Deep Science Publishing, 2025
https://doi.org/10.70593/978-93-7185-625-6_6

Chapter 6: Real-Time Monitoring Systems: From Sensor Networks to Predictive Analytics

6.1 Introduction

An array of industries employs real-time monitoring systems to curb expensive damage and reduce the risk of harm to human lives, especially when any infrastructure fails. The zone of increased demand includes fire, traffic, and activity, especially when associated with the management of crowded recreational places. Crowded societies and increased demand for services of recreational places, such as tourism and businesses in cities, have brought several drawbacks, such as more traffic, more fire accidents, more contaminated air, and a poor travel environment. Therefore, the public is worried about issues such as traffic jams, congestion during travel, traffic behavior, route planning, and the occurrence of weather emergencies such as fire.

Complex problems require complex solutions that can involve different well-established fields such as real-time monitoring, activity recognition, and prediction, contributing not only to fire safety but also to providing a better environment. Developed systems depend on monitoring and the recognition of activities through real-time image data or sensor-based data that extract essential attributes for making the right decision in the different activities of the monitoring environments, such as fire detection based on fire color analysis and activity recognition based on optical-flow divergence. Overcrowding may occur in any crowded place and can cause dangerous situations, such as in shopping malls, during concerts, or even in other major events. Controlling overcrowding can be realized by estimating the pattern of people movement—detecting, recognizing, and predicting people's activities in a crowded place.

6.1.1. Brief Introduction to Real-Time Monitoring Systems

Sensors are electronic devices capable of sensing or measuring the real-world environment and transforming such data into electrical signals before sending these signals to a command center for meaningful analysis. Examples of sensors include those that detect objects or surfaces or transform physical properties into electrical or wireless signals. Sensors may be deployed in robots for object detection or in automated self-driving vehicles for obstacle detection or to recognize and avoid accidents at crossing points. Humans cannot process data in bulk like robots, but teachers can still use answers furnished by students to evaluate individual success. Sensor networks incorporate multiple sensors to collect large amounts of data. One such type is the wireless sensor network (WSN). A WSN consists of distributed sensors that communicate via low-power radio-frequency (RF) technology within a limited area to perform long-distance sensing tasks. The data collected by these sensors is then delivered to a command center or base station to represent the sensed data. WSNs have been widely used in military applications, healthcare, shape-changing robots, ice-embedded robots, and climate monitoring applications. WSNs are also known as wireless networks or distributed sensor networks. The real-time transmission of streaming data from WSNs is most vulnerable to security problems and attacks, so securing a WSN is increasingly important. Moreover, it requires the best algorithms to generate the best human answer or output [1-3].

A deployed WSN, such as the sensor network in the smart city, collects data in real time and generates sensitive streaming data. Various applications generate sensitive streaming data that needs to be secured through the use of cloud environments. The cloud is a versatile and innovative system that provides various computing and storage services to its customers and users. Research in recent years has focused mostly on facilitating fast data transmission and ensuring a reliable cloud environment. Although a cloud environment facilitates data transmission through non-Maximum Suppression (NMS) algorithms, it still lacks real-time monitoring. Thus, the present work develops a real-time monitoring system using a sensor network through a cloud-based NMS framework.

6.2. Overview of Real-Time Monitoring Systems

Real-time monitoring systems enable the collection and analysis of immediate data over telecommunications and Ethernet networks. This capability allows professional teams to oversee their operations remotely, making informed, timely decisions. The benefits of these systems span across a diverse range of industries and applications—such as government agencies monitoring for illicit nuclear activities, environmentalists tracking forest conditions, tsunami warning centers, coastal surveillance, military radar operations, traffic monitoring, and air–traffic control. The application of real-time monitoring aligns with the Internet of Things (IoT) concept, where the network links sensors and actuators to supervisory control systems. IoT also supports areas such as smart meters, home appliances, transportation, and electric vehicles.

Fig 6 . 1 : Real-Time Monitoring Systems and Applications

Real-time monitoring systems typically comprise a set of event sensors connected to an event actuator, with supervisory control building the remaining part of the system. Monitoring entails supervising measured results on a real-time basis. In nuclear monitoring, sensors detect start and stop events, producing long-running outputs—as in the first example of the case study, where real-time monitoring helps identify clandestine nuclear activity. Real-time monitoring applies to the supervision and analysis of sensor events, turning actionable data into information and knowledge. Supervisory control occupies the highest level of control: it collects measurements, generates commands, manages buffers and queues, and performs scheduling. Specifically, supervisory control manages processing resources with delayed response—such as a nuclear spectrum analyzer or the floodgate of a tsunami warning center.

6.2.1. Key Components of Real-Time Monitoring Systems

Real-time monitoring is central to any real-time system, whether the domain is environmental protection, security and defense, space exploration, or any other area requiring timely information. It comprises four distinct components. The first is the system to be monitored, which in the case of industrial infrastructure is the equipment; in the case of environmental, the atmosphere or the ocean; in the case of security, the environment; and in the case of space exploration, all the planets. These systems require continuous monitoring to avoid dangerous situations such as system failure or support situations such as weather forecasting, atmospheric chemistry, or sensing the environment for target tracking and detection, which could also result in catastrophe.

The second component is the set of sensory elements deployed either on the surface of or in the vicinity of the systems requiring monitoring, equipped with proprietary onboard data-processing facilities and communications links facilitating exchange of data and control information with neighbors and with a central station for monitoring and control. While data gathering remains an important primary role of sensory elements in the network, these functions need to be supplemented with new capabilities that enable their adaptation to the dynamic environment they are monitoring. In essence, the dynamic network environment is charged with monitoring itself in a real-time intelligent loop. The third component is the task to be performed that falls into one of the following categories: a simple alarm indicating abnormal conditions of interest at the monitored site, the estimation of the source responsible for the disturbance and prediction of its subsequent evolution, or the control of one of the system parameters (e.g., ocean waves, atmospheric pollutant concentration).

6.3. Sensor Networks

Sensor networks are the invigorating pulse of a real-time monitoring system. In such an intelligent arrangement, several sensing nodes are spatially distributed, tasked with measuring variables such as temperature, pressure, humidity, or the intensity of radiation. After their assessment, the data circulate through the network's communication structure, ultimately reaching sink nodes known as gateways or concentrators. These gateways concentrate data before transmitting the information to a controlling server.

Upon arrival at the server, each measurement is duly signaled to the production management. This process of sending data in real time is oftentimes referred to as “data push.” As communication technologies evolve and systems become more sophisticated, adaptation is necessary. Paradoxically, several modern systems opt not to push data but instead to “pull” it. This approach uses scheduled tasks—called cron jobs in Linux environments—that request sensor information on a predetermined schedule. Moreover, with the constant shrinking of the industrial human workforce, new requirements arise that enable production management to receive and interpret data before taking action.

6.3.1. Types of Sensors

Properly and reliably detecting an event requires the use of different types of sensors. Appropriate sensors must be selected for specific operations, environmental conditions, destination, application, and operation field. A sensor is a device that measures a physical quantity from the environment and transforms the information into an electrical signal for further analysis [2,4,5]. The documents analyzed identify the following sensors:

Acoustic Sensor. An acoustic sensor is a device that detects and measures changes, noises, and vibrations in the air. One of the main advantages of this type of sensor is that it detects target objects without the need for visual contact. It is commonly deployed in noisy environments such as supramax ports, airports, dolphins, and oil piers to monitor the sound of ships and airborne noise created through industrial activities. The most used sensor is the hydrophone, which is designed to work under water with an omnidirectional deterioration of low frequency.

6.3.2. Sensor Deployment Strategies

Sensors can be deployed strategically across arbitrary environments, remotely controlled and programmed, in order to achieve quick and flexible integration. Sensor deployment implies the distribution of a vast number of small-sized and low-cost sensor nodes that are equipped with environmental sensors, radio transmitters, and receivers in order to communicate the collected data. They capture temporal, spatial, or environmental kinds of data. Sensor nodes can be equipped with light sensors, thermometers, accelerometers, or microphones, depending on the specific purpose. In addition, it is highly probable that computing clocks or other measuring devices are integrated, which are considered standard for many applications. Sensors collect data from their environment and send it to a base station, which controls the transfer of data and node distribution. The base station is responsible for gathering, storing, and displaying the collected information.

The output of the sensor nodes can be binary or continuous. Binary-type sensors transmit only two signals, e.g., 0 or 1. For instance, a vibration sensor recognizes whether an object is moving, while a magnetometer detects whether an object is magnetic. The output of such sensors can be used to measure the presence of an object, whether it has moved, as well as the creation of a particular phenomenon. Continuous sensory activity is usually generated by an angular measurement. A rotary sensor detects the rotation angular position, direction, or velocity. It is also possible to measure angles, velocities, or directions in all three axes, e.g., through the use of three accelerometers or a combination of an accelerometer with the rotary sensor. Along these lines, an inclinometer detects the spatial position of a surface, about the horizontal and vertical axes.

6.4. Data Acquisition Techniques

The large amounts of data collected by these sensor networks must be sent to a central computer where they are processed and stored. In applications requiring real-time, rapid data collection, the techniques used must capture measurements quickly and send this information with no delay. The data must be acquired, or retrieved, from the sensor network at high rates of periodic sampling and sent to a central processing unit that can handle large data volumes. To accomplish this, many different data-accessing techniques use wired and wireless real-time data-transmission methods over various protocols.

Many real-time data-acquisition protocols allow data to be accessed and sent efficiently and rapidly. When performing real-time monitoring, it is vital to connect and communicate with the sensors accurately. Real-time systems work by capturing the measurements and making them available as soon as the system allows. By doing so, continuous measurements from the sensors become rapidly accessible for use with cascading systems, such as real-time data storage and real-time analytics.

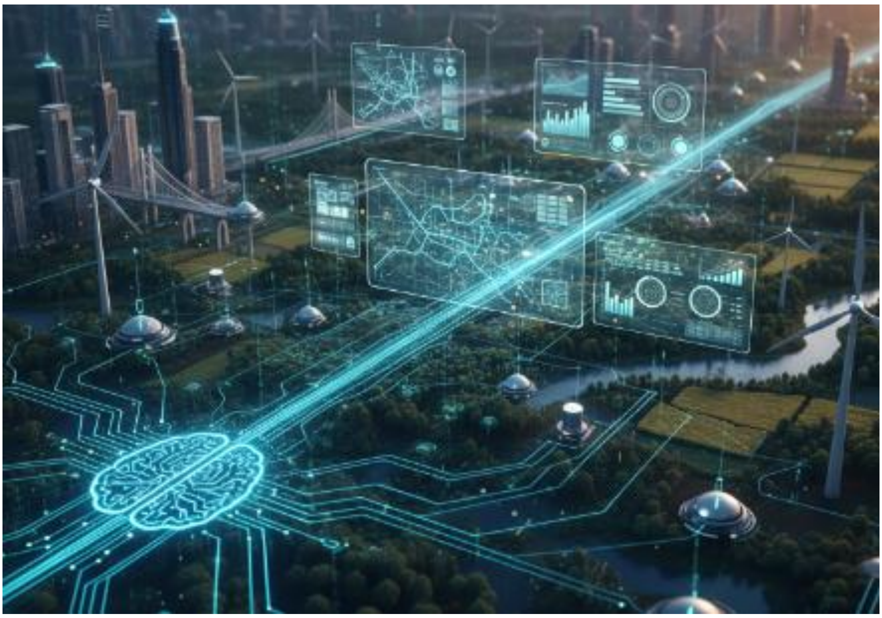

Fig 6 . 2 : Real-Time Data Collection and Analysis from Sensor Networks

6.4.1. Sampling Methods

Sampling is an essential step in data acquisition from sensor networks. It consists of determining the time interval between the execution of two consecutive samples for a given sensor. For time-dependent variables, the sampling rate according to the Nyquist–Shannon theorem must be greater than the bandwidth of the analyzed signal to avoid the aliasing effect. For slowly varying signals, such as air quality, temperature, humidity, or solar radiation, high-frequency sampling only generates larger data volume, resulting in an accelerated sensor battery discharge.

Sampling methods in sensor networks can be classified into uniform sampling and non-uniform sampling. Uniform sampling is the simplest method, which is easy to implement and understand, but at the same time, it can lead to wasted resources or capture insufficient details. On the other hand, non-uniform sampling obtains the data with variable intervals according to the state of the monitored environment. In the application of these sampling methods, the sampling interval ΔT is dynamically updated according to specific strategies.

6.4.2. Data Transmission Protocols

In real-time monitoring systems, once the data is acquired, it must be transmitted to a location at which it is processed. Single sensor systems may transmit data directly to the processing location, whereas data from general sensor networks may be collected into one terminal node and transmitted to the processing location from the terminal node. The transmission of data within large sensor networks can require the use of multi-hop communications, where the data is transmitted by multiple sensor nodes before reaching a sink node or terminal node.

The utilization of sensor networks often requires a trade-off between monitoring coverage and costs. For example, in large-scale water environments such as oceans, it is difficult to guarantee coverage using wired monitoring stations because they have geographical restrictions and are difficult to access. In this case, an unmanned aerial vehicle (UAV) payload system with a wireless sensor network can be a good choice. A battery-powered underwater wireless sensor network system can also be used for ocean monitoring, with careful routing properties, network topology determination, and node deployment schemes serving to increase the network lifetime and the overall monitoring coverage.

6.5. Data Processing and Storage

Data processing and storage underpin real-time monitoring applications. On-site data processing is frequently implemented at one or several cluster-heads of the sensor network, where the aggregation and filtering of data forego unnecessary communication. Storage is primarily housed in on-site controllers, but long-term data retention is commonly managed through central or cloud storage. High-speed data transfer coupled with powerful on-site servers can facilitate transfer and storage in these locations.

Additional on-site storage at a sensor or cluster-head can serve as a short-term memory to buffer data before off-site transfer, thereby preventing data loss even when network bandwidth is limited. The general flow, from sensor to central storage, proceeds through filtering, aggregation, and fusion. Filtering removes data points considered uninteresting. Aggregation consolidates the data set, typically reducing the sampling rate and data volume by combining individual components into a single overall picture of the measurement[6-8].

Data fusion extends the scope from a single sensor to the entire sensor network, using simultaneously gathered data to enhance sensing performance. Common applications include fault clearness and data reconstruction. Fault detection entails the time-based comparison of data from a single sensor; any abnormality suggests measurement issues, possibly indicating sensor failure requiring immediate replacement. Fault clearness—the identification of faulty sensors within the network—relies on space- and time-based comparison of data from multiple sensors. In case of abnormality, the sensor is tagged as faulty, triggering notifications requesting replacement or repair. Furthermore, data fusion can also reconstruct damaged or incomplete data based on information from other sensors.

6.5.1. Edge Computing

The advent of cloud and software-defined services has redefined the architecture of networked computing, turning it into an Internet of Services. Many applications, including finance, life science, and critical infrastructure, require deploying services close to various data sources—particularly sensors—to manipulate data locally and reduce the latency of the updating process. Edge computing is a new paradigm that addresses these needs. It brings computation and data storage closer to the sources of data, thus enabling real-time and context-aware services—processes that traditional cloud-based services struggle to support.

Edge computing certainly benefits the deployment of real-time monitoring systems. By enabling real-time services, localizing the formation, processing, and decision-making of data, it reduces data transportation. Edge computing can decrease monitoring latency and first-level decision-making latency at the network edge and inside local agencies. Moreover, it reduces the risk of data leakage and loss during transportation and scales down the gate of entry. The monitoring system, deployed between the sources and the cloud, makes the overall process more intelligent and capable of supporting the specific needs of real-time monitoring services.

6.5.2. Cloud Storage Solutions

Industry and business increasingly rely on software-as-a-service (SaaS) solutions to reduce their costs. Accordingly, cloud storage offers an attractive alternative for real-time monitoring systems as it enables accessing files securely anytime and from any place via the Internet without incurring additional costs for an in-house file server. For instance, cloud services such as Google Drive, Dropbox, and Microsoft OneDrive enable the unified storage of geo-distributed files, thereby simplifying file management and supporting coordinated collaboration. These companies guarantee reliable services based on robust infrastructures that distribute redundant data in multiple data centres around the world. Nevertheless, users have to accept a range of limitations and risks that can affect the deployment of a particular real-time monitoring system.

A sequence of tests was conducted to further investigate Cloud Storage Solutions that are not yet operating in real-time. During the study, each test was run in a browser using JavaScript, with each client uploading a file and saving it to the cloud. Then, every 5 s, an attempt was made to download the file and verify its contents, measuring the download latency [1,3,5]. Three cloud storage solutions were examined under this methodology: Google Drive, Microsoft OneDrive, and Dropbox. For Google Drive and Microsoft OneDrive, the upload requests take less than 2s on average, while the download ones show excessive latency, which reaches up to 16s, making the services not suitable for real-time video streaming. A different behaviour is observed for Dropbox, whose upload requests take more time to be completed, but its download latency remains low and stable regardless of the file size; it enables the gradual downloading of files as they are being uploaded (i.e., streaming), a very useful feature for real-time monitoring systems.

6.6. Real-Time Data Analytics

Real-time data analytics—defined by low latency or delay from data generation to action—goes beyond the capabilities of batch processing and standard operational business intelligence systems. Its short processing time, supported by operational data stores, enables swift pattern identification or frequencies with both low data volume and operational turnaround time. In a real-time data analytics system, information is prepared immediately for analysis. Data quality tuning is performed as the data moves into the system, and emergency handling quickly addresses sudden issues.

Real-time analytics offers greater responsiveness to emerging customer contexts, coupled with substantial support for strategic decision-making. Sometimes referred to as "Fast Data," it allows for timely insights into global business performance and functioning. In an age where business agility helps create sustainable competitive advantage, organizations have a profound need to focus on every aspect of their operations in real-time. As a result, real-time data analytics has become an indispensable component of business intelligence.

6.6.1. Streaming Data Analysis

Real-time data analysis is a rapidly growing topic in many research areas, since in certain situations it is better to monitor processes or phenomena as they happen and better understand their dynamics. Real-time data arise under several different circumstances, such as (i) monitoring of streaming online processes, (ii) analysis of online sensor networks, (iii) monitoring and analysis of web traffic, (iv) analysis of online financial data, and (v) the analysis of online healthcare data. In several cases, real-time data arise with the need for real-time decision making based on the available information at the time of decision. The most common application areas for analysis of real-time data include environmental monitoring, telecommunication services, finance, medicine, emergency and crime management, environmental crisis handling, and biosurveillance.

Fig 6 . 3 : Real-Time Data Analysis and Decision Making

The rapid technological advances in sensor design, sensor networks, and connectivity enable scientists to obtain large volumes of data in real time and from multiple sources. Real-time data analysis and decision making are essential for recent predictive analytics in many areas of analysis. For example, sensor data aims at predicting future states of the environment, health, and financial markets, to perform actions on the system to avoid undesired future states. Real-time data frequently arrives in streaming fashion and needs to be analyzed online as they are collected, or decisions need to be made if the process is operating within the preset specifications. Streaming data is usually dynamic and changing rapidly, which creates new challenges in the field of data analysis and decision-making.

6.6.2. Machine Learning Algorithms

Monitoring, prediction, and pre-alert of different phenomena are important in different areas such as health, industry, smart cities, smart houses, smart agriculture, and smart metering, among others. Teams in the environmental area are dedicating efforts to real-time monitoring, prediction, and pre-alert of different environmental phenomena. One of the monitoring activities involves the measurement of rain, water stored in reservoirs, humidity, temperature, or the level of water in a river. Additionally, the pre-alert and prediction of environmental phenomena are positively impacted by timely decisions and the adoption of security measures.

Within these activities, the use of automatic stations for measuring the level of water in rivers plays an important role. However, there are large temporal gaps in the historical time series of some measuring stations, generated by various causes, such as lack of maintenance, dependence on electrical energy supply, and the sensitivity of monitoring stations to lightning, among others. Artificial intelligence data treatment tools have made it possible to design models that not only reconstruct these missing data but also predict the level of water in a river using machine learning algorithms.

6.7. Predictive Analytics

Expressing a picture requires many colors, but what is important is the concentration and subtlety of colors; for example, a person’s face looks very natural if the artist uses a thin film of color on a white canvas without precisely pre-planning the picture. In the same way, placing many LMS sensors densely in real space may make pictures too noisy to visualize clearly. The best method is not mapping sensors on the map 1:1, but drawing the “average” elevation of each region by analyzing a big data set.

For this data analysis, the authors chose to use space-time kriging, a Gaussian process regression method. In this analysis, data points far away from the analysis point are assigned reduced weight, providing a natural function of smoothing noise. However, this method requires more computational resources and thus it is more suitable for offline analysis than for real-time use. Real-time calculation is required during an emergency disaster, but for hazard maps and evacuation planning, the results obtained after the events have ended are useful. redrawcolor

6.7.1. Statistical Models

Prediction of future events is an integral part of statistical analysis, with its significance growing alongside technological advancement. Accurate forecasting is critical for public and industrial safety, and devising methods to achieve it remains a core objective of statistics. However, in many scenarios, predictions are required for sequences of events rather than isolated incidents. For example, the failure detection of electrical generators during peak loads involves an urgent and logical request: Identify which devices are likely to fail next. The question is reversed: Identify the generators that have already failed. Instances of such problems are numerous.

The synchronous radar detection of low-orbit aircraft poses a similar question. At any time, indicate the planes that have passed a given point located on Earth's surface. Carriers of radar equipment are mounted on Earth, stationary or in continuous flight, at a given altitude. The arrival times of signals reflected from each plane are recorded. These flights, considered as a stationary process, form a point process. By classification, an estimate of the plane passage times is obtained. This is a prediction of the positions of the airplanes at some time in the past. Yet, the closest and most attractive example is signal processing [8-10]. Filters applied to noisy signals contain replicating blocks that require estimation of the signal at time points not previous to the time under consideration. The methods employed are under the generic name of prediction. Time series forecasting can be considered in a broader framework.

6.7.2. Time Series Forecasting

Both sensor and social sources have also been utilized for what is known as time series forecasting. A time series is an ordered sequence of data points recorded at regular time intervals, where the objective is to use the sequential history to predict the next point of the time series. Time series forecasting is widely used in social and economic domains. The main advantage of time series forecasting is that a time series can be used even if there is no knowledge or data about the underlying system. However, this may not be the best approach when there is enough knowledge about the system—for example, if a physical model exists.

Most time series forecasting approaches utilize one or a combination of the following three classes of models: (i) moving average, (ii) exponential smoothing, and (iii) autoregressive models. Moving average is a simple list of averages computed by sliding a time window across the data set, which is widely used for noise reduction in time series data. Additionally, it can be used for forecasting using the next point mean given a weight. Exponential smoothing assigns exponentially decreasing weights to previous observations. Any example value can be used for the first observation, and each of the following observations, the last forecast is computed using the last observation and the previous forecast. Autoregressive models use the relationship between current and earlier observations to model the time series data set and forecast the next value. An example of such a model is the autoregressive moving average (ARMA) model, which models the current observation as a weighted sum of past observations and past model errors.

6.8. Future Trends in Monitoring Systems

Organisations in every sector of the economy increasingly demand Basic Monitoring Systems (1–5). The ability to quickly monitor and assess any information demands presented by a key user group as circumstances change is now accepted practice. As attention shifts from monitoring to control, there is growing demand for systems with additional decision-making functionality to help users select any equipment to be used in an industrial environment. In a Basic Monitoring System, the sensors/instruments and the associated data interface play the central role. They must communicate, communicate reliably, communicate consistently, and do so in any order conforming to demand, while responding to the changing needs of the primary users. That communication is required in real time, and the results must be presented in a suitable format capable of rapid assimilation and/or action.

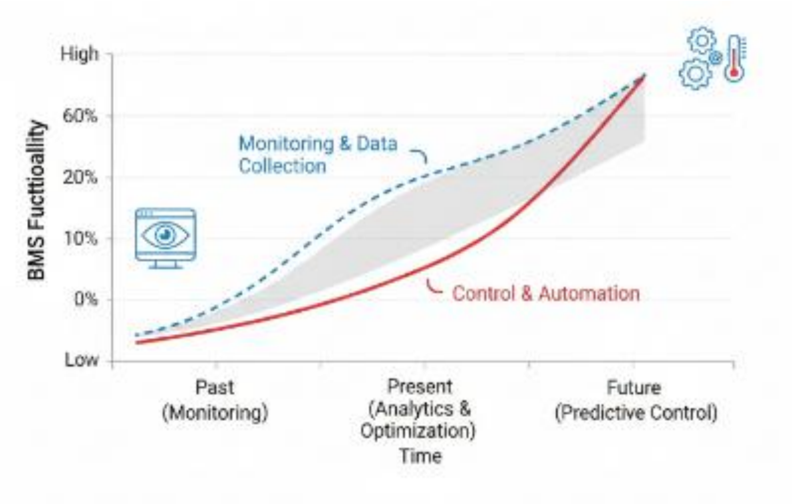

Fig 6 . 4 : Shifting Demand: From Monitoring to Control in BMS

The range of implemented Basic Monitoring Systems has rapidly expanded, with their development being largely led by technical advances in satellite communications. System growth has tended to be horizontal. New systems with different characteristics have been added to the range, but systems with differing far-end geographical characteristics have not been integrated. The large number of dedicated Basic Monitoring Systems is achieved by attempting to satisfy each user group’s distinctive needs, with the result that most of their messages tend to be generated and transmitted by the same set of sensors/instruments. Basically, these dedicated systems are performing the same task, developing Basic Monitoring Systems for sending essentially identical messages generated by weather sensors/instruments. Other Basic Monitoring Systems that monitor and control key environmental variables such as levels of industrial pollution have been developed for, although not devoted totally to, industrial activities.

6.8.1. Integration with IoT

A real-time monitoring system may utilize algorithms such as logistic regression, support vector machine (SVM), k-nearest neighbor (KNN), nearest mean classification (NMC), random forest (RF), artificial neural network (ANN), gradient boosting algorithm (GBM), and Naive Bayes (NB) algorithms to assess the health status of pumps. Integrating intelligent vibration monitoring systems into a smart factory connects each device directly to the cloud, enabling users to track the status of production equipment in real time.

The real-time condition monitoring system of equipment is an indispensable part of a smart factory that integrates the Internet of Things (IoT) with real-time monitoring technologies. The system combines offline historical data with real-time data for training and prediction and utilizes machine learning algorithms in the cloud. It evaluates the health status of each pump and equipment in the factory during operation and assigns appropriate maintenance priorities based on the predicted risk levels of the equipment.

6.8.2. Advancements in AI

Recent decades have witnessed rapid progress in the use of artificial intelligence (AI) for real-time monitoring systems. The integration of AI with other technological innovations creates vast potential for real-time monitoring applications. The implementation of a deep learning (DL) model for simultaneous vibration-based condition monitoring of a multiunit gearbox is proposed by leveraging untapped features in the transmission error signal. In particular, a multiobjective convolutional neural network, called MO-CNN, is developed by simultaneously optimizing multiple objectives that collectively contribute to the robustness and performance of the framework.

The shift from Vibration Analysis to Predictive Maintenance emphasizes that real-time monitoring delivers appropriate information to the right person at the right time in the right format, using online sensor technology to optimize performance monitoring. Condition-based maintenance is no longer reserved for monitoring large, high-value assets but can be applied to all rotating equipment in process industries. Although the theoretical benefits of the vibration condition-based maintenance practice have long been identified, actual implementation remains low due to the unpleasant experience of false alarms induced by unconfident diagnosis. A two-stage deep learning-based intelligent fault diagnosis framework is thus proposed to enhance the robustness of diagnosis.

6.9. Conclusion

Although numerous monitoring systems can be implemented, their implementation is invariably limited by budgets and priorities, preventing the inclusion of sophisticated features or even the basic infrastructure. In the presented study, the construction of a real-time monitoring system is reduced to a basic and very broad functional set. At least an alerting mechanism is implemented to inform decision-makers about potentially harmful changes across a monitored area. Any logging implemented during operation is considered a bonus. Aside from real-time operation, the main goal is to attract investment for comprehensive environmental monitoring systems by demonstrating the potential of even a minimum setup. This simple approach, capable of improving existing environmental monitoring with little effort and at a reasonable cost, can create demand for a more sophisticated follow-up installation.

However, a real-time aspect is rather imposing. A non-real-time system would eliminate several budgetary constraints because two key areas are saved: data transmission and automatic processing. These two areas become exponentially more expensive when trying to provide an environment where data is not held back for hours or days as a compilation for manual review, but where everyone can access the server live and use any functionality like alerting, visualization, or statistical computation. Even though it might seem paradoxical, it is cheaper to operate a non-real-time system with authentic sensors than to employ a satellite monitoring service. Although only a few measu-red parameters would be available, the satellite service would guarantee real-time data transmission accompanied by rapid processing and reliable alerting.

6.9.1. Final Thoughts and Future Directions

Automated monitoring systems are the future of water resources management. Near real-time spatial and temporal water quality and flow condition data are essential for understanding the health, status, and trends of a watershed. The data can also be used to explain the influences of a watershed, including flow volumes, pollutant transport, pollutant loadings, and changes. Agilent's expert water quality engineers can guide readers through their application and selection process, the necessary components, and important planning considerations, providing specific examples of water quality and flow conditions in Rivers of America.

Predicting ionospheric scintillation, which holds significant implications for global navigation satellite system receivers in equatorial regions, involves analyzing global positioning system signal characteristics, lunar phase, and various geomagnetic and geophysical parameters, employing neural network methodologies to forecast the S4 index at equatorial locations. The selection of input parameters substantially influences prediction accuracy; thus, using diverse input sets across multiple stations in central and southern Brazil helps determine optimal combinations for enhanced prediction. Predicted data reveal that scintillation activity remains intense during the early hours of the night and late lunar phases.

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