Internet of Things – A Model for Data Analytics of KPI Platform in Continuous Process Industry

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Internet of Things (IoT) is gaining momentum now a days to real time operational environment. The related technologies of IoT is converging to the main stream of industrial applications and replacing the conventional models of data acquisition, analysis, visualization and control in continuous manufacturing process industries. In this paper, we are proposing an IoT based model platform for acquiring various data that is generated in a continuous process manufacturing plant. This includes data from mobile devices and ERP systems as well. This is analyzed using machine learning and artificial intelligence technologies which leads to visualization of Key Performance Indicators (KPIs). It can be displayed on plant level as well as head office level in static and mobile devices. Control instructions can also be given from static devices as well as from mobile devices. Along with proposed platform concept, a prototype is also developed for cement manufacturing plant which is a core engineering continuous process manufacturing industry. The general KPIs in cement plants are explained and the KPIs generated in visualizing devices by the prototype platform are also provided in this paper.

Povzetek: Članek predlaga model IoT platforme za analitiko ključnih kazalnikov uspešnosti (KPI) v industriji kontinuiranih procesov, ki vključuje integracijo podatkov iz mobilnih naprav in ERP sistemov, uporabo strojnega učenja in AI za vizualizacijo KPI-jev v proizvodnji cementa.

1 Introduction

In continuous process industry [1], raw material moves from the beginning of the process and advances through each production step before converting to a final product. Once the process is initiated, the parameters such as pressure, temperature, speed, humidity etc. need to be controlled within the limits. The sensors can collect the data, compare that with requirements and take corrective actions wherever required. Cement manufacturing is an example of continuous manufacturing process industry.

Professionals working in continuous process manufacturing plants are expected to monitor performance of various machines and process parameters continuously. This should also be controlled in real time basis. The man power required for this activity is very high. In addition to this, there are possibilities of human error while monitoring manually. Presently, most of the continuous manufacturing process plants are reasonably automated. Their operations are with Programmable Logic Controllers (PLC) [2] or Distributed Control Systems (DCS) [3] and monitoring can be done from the control room. A PLC [4], is a ruggedized computer used for industrial automation. These controllers can automate a specific process, machine function, or even an entire production line. DCS [5] is a computerized control system for a process or plant that consists of a large number of control loops, in which autonomous controllers are distributed throughout the system with a central operator supervisory control.

Even though some level of autonomous control operations system is implemented in some manufacturing facility, the human experts need to be physically deployed in all areas of operation. If data collection, analysis, display and control can be done without human intervention, it will ensure less error in operations and activities can be done in a faster pace. The service of professionals who are presently involved in data collection, processing, analyzing and controlling activities can be utilized in other important focus areas like development of process and control, that meets future product, customer and environmental requirements. Presently engineers and managers are having access to smart phones and have reliable Internet connectivity in most of the places where plants are located. If they can get process information on their mobile phone, the need to be present in the control room all the time can be avoided. This will improve the flexibility of these personnel and hence it will result in improving open thinking and productivity. A platform that can acquire data from DCS or PLC [6] in real time, with capability to analyze and visualize on static as well as mobile devices with alerts for manual interventions as needed, can support industry to meet this requirement. As the sensors, wireless connectivity, computing and visualizing capabilities are in the developed phase, an Internet of Things (IoT) [7] based platform will be the right choice for meeting this requirement. IoT refers to a system of interrelated, Internet-connected things that are able to collect and transfer data over a network without human intervention. The things can be sensor, actuator or any equipment connected each other and to the Internet normally wireless and sometimes wired. The Industrial Internet of Things (IIoT) [8] refers to the extension and use of the IoT in industrial sectors and applications. This can be either connected to the Internet or work as an independent industrial network. An example for IIoT is the smart electrical grid which is interconnected with power generation, transmission and distribution with sensors, control system and actuators. IIoT needs to follow the components and communication standards required for that particular industry in which, it is implemented.

Platform [9] [10] is a digital hub which integrates the inputs from sensors, analyze the data and provides output for visualization or actions. In addition to automated sensor data, the inputs can be provided by manual intervention based on the policies and requirements. The development of IoT platform with capability of data acquisition, analysis and visualization in static and mobile devices will reduce human efforts, improve speed and will support for taking the right manual decisions when required. In an IoT enabled factory, there are many individual components like sensors, actuators etc. These may be interdependent components of a production line and will be aware of each other's activity in real time. So, the entire manufacturing process will become more efficient as well as much easy to monitor and manage with the platform. Data analytics [11] [12] [13] is the process of systematically applying statistical and/or logical techniques to describe and illustrate, condense, and evaluate data. In IIoT, the data collected by various sensors are processed, some process happens at the sensor end itself which is known as edge processing [14]. This is transferred to platform in which detailed analysis happen and the output is given for human visualization and/or for actuators to take actions. Many software tools such as, Python, R Programming, Hadoop etc. are used for analysis. For visualization software such as Tableau, Power BI etc. are used for Human Machine Interface (HMI) [15]. Predictive analytics capability on the platform will be able to predict possible breakdown scenarios well in advance and will help to take corrective actions.

2 Related work

PLC can be programmed for effective operation of the process with productivity, accuracy, precision and efficiency [16]. Before the introduction of PLC, the relay logic and contactor logics (RLC) were used [2] which include human intervention and resulted in errors. The introduction of microprocessors, microcontrollers, PLCs, Supervisory Control & Data Acquisition (SCADA) [17] [18] and DCS [19] have improved the control of manufacturing operations. These systems reduced human intervention and increased the flexibility in the process control. By automation, the working of a process or repetitive works can be done efficiently by proper controls within acceptable range. DCS made IoT implementation practically feasible. The communication from DCS to processor can be via Message Queuing Telemetry Transport (MQTT) protocol [20] [21]. For a robust system, the security enhancements should be compatible with MQTT Application Programming Interfaces (API) [22]. Open Platform Communications United Architecture (OPCUA) protocol [23] is another protocol which is getting wider acceptability in the industry. IIoT receives very large amount of data from sensors and other sources. IIoT search engines [24] are also presently available. Big data analytics can be used for analysis of these data. Predictive and prescriptive analytics [25] can be done by adding this to the operational processes. The sensor driven data analytics which is used for decision making will improve and optimize the process industry. An analytical platform [26] can support the collection, storage, processing and visualization of data. Such a platform will be able to connect to the existing plant environment and use the data gathered to build predictive functions to optimize the production process.

3 Background

Continuous manufacturing process industries like cement, steel, paper, sugar, petrochemicals, fertilizers etc. have a matured manufacturing process. In this industry, once capital equipment in the manufacturing facility is installed, it is expected to provide continuous service for next 30-40 years. Not much of the technical upgradations or changes are possible in this life span. During the earlier days, all the process in continuous manufacturing industry were sensed, measured and required changes were done manually. Later, mechanical automation for sensing temperature, pressure, volume and suitable automatic systems were introduced [27]. An example of this is automatic coal fire reduction when steam pressure reaches required value. With the wide use of electricity in industries, electro-mechanical sensing and automation systems were introduced. Electric switch cut-off with a thermostat when it reaches the preset heat is an example of this application. These systems were of unidirectional, which means that it does not have the capability to adjust the process, based on the feedback from output or other variable parameters. More over this control system hardware need to be custom developed as per the individual manufacturing plant or industry requirements. The introduction of PLC brought great flexibility by providing the option of using standard programmable controller irrespective of manufacturing plant or industry. The era of DCS brought a revolution by allowing standard computers to monitor and control manufacturing in process industries [28]. This helped to get real time data to the centralized control rooms and these control rooms can take remote actions by providing inputs to the actuators. Various technological improvements like change of wired sensor system to wireless, development of various industrial communication standards, high computational & storage capabilities, display options and control capabilities brought an IoT revolution to continuous process manufacturing industry.

3.1 State of the art

The new generation of sensors and actuators are small, energy efficient, accurate, reliable and identifiable electronically. The identification systems like beacons, Radio Frequency Identification (RFID) [29] [30], Near Field Communication (NFC) [31] [32] etc. helped for easy and accurate sensing. The development of industrial wireless communication standards as well as computation and control systems, initiated Industry 4.0, which is the digital factory concept. With the introduction of Industry 4.0 [33], manufacturing plants started real time sensing of data with sensors installed in various equipment as well as throughout the environment. This system has created an environment called Cyber Physical System (CPS) [34]. By connecting this system to Internet, IIoT came into existence. Presently IIoT is getting implemented in many industries with very less or controlled exposure to communication through Internet. Dependability and standardization are essential to the adoption of Wireless Sensor Networks (WSN) [35] in industrial applications. Communication standards such as ZigBee [36], Wireless HART [37], ISA100.11a [38] and WIA-PA [39] are well accepted presently. The development of technology for computing at the sensing point itself and transfer of data to central control room for supervisory and management analysis as per the required Key Performance Indicators (KPIs) [40] paved the way for the revolution of IIoT. Key Performance Indicator (KPI) is a quantifiable measure of performance over time for a specific objective. KPIs provide milestones to measure progress that help people across the organization to take right decisions. Most of the industry and organizations monitor and compare their performance based on the KPIs set up for that particular segment. KPIs are important for monitoring the performance and to identify opportunities for improvement of the industry. KPIs can be defined for individual equipment, sub processes as well as for the whole plant. Performances related to energy, raw material, final product, process control, operation, maintenance, etc. can be monitored by KPI. Benchmarking KPIs with similar equipment and plants is one method of setting industrial segment KPI standards. The outputs received as KPIs, are displayed at plant levels as well as at the head office. The KPIs from other plants also reach the head office for analysis at that level and comparison. The corrective and control instructions [41] can also be given from head office or plant level to supervisory or to the actuator level.

4 Problem identification

Covid-19 the pandemic, restricted employees and professionals in travelling to factories and offices as well as for conducting physical meetings. In this situation, information flow from continuous manufacturing plants to supervisory and management team became important for taking right decisions and running the operations smooth. The present infrastructure of PLC, DCS or IoT enabled manufacturing industries are having data visualization and process control facility available only in static devices located in plant control rooms or at offices. In this situation, to continue the manufacturing process seamlessly, there is a need of integrating mobile devices to the existing control system infrastructure for accessing the continuous process data and other operational information. The process control facility needs to be provided with authorized mobile devices and it should be capable of operating from anywhere in the world. To achieve this, the right connectivity methods matching present available infrastructure as well as ensuring security needs to be developed. The integration of existing IIoT to mobile devices meeting the security requirements is a challenge identified by continuous process manufacturing organizations.

5 Proposed solution

The solution that we propose to the identified problem is the development of industrial platform which can access data from wireless sensors, mobile devices, DCSs, PLCs, ERP and text files. In the proposed platform, data could be analyzed as per the KPI requirements. The machine learning and artificial intelligence algorithms [42] [43] need to be incorporated for taking autonomous regular or corrective actions. The platform can also provide predictive analysis outputs that can be utilized for advance actions. The analysis output, meeting the KPIs formats should be displayed in mobile devices as well as in static devices as per the requirement. It should also be able to provide control instructions from mobile devices.

5.1 Automation landscape

In a continuous process industry, the data is collected from sensors and actuators to take actions based on the inputs from PLC, Proportional Integral Derivative (PID) controller, DCS or Supervisory Control and Data Acquisition (SCADA). A PID controller is an instrument used in industrial control applications to regulate temperature, flow, pressure, speed and other process variables. PID controllers use a control loop feedback mechanism to control process variables and are the most accurate and stable controller. A SCADA [44] is an automation control system that is used in industries such as energy, oil and gas, water, power, and many more. This system can be a centralized one to monitor and control individual sites and all connected sites. Manufacturing Execution Systems (MES) are software solutions that ensure quality and efficiency. This is built into the manufacturing process and are proactively as well as systematically enforced. Enterprise Resource Planning (ERP) is a software system that utilizes a centralized database that contains all the necessary data in one location. Information Technology (IT) automation is the process of creating software and systems to replace repeatable processes and reduce manual intervention. With IT automation, software is used to take care of repeat instructions, process, or policies to save time and free up IT staff for some other strategic work. Operational technology involves hardware and software that detects or causes a change, through the direct monitoring and/or control of industrial equipment, assets, process and events. Figure 1 shows the convergence zone of operation /automation and information technology. The operation / automation technology involves sensors, actuators, PLC, PID, personnel computers and SCADA. ERP and MES combines to form the information technology area. The proposed platform will be in the convergence zone. Various operational technology channels are explained in Table 1 and information technology channels are described in Table 2.

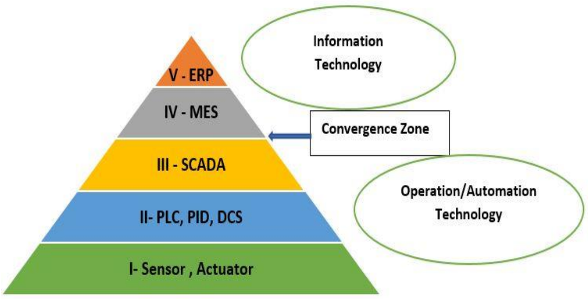

Figure 1: Convergence zone of operation/automation and information technology.

Table 1: Operational technology channels.

Operational Technology Channel	Description
OPC (Open Platform Communications)	Handles OPC connections using either OPC Unified Architecture (UA) specifications or OPC Data Access (DA) specifications. UA security is secured using certificates. DA security permissions can be applied using DCOM settings.
OPC Server	Acts as an OPC UA server. It can be accessed by a classic OPC client using a COM wrapper.
XML	Connects via a local or remote XML file.
CSV	Connects via a local or remote CSV file.
Webservice	Supports SOAP and REST communication and provides SOAP/REST host services. It runs as a server sending and receiving XML messages.
MQTT	Supports the ISO standard (ISO/IEC PRF 20922) protocol. ATS Bus supports encryption between the MQTT channel and the MQTT broker using X509 certificates.
RFID	Uses the Octane SDK to communicate with Impinj Speedway readers. The channel connects to the reader using a raw TCP/IP socket. These TCP/IP connections are not secured using certificates.
MTConnect	Supports communication with MTConnect agents that exchange information with CNC machines.
Socket	A bidirectional (client/server) TCP/IP communication channel. It can be used to process CSV, text or binary data. As a server the channel binds to a port. As a client the channel connects to a host name and port. It does not provide data encryption.
Serial Port	A bidirectional (client/server) RS-232 communication channel. It supports CSV, text and binary data payloads. COM ports can be virtual or physical.
Database	Communicates with Microsoft SQL Server and Oracle databases.

Table 2: Information technology channels.

Information Technology Channel	Description
XML	Connects via a local or remote XML file.
ActiveMQ	Connects via Apache ActiveMQ messaging service. Apache ActiveMQ is an open-source messaging and integrations patterns server. Encryption is not supported on this channel.
Webservice Server	Supports WCF and REST communication and provides WCF/REST host services. It runs as a server sending and receiving XML messages.
Webservice Client	Exchanges information with REST, SOAP and HTTP based web services.
Extension	Required when other IT channels don't have the functionality required to communicate with a customer's software. It read and write to a plug-in (.NET assembly) using a standard interface. It may or may not have secure communications depending on how it's used.

5.2 Line diagram

The line diagram of IoT based KPI platform for the continuous process manufacturing industry having multiple plant facilities is shown in Figure 2. The proposed platform will be installed in each plant as well as in head office. The data from each manufacturing plant will be transmitted to the plant level KPI platform from DCS through MQTT/OPC/Modbus channel. The data from the ERP will also be transferred similarly. Each plant will be connected to head office KPI platform through the Internet. Firewall will be placed at the point where each plant is connected to Internet as well as where the head office is connected to Internet.

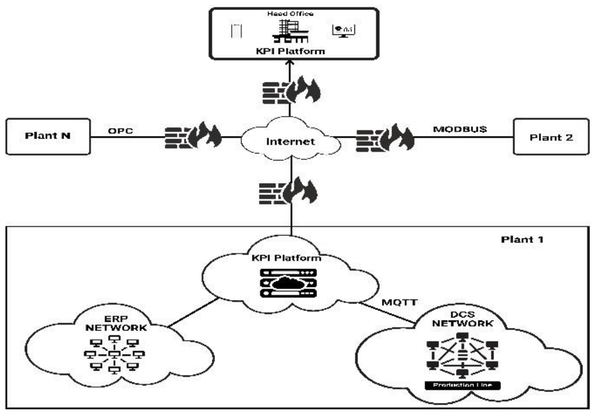

Figure 2: Line diagram of IoT based KPI platform.

5.3 Platform architecture

In the proposed IIoT platform, the operation/automation and the Information Technology will converge. Figure 3 shows the architecture of proposed KPI platform.

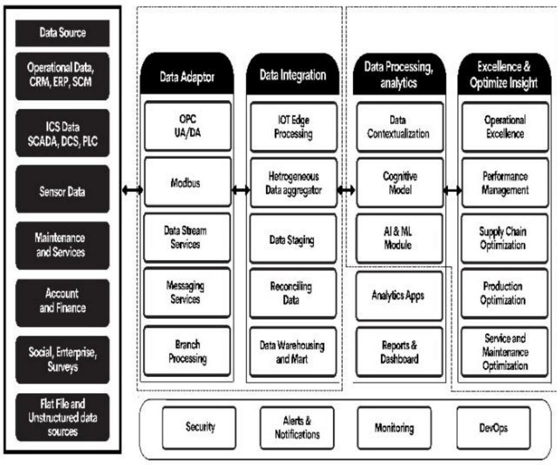

Figure 3: Architecture of KPI platform.

The proposed architecture has modules for acquiring inputs from various data sources. These sources can be sensor data, Industrial Control Systems (ICS), ERP, mobile applications etc. It can accept manual input data which comes as flat file as well as social media data which will be in the unstructured format. The data adaptor can be OPC, Modbus, MQTT etc. The data integration module integrates the data and will be made available for analysis. The artificial intelligence and machine learning applications are incorporated in data processing and analytics module. The output of this will be made available to dashboards. The security, monitoring, notifications, development, quality and operation modules will be common to all modules.

6 Implementation in cement manufacturing

Cement manufacturing [45] is highly automated continuous manufacturing process industry. The main stages of cement manufacturing are lime stone crushing, raw material handling, raw mill, kiln, coal mill and cement mill. The process needs to be monitored and controlled from starting point to final product end. Figure 4 shows the process of cement manufacturing.

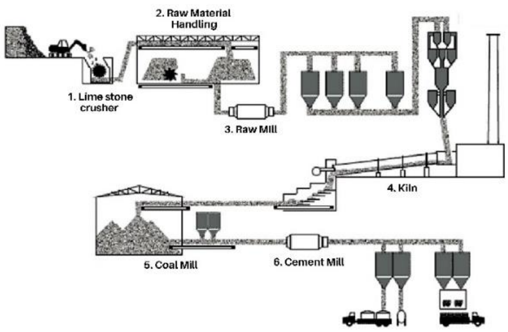

Figure 4: Process of cement manufacturing.

The identified KPIs [46] [47] normally using in cement manufacturing industry are provided. Table 3 explains the KPI for critical process parameters [48]. Table 4 shows the KPIs related to environment. Table 5 shows the material stock KPI. Table 6 explains the KPI for quality control parameters. These KPIs will be generated by the platform based on the inputs from IoT sensors.

Table 3: KPI for critical process parameters.

No.	Process	Parameter	Unit of Measurement
1	Lime Stone Crusher	Apron Feeder Speed	Rotations/Minute
		Crusher Motor Load	Kilowatt
		Limestone to Stacker	Tons/Hour
2	Raw Material Handling	Limestone Reclaimer	Tons/Hour
		Raw Mill Additive Reclaimer	Tons/Hour
		Raw coal reclaimer	Tons/Hour
		Cement Mill Additive Reclaimer	Tons/Hour
3	Raw Mill	Limestone Weigh Feeder	Tons/Hour
		Bauxide Weigh Feeder	Tons/Hour
		Hammetite Weigh Feeder	Tons/Hour
		Raw mill Total Feed	Tons/Hour
		Raw mill Motor Load	Kilowatt
		Raw Mill Differential Pressure	Millimeter Water Gauge
		Raw Fan Motor Load	Kilowatt
		Raw Mill Fan Speed	%
		Raw Mill Fan Flow	m3/Hour
		Bag House/ESP Fan Load	Kilowatt
		Bag House/ESP Fan Speed	%
		Bag House/ESP Fan Flow	m3/Hour
		Bag House/ESP Differential Pressure	Millimeter Water Gauge
		Classifier Speed	%
4	Kiln	Pre heater Fan Motor Load	Kilowatt
		Pre heater Fan Speed	%
		Pre heater Fan Flow	m3/Hour
		PH I/L O2	%
		PH I/L CO	%
		Calciner O2	%
		Calciner CO	%
		Calciner NOX	PPM
		Kiln I/L O2	%
		Kiln I/L CO	%
		Kiln I/L NOX	PPM
		Kiln Firing Coal	Tons/Hour
		Calciner Firing Coal	Tons/Hour
		Calciner Temperature	Degree Centigrade
		Kiln Feed	Tons/Hour
		Kiln motor Load	Kilowatt

		Kiln Speed	Rotations/Minute
		Kiln I/L Temperature	Degree Centigrade
		Burning Zone Temperature	Degree Centigrade
		Tertiary Air Temperature	Degree Centigrade
		Secondary air Temperature	Degree Centigrade
		Kiln Hood Draft	Millimeter Water Gauge
		Cooler Compartment Pressure	Millimeter Water Gauge
		Cooler Grate Speed	Rotations/Minute
		Clinker Temperature	Degree Centigrade
		Cooler ESP Fan Load	KW
		Cooler ESP Fan Speed	%
		Cooler ESP Fan Flow	M3/Hour
5	Coal Mill	Raw Coal Weigh Feeder	Tons/Hour
		Coal mill Motor Load	Kilowatt
		Coal Mill Differential Pressure	Millimeter Water Gauge
		Coal Mill Fan Motor Load	Kilowatt
		Coal Mill Fan Speed	%
		Coal Mill Fan Flow	M3/Hour
		Bag House Fan Load	Kilowatt
		Bag House Fan Speed	%
		Bag House Fan Flow	m3/Hour
		Bag House Differential Pressure	Millimeter Water Gauge
		Bag House I/L O2	%
		Bag House I/L CO	%
		Fine Coal Silo CO	%
		Bag House I/L Temperature	Degree Centigrade
		Classifier Speed	%
6	Cement Mill	Clinker Weigh Feeder	Tons/Hour
		Gypsum Weigh Feeder	Tons/Hour
		Puzzolana Weigh Feeder	Tons/Hour
		Cement mill Total Feed	Tons/Hour
		Cement mill Motor Load	Kilowatt
		Cement Mill Differential Pressure	Millimeter Water Gauge
		Cement Mill Fan Motor Load	Kilowatt
		Cement Mill Fan Speed	%
		Cement Mill Fan Flow	m3/Hour
		Bag House Fan Load	Kilowatt
		Bag House Fan Speed	%
		Bag House Fan Flow	m3/Hour
		Bag House Differential Pressure	Millimeter Water Gauge
		Classifier Speed	%

Cement is a commonly used construction material that requires large number of resources to manufacture and the manufacturing process have significant environmental impact [46]. The cement industries are facing challenges to implement sustainable manufacturing into their products and processes. Cement manufacturing is an intensive consumer of natural raw materials, fossil fuels, energy, and a major source of multiple pollutants. Thus, evaluating the sustainable manufacturing in this industry has become a necessity [49]. To meet the environmental requirements, the parameters related to manufacturing operations need to be monitored and is included as one of the KPIs.

Table 4: KPIs related to environment.

No.	Parameter	Unit of Measurement
1	Kiln Stack Emission	mg/Nm3
2	Coal Stack Emission	mg/Nm3
3	Cooler Stack Emission	mg/Nm3
4	Cement Stack Emission	mg/Nm3
5	Ambient Air Quality	Index
6	Water Consumption	m3/hr.
7	Waste water	m3/hr.

The information of raw material stock, material in process and finished goods availability is very important for business operations and planning. The availability of various chemicals and consumables using in manufacturing process also need to be monitored for optimum production to take place.

Table 5: Material stock KPI.

No.	Description	Unit of Measurement
1	Limestone Stock Pile	Ton
2	Raw mill Additives	Ton
3	Raw Meal Silo	Ton
4	Raw Coal Stock Pile	Ton
5	Fine Coal Silo	Ton
6	Clinker Stock Pile	Ton
7	Cement Mill Additives Gypsum	Ton
8	Cement Mill Additives Fly Ash	Ton
9	Cement Mill Performance Improver	Ton
10	Grinding Aid	Ton
11	Cement Silo	Ton
12	Water Reservoir	Litre
13	Diesel Stock	Litre

Table 6: KPI for quality control parameters.

No.	Parameter
1	Cao
2	LSF
3	Liter weight
4	Free Lime
5	C3S
6	C2S
7	Blain (OPC)
8	Blain (PPC)
9	Cement Particle Size

For monitoring KPIs, Data Acquisition Module (DAM) is installed on each site. It collects data from equipment in real time from various sensors. The platform is installed in the server available in customer premises. The data from each site is sent to platform server over Internet. Platform server processes the data with intelligence and presents it to different types of users like support team, managers, top management etc. Access control is in place so that each user sees what is relevant to user. Figure 5 shows the proposed architecture for deployment. This platform is developed based on line diagram of IoT based KPI platform shown in Figure 2 and architecture of KPI platform shown in Figure 3.

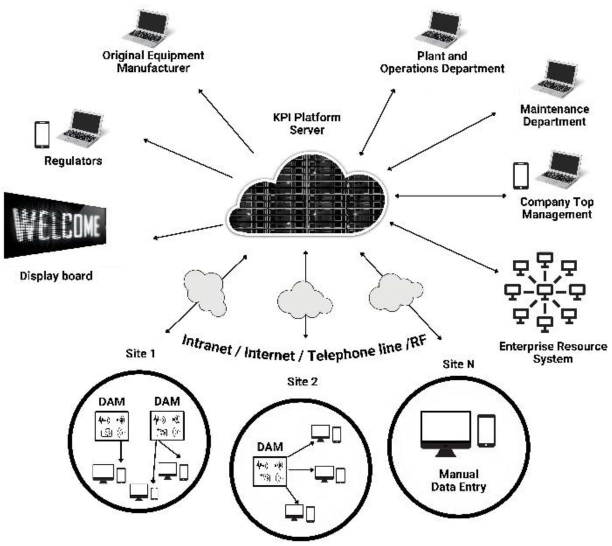

Figure 5: Proposed architecture for deployment.

The proof-of-concept platform is developed and the testing is done on a simulated environment. Few of the KPI reports generated in a mobile device are provided. Figure 6 shows the process parameter KPIs generated in visualizing device as output from platform. Environmental KPIs are shown in Figure 7. The material stock KPIs are provided in Figure 8. Quality control KPIs are shown in Figure 9. Production KPI is in Figure 10. Fuel consumption KPI is shown in Figure 11 and the power consumption is shown in Figure 12. Consolidation of data of all plants is also possible for head office application. Comparison of KPI between units within a plant or between other plants of similar size is also possible.

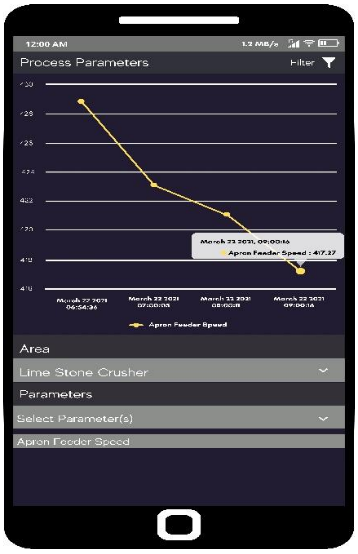

Figure 6: Process parameter KPIs.

Figure 7: Environmental KPIs.

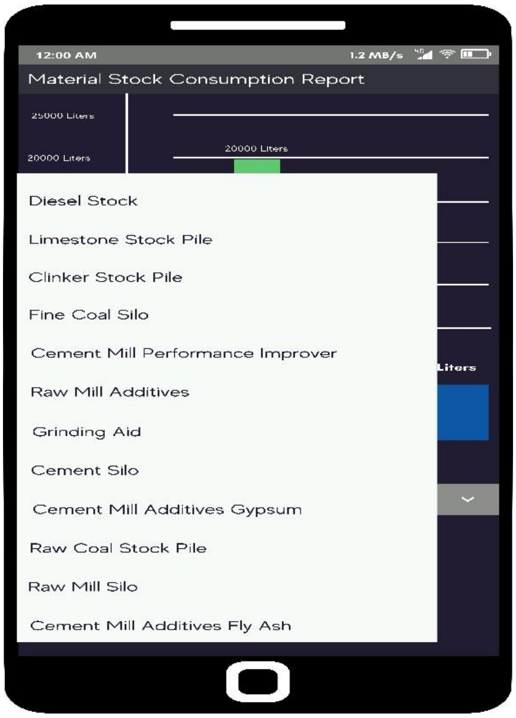

Figure 8: Material stock KPIs.

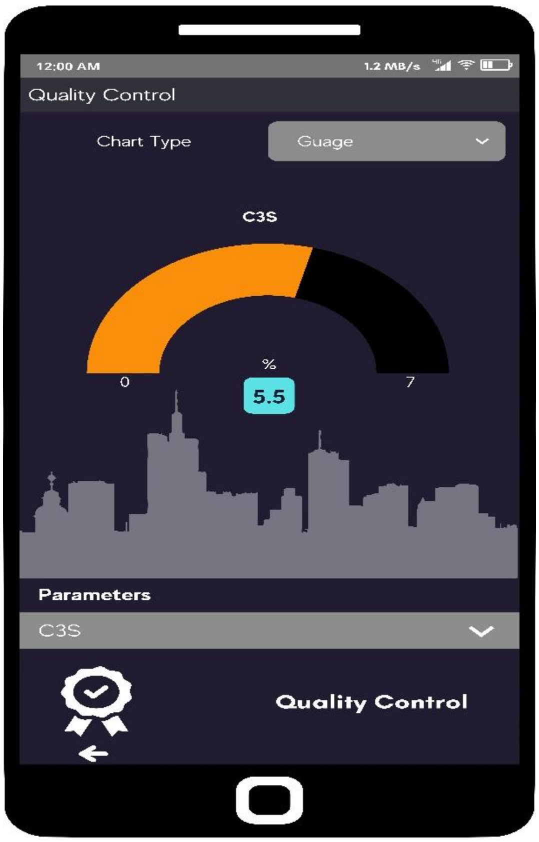

Figure 9: Quality control KPIs.

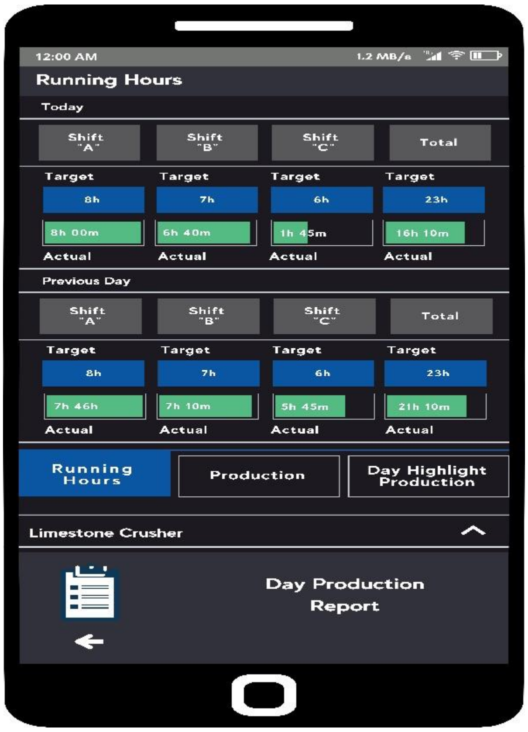

Figure 10: Production KPIs.

Figure 11: Fuel consumption KPIs.

Figure 12: Power consumption KPIs.

7 Conclusion

The developed platform is the solution for integrating mobile devices to the IoT based automation and control system of a continuous process industry. This platform is implemented at the convergence area of operations/automation and Information Technology. The platform is able to acquire various types of data, analyze the data collected and provide the required outputs to the static and mobile devices. The prototype platform developed is implemented in one of the cement manufacturing industries at the plant server and at the head office server as well. The KPIs required for this cement manufacturing plant is identified and deployed in this platform. This developmental model can be extended to steel, petrochemicals, sugar, paper, fertilizer, food, pharmaceutical industry etc. As a future work, the platform can be installed in the cloud which can be accessed by plants as well as head office. With the acceptance and popularity in industry with IoT based KPI platform, it can be developed in the cloud and provide Platform as a Service (PaaS) to customers.

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