MODULE 4

APPLICATION PROTOCOLS FOR IOT

3.1 Application Protocols for IoT

Application protocols that are sufficient for generic nodes and traditional networks often are not well suited for constrained nodes and networks. So here the focus is on how higher-layer IoT protocols are transported with following sections:

i. The Transport Layer: IP-based networks use either TCP or UDP. However, the constrained nature of IoT networks requires a closer look at the use of these traditional transport mechanisms.

ii. IoT Application Transport Methods: This section explores the various types of IoT application data and the ways this data can be carried across a network.

As in traditional networks, TCP or UDP are utilized in most cases when transporting IoT application data. With the lower-layer IoT protocols, there are typically multiple options and solutions presented for transporting IoT application data. This is because IoT is still developing and maturing and has to account for the transport of not only new application protocols and technologies but legacy ones as well.

3.2 The Transport Layer

This section reviews the selection of a protocol for the transport layer as supported by the TCP/IP architecturein the context of IoT networks. With the TCP/IP protocol, two main protocols are specified for the transportlayer:

i. Transmission Control Protocol (TCP): This connection-oriented protocol requires a session to get established between the source and destination before exchanging data. It can be viewed equivalent to a traditional telephone conversation, in which two phones must be connected and the communication link established before the parties can talk.

i. User Datagram Protocol (UDP): With this connectionless protocol, data can be quickly sent between source and destination—but with no guarantee of delivery. This is analogous to the traditional mail delivery system, in which a letter is mailed to a destination. Confirmation of the reception of this letter does not happenuntil another letter is sent in response.

With the predominance of human interactions over the Internet, TCP is the main protocol used at the transport layer. This is largely due to its inherent characteristics, such as its ability to transport large volumes of data into smaller sets of packets. In addition, it ensures reassembly in a correct sequence, flow control and window adjustment, and retransmission of lost packets. These benefits occur with the cost of overhead per packet and per session, potentially impacting overall packet per second performances and latency.

In contrast, UDP is most often used in the context of network services, such as Domain Name System (DNS), Network Time Protocol (NTP), Simple Network Management Protocol (SNMP), and Dynamic Host Control Protocol (DHCP), or for real-time data traffic, including voice and video over IP. In these cases, performance and latency are more important than packet retransmissions because re-sending a lost voice or video packet does not add value. When the reception of packets must be guaranteed error free, the applicationlayer protocol takes care of that function.

When considering the choice of a transport layer by a given IoT application layer protocol, it is recommended to evaluate the impact of this choice on both the lower and upper layers of the stack. For example, most of the industrial application layer protocols, are implemented over TCP, while their specifications may offer support for both transport models. The reason for this is that often these industrial application layer protocols are older and were deployed when data link layers were often unreliable and called for error protection.

While the use of TCP may not strain generic compute platforms and high-data-rate networks, it can be challenging and is often overkill on constrained IoT devices and networks. This is particularly true when an IoT device needs to send only a few bytes of data per transaction. When using TCP, each packet needs to add a minimum of 20 bytes of TCP overhead, while UDP adds only 8 bytes. TCP also requires the establishment and potential maintenance of an open logical channel.

This may explain why a new IoT application protocol, such as Constrained Application Protocol (CoAP), almost always uses UDP and why implementations of industrial application layer protocols may call for the optimization and adoption of the UDP transport layer if run over LLNs. For example, the Device Language Message Specification/Companion Specification for Energy Metering (DLMS/COSEM) application layer protocol, a popular protocol for reading smart meters in the utilities space, is the standardin Europe. Adjustments or optimizations to this protocol should be made depending on the IoT transport protocols that are present in the lower layers.

When transferring large amounts of DLMS/COSEM data, cellular links are preferred to optimize each open association. Smaller amounts of data can be handled efficiently over LLNs. Because packet loss ratios are generally higher on LLNs than on cellular networks, keeping the data transmission amounts small over LLNs limits the retransmission of large numbers of bytes. Multicast requirements are also impacted by the protocol selected for the transport layer. With multicast, a single message can be sent to multiple IoT devices.This is useful in the IoT context for upgrading the firmware of many IoT devices at once. Also, keep in mindthat multicast utilizes UDP exclusively.

3.3 IoT Application Transport Methods

The following categories of IoT application protocols and their transport methods are explored in the following sections:

- **Application layer protocol not present:** In this case, the data payload is directly transported on top of the lower layers. No application layer protocol is used.
- **Supervisory control and data acquisition (SCADA):** SCADA is one of the most common industrial protocols in the world, but it was developed long before the days of IP, and it has been adapted for IP networks.
- **Generic web-based protocols:** Generic protocols, such as Ethernet, Wi-Fi, and 4G/LTE, are found on many consumer- and enterprise-class IoT devices that communicate over non- constrained networks.
- **IoT application layer protocols:** IoT application layer protocols are devised to run on constrained nodes with a small compute footprint and are well adapted to the network bandwidth constraints on cellular or satellite links or constrained 6LoWPAN networks. Message Queuing Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP), are two examples of IoT application layer protocols.

3.3.1 Application Layer Protocol Not Present

IETF RFC 7228 devices defined as class 0 send or receive only a few bytes of data. For myriad reasons, such as processing capability, power constraints, and cost, these devices do not implement a fully structured network protocol stack, such as IP, TCP, or UDP, or even an application layer protocol. Class 0 devices are usually simple smart objects that are severely constrained. Implementing a robust protocol stack is usually not useful and sometimes not even possible with the limited available resources.

For example, consider low-cost temperature and relative humidity(RH) sensors sending data over an LPWA LoRaWAN infrastructure. Temperature is represented as 2 bytes and RH as another 2 bytes of data. Therefore, this small data payload is directly transported on top of the LoRaWAN MAC layer, without the use of TCP/IP. Example 3-1 shows the raw data for temperature and relative humidity and how it can be decoded by the application.

Example 3-1 *Decoding Temperature and Relative Humidity Sensor Data*

Temperature data payload over the network: Tx = 0x090c Temperature conversion required by the application

T = Tx/32 - 50

T = 0x090c/32 - 50

T = 2316/32 - 50 = **22.4°**

RH data payload over the network: RHx = 0x062e RH conversion required by the application:

100RH = RHx/16-24

100RH = 0x062e/16-24 = 74.9

RH **= 74.9%**

While many constrained devices, such as sensors and actuators, have adopted deployments that have no application layer, this transportation method has not been standardized. This lack of standardization makes it difficult for generic implementations of this transport method to be successful from an interoperability perspective.

Imagine expanding Example 3-1 to different kinds of temperature sensors from different manufacturers. These sensors will report temperature data in varying formats. A temperature value will always be present in the data transmitted by each sensor, but decoding this data will be vendor specific. If same scenario is scaled across hundreds or thousands of sensors, the problem of allowing various applications to receive and interpret temperature values delivered in different formats becomes increasingly complex. The solution to this problem is to use an IoT data broker, as detailed in Figure 3.11. An IoT data broker is a piece of middleware that standardizes sensor output into a common format that can then be retrieved by authorized applications.
In Figure 3.11, Sensors X, Y, and Z are all temperature sensors, but their output is encoded differently. The IoT data broker understands the different formats in which the temperature is encoded and is therefore able todecode this data into a common, standardized format. Applications A, B, and C in Figure 3.11 can access thistemperature data without having to deal with decoding multiple temperature data formats.

IoT data brokers are also utilized from a commercial perspective to distribute and sell IoT data to third parties. Companies can provide access to their data broker from another company's application for a fee. This makes an IoT data broker a possible revenue stream, depending on the value of the data it contains.

3.3.2 SCADA

In the world of networking technologies and protocols, IoT is relatively new. Combined with the fact that IP is the de facto standard for computer networking in general, older protocols that connected sensors and

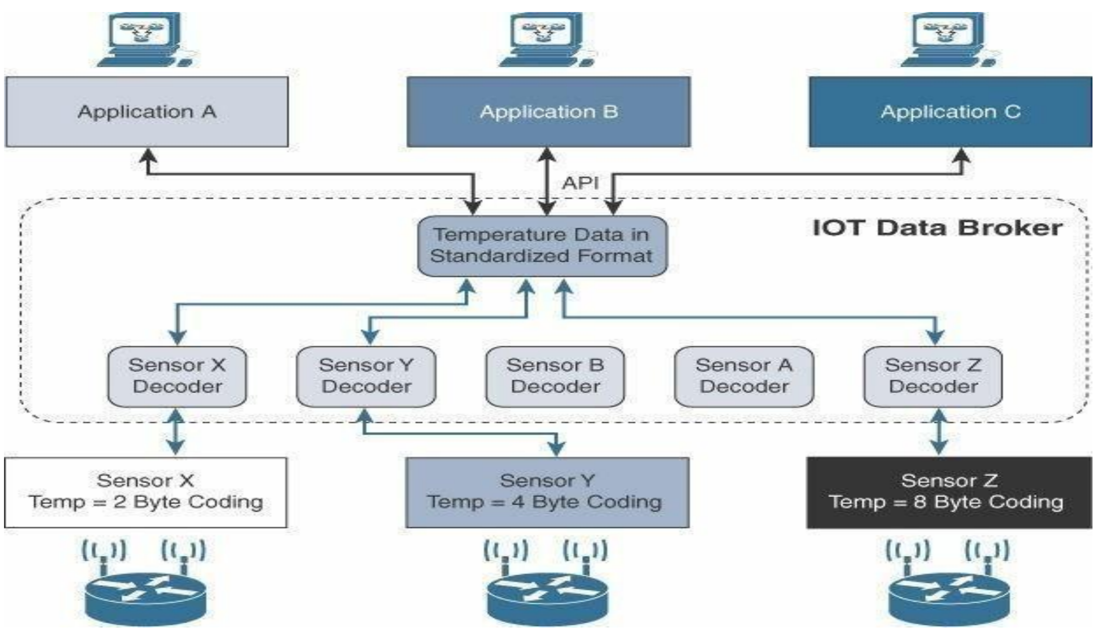


Figure 3.11 *IoT Data Broker*

actuators have evolved and adapted themselves to utilize IP.

A prime example of this evolution is **supervisory control and data acquisition (SCADA)**. Designed decades ago, SCADA is an automation control system that was initially implemented without IP over seriallinks, before being adapted to Ethernet and IPv4.

A Little Background on SCADA

For many years, vertical industries have developed communication protocols that fit their specific requirements. Many of them were defined and implemented when the most common networking technologies were serial link-based, such as RS-232 and RS-485. This led to SCADA networking protocols, which were well structured compared to the protocols described in the previous section, running directly over serial physical and data link layers.

At a high level, SCADA systems collect sensor data and telemetry from remote devices, while also providing the ability to control them. Used in today's networks, SCADA systems allow global, real- time, data-driven decisions to be made about how to improve business processes.

SCADA networks can be found across various industries, but SCADA is found mainly concentrated in the utilities and manufacturing/industrial verticals. Within these specific industries, SCADA commonly uses certain protocols for communications between devices and applications. For example, Modbus and its variantsare industrial protocols used to monitor and program remote devices via a master/slave relationship. Modbus is also found in building management, transportation, and energy applications. The DNP3 and International Electrotechnical Commission (IEC) 60870-5-101 protocols are found mainly in the utilities industry, alongwith DLMS/COSEM and ANSI C12 for advanced meter reading (AMR).

3.7.2.1 Adapting SCADA for IP

In the 1990s, the rapid adoption of Ethernet networks in the industrial world drove the evolution of SCADA application layer protocols. For example, the IEC adopted the Open System Interconnection (OSI) layer modelto define its protocol framework. Other protocol user groups also slightly modified their protocols to run overan IP infrastructure. Benefits of this move to Ethernet and IP include the ability to leverage existing equipment and standards while integrating seamlessly the SCADA subnetworks to the corporate WAN infrastructures.

To further facilitate the support of legacy industrial protocols over IP networks, protocol specifications were updated and published, documenting the use of IP for each protocol. This included assigning TCP/UDP port numbers to the protocols, such as the following:

- DNP3 (adopted by IEEE 1815-2012) specifies the use of TCP or UDP on port 20000 for transporting DNP3 messages over IP.
- The Modbus messaging service utilizes TCP port 502.
- IEC 60870-5-104 is the evolution of IEC 60870-5-101 serial for running over Ethernet and IPv4 usingport 2404.
- DLMS User Association specified a communication profile based on TCP/IP in the DLMS/COSEM Green Book (Edition 5 or higher), or in the IEC 62056-53 and IEC 62056-47 standards, allowing data exchange via IP and port 4059.

These legacy serial protocols have adapted and evolved to utilize IP and TCP/UDP as both networking and transport mechanisms. This has allowed utilities and other companies to continue leveraging their investment in equipment and infrastructure, supporting these legacy protocols with modern IP networks. Let's dig deeper into how these legacy serial protocols have evolved to use IP by looking specifically at DNP3 as a representative use case.Like many of the other SCADA protocols, DNP3 is based on a master/slave relationship. The term *master* in this case refers to what is typically a powerful computer located in the control center of a utility, and a *slave* is a remote device with computing resources found in a location such as a substation. DNP3 refers to slaves specifically as *outstations*.

Outstations monitor and collect data from devices that indicate their state, such as whether a circuit breaker is on or off, and take measurements, including voltage, current, temperature, and so on. This data is then transmitted to the master when it is requested, or events and alarms can be sent in an asynchronous manner. The master also issues control commands, such as to start a motor or reset a circuit breaker, and logs the incoming data.

The IEEE 1815-2012 specification describes how the DNP3 protocol implementation must be adapted torun either over TCP (recommended) or UDP. This specification defines connection management between theDNP3 protocol and the IP layers, as shown in Figure 3.12. Connection management links the DNP3 layers with the IP layers in addition to the configuration parameters and methods necessary for implementing thenetwork connection. The IP layers appear transparent to the DNP3 layers as each piece of the protocol stackin one station logically communicates with the respective part in the other. This means that theDNP3 endpointsor devices are not aware of the underlying IP transport that is occurring.

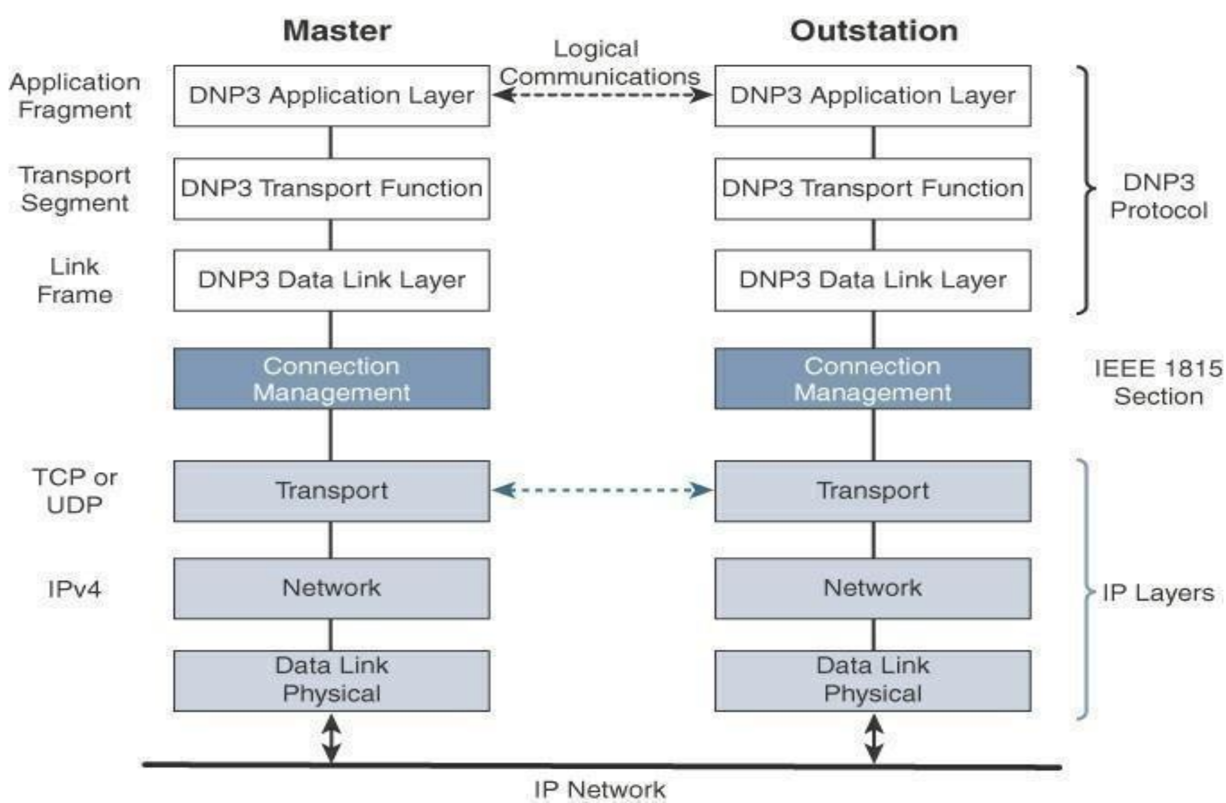


Figure 3.12 *Protocol Stack for Transporting Serial DNP3 SCADA over IP*

In Figure 3.12, the master side initiates connections by performing a TCP active open. The outstation listens for a connection request by performing a TCP passive open. *Dual endpoint* is defined as a process that can both listen for connection requests and perform an active open on the channel if required.

Master stations may parse multiple DNP3 data link layer frames from a single UDP datagram, while DNP3 data link layer frames cannot span multiple UDP datagrams. Single or multiple connections to the master may get established while a TCP keepalive timer monitors the status of the connection. Keepalive messages are implemented as DNP3 data link layer status requests. If a response is not received to a keepalive message, the connection is deemed broken, and the appropriate action is taken.

3.7.2.2 Tunneling Legacy SCADA over IP Networks

Deployments of legacy industrial protocols, such as DNP3 and other SCADA protocols, in modern IP networks call for flexibility when integrating several generations of devices or operations that are tied to various releases and versions of application servers. Native support for IP can vary and may require different solutions. Ideally, end-to-end native IP support is preferred, using a solution like IEEE 1815-2012 in the case of DNP3. Otherwise, transport of the original serial protocol over IP can be achieved either by tunneling using raw sockets over TCP or UDP or by installing an intermediate device that performs protocol translation between the serial protocol version and its IP implementation.

A raw socket connection simply denotes that the serial data is being packaged directly into a TCP or UDP transport. A socket in this instance is a standard application programming interface (API) composed of an IP address and a TCP or UDP port that is used to access network devices over an IP network. More modern industrial application servers may support this capability, while older versions typically require another device or piece of software to handle the transition from pure serial data to serial over IP using a raw socket. Figure 3.13 details raw socket scenarios for a legacy SCADA server trying to communicate with remote serial devices.

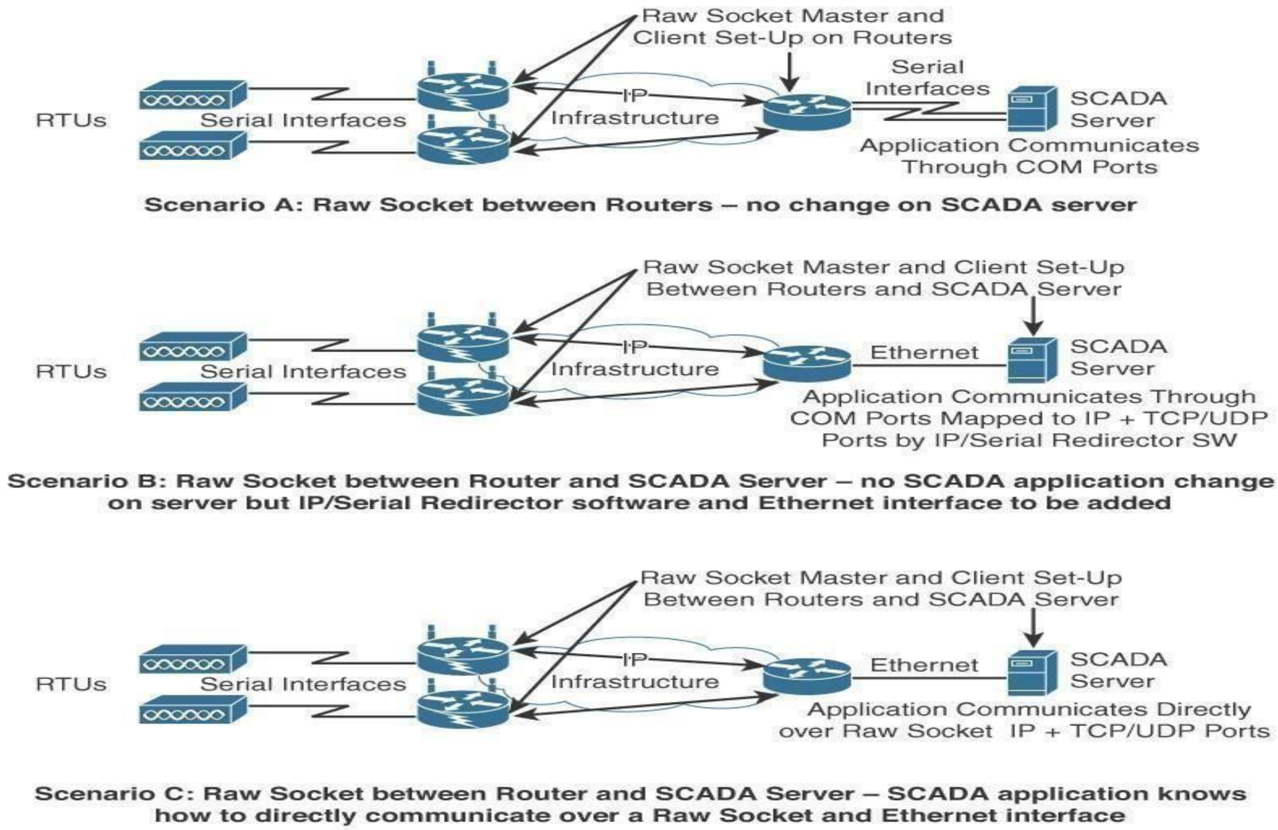


Figure 3.13 *Raw Socket TCP or UDP Scenarios for Legacy Industrial Serial Protocols*

In all the scenarios in Figure 3.13, notice that routers connect via serial interfaces to the remote terminal units (RTUs), which are often associated with SCADA networks. An RTU is a multipurpose device used to monitor and control various systems, applications, and devices managing automation. From the master/slave perspective, the RTUs are the slaves. Opposite the RTUsin each Figure 3.13 scenario is a SCADA server, or master, that varies its connection type. In reality, other legacy industrial application servers could be shownhere as well.

Scenario A in Figure 3.13, both the SCADA server and the RTUs have a direct serial connection to their respective routers. The routers terminate the serial connections at both ends of the link and use raw socket encapsulation to transport the serial payload over the IP network.

Scenario B has a small change on the SCADA server side. A piece of software is installed on the SCADA server that maps the serial COM ports to IP ports. This software is commonly referred to as an IP/serial redirector. The IP/serial redirector in essence terminates the serial connection of the SCADA server and converts it to a TCP/IP port using a raw socket connection.

Scenario C in Figure 3.13, the SCADA server supports native raw socket capability. Unlike in Scenarios A and B, where a router or IP/serial redirector software has to map the SCADA server's serial ports to IP ports, in Scenario C the SCADA server has full IP support for raw socket connections.

3.7.2.3 SCADA Protocol Translation

As mentioned earlier, an alternative to a raw socket connection for transporting legacy serial data across an IP network is protocol translation. With protocol translation, the legacy serial protocol is translated to a corresponding IP version. For example, Figure 3.14 shows two serially connected DNP3 RTUs and two master applications supporting DNP3 over IP that control and pull data from the RTUs. The IoT gateway in this figure performs a protocol translation functionthat enables communication between the RTUsand servers, despite the fact that a serial connection is present on one side and an IP connection is used on the other.

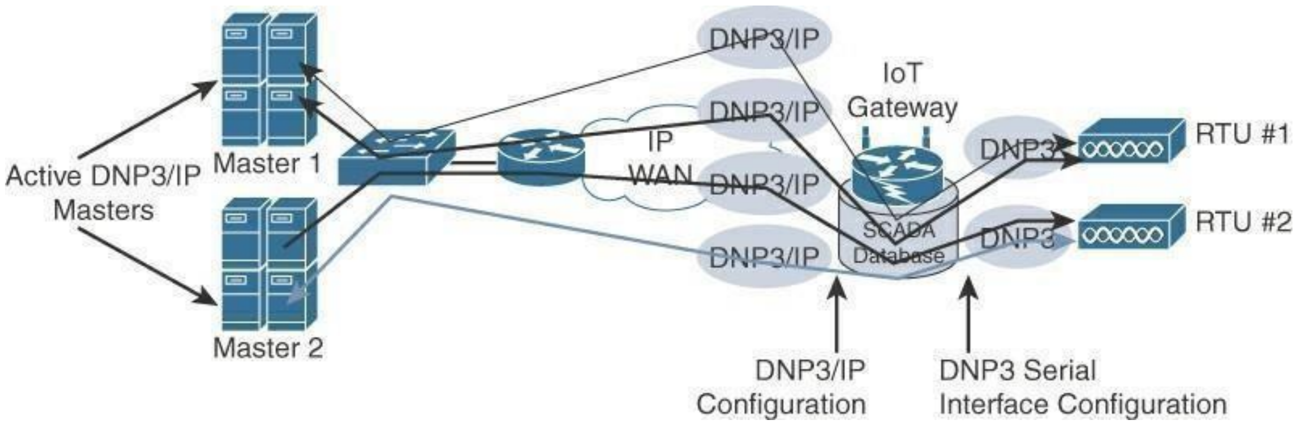


Figure 3.14 *DNP3 Protocol Translation*

By running protocol translation, the IoT gateway connected to the RTUs in Figure 3.14 is implementing a computing function close to the edge of the network. Adding computing functions close to the edge helps scale distributed intelligence in IoT networks. This can be accomplished by offering computing resources on IoT gateways or routers, as shown in this protocol translation example. Alternatively, this can also be performed directly on a node connecting multiple sensors. In either case, this is referred to as fog computing.

3.7.2.4 SCADA Transport over LLNs with MAP-T

Due to the constrained nature of LLNs, the implementation of industrial protocols should at a minimum be done over UDP. This in turn requires that both the application servers and devices support and implement UDP. While the long-term evolution of SCADA and other legacy industrial protocols is to natively support IPv6, it must be highlighted that most, if not all, of the industrial devices supporting IP today support IPv4 only. When deployed over LLN subnetworks that are IPv6 only, a transition mechanism, such as MAP-T (Mapping of Address and Port using Translation, RFC 7599), needs to be implemented. This allows the deployment to take advantage of native IPv6 transport transparently to the application and devices.

Figure 3.15 depicts a scenario in which a legacy endpoint is connected across an LLN running 6LoWPAN to an IP-capable SCADA server. The legacy endpoint could be running various industrial and SCADA protocols, including DNP3/IP, Modbus/TCP, or IEC 60870-5-104. In this scenario, the legacy devices and the SCADA server support only IPv4 (typical in the industry today). However, IPv6 (with 6LoWPAN and RPL) is being used for connectivity to the endpoint. 6LoWPANis a standardized protocol designed for constrained networks, but it only supports IPv6. In this situation, the end devices, the endpoints, and the SCADA server support only IPv4, but the network in the middle supports onlyIPv6.

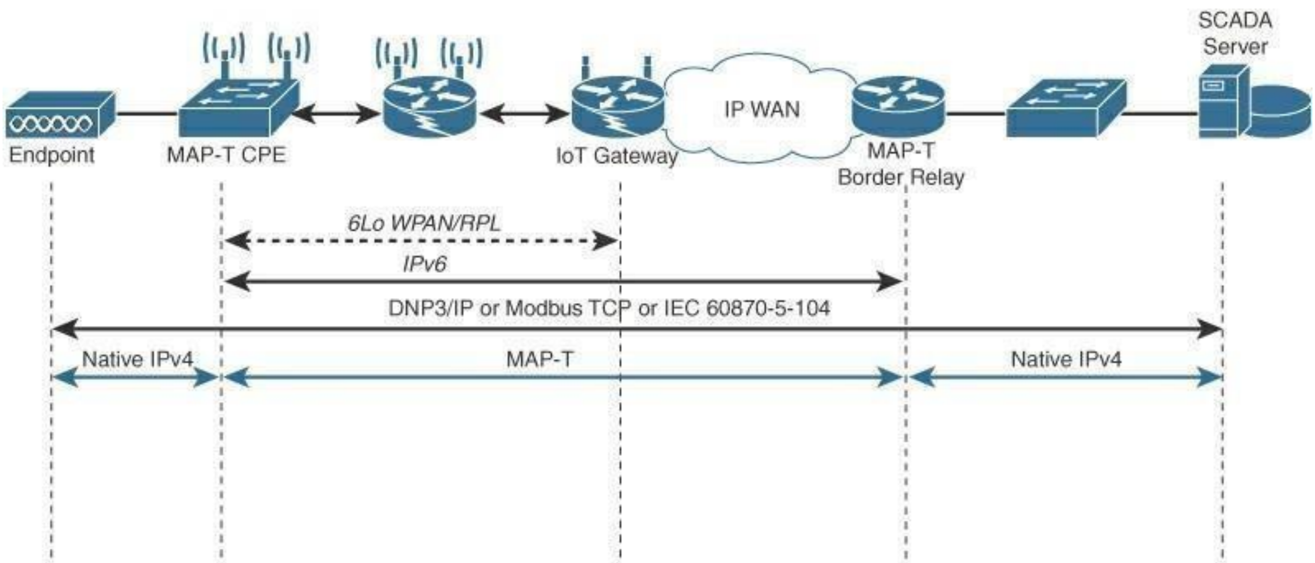


Figure 3.15 *DNP3 Protocol over 6LoWPAN Networks with MAP-T*

The solution to this problem is to use the protocol known as MAP-T, MAP-T makes the appropriate mappingsbetween IPv4 and the IPv6 protocols. This allows legacy IPv4 traffic to be forwarded across IPv6 networks.In other words, older devices and protocols can continue running IPv4 even though the network is requiringIPv6.

In Figure 3.15 the IPv4 endpoint on the left side is connected to a Customer Premise Equipment (CPE) device. The MAP-T CPE device has an IPv6 connection to the RPL mesh. On the right side, a SCADA server with native IPv4 support connects to a MAP-T border gateway. The MAP-T CPE device and MAP-T border gateway are thus responsible for the MAP-T conversion from IPv4 to IPv6.

Legacy implementations of SCADA and other industrial protocols are still widely deployed across many industries. While legacy SCADA has evolved from older serial connections to support IP, still it can be expected to see mixed deployments for many years. To address this challenge, OT networks require mechanisms such as raw sockets and protocol translation to transport legacy versions over modern IP networks. Even when the legacy devices have IPv4 capability, the constrained portions of the network oftenrequire IPv6, not IPv4. In these cases, a MAP-T solution can be put in place to enable IPv4 data to be carriedacross an IPv6 network.

3.3.3 Generic Web-Based Protocols

Over the years, web-based protocols have become common in consumer and enterprise applications and services. Therefore, it makes sense to try to leverage these protocols when developing IoT applications, services, and devices in order to ease the integration of data and devices from prototyping to production.The level of familiarity with generic web-based protocols is high. Therefore, programmers with basic web programming skills can work on IoT applications, and this may lead to innovative ways to deliver and handle real-time IoT data. For example, an IoT device generating an event can have the result of launching a video capture, while at the same time a notification is sent to a collaboration tool, such as a Cisco Spark room. This notification allows technicians and engineers to immediately start working on this alert. In addition to a generally high level of familiarity with web-based protocols, scaling methods for web environments are also well understood—and this is crucial when developing consumer applications for potentially large numbers of IoT devices.

Once again, the definition of constrained nodes and networks must be analyzed to select the most appropriate protocol. On non- constrained networks, such as Ethernet, Wi-Fi, or 3G/4G cellular, where bandwidth is not perceived as a potential issue, data payloads based on a verbose data model representation, including XML or JavaScript Object Notation (JSON), can be transported over HTTP/HTTPS or WebSocket. This allows implementers to develop their IoT applications in contexts similar to web applications.

The HTTP/HTTPS client/server model serves as the foundation for the World Wide Web. Recent evolutions of embedded web server software with advanced features are now implemented with very little memory (in the range of tens of kilobytes in some cases). This enables the use of embedded web services software on some constrained devices.

When considering web services implementation on an IoT device, the choice between supporting the client or server side of the connection must be carefully weighed. IoT devices that only push data to an application (for example, an Ethernet- or Wi-Fi-based weather station reporting data to a weather map application or a Wi-Fi–enabled body weight scale that sends data to a health application) may need to implement web services on the client side. The HTTP client side only initiates connections and does not accept incoming ones.

On the other hand, some IoT devices, such as a video surveillance camera, may have web services implemented on the server side. However, because these devices often have limited resources, the number of incoming connections must be kept low. In addition, advanced development in data modeling should be considered as a way to shift the workload from devices to clients, including web browsers on PCs, mobile phones, tablets, and cloud applications.

Interactions between real-time communication tools powering collaborative applications, such as voice and video, instant messaging, chat rooms, and IoT devices, are also emerging. This is driving the need for simpler communication systems between people and IoT devices. One protocol that addresses this need is Extensible Messaging and Presence Protocol (XMPP).

3.3.4 IoT Application Layer Protocols

When considering constrained networks and/or a large-scale deployment of constrained nodes, verbose web- based and data model protocols, as discussed in the previous section, maybe too heavy for IoT applications. To address this problem, the IoT industry is working on new lightweight protocols that are better suited to large numbers of constrained nodes and networks. Two of the most popular protocols are CoAP and MQTT. Figure 3.16 highlights their position in a common IoT protocol stack.

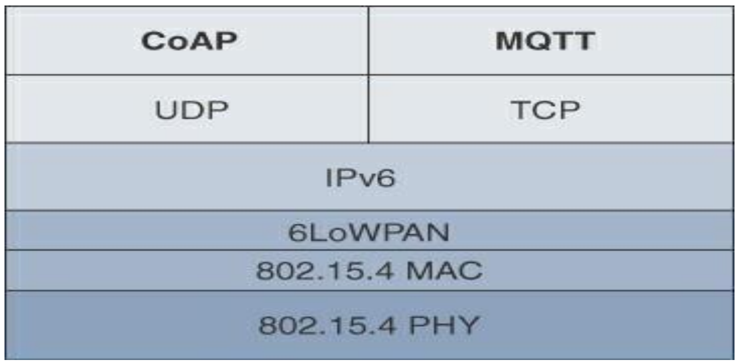


Figure 3.16 *Example of a High-Level IoT Protocol Stack for CoAP and MQTT*

In Figure 3.16, CoAP and MQTT are naturally at the top of this sample IoT stack, based on an IEEE 802.15.4 mesh network. While there are a few exceptions, like CoAP deployed over UDP and MQTT running over TCP. The following sections take a deeper look at CoAP and MQTT.

3.7.4.1 CoAP

Constrained Application Protocol (CoAP) resulted from the IETF Constrained RESTful Environments (CoRE) working group's efforts to develop a generic framework for resource-oriented applications targeting constrained nodes and networks.

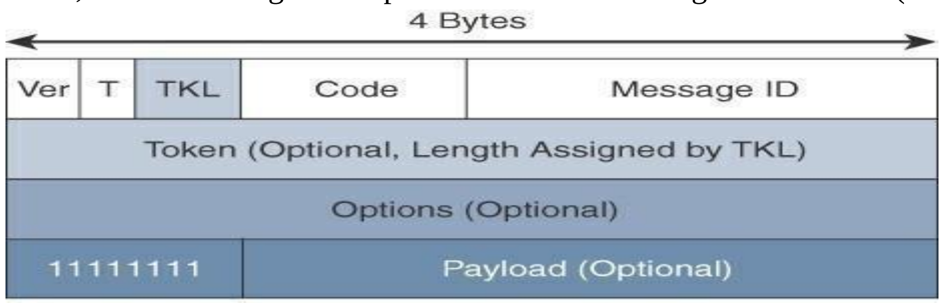
The CoAP framework defines simple and flexible ways to manipulate sensors and actuators for data or device management. The IETF CoRE working group has published multiple standards-track specifications for CoAP, including the following:

- **RFC 6690:** Constrained RESTful Environments (CoRE) Link Format
- **RFC 7252:** The Constrained Application Protocol (CoAP)
- **RFC 7641:** Observing Resources in the Constrained Application Protocol (CoAP)
- **RFC 7959:** Block-Wise Transfers in the Constrained Application Protocol (CoAP)
- **RFC 8075:** Guidelines for Mapping Implementations: HTTP to the Constrained Application Protocol (CoAP)

The CoAP messaging model is primarily designed to facilitate the exchange of messages over UDP between endpoints, including the secure transport protocol Datagram Transport Layer Security (DTLS). The IETF CoRE working group is studying alternate transport mechanisms, including TCP, secure TLS, and WebSocket. CoAP over Short Message Service (SMS) as defined in Open Mobile Alliance for Lightweight Machine-to-

Machine (LWM2M) for IoT device management is also being considered.

RFC 7252 provides more details on securing CoAP with DTLS. It specifies how a CoAP endpoint is provisioned with keys and a filtering list. Four security modes are defined: NoSec, PreSharedKey, RawPublicKey, and Certificate. The NoSec and RawPublicKey implementations are mandatory. From a formatting perspective, a CoAP message is composed of a short fixed-length Header field (4 bytes), a variable-



length but mandatory Token field (0–8 bytes), Options fields if necessary, and the Payload field. Figure 3.17 details the CoAP message format, which delivers low overhead while decreasing parsing complexity.

Figure 3.17 *CoAP Message Format*

From Figure 3.17, the CoAP message format is relatively simple and flexible. It allows CoAP to deliver low overhead, which is critical for constrained networks, while also being easy to parse and process for constrained devices. Table 6-1 provides an overview of the various fields of a CoAP message.

Table 6-1 *CoAP Message Fields*

CoAP Message Field	Description
Ver (Version)	Identifies the CoAP version.
T (Type)	Defines one of the following four message types: Confirmable (CON), Non-confirmable (NON), Acknowledgement (ACK), or Reset (RST). CON and ACK are highlighted in more detail in Figure 6-9.
TKL (Token Length)	Specifies the size (0–8 Bytes) of the Token field.
Code	Indicates the request method for a request message and a response code for a response message. For example, in Figure 6-9, GET is the request method, and 2.05 is the response code. For a complete list of values for this field, refer to RFC 7252.
Message ID	Detects message duplication and used to match ACK and RST message types to Con and NON message types.
Token	With a length specified by TKL, correlates requests and responses.
Options	Specifies option number, length, and option value. Capabilities provided by the Options field include specifying the target resource of a request and proxy functions.
Payload	Carries the CoAP application data. This field is optional, but when it is present, a single byte of all 1s (0xFF) precedes the payload. The purpose of this byte is to delineate the end of the Options field and the beginning of Payload.

CoAP can run over IPv4 or IPv6. However, it is recommended that the message fit within a single IP packet and UDP payload to avoid fragmentation. For IPv6, with the default MTU size being 1280 bytes and allowing for no fragmentation across nodes, themaximum CoAP message size could be up to 1152 bytes, including 1024 bytes for the payload. In the case of IPv4, as IP fragmentation may exist across the network, implementations should limit themselves to more conservative values and set the IPv4 Don't Fragment (DF)bit.

While most sensor and actuator traffic utilizes small-packet payloads, some use cases, such as firmware upgrades, require the capability to send larger payloads. CoAP doesn't rely on IP fragmentation but defines (in RFC 7959) a pair of Block options for transferring multiple blocks of information from a resource representation in multiple request/response pairs.

As illustrated in Figure 3.18, CoAP communications across an IoT infrastructure can take various paths. Connections can be between devices located on thesame or different constrained networks or between devices and generic Internet or cloud servers, all operating over IP. Proxy mechanisms are also defined, and RFC 7252 details a basic HTTP mapping for CoAP. As both HTTP and CoAP are IP-based protocols, the proxy function can be located practically anywhere in the network, not necessarily at the border between constrained and non-constrained networks.

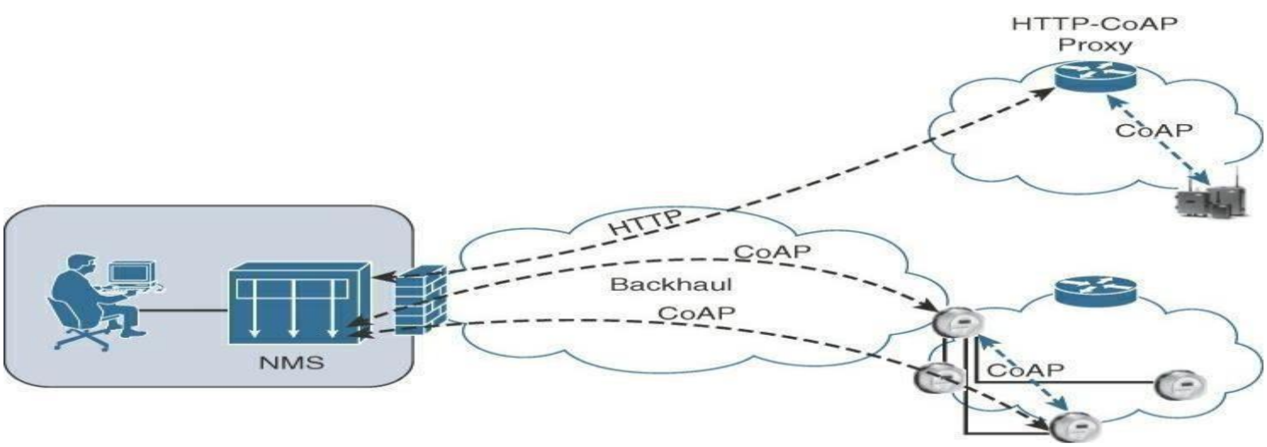


Figure 3.18 *CoAP Communications in IoT Infrastructures*

Just like HTTP, CoAP is based on the REST architecture, but with a "thing" acting as both the client and the server. Through the exchange of asynchronous messages, a client requests an action via a method code on a server resource. A uniform resource identifier (URI) localized on the server identifies this resource. The server responds with a response code that may include a resource representation. The CoAP request/responsesemantics include the methods GET, POST, PUT, and DELETE.

CoAP defines four types of messages: confirmable, non-confirmable, acknowledgement, and reset. Method codes and response codes included in some of these messages make them carry requests or responses.CoAP code, method and response codes, option numbers, and content format have been assigned by IANA asConstrained RESTful Environments (CoRE) parameters.

While running over UDP, CoAP offers a reliable transmission of messages when a CoAP header is marked as "confirmable." In addition, CoAP supports basic congestion control with a default time-out, simple stop and wait retransmission with exponential back-off mechanism, and detection of duplicate messages through a message ID. If a request or response is tagged as confirmable, the recipient must explicitly either acknowledge or reject the message, using the same message ID, as shown in Figure 3.19. If a recipient can't process a non-confirmable message, a reset message is sent.

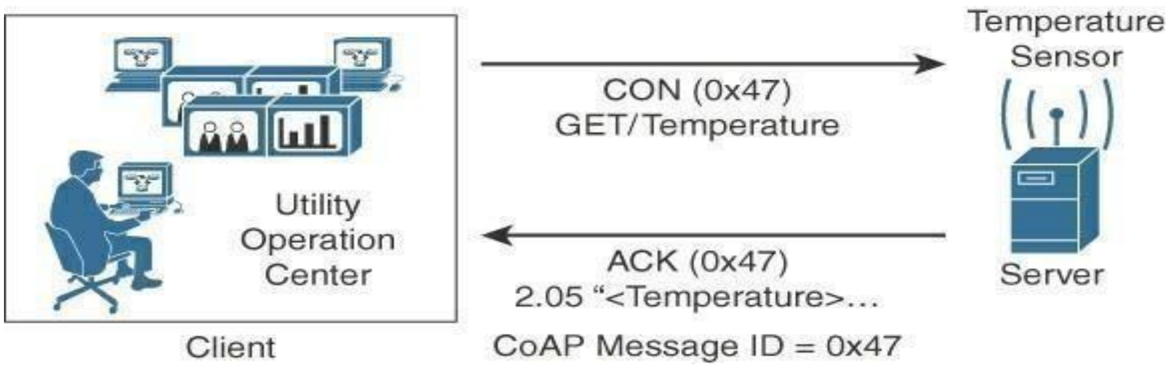


Figure 3.19 *CoAP Reliable Transmission Example*

Figure 3.19 shows a utility operations center on the left, acting as the CoAP client, with the CoAP server being a temperature sensor on the right of the figure. The communication between the client and server uses a CoAP message ID of 0x47. The CoAP Message ID ensures reliability and is used to detect duplicate messages. The client in Figure 3.19 sends a GET message to get the temperature from the sensor. Notice that the 0x47 message ID is present for this GET message and that the message is also marked with CON. A CON, or confirmable, marking in a CoAP message means the message will be retransmitted until the recipient sends an acknowledgement (or ACK) with the same message ID.

In Figure 3.19, the temperature sensor does reply with an ACK message referencing the correct message ID of 0x47. In addition, this ACK message piggybacks a successful response to the GET request itself. This is indicated by the 2.05 response code followed by the requested data. CoAP supports data requests sent to a group of devices by leveraging the use of IP Multicast. Implementing IP Multicast with CoAP requires the use of all-CoAP-node multicast addresses. For IPv4 this address is 224.0.1.187, and for IPv6 it is FF0X::FD. These multicast addresses are joined by CoAP nodes offering services to other endpoints while listening on the default CoAP port, 5683. Therefore, endpoints can find available CoAP services through multicast service discovery. A typical use case for multicasting is deploying a firmware upgrade for a group of IoT devices, such as smart meters.

With often no affordable manual configuration on the IoT endpoints, a CoAP server offering services and resources needs to be discovered by the CoAP clients. Services from a CoAP server can either be discovered by learning a URI in a namespace or through the "All CoAP nodes" multicast address. When utilizing the URI scheme for discovering services, the default port 5683 is used for non-secured CoAP, or **coap**, while port 5684 is utilized for DTLS-secured CoAP, or **coaps**. The CoAP server must be in listening state on these ports, unless a different port number is associated with the URI in a namespace. Much as with accessing web server resources, CoAP specifications provide a description of the relationships between resources in RFC 6690, "Constrained RESTful Environments (CoRE) Link Format."

To improve the response time and reduce bandwidth consumption, CoAP supports caching capabilities based on the response code. To use a cache entry, a CoAP endpoint must validate the presented request and stored response matches, including all options (unless marked as No CacheKey). This confirms thatthe stored response is fresh or valid. A wide range of CoAP implementations are available. Some are published with open source licenses, and others are part of vendor solutions

3.7.4.2 Message Queuing Telemetry Transport (MQTT)

At the end of the 1990s, engineers from IBM and Arcom (acquired in 2006 by Eurotech) were looking for a reliable, lightweight, and cost-effective protocol to monitor and control a large number of sensors and theirdata from a central server location, as typically used by the oil and gas industries.
Their research resulted in the development and implementation of the Message Queuing Telemetry Transport (MQTT) protocol that is now standardized by the Organization for the Advancement of Structured Information Standards (OASIS).

Considering the harsh environments in the oil and gas industries, an extremely simple protocol with only a few options was designed, with considerations for constrained nodes, unreliable WAN backhaul communications, and bandwidth constraints with variable latencies. These were some of the rationales for the selection of a client/server and publish/subscribe framework based on the TCP/IP architecture, as shown in Figure 6-10.

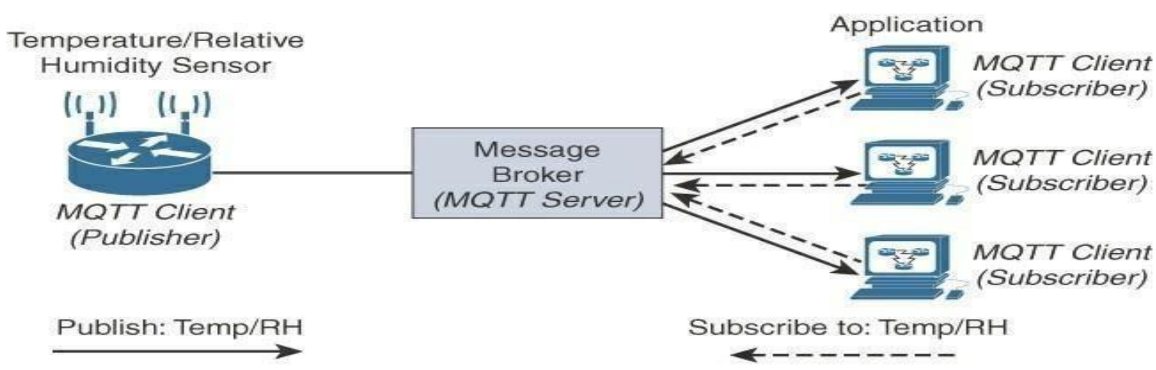


Figure 3.20 *MQTT Publish/Subscribe Framework*

An MQTT client can act as a publisher to send data (or resource information) to an MQTT server acting as an MQTT message broker. In the example illustrated in Figure 3.20, the MQTT client on the left side is a temperature (Temp) and relative humidity (RH) sensor that publishes its Temp/RH data. The MQTT server (or message broker) accepts the network connection along with application messages, such as Temp/RH data, from the publishers. It also handles the subscription and unsubscription process and pushes the application data to MQTT clients acting as subscribers.

The application on the right side of Figure 3.20 is an MQTT client that is a subscriber to the Temp/RH data being generated by the publisher or sensor on the left. This model, where subscribers express a desire to receive information from publishers, is well known. A great example is the collaboration and social networking application Twitter.

With MQTT, clients can subscribe to all data (using a wildcard character) or specific data from the information tree of a publisher. In addition, the presence of a message broker in MQTT decouples the data transmission between clients acting as publishers and subscribers. In fact, publishers and subscribers do not even know (or need to know) about each other. A benefit of having this decoupling is that the MQTT message broker ensures that information can be buffered and cached in case of network failures. This also means that publishers and subscribers do not have to be online at the same time.

MQTT control packets run over a TCP transport using port 1883. TCP ensures an ordered, lossless stream of bytes between the MQTT client and the MQTT server. Optionally, MQTT can be secured using TLS on port 8883, and WebSocket (defined in RFC 6455) can also be used.

MQTT is a lightweight protocol because each control packet consists of a 2-byte fixed header with optional variable header fields and optional payload. Control packet can contain a payload up to 256 MB.

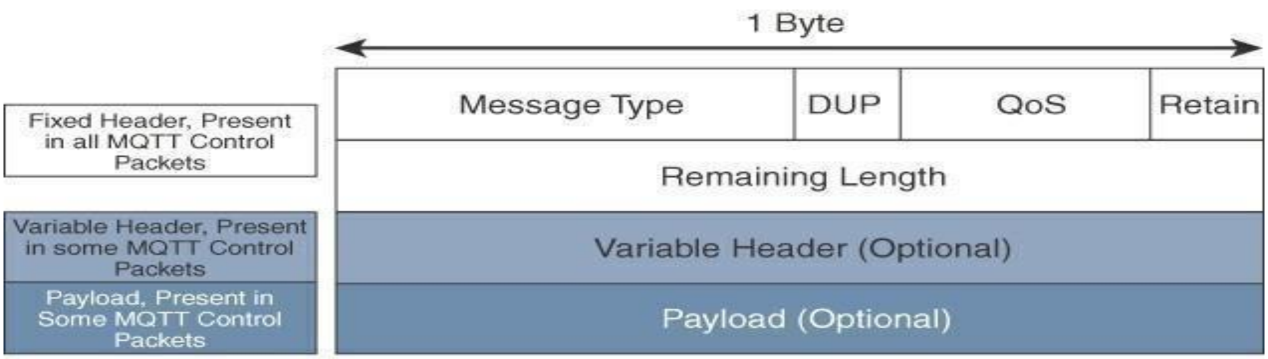


Figure 3.21 *MQTT Message Format*

Compared to the CoAP message format in Figure 3.17, MQTT contains a smaller header of 2 bytes compared to 4 bytes for CoAP. The first MQTT field in the header is Message Type, which identifies thekind of MQTT packet within a message. Fourteen different types of control packets are specified in MQTT version 3.1.1. Each of them has a unique value that is coded into the Message Type field. Note that values 0 and 15 are reserved. MQTT message types are summarized in Table3.2.

The next field in the MQTT header is DUP (Duplication Flag). This flag, when set, allows the client to notate that the packet has been sent previously, but an acknowledgement was not received. The QoS header field allows for the selection of three different QoS levels. The next field is the Retain flag. Only found in a PUBLISH message, the Retain flag notifies the server to hold onto the message data. This allows new subscribers to instantly receive the last known value without having to wait for the next update from the publisher. The last mandatory field in the MQTT message header is Remaining Length. This field specifies thenumber of bytes in the MQTT packet following this field.

Table 6-2 *MQTT Message Types*

Message Type	Value	Flow	Description
CONNECT	1	Client to server	Request to connect
CONNACK	2	Server to client	Connect acknowledgement
PUBLISH	3	Client to server Server to client	Publish message
PUBACK	4	Client to server Server to client	Publish acknowledgement
PUBREC	5	Client to server Server to client	Publish received
PUBREL	6	Client to server Server to client	Publish release
PUBCOMP	7	Client to server Server to client	Publish complete
SUBSCRIBE	8	Client to server	Subscribe request
SUBACK	9	Server to client	Subscribe acknowledgement
UNSUBSCRIBE	10	Client to server	Unsubscribe request
UNSUBACK	11	Server to client	Unsubscribe acknowledgement
PINGREQ	12	Client to server	Ping request
PINGRESP	13	Server to client	Ping response
DISCONNECT	14	Client to server	Client disconnecting

The MQTT protocol offers three levels of quality of service (QoS). QoS for MQTT is implemented when exchanging application messages with publishers or subscribers, and it is different from the IP QoS thatmost people are familiar with. The delivery protocol is symmetric. This means the client and server can eachtake the role of either sender or receiver. The delivery protocol is concerned solely with the delivery of anapplication message from a single sender to a single receiver. These are the three levels of MQTTQoS:

- **QoS 0:** This is a best-effort and unacknowledged data service referred to as “at most once” delivery. The publisher sends its message one time to a server, which transmits it once to the subscribers. No response is sent by the receiver, and no retry is performed by the sender. The message arrives at the receiver either once or not at all.
- **QoS 1:** This QoS level ensures that the message delivery between the publisher and server and then between the server and subscribers occurs at least once. In PUBLISH and PUBACK packets, a packet identifier is included in the variable header. If the message is not acknowledged by a PUBACK packet,it is sent again. This level guarantees “at least once” delivery.
- **QoS 2:** This is the highest QoS level, used when neither loss nor duplication of messages is acceptable. There is an increased overhead associated with this QoS level because each packet contains an optional variable header with a packet identifier. Confirming the receipt of a PUBLISH message requires a two-step acknowledgement process. The first step is done through the PUBLISH/PUBREC packet pair, and the second is achieved with the PUBREL/PUBCOMP packet pair. This level provides a “guaranteed service” known as “exactly once” delivery, with no consideration for the number of

retries as long as the message is delivered once.

As mentioned earlier, the QoS process is symmetric in regard to the roles of sender and receiver, but two separate transactions exist. One transaction occurs between the publishing client and the MQTT server, and the other transaction happens between the MQTT server and the subscribing client. Figure 3.22 provides an overview of the MQTT QoS flows for the three different levels.

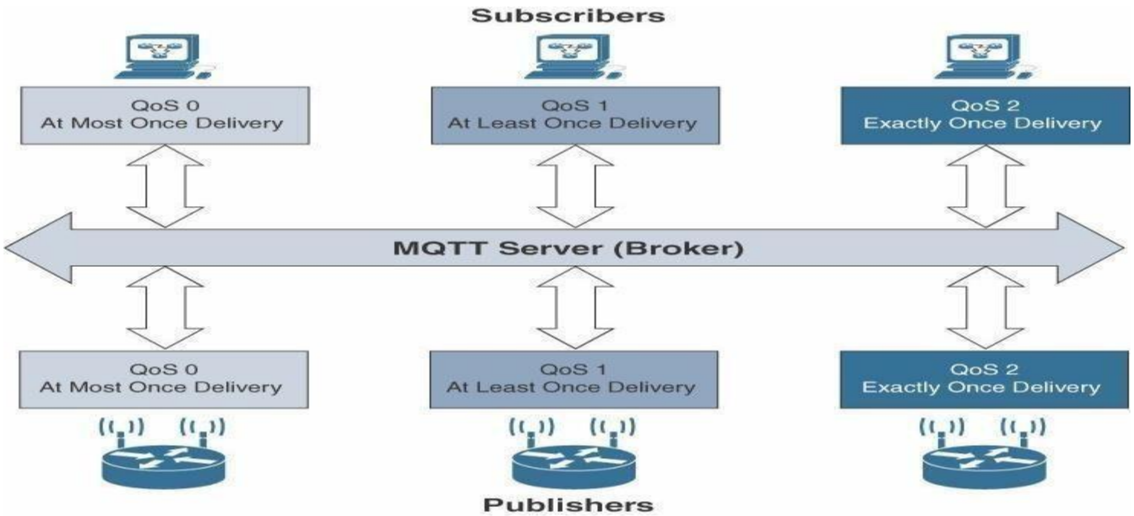


Figure 3.22 *MQTT QoS Flows*

As with CoAP, a wide range of MQTT implementations are now available. They are either published as opensource licenses or integrated into vendors' solutions, such as Facebook Messenger.

Both CoAP and MQTT have been discussed in detail, there arises questions like "Which protocol is better for a given use case?" and "Which one should I used in my IoT network?" Unfortunately, the answer is not always clear, and both MQTT and CoAP have their place. Table 3-3 provides an overview of the differences between MQTT and CoAP, along with their strengths and weaknesses from an IoT perspective.

Table 3-3 *Comparison Between CoAP and MQTT*

Factor	CoAP	MQTT
Main transport protocol	UDP	TCP
Typical messaging	Request/response	Publish/subscribe
Effectiveness in LLNs	Excellent	Low/fair (Implementations pairing UDP with MQTT are better for LLNs.)
Security	DTLS	SSL/TLS
Communication model	One-to-one	many-to-many
Strengths	Lightweight and fast, with low overhead, and suitable for constrained networks; uses a RESTful model that is easy to code to; easy to parse and process for constrained devices; support for multicasting; asynchronous and synchronous messages	TCP and multiple QoS options provide robust communications; simple management and scalability using a broker architecture
Weaknesses	Not as reliable as TCP-based MQTT, so the application must ensure reliability.	Higher overhead for constrained devices and networks; TCP connections can drain low-power devices; no multicasting support

MODULE -4
(Continued…)
Data and Analytics for IoT

4.1 An Introduction to Data Analytics for IoT

In the world of IoT, the creation of massive amounts of data from sensors is common and one of the biggest challenges—not only from a transport perspective but also from a data management standpoint. A great example of the deluge of data that can be generated by IoT is found in the commercial aviation industry and the sensors that are deployed throughout an aircraft.

Modern jet engines are fitted with thousands of sensors that generate a whopping 10GB of data per second. For example, modern jet engines, similar to the one shown in Figure 7-1, maybe equipped with around 5000 sensors. Therefore, a twin-engine commercial aircraft with these engines operating on average 8 hours a day will generate over 500 TB of data daily, and this is just the data from the engines! Aircraft today have thousands of other sensors connected to the airframe and other systems. In fact, a single wing of a modern jumbo jet is equipped with 10,000 sensors.

Figure 7-1 *Commercial Jet Engine*

The potential for a petabyte (PB) of data per day per commercial airplane is not farfetched—and this is just for *one* airplane. Across the world, there are approximately 100,000 commercial flights per day. The amount of IoT data coming just from the commercial airline business is overwhelming.

4.1.1 Structured Versus Unstructured Data

Structured data and unstructured data are important classifications as they typically require different toolsets from a data analytics perspective. Figure 7-2 provides a high-level comparison of structured data and unstructured data.

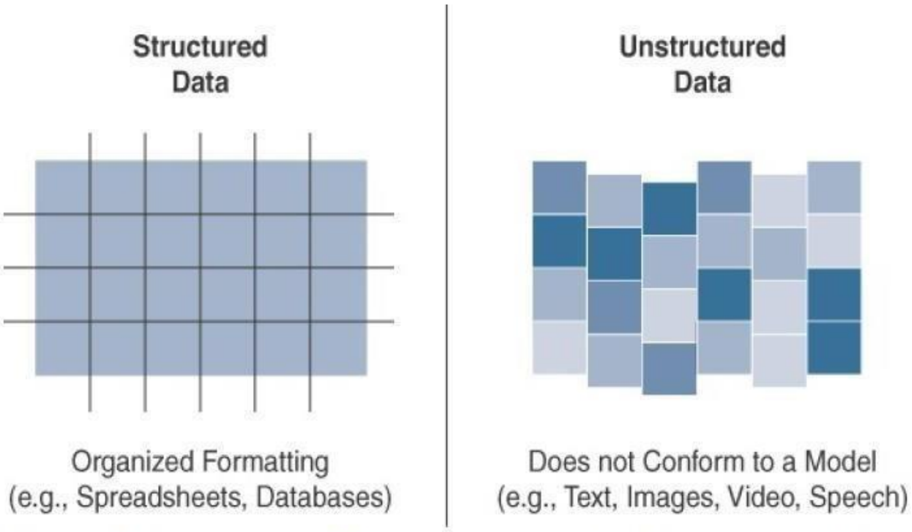


Figure 7-2 *Comparison Between Structured and Unstructured Data*

Structured data means that the data follows a model or schema that defines how the data is represented or organized, meaning it fits well with a traditional relational database management system (RDBMS). In many cases you will find structured data in a simple tabular form—for example, a spreadsheet where data occupies a specific cell and can be explicitly defined and referenced.

Structured data can be found in most computing systems and includes everything from banking transaction and invoices to computer log files and router configurations. IoT sensor data often uses structured values, such as temperature, pressure, humidity, and so on, which are all sent in a known format. Structured data is easily formatted, stored, queried, and processed; for these reasons, it has been the core type of data used for making business decisions.

Unstructured data lacks a logical schema for understanding and decoding the data through traditional programming means. Examples of this data type include text, speech, images, and video. As a general rule, any data that does not fit neatly into a predefined data model is classified as unstructured data.

According to some estimates, around 80% of a business's data is unstructured. Because of this fact, data analytics methods that can be applied to unstructured data, such as cognitive computing and machine learning, are deservedly garnering a lot of attention. With machine learning applications, such as natural language processing (NLP), you can decode speech. With image/facial recognition applications, you can extract critical information from still images and video.Data in Motion Versus Data at Rest

As in most networks, data in IoT networks is either in transit ("data in motion") or being held or stored ("data at rest"). Examples of data in motion include traditional client/server exchanges, such as web browsing and file transfers, and email. Data saved to a hard drive, storage array, or USB drive is data at rest.

From an IoT perspective, the data from smart objects is considered data in motion as it passes through the network en route to its final destination. This is often processed at the edge, using fog computing. When data is processed at the edge, it may be filtered and deleted or forwarded on for further processing and possible storage at a fog node or in the data center. Data does not come to rest at the edge.

Data at rest in IoT networks can be typically found in IoT brokers or in some sort of storage array at the data center. Myriad tools, especially tools for structured data in relational databases, are available from a data analytics perspective. The best known of these tools is Hadoop. Hadoop not only helps with data processing but also data storage.

4.1.2 IoT Data Analytics Overview

The true importance of IoT data from smart objects is realized only when the analysis of the data leads to actionable business intelligence and insights. Data analysis is typically broken down by the types of results that are produced. As shown in Figure 7-3, there are four types of data analysis results:

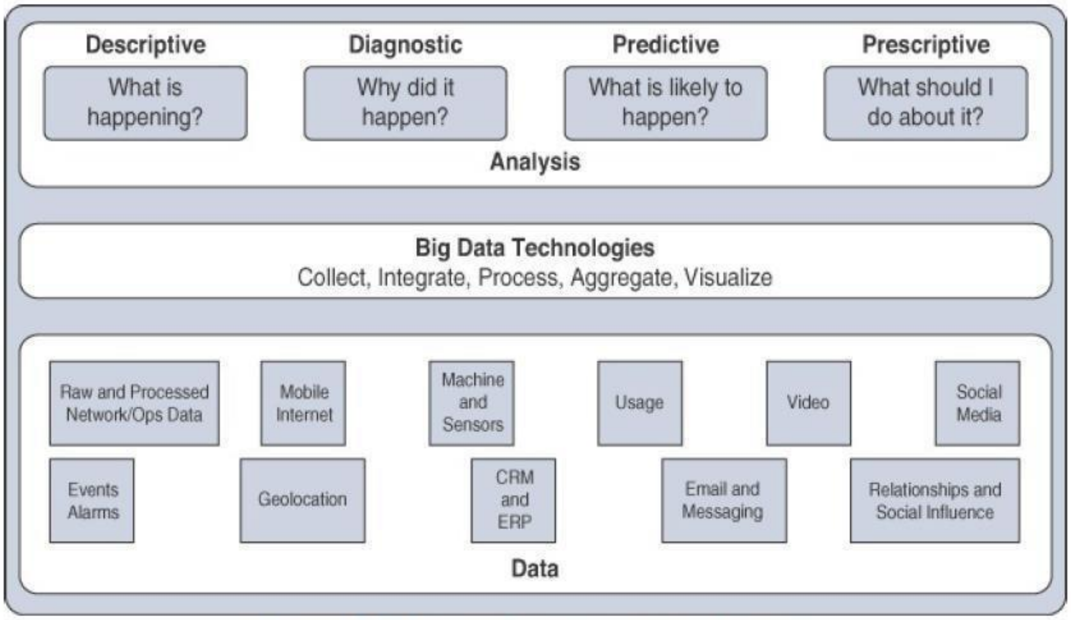


Figure 7-3 *Types of Data Analysis Results*

4.1.2.1 **Descriptive:** Descriptive data analysis tells you what is happening, either now or in the past. For example, a thermometer in a truck engine reports temperature values every second. From a descriptive analysis perspective, you can pull this data at any moment to gain insight into the current operating condition of the truck engine. If the temperature value is too high, then there may be a cooling problem or the engine may be experiencing too much load.

4.1.2.2 **Diagnostic:** When you are interested in the "why," diagnostic data analysis can provide the answer. Continuing with the example of the temperature sensor in the truck engine, you might wonder why the truck engine failed. Diagnostic analysis might show that the temperature of the engine was too high, and the engine overheated. Applying diagnostic analysis across the data generated by a wide range of smart objects can provide a clear picture of why a problem or an event occurred.

4.1.2.3 **Predictive:** Predictive analysis aims to foretell problems or issues before they occur. For example, with historical values of temperatures for the truck engine, predictive analysis could provide an estimate on the remaining life of certain components in the engine. These components could then be proactively replaced before failure occurs. Or perhaps if temperature values of the truck engine start to rise slowly over time, this could indicate the need for an oil change or some other sort of engine cooling maintenance.

4.1.2.4 **Prescriptive:** Prescriptive analysis goes a step beyond predictive and recommends solutions for upcoming problems. A prescriptive analysis of the temperature data from a truck engine might calculate various alternatives to cost-effectively maintain our truck. These calculations could range from the cost necessary for more frequent oil changes and cooling maintenance to installing new cooling equipment on the engine or upgrading to a lease on a model with a more powerful engine. Prescriptive analysis looks at a variety of factors and makes the appropriate recommendation.

Both predictive and prescriptive analyses are more resource intensive and increase complexity, but the value they provide is much greater than the value from descriptive and diagnostic analysis. Figure 7-4 illustrates the four data analysis types and how they rank as complexity and value increase. You can see that descriptive analysis is the least complex and at the same time offers the least value. On the other end, prescriptive analysis provides the most value but is the most complex to implement. Most data analysis in the IoT space relies on descriptive and diagnostic analysis, but a shift toward predictive and prescriptive analysis is understandably occurring for most businesses and organizations.

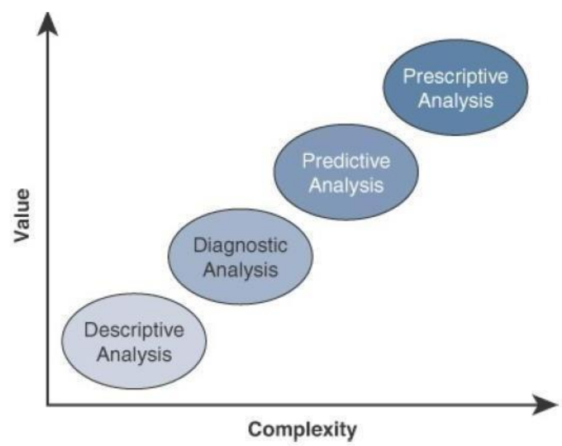


Figure 7-4 *Application of Value and Complexity Factors to the Types of Data Analysis*

As IoT has grown and evolved, it has become clear that traditional data analytics solutions were not always adequate. For example, traditional data analytics typically employs a standard RDBMS and corresponding tools, but the world of IoT is much more demanding. While relational databases are still used for certain data types and applications, they often struggle with the nature of IoT data. IoT data places two specific challenges on a relational database:

4.1.2.5 **Scaling problems:** Due to the large number of smart objects in most IoT networks that continually send data, relational databases can grow incredibly large very quickly. This can result in performance issues that can be costly to resolve, often requiring more hardware and architecture changes.

4.1.2.6 **Volatility of data:** With relational databases, it is critical that the schema be designed correctly from the beginning. Changing it later can slow or stop the database from operating. Due to the lack of flexibility, revisions to the schema must be kept at a minimum. IoT data, however, is volatile in the sense that the data model is likely to change and evolve over time. A dynamic schema is often required so that data model changes can be made daily or even hourly.

To deal with challenges like scaling and data volatility, a different type of database, known as NoSQL, is being used. Structured Query Language (SQL) is the computer language used to communicate with an RDBMS. As the name implies, a NoSQL database is a database that does not use SQL. It is not set up in the traditional tabular form of a relational database. NoSQL databases do not enforce a strict schema, and they support a complex, evolving data model. These databases are also inherently much more scalable.

4.2 Machine Learning

ML is indeed central to IoT. Data collected by smart objects needs to be analyzed, and intelligent actions need to be taken based on these analyses. Performing this kind of operation manually is almost impossible (or very, very slow and inefficient).

Machines are needed to process information fast and react instantly when thresholds are met. For example, every time a new advance is made in the field of self-driving vehicles, abnormal pattern recognition in a crowd, or any other automated intelligent and machine-assisted decision system, ML is named as the tool that made the advance possible. But ML is not new. It was invented in the middle of the twentieth century and actually fell out of fashion in the 1980s

4.2.1 Machine Learning Overview

ML is concerned with any process where the computer needs to receive a set of data that is processed to help perform a task with more efficiency. ML is a vast field but can be simply divided in two main categories: supervised and unsupervised learning.

Supervised Learning

In supervised learning, the machine is trained with input for which there is a known correct answer. For example, suppose that you are training a system to recognize when there is a human in a mine tunnel. A sensor equipped with a basic camera can capture shapes and return them to a computing system that is responsible for determining whether the shape is a human or something else (such as a vehicle, a pile of ore, a rock, a piece of wood, and so on.). With supervised learning techniques, hundreds or thousands of images are fed into the machine, and each image is labeled (human or nonhuman in this case). This is called the *training set*. An algorithm is used to determine common parameters and common differences between the images. The comparison is usually done at the scale of the entire image, or pixel by pixel. Images are resized to have the same characteristics (resolution, color depth, position of the central figure, and so on), and each point is analyzed. Human images have certain types of shapes and pixels in certain locations (which correspond to the position of the face, legs, mouth, and so on). Each new image is compared to the set of known “good images,” and a deviation is calculated to determine how different the new image is from the average human image and, therefore, the probability that what is shown is a human figure. This process is called *classification*.

After training, the machine should be able to recognize human shapes. Before real field deployments, the machine is usually tested with unlabeled pictures— this is called the validation or the test set, depending on the ML system used—to verify that the recognition level is at acceptable thresholds. If the machine does not reach the level of success expected, more training is needed.

Unsupervised Learning

In some cases, supervised learning is not the best method for a machine to help with a human decision. Suppose that you are processing IoT data from a factory manufacturing small engines. You know that about 0.1% of the produced engines on average need adjustments to prevent later defects, and your task is to identify them before they get mounted into machines and shipped away from the factory. With hundreds of parts, it may be very difficult to detect the potential defects, and it is almost impossible to train a machine to recognize issues that may not be visible. However, you can test each engine and record multiple parameters, such as sound, pressure, temperature of key parts, and so on. Once data is recorded, you can graph these elements in relation to one another (for example, temperature as a function of pressure, sound versus rotating speed over time). You can then input this data into a computer and use mathematical functions to find groups. For example, you may decide to group the engines by the sound they make at a given temperature. A standard function to operate this grouping, *K-means clustering*, finds the mean values for a group of engines (for example, mean value for temperature, mean frequency for sound). Grouping the engines this way can quickly reveal several types of engines that all belong to the same category (for example, small engine of chainsaw type, medium engine of lawnmower type). All engines of the same type produce sounds and temperatures in the same range as the other members of the same group.

There will occasionally be an engine in the group that displays unusual characteristics (slightly out of expected temperature or sound range). This is the engine that you send for manual evaluation. The computing process associated with this determination is called *unsupervised learning*. This type of learning is unsupervised because there is not a “good” or “bad” answer known in advance. It is the variation from a group behavior that allows the computer to learn that something is different. The example of engines is, of course, very simple. In most cases, parameters are multidimensional. In other words, hundreds or thousands of parameters are computed, and small cumulated deviations in multiple dimensions are used to identify the exception. Figure 7-5 shows an example of such grouping and deviation identification logic. Three parameters are graphed (components 1, 2, and 3), and four distinct groups (clusters) are found. You can see some points that are far from the respective groups. Individual devices that display such "out of cluster" characteristics should be examined more closely individually.

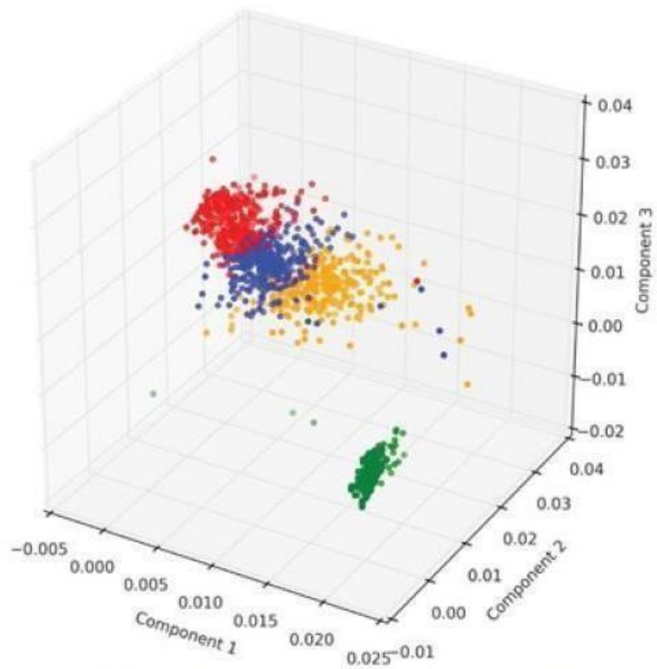


Figure 7-5 *Clustering and Deviation Detection Example*

Neural Networks

Distinguishing between a human and a car is easy. The computer can recognize that humans have distinct shapes (such as legs or arms) and that vehicles do not. Distinguishing a human from another mammal is much more difficult (although nonhuman mammals are not common occurrences in mines). The same goes for telling the difference between a pickup truck and a van. You can tell when you see one, but training a machine to differentiate them requires more than basic shape recognition. This is where neural networks come into the picture. Neural networks are ML methods that mimic the way the human brain works. When you look at a human figure, multiple zones of your brain are activated to recognize colors, movements, facial expressions, and so on. Your brain combines these elements to conclude that the shape you are seeing is human. Neural networks mimic the same logic. The information goes through different algorithms (called *units*), each of which is in charge of processing an aspect of the information. The resulting value of one unit computation can be used directly or fed into another unit for further processing to occur. In this case, the neural network is said to have several layers. For example, a neural network processing human image recognition may have two units in a first layer that determines whether the image has straight lines and sharp angles—because vehicles commonly have straight lines and sharp angles, and human figures do not. If the image passes the first layer successfully (because there are no or only a small percentage of sharp angles and straight lines), a second layer may look for different features (presence of face, arms, and so on), and then a third layer might compare the image to images of various animals and conclude that the shape is a human (or not). The great efficiency of neural networks is that each unit processes a simple test, and therefore computation is quite fast. This model is demonstrated in Figure 7-6.

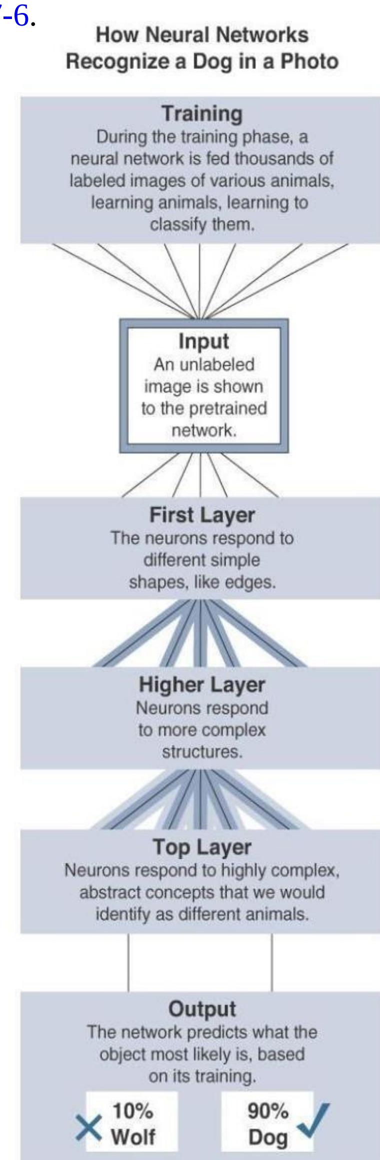


Figure 7-6 *Neural Network Example*

By contrast, old supervised ML techniques would compare the human figure to potentially hundreds of thousands of images during the training phase, pixel by pixel, making them difficult and expensive to implement (with a lot of training needed) and slow to operate. Neural networks have been the subject of much research work. Multiple research and optimization efforts have examined the number of units and layers, the type of data processed at each layer, and the type and combination of algorithms used to process the data to make processing more efficient for specific applications. Image processing can be optimized with certain types of algorithms that may not be optimal for crowd movement classification. Another algorithm may be found in this case that would revolutionize the way these movements are processed and analyzed. Possibilities are as numerous as the applications where they can be used.

4.2.2 Machine Learning and Getting Intelligence from Big Data

When the principles of machine learning are clear, the application to IoT becomes obvious. The difficulty resides in determining the right algorithm and the right learning model for each use case. Such an analysis goes beyond the scope of this chapter, but it can be useful to organize ML operations into two broad subgroups:

4.2.2.1 **Local learning:** In this group, data is collected and processed locally, either in the sensor itself (the edge node) or in the gateway (the fog node).

4.2.2.2 **Remote learning:** In this group, data is collected and sent to a central computing unit (typically the data center in a specific location or in the cloud), where it is processed.

Regardless of the location where (and, therefore, the scale at which) data is processed, common applications of ML for IoT revolve around four major domains:

4.2.2.3 **Monitoring:** Smart objects monitor the environment where they operate. Data is processed to better understand the conditions of operations. These conditions can refer to external factors, such as air temperature, humidity, or presence of carbon dioxide in a mine, or to operational internal factors, such as the pressure of a pump, the viscosity of oil flowing in a pipe, and so on. ML can be used with monitoring to detect early failure conditions (for example, K-means deviations showing out-of-range behavior) or to better evaluate the environment (such as shape recognition for a robot automatically sorting material or picking goods in a warehouse or a supply chain).

4.2.2.4 **Behavior control:** Monitoring commonly works in conjunction with behavior control. When a given set of parameters reach a target threshold — defined in advance (that is, supervised) or learned dynamically through deviation from mean values (that is, unsupervised)—monitoring functions generate an alarm. This alarm can be relayed to a human, but a more efficient and more advanced system would trigger a corrective action, such as increasing the flow of fresh air in the mine tunnel, turning the robot arm, or reducing the oil pressure in the pipe.

4.2.2.5 **Operations optimization:** Behavior control typically aims at taking corrective actions based on thresholds. However, analyzing data can also lead to changes that improve the overall process. For example, a water purification plant in a smart city can implement a system to monitor the efficiency of the purification process based on which chemical (from company A or company B) is used, at what temperature, and associated to what stirring mechanism (stirring speed and depth). Neural networks can combine multiples of such units, in one or several layers, to estimate the best chemical and stirring mix for a target air temperature. This intelligence can help the plant reduce its consumption of chemicals while still operating at the same purification efficiency level. As a result of the learning, behavior control results in different machine actions. The objective is not merely to pilot the operations but to improve the efficiency and the result of these operations.

4.2.2.6 **Self-healing, self-optimizing:** A fast-developing aspect of deep learning is the closed loop. ML-based monitoring triggers changes in machine behavior (the change is monitored by humans), and operations optimizations. In turn, the ML engine can be programmed to dynamically monitor and combine new parameters (randomly or semi-randomly) and automatically deduce and implement new optimizations when the results demonstrate a possible gain. The system becomes self-learning and self-optimizing. It also detects new K-means deviations that result in predilection of new potential defects, allowing the system to self-heal. The healing is not literal, as external factors (typically human operators) have to intervene, but the diagnosis is automated. In many cases, the system can also automatically order a piece of equipment that is detected as being close to failure or automatically take corrective actions to avoid the failure (for example, slow down operations, modify a machine's movement to avoid fatigue on a weak link).

4.2.3 Predictive Analytics

Multiple smart objects measure the pull between carriages, the weight on each wheel, and multiple other parameters to offer a form of cruise control optimization for the driver. At the same time, cameras observe the state of the tracks ahead, audio sensors analyze the sound of each wheel on the tracks, and multiple engine parameters are measured and analyzed. All this data can be returned to a data processing center in the cloud that can re-create a virtual twin of each locomotive. Modeling the state of each locomotive and combining this knowledge with anticipated travel and with the states (and detected failures) of all other locomotives of the same type circulating on the tracks of the entire city, province, state, or country allows the analytics platform to make very accurate predictions on what issue is likely to affect each train and each locomotive. Such predictive analysis allows preemptive maintenance and increases the safety and efficiency of operations.

Big Data Analytics Tools and Technology

Generally, the industry looks to the "three *V*s" to categorize big data:

- **Velocity:** *Velocity* refers to how quickly data is being collected and analyzed. Hadoop Distributed File System is designed to ingest and process data very quickly. Smart objects can generate machine and sensor data at a very fast rate and require database or file systemscapable of equally fast ingest functions.
- **Variety:** *Variety* refers to different types of data. Often you see data categorized as structured, semi-structured, or unstructured. Different database technologies may only be capable of accepting one of these types. Hadoop is able to collect and store all three types.This can be beneficial when combining machine data from IoT devices that is very structured in nature with data from other sources, such as social media or multimedia that is unstructured.
- **Volume:** *Volume* refers to the scale of the data. Typically, this is measured from gigabytes on the very low end to petabytes or even exabytes of data on the other extreme. Generally, big data implementations scale beyond what is available on locally attached storage disks on a single node. It is common to see clusters of servers that consist of dozens, hundreds, or even thousands of nodes for some large deployments.

The characteristics of big data can be defined by the sources and types of data. First is machine data, which is generated by IoT devices and is typically unstructured data. Second is transactional data, which is from sources that produce data from transactions on these systems, and, have high volume and structured. Third is social data sources, which are typically high volume and structured. Fourth is enterprise data, which is data that is lower in volume and very structured. Hence big data consists of data from all these separate sources.

Massively Parallel Processing Databases

Massively parallel processing (MPP) databases were built on the concept of the relational data warehouses but are designed to be much faster, to be efficient, and to support reduced query times. To accomplish this, MPP databases take advantage of multiple nodes (computers) designed in a scale-out architecture such that both data and processing are distributed across multiple systems.

MPPs are sometimes referred to as *analytic databases* because they are designed to allow for fast query processing and often have built-in analytic functions. As the name implies, these database types process massive data sets in parallel across many processors and nodes. An MPP architecture (see Figure 7-7) typically contains a single master node that is responsible for the coordination of all the data storage and processing across the cluster. It operates in a "shared nothing" fashion, with each node containing local processing, memory, and storage and operating independently. Data storage is optimized across the nodes in a structured SQL- like format that allows data analysts to work with the data using common SQL tools and applications. The earlier example of a complex SQL query could be distributed and optimized, resulting in a significantly faster response. Because data stored on MPPs must still conform to thisrelational structure, it may not be the only database type used in an IoT implementation. The sources and types of data may vary, requiring a database that is more flexible than relational databases allow.

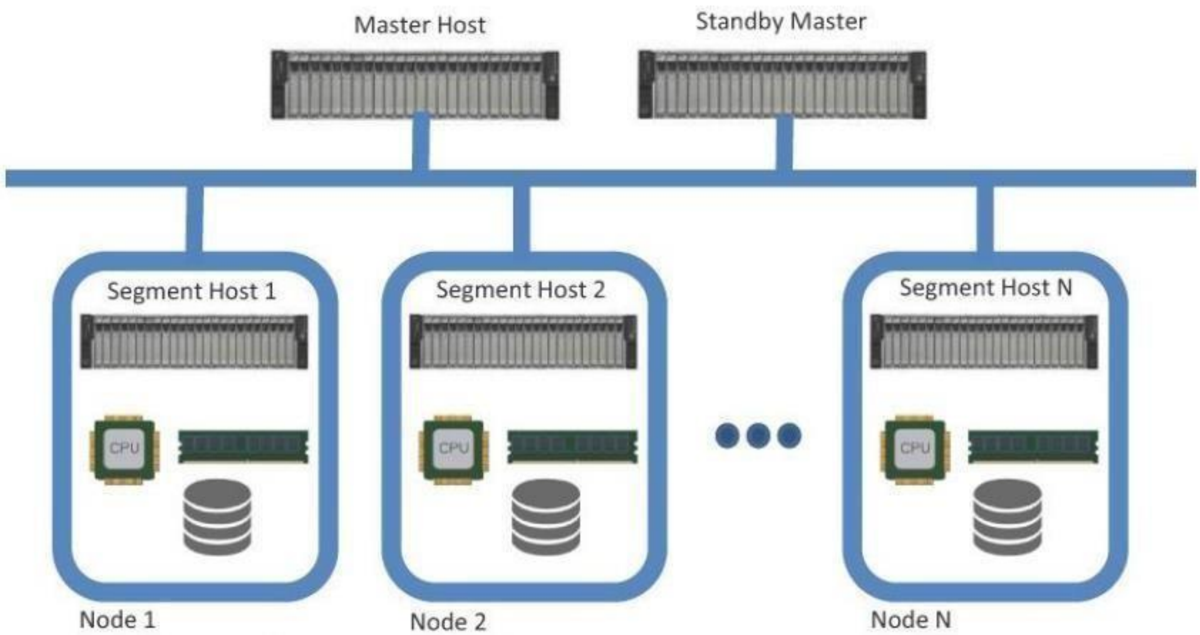


Figure 7-7 *MPP Shared-Nothing Architecture*

NoSQL Databases

NoSQL ("not only SQL") is a class of databases that support semi-structured and unstructured

data, in addition to the structured data handled by data warehouses and MPPs. NoSQL is not a specific database technology; rather, it is an umbrella term that encompasses several different types of databases, including the following:

- **Document stores:** This type of database stores semi-structured data, such as XML or JSON. Document stores generally have query engines and indexing features that allow for many optimized queries.
- **Key-value stores:** This type of database stores associative arrays where a key is paired with an associated value. These databases are easy to build and easy to scale.
- **Wide-column stores:** This type of database stores similar to a key-value store, but the

formatting of the values can vary from row to row, even in the same table.

- **Graph stores:** This type of database is organized based on the relationships between elements. Graph stores are commonly used for social media or natural language processing,where the connections between data are very relevant. NoSQL was developed to support the high-velocity, urgent data requirements of modern web applications that typically do not require much repeated use. The original intent was to quickly ingest rapidly changing server logs and clickstream data generated by web-scale applications that did not neatly fit into the rows and columns required by relational databases. Similar to other data stores, likeMPPs and Hadoop (discussed later), NoSQL is built to scale horizontally, allowing the database to span multiple hosts, and can even be distributed geographically.

Expanding NoSQL databases to other nodes is similar to expansion in other distributed data systems, where additional hosts are managed by a master node or process. This expansion can be automated by some NoSQL implementations or can be provisioned manually. This level of flexibility makes NoSQL a good candidate for holding machine and sensor data associated with smart objects.

Hadoop

Hadoop is the most recent entrant into the data management market, but it is arguably the most popular choice as a data repository and processing engine.

Hadoop was originally developed as a result of projects at Google and Yahoo!, and the original intent for Hadoop was to index millions of websites and quickly return search results for open source search engines. Initially, the project had two key elements:

- **Hadoop Distributed File System (HDFS):** A system for storing data across multiple nodes
- **MapReduce:** A distributed processing engine that splits a large task into smaller ones that can be run in parallel.

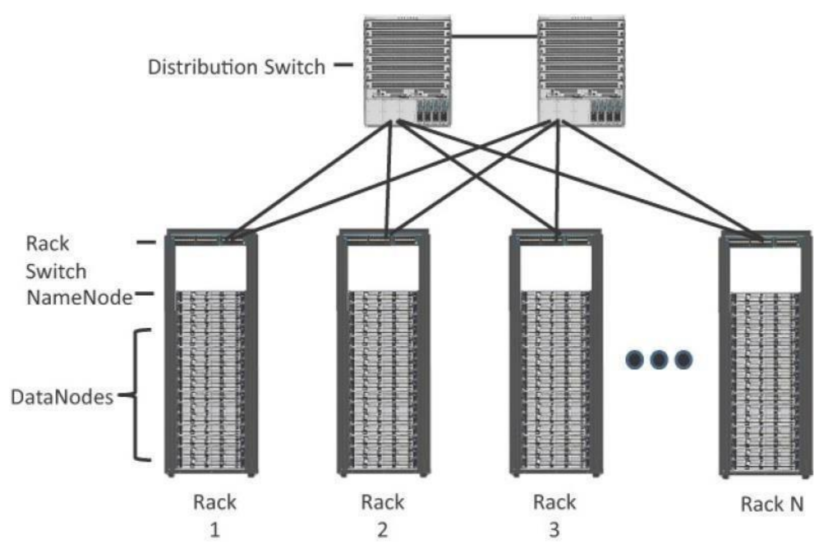


Figure 7-8 *Distributed Hadoop Cluster*

Much like the MPP and NoSQL systems discussed earlier, Hadoop relies on a scale-out architecture that leverages local processing, memory, and storage to distribute tasks and provide a scalable storage system for data. Both MapReduce and HDFS take advantage of this distributed architecture to store and process massive amounts of data and are thus able to leverage resources from all nodes in the cluster.

For HDFS, this capability is handled by specialized nodes in the cluster, including Name Nodes and Data Nodes (see Figure 7-8):

- **NameNodes:** These are a critical piece in data adds, moves, deletes, and reads on HDFS. They coordinate where the data is stored, and maintain a map of where each block of data is stored and where it is replicated. All interaction with HDFS is coordinated through the primary (active) NameNode, with a secondary (standby) NameNode notified of the changes in the event of a failure of the primary. The NameNode takes write requests from clients and distributes those files across the available nodes in configurable block sizes, usually 64 MB or 128 MB blocks. The NameNode is also responsible for instructing the DataNodes where replication should occur.
- **DataNodes**: These are the servers where the data is stored at the direction of the NameNode. It is common to have many DataNodes in a Hadoop cluster to store the data. Data blocks are distributed across several nodes and often are replicated three, four, or more times across nodes for redundancy. Once data is written to one of the DataNodes, the DataNode selects two (or more) additional nodes, based on replication policies, to ensure data redundancy across the cluster. Disk redundancy techniques such as Redundant Array of Independent Disks (RAID) are generally not used for HDFS because the NameNodes and DataNodes coordinate blocklevel redundancy with this replication technique. Figure 7-9 shows the relationship between NameNodes and DataNodes and how data blocks are distributed across the cluster.

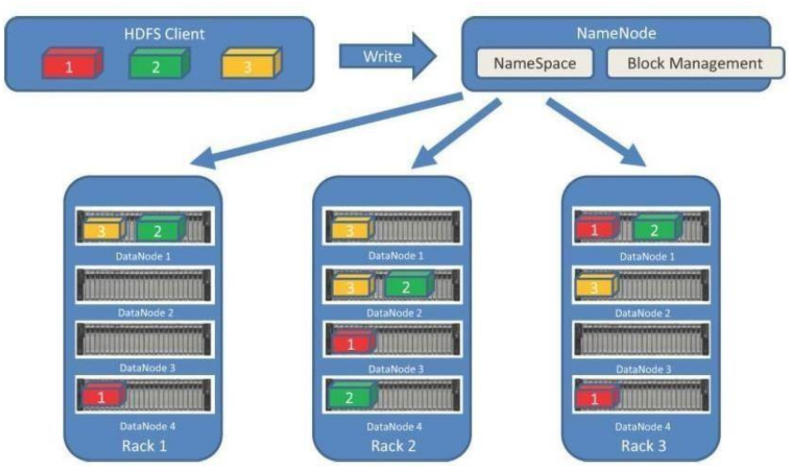


Figure 7-9 *Writing a File to HDFS*

MapReduce leverages a similar model to batch process the data stored on the cluster nodes. Batch processing is the process of running a scheduled or ad hoc query across historical data stored in the HDFS. A query is broken down into smaller tasks and distributed across all the nodes running MapReduce in a cluster. While this is useful for understanding patterns and trending in historical sensor or machine data, it has one significant drawback: time

YARN

Introduced with version 2.0 of Hadoop, YARN (Yet Another Resource Negotiator) was designed to enhance the functionality of MapReduce. With the initial release, MapReduce was responsible for batch data processing and job tracking and resource management across the cluster. YARN was developed to take over the resource negotiation and job/task tracking, allowing MapReduce to be responsible only for data processing.

With the development of a dedicated cluster resource scheduler, Hadoop was able to add additional data processing modules to its core feature set, including interactive SQL and real-timeprocessing, in addition to batch processing using MapReduce.

The Hadoop Ecosystem

As mentioned earlier, Hadoop plays an increasingly big role in the collection, storage, and processing of IoT data due to its highly scalable nature and its ability to work with large volumes of data.

Hadoop now comprises more than 100 software projects under the Hadoop umbrella, capable of nearly every element in the data lifecycle, from collection, to storage, to processing, to analysis and visualization. Each of these individual projects is a unique piece of the overall data management solution. The following sections describe several of these packages and discuss how they are used to collect or process data.

Apache Kafka

Part of processing real-time events, such as those commonly generated by smart objects, is having them ingested into a processing engine. The process of collecting data from a sensor or log file and preparing it to be processed and analyzed is typically handled by messaging systems. Messaging systems are designed to accept data, or messages, from where the data is generated and deliver the data to stream-processing engines such as Spark Streaming or Storm.

Apache Kafka is a distributed publisher-subscriber messaging system that is built to be scalable and fast. It is composed of topics, or message brokers, where producers write data and consumers read data from these topics. Figure 7-10 shows the data flow from the smart objects (producers), through a topic in Kafka, to the real-time processing engine. Due to the distributed nature of Kafka, it can run in a clustered configuration that can handle many producers and consumers simultaneously and exchanges information between nodes, allowing topics to be distributed over multiple nodes. The goal of Kafka is to provide a simple way to connect to data sources and allow consumers to connect to that data in the way they would like. The following sections describe several of these packages and discusses how they are used to collect or process data

in the Hadoop ecosystem. The "in-memory" characteristic of Spark is what enables it to run jobs very quickly. At each stage of a MapReduce operation, the data is read and written back to the disk, which means latency is introduced through each disk operation. However, with Spark, the processing of this data is moved into high-speed memory, which has significantly lower latency. This speeds the batch processing jobs and also allows for near-real-time processing of events.

Apache Storm and Apache Flink

As you work with the Hadoop ecosystem, you will inevitably notice that different projects are very similar and often have significant overlap with other projects. This is the case with data streaming capabilities. For example, Apache Spark is often used for both distributed streaming analytics and batch processing. Apache Storm and Apache Flink are other Hadoop ecosystem projects designed

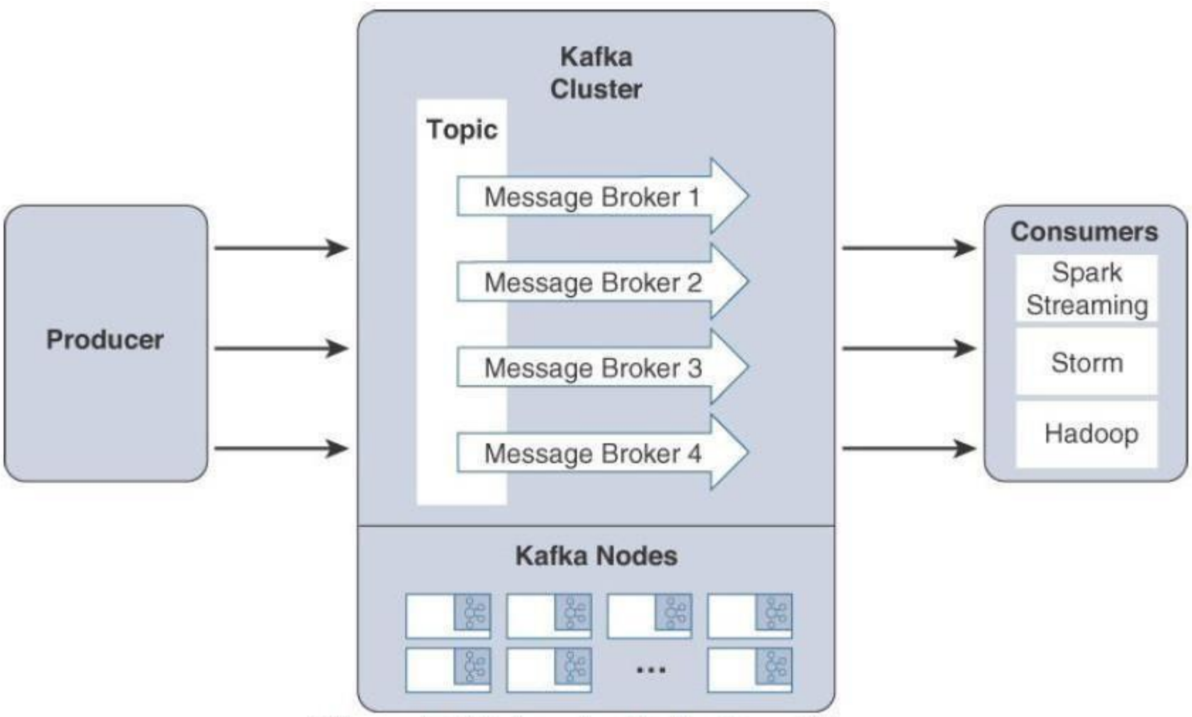


Figure 7-10 *Apache Kafka Data Flow*

for distributed stream processing and are commonly deployed for IoT use cases. Storm can pull data from Kafka and process it in a near-real-time fashion, and so can Apache Flink. This space is rapidly evolving, and projects will continue to gain and lose popularity as they evolve.

Lambda Architecture

Ultimately the key elements of a data infrastructure to support many IoT use cases involves the collection, processing, and storage of data using multiple technologies. Querying both data in motion (streaming) and data at rest (batch processing) requires a combination of the Hadoop ecosystem projects discussed.

One architecture that is currently being leveraged for this functionality is the Lambda Architecture. Lambda is a data management system that consists of two layers for ingesting data (Batch and Stream) and one layer for providing the combined data (Serving). These layers allow for the packages discussed previously, like Spark and MapReduce, to operate on the data independently, focusing on the key attributes for which they are designed and optimized. Data is taken from a message broker, commonly Kafka, and processed by each layer in parallel, and the resulting data is delivered to a data store where additional processing or queries can be run. Figure 7-11 shows this parallel data flow through the Lambda Architecture.

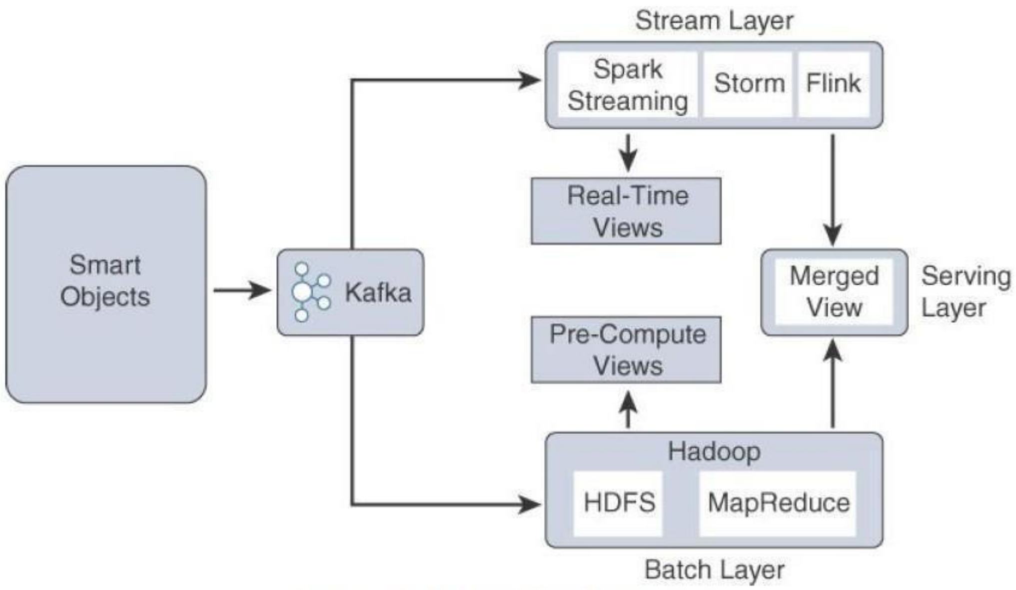


Figure 7-11 *Lambda Architecture*

The Lambda Architecture is not limited to the packages in the Hadoop ecosystem, but due to its breadth and flexibility, many of the packages in the ecosystem fill the requirements of each layer nicely:

- **Stream layer:** This layer is responsible for near-real-time processing of events. Technologies such as Spark Streaming, Storm, or Flink are used to quickly ingest, process, and analyze data on this layer. Alerting and automated actions can be triggered on events that require rapid response or could result in catastrophic outcomes if not handled immediately.
- **Batch layer:** The Batch layer consists of a batch-processing engine and data store. If an organization is using other parts of the Hadoop ecosystem for the other layers, MapReduce and HDFS can easily fit the bill. Other database technologies, such as MPPs, NoSQL, or data warehouses, can also provide what is needed by this layer.
- **Serving layer:** The Serving layer is a data store and mediator that decides which of the ingest layers to query based on the expected result or view into the data. If an aggregate or historical view is requested, it may invoke the Batch layer. If real-time analytics is needed, it may invoke the Stream layer. The Serving layer is often used by the data consumers to access both layers simultaneously.

4.3 Edge Streaming Analytics

One industry where data analytics is used extensively is the world of automobile racing. For example, in Formula One racing, each car has between 150 to 200 sensors that, combined, generate more than 1000 data points per second, resulting in hundreds of gigabytes of raw data per race. The sensor data is transmitted from the car and picked up by track-side wireless sensors. During a race, weather conditions may vary, tire conditions change, and accidents or other racing incidents almost always require an adaptable and flexible racing strategy. As the race develops, decisions such as when to pit, what tires to use, when to pass, and when to slow down all need to be made in seconds. Teams have found that enormous insights leading to better race results can be gained by analyzing data on the fly—and the data may come from many different sources, including trackside sensors, car telemetry, and weather reports.

Comparing Big Data and Edge Analytics

From a business perspective, streaming analytics involves acting on data that is generated while it is still valuable, before it becomes stale. For example, roadway sensors combined with GPS way finding apps may tell a driver to avoid a certain highway due to traffic. This data is valuable for only a small window of time. Historically, it may be interesting to see how many traffic accidents or blockages have occurred on a certain segment of highway or to predict congestion based on past traffic data. However, for the driver in traffic receiving this information, if the data is not acted upon immediately, the data has little value.

From a security perspective, having instantaneous access to analyzed and preprocessed data at the edge also allows an organization to realize anomalies in its network so those anomalies can be quickly contained before spreading to the rest of the network.

To summarize, the key values of edge streaming analytics include the following:

- **Reducing data at the edge:** The aggregate data generated by IoT devices is generally in proportion to the number of devices. The scale of these devices is likely to be huge, and so is the quantity of data they generate. Passing all this data to the cloud is inefficient and is unnecessarily expensive in terms of bandwidth and network infrastructure.

Analysis and response at the edge: Some data is useful only at the edge (such as a factory control feedback system). In cases such as this, the data is best analyzed and acted upon where it is generated.

- **Time sensitivity:** When timely response to data is required, passing data to the cloud for future processing results in unacceptable latency. Edge analytics allows immediate responses to changing conditions.

Edge Analytics Core Functions

To perform analytics at the edge, data needs to be viewed as real-time flows. Whereas big data analytics is focused on large quantities of data at rest, edge analytics continually processes streaming flows of data in motion. Streaming analytics at the edge can be broken down into three simple stages:

- **Raw input data:** This is the raw data coming from the sensors into the analytics processing unit.
- **Analytics processing unit (APU):** The APU filters and combines data streams (or separates the streams, as necessary), organizes them by time windows, and performs various analytical functions. It is at this point that the results may be acted on by micro services running in the APU.
- **Output streams:** The data that is output is organized into insightful streams and is used to influence the behavior of smart objects, and passed on for storage and further processing in the cloud. Communication with the cloud often happens through a standard publisher/subscriber messaging protocol, such as MQTT.

Distributed Analytics Systems

Depending on the application and network architecture, analytics can happen at any point throughout the IoT system. Streaming analytics may be performed directly at the edge, in the fog, or in the cloud data center. There are no hard and-fast rules dictating where analytics should be done, but there are a few guiding principles. We have already discussed the value of reducing the data at the edge, as well as the value of analyzing information so it can be responded to before it gets stale. There is also value in stepping back from the edge to gain a wider view with more data. It’s hard to see the forest when you are standing in the middle of it staring at a tree. In other words, sometimes better insights can be gained and data responded to more intelligently when we step back from the edge and look at a wider data set.

Figure 7-15 shows an example of an oil drilling company that is measuring both pressure and temperature on an oil rig. While there may be some value in doing analytics directly on the edge, in this example, the sensors communicate via MQTT through a message broker to the fog analytics node, allowing a broader data set.

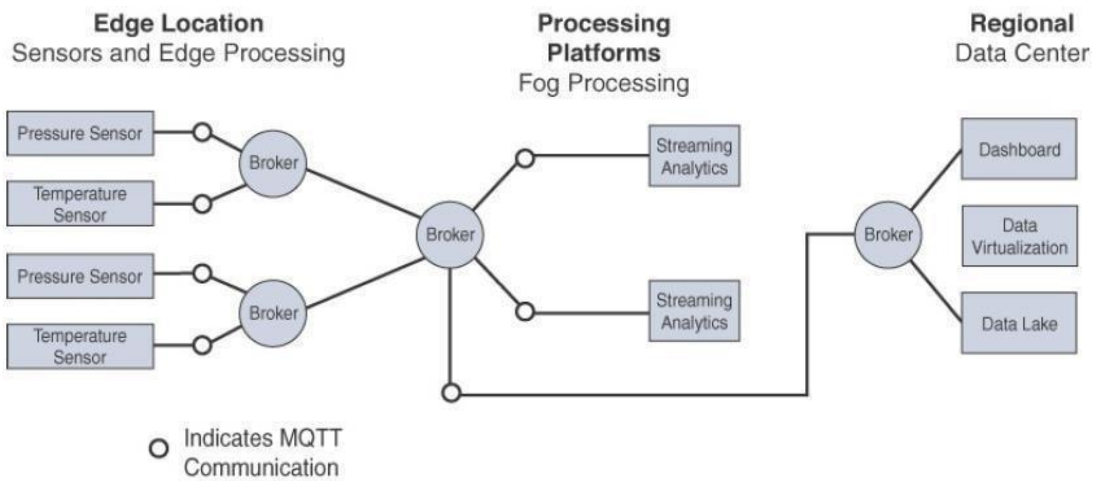


Figure 7-15 *Distributed Analytics Throughout the IoT System*

Network Analytics

Network analytics has the power to analyze details of communications patterns made by protocols and correlate this across the network. It allows you to understand what should be considered normal behavior in a network and to quickly identify anomalies that suggest network problems due to suboptimal paths, intrusive malware, or excessive congestion. Analysis of traffic patterns is one of the most powerful tools in an IoT network engineer's troubleshooting arsenal.

This behavior represents a key aspect that can be leveraged when performing network analytics: Network analytics offer capabilities to cope with capacity planning for scalable IoT deployment as well as security monitoring in order to detect abnormal traffic volume and patterns (such as an unusual traffic spike for a normally quiet protocol) for both centralized or distributed architectures, such as fog computing.

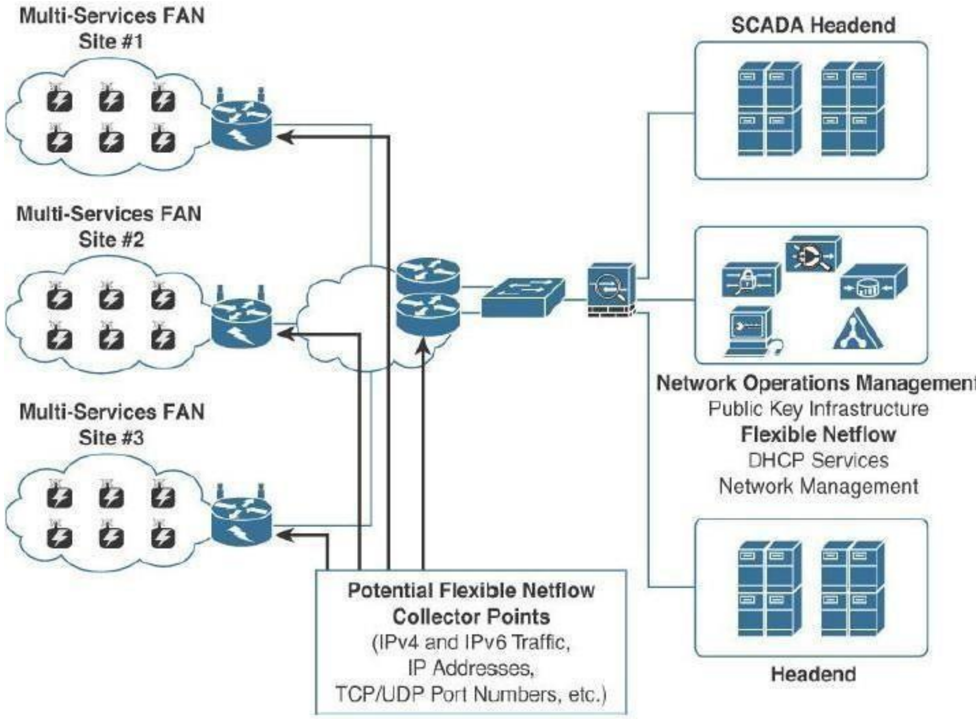


Figure 7-16 *Smart Grid FAN Analytics with NetFlow Example*

Consider that an IoT device sends its traffic to specific servers, either directly to an application or an IoT broker with the data payload encapsulated in a given protocol. This represents a pair of source and destination addresses, as well as application layer–dependent TCP or UDP port numbers, which can be used for network analytics.