems, ingests, cleanses, and aggregates the data, and creates a model that predicts the behavior of various assets. By defining intelligible conditions and decisions, the solution simulates the results of the different scenarios. The lean team then selects optimum scenarios, implements the changes, and monitors the results. After past data is provided, the models need to be updated only occasionally. Advanced Business Process Management and Business Activity Monitoring from Business Process Management and Business Intelligence feed the data-driven optimization solution. Scenarios are continuously simulated to improve business results.

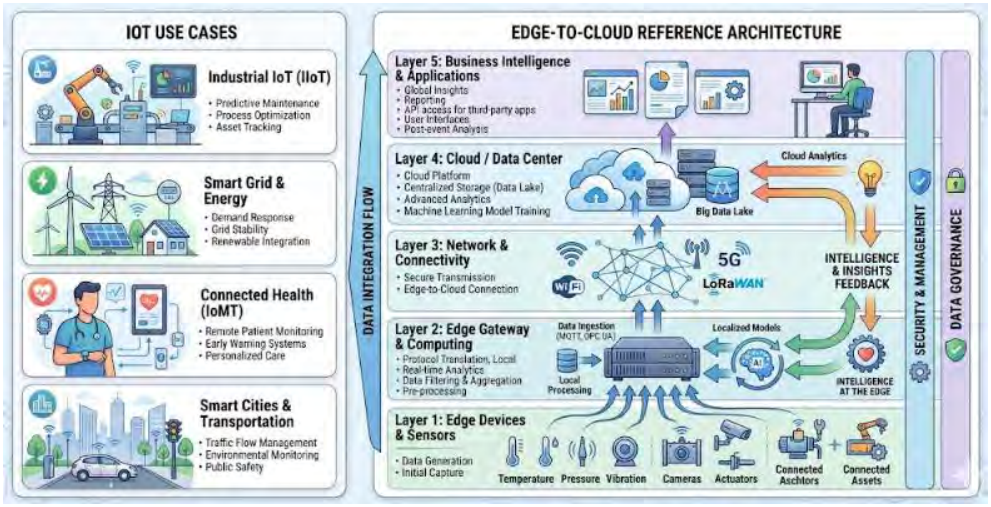

Fig 7.3: Cases and Reference Architectures

7.6.1. Industrial IoT and Predictive Maintenance

Data-driven optimization and predictive maintenance remain among the most prominent application domains for the Industrial Internet of Things (IIoT). A relay-based predictive maintenance use case is presented, using a smart wireless condition-monitoring system to detect hinge movement in a railroad switch. The testbed enables real-time vibration data acquisition and surveillance at low cost. A data lake is built using cloud-based Azure services, supporting video, time series, and event data capturing for proof-of-concept support of the predictive-maintenance use case. Monitoring and predictive, conditional alerts form the basis for subsequent pilot and trial deployments.

Despite significant advancements in Industrial-IoT and Edge-to-Cloud Data Intelligence technology, research benefits from addressing deployment readiness in operational environments within important domains such as predictive maintenance. Continuous monitoring and predictive maintenance of industrial assets inevitably induce massive data capture, storage, and analysis challenges. A Smart-Condition-Monitoring framework addresses these requirements, implementing video, time-series, and event-based data-capture techniques on a jointly developed trailer-trailer controlled-unit testing rig. A wireless, vibration-based switch-connector monitor provides a proof of concept for condition-based maintenance decoupling of hinge movement detection from the typical vibration signature monitoring of background-noise-dominant rail-switch zones.

7.6.2. Smart Cities and Environmental Monitoring

Data generated in smart city scenarios are characterized by high velocity, volume, variety, and, often, low value, thus making Cloud-only solutions for data ingestion, storage, processing, and analysis less efficient in terms of latency, throughput, bandwidth, and cost. Deployed for global-scale environmental monitoring, sensor networks in cities can benefit from mobile-edge and Fog Computing enabling low-cost, low-power data acquisition and processing at the edge. Ingestion processes can be designed as real-time streams with periodic burstiness. Facilitat- ing dynamic data fusion at different stages of data processing—streaming, real-time, and batch—opens opportunities for innovation and optimization in scientific environments where data volume and velocity impede traditional processing architectures.

In general, edge-to-Cloud Intelligence in Smart City scenarios requires scalability in data acquisition and storage as well as efficiency and timeliness in data processing. High data-ition frequency, with locally relevant data generating at lower cost and effort, is a key requirement for latency-critical applications. Urban environments, however, introduce a different bottleneck: sensor accuracy. In environments where sensor nodes can be deployed, data acquisition cost is not as critical; hence, advanced sensor networks with high-precision sensors can be installed and maintained with more human and monetary resources. The distributed nature of sensor networks also opens possibilities for data fusion and other smart-data-generation techniques.

7.6.3. Healthcare and Connected Devices

Consonant with the integration principle discussed earlier—encompassing heterogeneity mitigation, interoperability provision, and trust establishment—connected devices and systems in Healthcare IoT, e-Health, and M-Health applications need to support end-to-

end, efficient Data Integration. When assessing Data Integration in the context of connected objects, it is important to highlight use cases exhibiting Data Integration from the end-user's perspective. Privacy, security, and legal issues remain key challenges that ultimately influence the adoption of connected objects in different domains. Therefore, such topics have emerged as extremely relevant at the scientific level. They deal with general IoT architectures, health region data management, data provenance investigation, connected objects for domains such as Agriculture and different aspects of Security and Privacy for Smart Cities.

In the Healthcare domain, both e-Health and M-Health represent promising applications of IoT for detecting, preventing, and controlling diseases. The positive influence of Data Integration is twofold: on one hand, it is the key to ensure the integration of different types of data and sensor sources, thus making them useful for clinical purposes; on the other side, the use of connected objects makes Data Integration more critical. Solutions should guarantee the necessary performance to ensure an adequate quality of service in terms of intervals compatible with the conditions of the patient and at affordable costs. Possible areas of application include Telecardiology, Telepathology, Teleandrology, Teledermatology, and Transplantation. They span from real-time support for data with high velocity, such as ECG, to data specific for diagnosis or considered less critical, like images used for diagnosis gathered via Wireless Wristbands offering different healthcare functionalities for patients.

7.7. Conclusion

Two decades of development transformed the Internet of Things from a vision into an emergent reality with important economic implications. Businesses have invested billions of dollars developing infrastructure for connecting smart devices, and many preliminary Internet of Things applications have been developed, including applications for managing smart homes and buildings, managing industrial equipment, monitoring transportation systems, tracking goods and assets, managing supply chains, managing fleets, managing water utility networks, and establishing sensor networks for environmental monitoring and disaster management.

Despite ongoing development of the core Internet of Things infrastructure and an emerging body of pilot applications, the vision of a blooming Internet of Things has yet to materialize. There are still many outstanding challenges that need to be resolved before the long-promised transformative impact can be unleashed: the quality and quantity of data must be sufficient to enable accurate predictions across diverse domains, data originating from different sources and domains must be fused, combinations of predictions from different areas must be considered, and the underlying infrastructure must be secure and reliable.

7.7.1. Future Directions

This research constitutes an extensive examination of IoT data integration and intelligence generation across the edge-to-cloud continuum. Despite its breadth, the review remains preliminary in nature. The many avenues left unexplored portend rich prospects for development in both research and practice, particularly as more sophisticated applications, services, and products emerge. Standards remain a crucial factor for successful deployment, and the emphasis remains on making progress toward formalizing them. IoT integration has become a central topic, but the proven perspectives in data quality and metadata development warrant further examination. Data fusion and the further development of federated analytics are anticipated in response to ever-stronger industry demand. Suppliers committed to intelligent solutions need to support and invest in these areas.

The current interest in smart cities and community applications suggest exciting developments surrounding sensor networks. With cities prone to frequent disturbances, concerns about city monitoring typically arise from multiple sources. Parsing these to extract useful information for governments remains a challenge. Early initiatives focused on data duplication and availability, but the limited number of sensors made trend analysis easy. Researchers are now addressing the growth in such networks, proposing federated designs, scalable data fusion, and the impact of sensor lifetime on quality. The complex nature of cities also justifies further research on private, patient-centered designs in healthcare, especially with respect to clinical vulnerabilities, software-in-the-loop, and long-term monitoring of BP, HR, ECG, and activity..

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