Smart Monitoring in Tactile Cyber-Physical Systems

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***Abstract*—We consider the development problem of smart monitoring systems for Internet of Things (IoT) environments. Such systems form a special class of Tactile Cyber-Physical Systems (TCPS) with the essential role of sensorics and artificial intelligence (AI). Sensorics enables the touching sense when a remote object is monitored in Tactile Internet (TI). IoT and AI technologies support near real-time data processing and feedback to perceive and control the object. The applicability of strain gauges is discussed for the needs of emerging applications of smart monitoring in manufacturing, building construction, and vehicle operation. We introduce a multi-layer architecture of TCPS that focuses on the bigdata and smart interaction requirements of industrial monitoring systems. The architecture takes into account the Information&Communication Technologies (ICT) that have already shown efficiency in the industrial settings.**

***Index Terms*—Smart Monitoring, Sensorics, Tactile Internet, Cyber-Physical System, Bigdata Processing.**

I. Introduction

We consider the development problem of smart monitoring systems for Internet of Things (IoT). In particular, such systems are rapidly developed in Industrial Internet or Industrial IoT (IIoT) for the case of machinery equipment monitoring, e.g., see [1]. The data come from multiple sensors that surround the equipment (and its assembly parts—nodes). Monitoring implements functions for recognition of technical state and utilization condition.

Smart monitoring assumes consideration of the following requirements to the system development.

1) *The bigdata requirement (R_{BD}):* Data processing is based on Artificial Intelligence (AI) with advanced methods of Machine Learning (ML) and recognition for Bigdata analytics [2], [3].
2) *The smart interaction requirement (R_{SI}):* System components act as smart IoT objects that interact in IoT environment to construct services using Ambient Intelligence (AmI) [4], [5].

The progress in the IoT/IIoT technology leads to shortening the distance between the human and monitored objects. The results of analytics can be delivered to the user in near real-time. As a result, a person can extend her/his sensory system despite the physical distance (five senses: eyesight, hearing, taste, touch, and smell). In particular, the emerging technology of Tactile Internet (TI) introduced haptic data related to the human perception of objects through its sensory nervous system [6]. This human perception property is considered in Ambient Intelligence (AmI) when human is in a digital environment (e.g., IoT environment) and surrounding devices construct various recognition services by monitoring the physical, informational, and social worlds [4], [7], [8].

The bigdata and smart interaction requirements can be implemented using the concept of Cyber-Physical System (CPS) [9]. CPS components act as data producers (sensing) and consumers (processing) from the physical, informational, and social worlds [4]. Integration of physical and information processes in an AmI environment provides the ability to perceive the environment and its participants based on analysis of the sensed data.

We limit this study with the tactile sense, aiming at monitoring systems that are based on sensing deformations and mechanical stresses. Production machinery (under monitoring) is equipped with various strain gauges, which we elaborated in our previous work [10]. Our target case is Tactile Cyber-Physical System (TCPS).

In this paper, we consider the applicability of strain sensorics in development of IoT monitoring systems, such as manufacturing, building construction, robot movement, wearable sensorics, and vehicle operation. TCPS implements regular measurements (in real-time) of various deformations and mechanical stresses. Application examples and possible strain gauges can be found in [11]–[13]. In particular, magnetic strain sensors and their use are considered in [14].

The key contribution of this paper is the proposal of a multi-layer TCPS architecture for sensed data processing, either in batch mode or near real-time mode. The proposed architecture is based on the latest technologies from IoT, TI, AmI, AI, and Bigdata. The technologies are selected based on our review of existing industrial solutions. Although the architecture is oriented to the specific characteristics of data sensed from various strain gauges, other sensors can be added to TCPS. Easy addition is supported by the layered structure.

The rest of the paper is organized as follows. Section II introduces the problem of applying TCPS in industry, where strain gauges are used to implement the required tactile sense. Section III proposes our multi-layer TCPS architecture for data processing of sensed data, either in batch mode or real-time. Section IV summarizes the key findings of this study.

II. Smart Monitoring with the Tactile Sense

Smart monitoring is widely used in AmI environments, where CPS components act as data producers and consumers from the physical, informational, and social worlds [4]. Integration of physical and information processes in an AmI environment provides the ability to perceive the environment and its participants based on analysis of the sensed data.

In the context of Industry 4.0 and IIoT, a given CPS implements monitoring functions related to recognize equipment technical state and utilization condition, diagnostics and prognosis, making recommendations for maintenance, and selecting optimal operating modes [15]. Such monitoring functions supports analytics of sensed data for diagnostics, prediction, and prescriptive maintenance. In this study, we focus on the monitoring problem machinery equipment.

A monitoring system implements of iterations for manipulating objects (sending commands and receiving feedback). The iterations support construction of the informational and control services. An example of the informational service is predicting technical state of nodes in the machinery equipment (e.g., bearing and their defects [16]). Examples of control service are manipulating effects with feedback in real-time to achieve the desired results [17].

For monitoring and manipulation with real objects, a system is needed for collecting and processing the data from sensors. We focus on tactile sensors, which enhance such a human sense as "touch". The monitoring CPS acts as TCPS [18]. TCPS extend a set of applications and services by combining machine-to-machine and human-to-machine interactions. The following properties are typical for sensorics in a TCPS [11], [12].

- Digitalization of the primary results of measurements.
- Use of many sensors and sensor nodes for monitoring the state of one object as well as processing of the data obtained in parallel from many sensors.
- Correction for noninformative factors (e.g., the influence of temperature on strain sensors).
- Recognition of failures of nodes or communication lines and built-in fault-tolerance capability.
- The sensors used for monitoring are by themselves smart and able to function as nodes of IIoT.
- Wireless connection of the components of the system.
- The ability of the components of the system to communicate with each other in real-time mode.
- High-level characterization of the state of the object under monitoring (e.g., normal or dangerous).
- Recognition of abnormal behavior of the object and making decisions on this base.
- The use of the machine learning (ML) methods for classification of the states of the object under monitoring.
- Flexibility of the system, i.e., possibility to re-configure when necessary.

An example of a TCPS application is remote manipulation of real or virtual robotic industrial equipment in inaccessible and dangerous conditions. In TCPS, an operator remotely controls a robot (e.g., a manipulator) to perform production operations using robotic equipment. Even though the sense of presence can be provided through the exchange of audio/video information, complete immersion is impossible without the exchange of haptic information.

The haptic feedback gives the operator a sense of force, movement, vibration, etc. For example, the operator can adjust the position and grip of the manipulator. The exchange of tactile sense includes commands to the object and feedback from the object. The network round-trip latency in such a loop cannot exceed a few milliseconds to solve the problem of delayed and asynchronous feedback [19]. Reaching the boundary values of delay imposes additional requirements on the development of hardware and software architecture, algorithms, and protocols for TCPS.

Almost any TCPS is characterized by multi-source multi-type data sensing and information exchange followed by data fusing. Strain gauges can serve as an additional source of information on the technical state and utilization condition of production machineries (metalworking machines, gas turbine equipment, presses, pumps, etc.). Multiple data sources provide "redundancy" in measurements. The redundancy can be used to improve the accuracy, reliability, objectivity and validity of technical state assessment and operating conditions. In this regard, measurements of elastic deformations can be based on non-destructive testing methods [20]. This kind of measurements of physical parameters can be used to improve the accuracy of solving a wide class of promising production problems, as we summarized in Table I.

III. Multi-Layer Architecture

We propose the multi-layer TCPS architecture for data processing of sensed data, either in batch mode or near real-time mode. The model is shown in Figure 1. The proposed architecture combines a number of the well-proven technologies used in the digitalization of manufacturing industry. In particular, the bigdata technologies aims at storing and processing huge (in most cases, redundant) sets of continuously arriving sensor data with the possibility of horizontal scaling [3].

A related concept for TCPS is Digital Shadow (the basic component of Digital Twin) [21]. The architecture maintains connections and dependencies (rules) that describe the behavior of a real object under normal operating conditions. Also, any digital object is augmented with additional data collected from the corresponding real object using the IIoT technology [22].

The architecture is based on the data life cycle model "data-information-knowledge-decisions" [2]. The following concept layers are used: (1) physical layer; (2) edge layer; (3) network layer; (4) gateway layer; (5) storage layer; (6) computation layer; (7) analytics layer; (8) service layer.

The physical layer (together with the edge layer) implements the hardware and software enclosure for measuring control around a monitoring and manipulation object—industrial equipment. The measuring control enclosure is created without making any structural changes and does not require taking the

TABLE I
TCPS APPLICATIONS IN INDUSTRY USING STRAIN GAUGES

Application	Use of tactile sensors
1. Remote manipulation of real or virtual objects in inaccessible and dangerous conditions.	Tracking movement and position of human body parts by flexible strain sensors.
2. Monitoring the state of transport vehicles, ship hulls and airframes, wind turbines, railway lines, dams, oil drilling platforms, structural components of bridges and buildings.	Detection of early structural damage based on the analysis of strain measurements; data source in wireless telemetry system; measurement of mechanical resonance frequencies of structures.
3. Design and exploitation of aerospace and aircraft technologies.	Comparison of deformations arising under the action of various forces with the results of CAD (Computer Aided Design) and FEA (Finite Element Analysis) simulations; monitoring the actual stresses in mechanical parts during flight to ensure that it is safe.
4. The control of deformations of parts during processing to adjust the pressing forces by robotic metalworking equipment.	Strain measuring of the part during machine processing by the pressure of the cutter (e.g., during drilling).
5. Measurement of the torque applied by a motor, turbine, etc. to generators, wheels, etc. for optimization of the regime of the equipment	The torque is calculated from the measured strain and the rotational speed on a shaft.
6. Manufacturing of weight and pressure measuring devices for the creation of robotic systems for industrial production.	Strain sensors are the basic (sensing) elements of load cells.

industrial equipment out of operation. The physical layer contains many heterogeneous high intensity sensors and actuators. Industrial automation sensor equipment is used as the main sources of information on the technical state, operation, and operating conditions.

Stresses and strains are the main parameters for monitoring and manipulating the state of objects (including industrial ones), which must withstand dynamic loads. To ensure redundancy of information and coverage of most application scenarios in TCPS, strain measurement should be performed together with such physical parameters as vibration, current, rpm (revolutions per minute), and temperature. For example, using vibration and strain data in integration, one can determine the critical stretch of material and reduce vibration so that this limit is not exceeded. There is also a relationship between shock events and deformation values.

The edge layer ensures that a significant part of the data processing computations is performed close to the data sources and the object under monitoring. Preprocessing data on edge devices increases the performance of upstream digital diagnostics and predictive analytics algorithms by reducing the amount of streaming data and network latency, as well as by distributing the load across edge compute nodes. For edge devices, algorithms must be not only mathematically simple, but also energy efficient to execute them on microcontrollers.

Raw data are collected and presented in a summary form for further time-domain statistics [23]. The summary form for an individual strain data processing stream is determined by a set of such statistical metrics as Root Mean Square (RMS), max, min, crest factor, and kurtosis within a given time window for providing initial, approximate information about faults. We follow the model of [24], where such computation is implemented by so-called sensor computing modules (SCM—data acquisition system instance, DAQ), which can collect data from high-resolution sensors with high-speed measurement. The sensor data are digitized with high precision, preprocessed using basic mathematical transform operations (e.g., Fast Fourier Transform—FFT). SCM uses an external ADC with 24-bit resolution operating (ADS127L01) and a maximum sampling rate of 512 kSPS (Samples Per Second).

A single SCM can connect from 1 to 15 sensors of different types. The sampling rates and duration of sampling are customized along with algorithms to establish an appropriate value for them. In the monitoring system using 10 modules, the daily total volume for the continuous flow of raw and preprocessing data can reach 1.236 TB. In this regard, TCPS faces with Bigdata challenges and specialized technologies and architecture patterns are required to organize storage, stream synchronization, and data processing when designing the overlying architecture layers [3].

Due to the significant requirements for computing resources and the possibility of horizontal scaling, systems for working with Bigdata are developed mainly as distributed systems that implement parallel processing of large data sets [25]. The architecture is with Massive Parallel Processing (MPP) [26]. Many independent computing nodes are connected by a high-bandwidth LAN. A local dedicated server is deployed at the edge. The nodes provide initial data to the local server. The server transmits the processed data further to a data center.

The network layer connects the edge layer and the Bigdata-oriented layers, providing an environment for communication over wireless or wired network channels (Wi-Fi, ZigBee, Ethernet, Bluetooth, RS-485, CAN and similar network protocols). Such protocols as MQTT, CoAP, AMQP, and DDS provides standardized data transfer based on IoT solutions [27]. Nevertheless, proprietary protocols can also be developed to provide lightweight options for polling the DAQ system, requesting a one-time fetch of data from a sensor, and requesting a continuous data acquisition (subscription) [24]. For secure access to both external data sources and a private data center, a virtual private network is used with the creation of dedicated secure circuits and with tunneling protocols [28].

When working with large data sets, the execution is time-consuming for queries to implement the application functions. Many queries cannot be executed in real-time, since they require the execution of algorithms that work with distributed

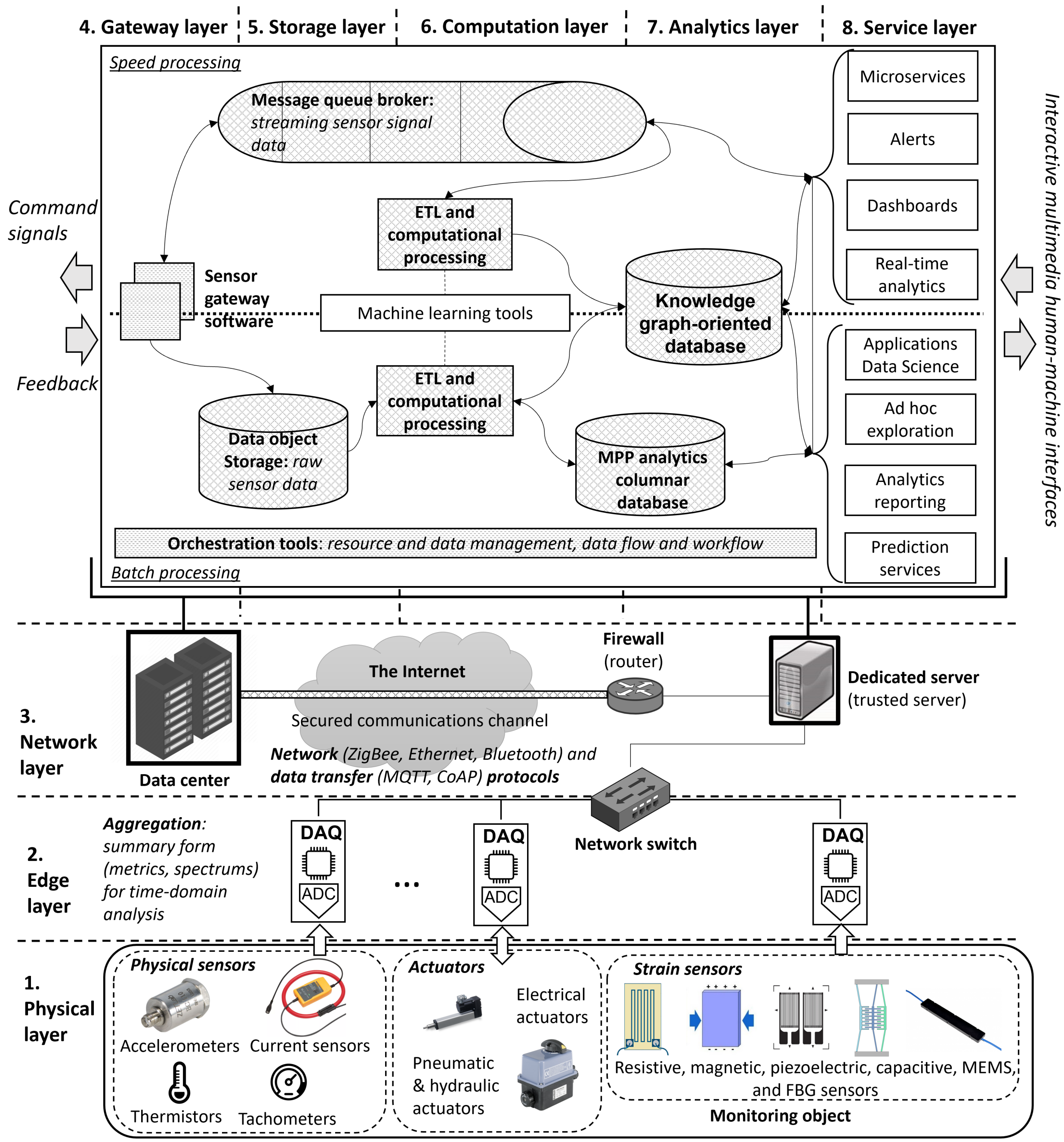

Fig. 1. The multi-layer TCPS architecture model for near real-time intelligent analysis of sensor data.

storages on several nodes of the data center, processing data in parallel. The processing can take several hours, making the results irrelevant. Specialized architectural patterns are needed for obtaining the results in near real-time (likely, with some loss of accuracy) and for complementing them based on executed slow queries over a large set of retrospective data [29].

In particular, the Lambda architecture design pattern separates real-time and batch data processing [30]. The Lambda pattern is applied in many practical industrial applications. Our TCPS architecture (in Figure 1) follows the basic principles of the Lambda pattern. Our model combines the batch processing path (bottom) and the speed processing path (top), so providing a unified, merged view to the service layer. Moreover, the users are not interested to consider these two data streams. The users simply need the analytics results. In particular, if real-time analytics is needed then the accuracy becomes lower, since the result comes from the speed path. Nevertheless, after the completion of complex distributed queries on the batch path, the results obtained by users can be enriched or updated with more accurate information after long-term, deep analytics.

The batch processing path performs heavy-weight, time-

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consuming, and resource-intensive queries with no real-time requirements. Free time slots can be used to perform data processing (depending on the schedule, e.g., at night). In this case, reports and various statistics are built only on retrospective data (e.g., for the last day, months, etc.). The result is completed after some time (e.g., tomorrow). However, such results are significantly more accurate and reliable. Note that all incoming data on the batch path is always appended to the existing one, i.e., previous data are not overwritten (by the "log" storage type), allowing storing the history for deeper analytics.

The speed processing path implements near real-time processing. The trade-off is the loss of accuracy with respect to fast ready-made results. On this path, some small data processing functions (e.g., average, some aggregation) operate on individual records in a sensor data stream or in a sliding window mode.

The gateway layer is used to receive, transform, and store information from edge devices and external sources. Control of edge devices is possible by sending configurations to adjust the intensity and content of data streams (depending on the needs of the data processing). According to the data source and destination, the sensed data are forwarded to the batch path (for retrospective data, at rest) or to the speed path (for streaming data, in motion).

For processing streaming data, time synchronization is needed as many streams from various sources. A stream can be aggregated (by types of data sources with reference to a specific equipment node) to provide services in real-time (e.g., diagnostics). Message brokers are used for distributed streaming and data processing (e.g., Apache Kafka, RabbitMQ) [31]. A broker has low latency, since all data processing is executed in-memory, with no slow disk access.

The data-driven interaction between data producers and consumers follows the publish/subscribe model using a message broker [32]. Another equally important task is the creation of a retrospective storage of raw data of physical measurements (batch data) for the further execution of analytical computations and training of neural networks on the results. Software tools designed to automate the transfer of large data batches from data sources to TCPS use the concept of "extract, transform, load" (ETL), e.g., Apache NiFi, Sqoop [25].

The storage layer is critical for the Bigdata requirement in TCPS. Storage and processing of accumulated data from sensors and recognized knowledge are the most resource-intensive operations that uses distributed computing [21], [33]. A MPP architecture is commonly applied to data lakes and databases (or data warehouse) [26], [34]. Data processing is performed by multiple computing nodes. Each node has its own storage and computing resources to resolve a part of the overall data query. Depending on the volume, structure, variety, and variability of data, a storage location is selected.

A data lake is an object storage designed to store various data (structured, semi-structured, or unstructured) in its original, raw form (only the file object and the path to it) without using schemas, types, and data models. A data lake involves storing data in a distributed file system. Hadoop Distributed File System (HDFS) is fault-tolerant and low-cost object storage with low performance when working with small data amounts (file block size from 128MB) [35]. HDFS is suitable for storing samples of raw physical measurements, grouped in large files, e.g., by sampling period (file size depends on the length of the period and the sampling frequency).

A database is suitable for semi-structured and structured data with support for data queries. Compared to a data lake, a database uses a data model that defines how to store, organize, and process data. There are three classes of databases [25], [34], [36]: relational database management systems (RDBMS), NoSQL, and NewSQL databases. RDBMS provide operation of transactional systems using the "online transaction processing" (OLTP) approach (e.g., MySQL, Oracle).

NoSQL databases emerged as an alternative to traditional relational databases with a tabular data organization format (e.g., MongoDB, Neo4j). Depending on the problem being solved, NoSQL databases offer the following set of fundamental data structures: wide column, document, key-value pair, or graph.

NewSQL databases emerged as a combination of the NoSQL and RDBMS advantages. They solve the ACID problems (atomicity, consistency, isolation, durability) with horizontal scalability of OLTP databases (e.g., Clustrix, NuoDB). Therefore, RDBMS and NewSQL databases focus on transactional loads. They are rarely used in TCPS, since the key issue is the analytics of large sets of time series from physical parameters measurements and predicting the technical state of machinery equipment [25].

Nevertheless, columnar NoSQL databases are traditionally designed to support business analytics (e.g., Vertica, ClickHouse) [37]. Typical use is a large data warehouse solving analytical problems using the "online analytical processing" (OLAP) approach. An analytical database is at a level higher than a data lake. Data are further processed (partitioning, compression) to make analytics easy and fast. In turn, graph-oriented NoSQL databases [38] can be used for digital virtualization of the monitoring and manipulation object (sensors, actuators, nodes) and the surrounding context (employee profiles, operating conditions). Detection of composite events is possible to understand the nature of cause-and-effect chains and the simultaneity of a set of basic events for decision making (a knowledge base is created).

Fusing (linking) data in a graph model is the process of combining data sets obtained from heterogeneous sources to form a unique consistent view and to reduce the uncertainty of multi-source information. "Reducing uncertainty" means moving to a new level of abstraction, with a more reliable and accurate way to identify events occurring within TCPS [39].

The computation layer is core in the Bigdata architecture. Data sources are heterogeneous both in structure and content. As we considered above, the two computing modes are used: batch processing and stream processing. In batch processing, a large data block (batch) is received at the input processed in certain time period. In streaming data processing is not limited with beginning and end points. Data processing acts in a sliding window or as individual records. It is necessary to process data on the fly, i.e., in near real time. Stream processing is easily scalable by creating new handlers on a given stream. Spark is a versatile large-scale batch and stream computing engine suitable for industrial applications [40]. Generally, the computation layer also handles data preparation, aggregation, fusing, and cleansing.

The analytics layer is designed to extract information and knowledge for decision making from the collected Bigdata. Two areas of analytics can be distinguished [39]: 1) online analytical processing (OLAP) using analytical queries, 2) data mining and machine learning algorithms (e.g., decision trees, convolutional artificial neural networks, regression, support vector machines). A toolkit is used depending on the requirements of the system. Spark SQL is used in analytics over structured batch data [40]. Spark Streaming is used for stream analytics [41]. MLlib and TensorFlow are used for machine and deep learning [42].

OLAP databases provide their set of tools in the form of a query language (usually SQL) for advanced analytics and business intelligence (e.g., Greenplum, Teradata). Analyzing streaming and retrospective data, analytical tools can recognize knowledge for decision making in TCPS (e.g., statistical metrics and spectral images for vibration diagnostics of rotary equipment, events about equipment deviations from normal operation modes, residual equipment life).

Data-driven extrapolation requires strain measurements to be made in all states of interest over a representative time period [43]. The collected strain data can be used to train the extrapolation algorithm. If there are no data for training, the missing data (beyond the range) are generated by simulation. In particular, the correlation between deformation and applied loads is non-linear under extreme stress conditions, so calculating and predicting deformation of equipment assemblies is difficult with traditional numerical methods. A back propagation neural network (improved by particle swarm optimization) can be used for determining the non-linear relationship between strain and load [44].

The service layer is on the top of our architecture. The layer is based on interactive multimedia human-machine interfaces. They provide users with a set of information and analytical services. The provision is a merged, seamless view, while hiding advanced analytical algorithms and differences in streaming and batch processing from the users. This view visualizes the results of the underlying layers using dashboards, reports, and plots. The service layer combines business and artificial intelligence with visualization to help in interacting the users and machines, in making decisions based on collected data, analytics, and expert evaluation [45].

On this layer, an interactive situational center is constructed to implement the “data–information–recommendation–evaluation–decision” cycle. Decisions are made based on the representation of the object’s state. In particular, a decision is on timely equipment maintenance and the feedback is monitored. Recommendation services provide an evaluation of remaining life of machinery equipment components. Such decision making reduces maintenance costs and improves overall production reliability.

Reports are generated (according to plan and online) with information about the residual resource, recent and predicted state of the machinery equipment. Managing workflows for business, data processes, and resources requires orchestration tools that are used on all layers of the architecture, especially along the batch processing path [46]. A data workflow is a set of interrelated time steps that trigger specific jobs, such as Spark job or SQL query. Apache NiFi can be used as an orchestration tool for creating data streams and integrating data with the interactive service layer.

IV. Conclusion

This paper studied the use of TCPS to smart monitoring. We considered the two requirements of the system development: the bigdata requirement (R_{BD}) and the smart interaction requirement (R_{SI}). The role of the requirements was shown with respect to the tactile sense. A particular application area in demand is monitoring of various production machineries in real-time. We analyzed the properties from practical application problems and existing technologies for industrial data processing. We proposed the multi-layer TCPS architecture for effective processing of sensed data, either in batch mode or near real-time mode. Elements of the TCPS architecture have been already implemented in several monitoring applications. Our plan is to continue the development of smart monitoring IoT/IIoT systems based on the proposed generic architecture. We expect that the role of the tactile property becomes increasing in manufacturing, building construction, vehicle operation, robotics, and mobile healthcare.

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