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IoT Based monitoring and control of fluid transportation using machine learning

Priyanka E. Bhaskaran [a,*], C. Maheswari [b], S. Thangavel [b], M. Ponnibala [c], T. Kalavathidevi [c], N.S. Sivakumar [d]

[a] *Senior Research Fellow, Department of Mechatronics Engineering, Kongu Engineering College, Perundurai, India*
[b] *Faculty, Department of Mechatronics Engineering, Kongu Engineering College, Perundurai, India*
[c] *Department of Electronics and Instrumentation Engineering, Kongu Engineering College, Perundurai*
[d] *Faculty, Department of Mechatronics Engineering, Tishk International University(TIU), Erbil, Iraq*

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ABSTRACT

It is important to concentrate on monitoring and control of the pipeline transportation system before the failure resulting in fatal accidents. To enhance the supervision performances, the SCADA (Supervisory Control and Data Acquisition) platform is incorporated with IoT by utilizing the NB-IOT module holding a high-level engineering interface. In the proposed methodology, SCADA with the LQR-PID controller serves as Local Intelligence. When the local intelligence fails to react proactively during risk occurrences, immediately its performance is deactivated by the webserver through the NB (Narrow Band)-IoT module. For experimental real-time validation of the proposed work, a lab-scale DCS (Distributed Control System) based fluid transportation system is undertaken where flow and pressure prevail to be the most influencing parameters during risk occurrences in the pipelines. Also, the performance analyses are validated experimentally using unsupervised K-means clustering to identify abnormality caused by blockage and crack in the pipeline on the cloud-stored data.

1. Introduction

In recent years, communication occurs wirelessly to the remote information analytics center to examine and interpret the process behavior and provide the appropriate decision in case of risk circumstances. Through the use of the Proportional-Integral-Derivative (PID) controller, automated control systems facilitate complex transportation processes to be functioning safely and cost-effectively. This is attained by continually measuring operating parameters such as temperature, pressure, level, flow, and concentration, and creating decisions to open or close a valve, slow down or speed up a pump, or increase or decrease heat so that selected process measurements are sustained at the set range values. The main motivation for advanced control systems is safety since the loops having adequate performance are only 68% which are in manual mode. Hence in recent scenarios, the need for an advanced controller is increased to determine the optimal system performances [1]. Remote monitoring and controlling of the sub-station equipment are an important issue for the transportation management department which is normally done manually or using an expensive PLC and SCADA system. With the emergence of the internet and the computational era, a smart monitoring and reliable controlling system over the entire pipeline sensor parameters are highly desirable that can be achieved by introducing the Internet of Things (IoT) technology.

* Corresponding author.
E-mail address: priyankabhaskaran1993@gmail.com (P.E. Bhaskaran).

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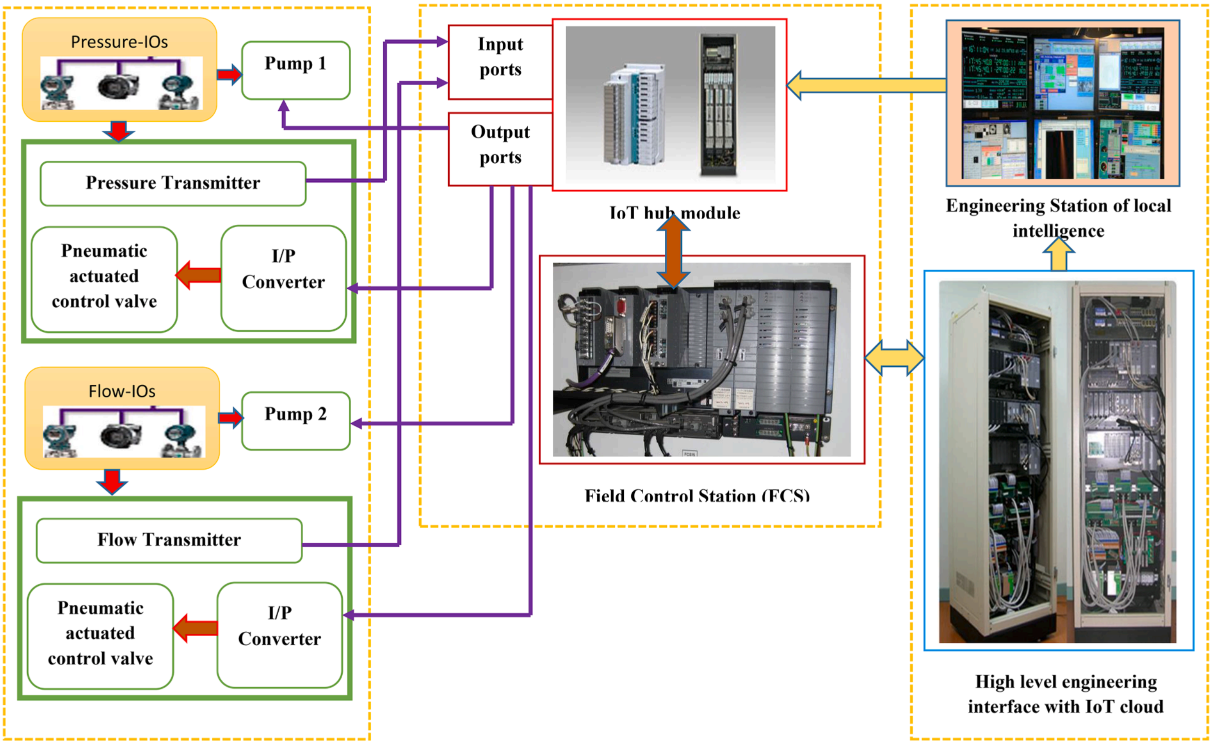

Fig. 1. IoT based architecture with local intelligence for the process.

IoT is the network of physical devices embedded with electronics, software, sensors, actuators and network connectivity which can identify, collect and exchange the data [2]. Each thing is uniquely identifiable through its embedded computing system and able to interoperate within the existing internet infrastructure. Because of low-cost, networkable micro-controller modules, the Internet of Things is considered as the key technology to establish a smart sub-station. However, IoT itself has still not reached maturity and many IoT communication protocols such as CoAP, MQTT, XMPP have been proposed as IoT standards. These protocols vary in characteristics with different strengths and limitations. Finally, due to the technological revolution all over the world, smart technologies are replacing old ones. In the power sector, IoT technology is becoming more attractive nowadays. It is expected that within 2025, around 20–50 billion things would be connected to the internet throughout the world [3].

Several relevant studies carried out on the IoT technology are summarized here. According to IoT technology in the smart metering system has already been implemented worldwide for grid power measurement and residential electricity billing system. In the power sector, many studies have been conducted for improving the energy crisis by adopting renewable energy sources [4]. The main aim of this work is to develop a fully automated SCADA with IoT based fluid transportation system that can be protected, monitored and controlled from any place in the world only by the authorized personnel at a very low cost. Reliability and reduction of manpower using IoT technology are also the prime concerns while developing the NB-IoT with SCADA-PID controller framework with data analysis using unsupervised K-means clustering-machine learning technique gives visual and statistical results to the inspection engineer to predict the risk occurrences promptly. The main advantage is that developed local intelligence performs better control actions only when the parameter changes are within the threshold limit when it goes beyond the monitoring range, it fails to provide appropriate decisions. Due to the IoT incorporation, the controller performances and local control unit control signals are stored and analyzed in the cloud to provide instantaneous solution before it leads to catastrophic situations. By implementing K-means clustering, the exact risk rate by extreme pressure rise or drop can be interpreted at the early stage from the transportation pipeline system.

The rest of the paper is organized as follows. A detailed proposed methodology of combining SCADA with LQR-PID and IoT for fluid transportation system is discussed in Section 2. Section 3 brief out the experimental hardware setup of the DCS based fluid transport system. Section 4 illustrates the developed NB-IoT module with its features, real-time interfacing and performance measures validations are provided. Section 5 represents the design and real-time experimental analyses of the LQR-PID controller with SCADA on the fluid transportation plant for pressure and flow control are discussed. Section 6 includes the real-time validation of the proposed methodology of IoT and K-means clustering machine learning technique statistical results on pressure data analysis are described. Finally, Section 7 concludes this paper.

2. Enhanced scada platform with LQR-PID controller and IoT

The block diagram with enhanced Integrated IoT architecture with local intelligence (SCADA+ LQR-PID) for the lab-scale

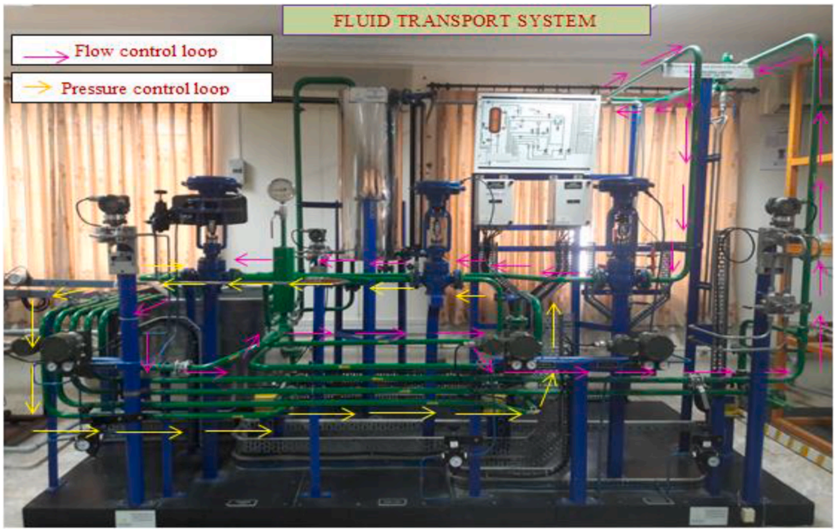

Fig. 2. The lab-scale experimental setup of the fluid transport system.

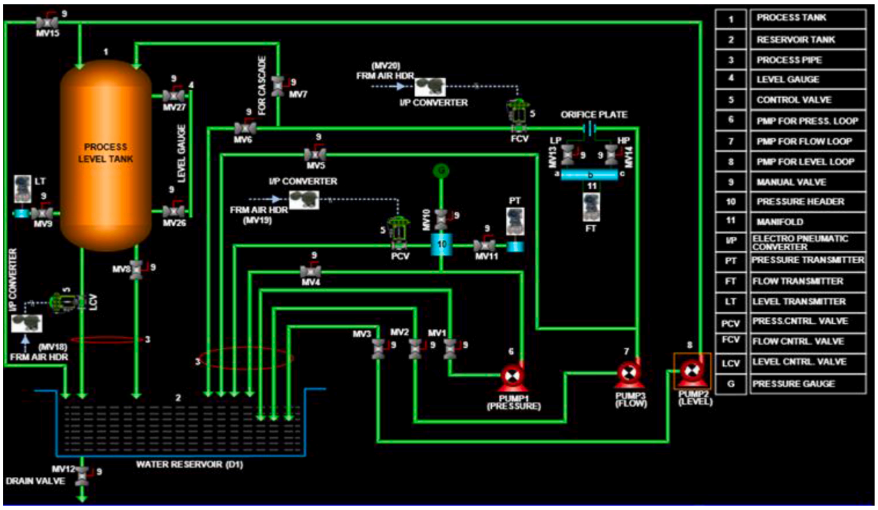

Fig. 3. SCADA view of the lab-scale experimental fluid transport system.

experimental DCS plant visualizing the sensors and actuators positioned with the piping having directional tracks of their controls is shown in Fig. 1. A real-time pump status, pressure and flow rate sensors data which are regulated by the developed local intelligence (SCADA+ LQR-PID) are given to the fabricated smart module which comprises of I/O connectivity, controller and Wi-Fi module. This smart module will uphold the received input and push that to the cloud. In the cloud-centric storage, these sensor data will be updated frequently and it will put to data analytics to monitor and control the process plant field parameters. When it finds out any abnormality in these sensor data, it will send the control activation signal to the process plant. If the local intelligence did not respond to the detected abnormality in the process field parameters within the span of computation time, then the Cloud-centric server will take the role to regulate and control the pressure and flow rate before it reaches the state of over the threshold. Since this paper includes the development and application of local intelligence comprised of the LQR-PID controller with SCADA, the performance of local SCADA with the LQR controller can remotely monitor and controlled through IoT monitoring front end interface. This IoT front end is operated as a stand-alone station without depending on a central server with mutual backup configuration by regulating the operation of the corresponding pumps during cracks and leaks caused by extreme pressure and flow rate variations. Hence to upgrade the conventional control technique with the monitoring system in an industrial process plant, the developed LQR-PID controller with SCADA offers a local field station monitoring and control to progress functioning effectiveness in an integral part of DCS by exploiting CENTUM VP. A DCS plant of the fluid transport system can be supervised and functioned in real-time remotely by integrating local SCADA with the LQR-PID controller incorporated in IoT application creating automatic activation with trends, practically enlightening engineering ability and working safety.

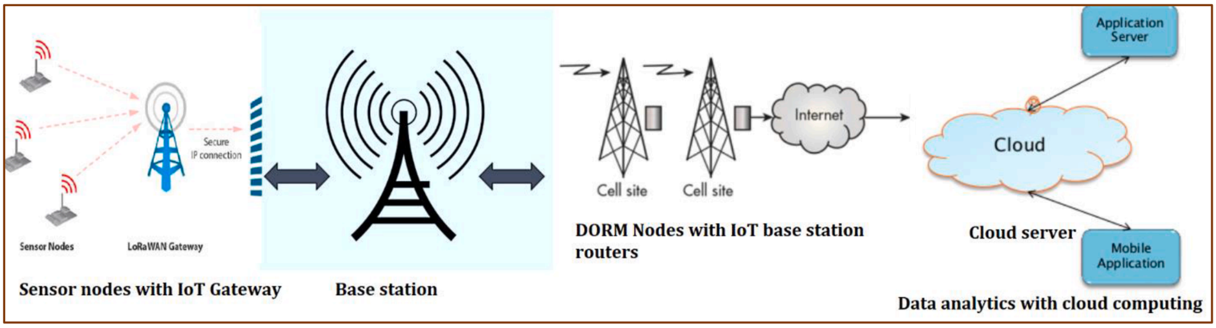

Fig. 4. The architecture of the NB-IOT module in data communication.

3. Lab scale experimental setup of fluid transport system

The process plant consists of two sections consisting of an electric pump, differential pressure transmitter holding a range of 03-15psi (0.1–3kg/cm^2), and a pressure control valve at one section along with an orifice flow meter having the limit of 0-1800lph (Liters Per Hour), pump and flow control valve at another section. When the process plant is on track to run, initially reservoir tank fills up to 20% of its capacity, and then the electric pump is actuated to suck the fluid from the tank to transmit the fluid to each section. When the fluid starts to pass through the pipelines its corresponding pressure and flow transmitter send its present pressure and flow rate data to the I/O hub module station. During transportation to regulate the pressure and flow rate of the transmitting fluid, the opening, and closing of the control valves are operated by the I/P converter to maintain its preferred effective range limits until the destination of the long run, till it drains from the process tank as shown in Fig. 2. The experimentation using the LQR-PID controller can remotely monitor and control the pressure and flow rate as a separate loop through SCADA. It can be operated as a stand-alone station without depending on a central server with mutual backup configuration by regulating the operation of the corresponding control valves to reach its desired operating points of pressure and flow rate through CENTUM V-NET/IP protocol.

The SCADA incorporating an LQR-PID controller is developed for the experimental setup of the fluid transport system to deal with remote surveillance and control of the entire DCS plant with interface displays for flow rate and its respective pressure monitoring/control panel as shown in Fig. 3. The developed SCADA provides more functional utility options like system message banner, graphic view with graphics and control attributes, trend view, browser bar and tuning window. The system message banner expresses the alarm occurrence status visually. The alarm occurrence status is shown by colors and flashing of operation buttons, and the message display. The system message banner is always displayed at the top of the display, so it will never be hidden behind other windows. The browser bar is used to call up operation and monitoring windows. It can display a list of operations and monitoring windows and plant hierarchical structures in a tree-like fashion, allowing the entire system to be easily confirmed. The graphics view with graphics attributes displays system conditions which can be automatically operated and monitored [5]. The graphics view with the control attribute displays the function block statuses using instrument faceplates.

4. Characterization and evaluation of multi-band IoT module for fluid pipeline system

The main aim is to replace all heavy wiring in factories with an intelligent and alert system based on smart things and intelligent communication for control and monitoring. In this part of our paper, industrial communication is based on the IoT and multiband communication using Nb-IoT technology and the RS485. NB-IoT (Narrowband Internet of Things) is wireless communication technology. NB-IoT competes directly with solutions such as Lora and Sigfox. Like the latter, it is characterized by very good indoor and outdoor coverage, low latency, very low connectivity costs, low power consumption and optimized network architecture. NB-IoT eliminates usage limitations, interference and congestion, which are often the biggest problems in unlicensed radio spectrum applications. With extensive radio coverage, NB-IoT is based on 4G benefits from existing infrastructure. Besides, the frequency band used makes it possible to improve penetration inside buildings or underground [7]. This industrial gateway is a universal IoT device that allows data collection from several Modbus-based serial devices (ASCII, RTU) on the RS485 link simultaneously. Transfer of this data to industrial applications using multiple bands, to use a well-defined bandwidth for each level of the CIM pyramid (WSN, Machines, SCADA, ERP and EMS) via the NB-IoT network. The three layers of this NB-IoT system can be categorized as under:

- Perception layer (DORM nodes are deployed across a fluid transport system for sensing the surroundings)
- Network Layer (Base-station is installed near an experimental setup that supports 5G network)
- Cloud Platform (Cumulocity server is set up for supporting and interfacing users' applications)

DORM (integrateD cOmpact naRrowband platforM) nodes are deployed at the "Network Layer", a commercial Base-station (BS), supports LTE Cat-NB1 network to collect all the transmitted data from the deployed nodes and send it further to the highest layer of the NB-IoT system, "Cloud Platform Server". The "Cloud Platform Server" provides an interface for secure communication between the NB-IoT Network and the users' applications, data analytics for decision making and data storage for backup and future use. Fig. 4 shows

Table 1
The validated performance measure of SNR and RSSI value of deployed NB-IOT module in fluid transport system lab setup.

Observation point	Average SNR value (dB)	Average RSSI value (dBm)	Signal strength
Node at 15m	17.99	−65.21	Good
Node at 12m	17.43	−66.90	Good
Node at 9m	19.56	−67.54	Good
Node at 3m	19.91	−68.49	Good
Node at 0m	21.37	−69.55	Good

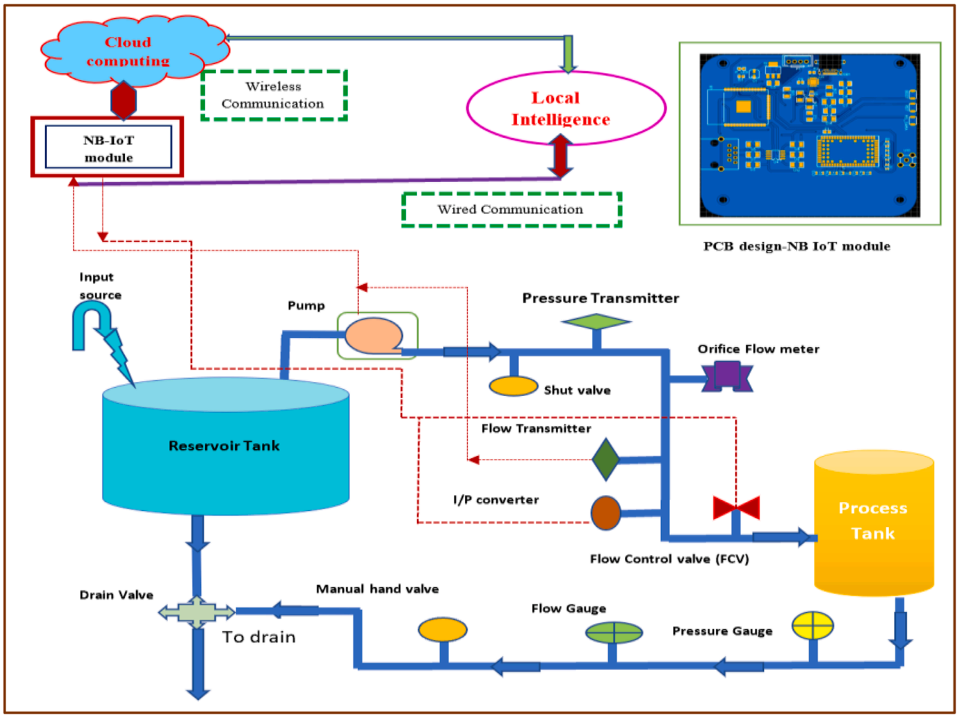

Fig. 5. Interfacing the NB-IoT module with the fluid transportation system.

the architecture of the NB-IoT module with the transmission of data from the base station to the cloud.

To evaluate the performance of the NB-IoT module, the nodes are assigned at different locations which are away around 300m from the base station. Since the hardware setup is 15m long, the first node is placed at 0m, then it continues with 3m, 9m, 12 m and finally 15m respectively in the fluid transportation system zone. From the Cumulocity testing platform, the SNR (Signal to Noise ratio) and RSSI (Received Signal Strength Indicator) value of the deployed IoT module is measured for 5 hours and given in Table 1.

From Table 1, it is confirmed that the RSSI value shows the estimated measure of power level that a client device is receiving from an access point. At larger distances, the signal gets stronger and the wireless data rates get higher, leading to higher overall data throughput. SNR value directly impacts the performance of a wireless LAN connection. A higher SNR value means that the signal strength is stronger concerning the noise levels, which allows higher data rates and fewer retransmissions. The obtained SNR and RSSI values show that the installed NB-IoT system at a fluid transport system provides good connectivity to satisfy the IoT application requirements in outdoor environments for different location levels.

4.1. Interfacing of iot module with the sensors in the experimental setup

Fig. 5 gives the interfacing of experimental hardware with the NB-IoT module along with the top view design of the PCB design of the NB-IoT module. An NB-IoT module is interfaced at the station which receives data from the pressure and flow rate transmitter which is operated through local intelligence using the LQR-PID controller with SCADA. In the IoT front end operator interface, the pressure transmitter data is labeled as IP1 and flow rate data is assigned as IP4. In the experimentation, only two field parameters such as pressure from the boosting station and flow rate from the final delivery station are acquired for remote monitoring and control purposes.

In the IoT module, the analog current input port of AC1 is conFig.d to receive the pressure transmitter signal and AC4 is assigned to acquire flow transmitter data which is then transmitted to the cloud for storage and analysis. The digital output port of DO2 is

Table 2
Open-loop response analyses of Pressure and flow for a different level of control valve openings.

Percentage of control valve opening (in %)	Flow rate (in lph) (Liters Per Hour)	Pressure (in kg/cm^2)
10	179	2.20
20	230	1.92
30	373	1.83
40	468	1.71
50	585	1.48
60	757	1.21
70	919	0.91
80	1137	0.55
90	1429	0.36
100	1792	0.22

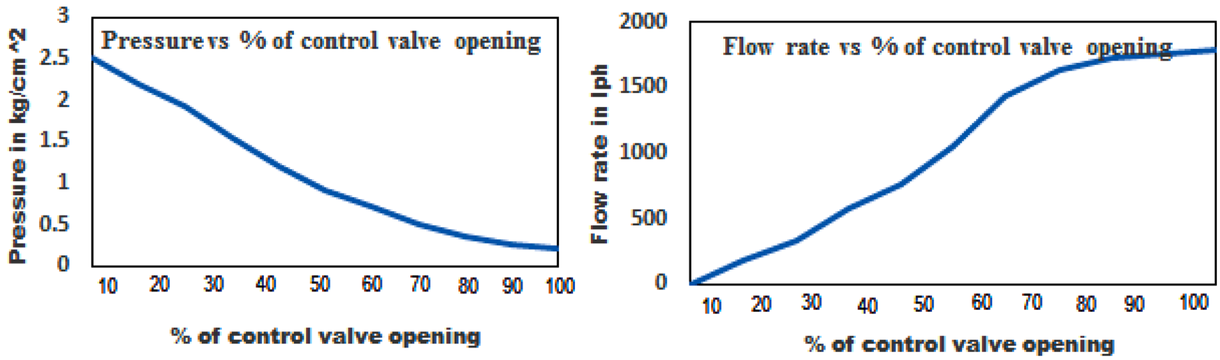

Fig. 6. Real-time recorded pressure and flow rates of the fluid for the different level of control valve opening.

Table 3
Recognized model parameters of fluid transport system from real-time experimental data.

Percentage of control valve opening (%)	Flow rate			Pressure		
	k_p	$\tau_p(s)$	$\theta(s)$	k_p	$\tau_p(s)$	$\theta(s)$
20	0.329	11.941	7.91	**1.681**	4.95	**13.58**
40	0.485	**8.317**	12.83	1.364	6.43	22.84
60	**0.914**	9.084	15.72	1.649	**4.026**	35.59
80	0.046	13.51	9.89	1.024	9.88	21.91
100	0.871	17.46	**5.16**	0.995	14.32	29.92

Note: Bold values indicates the worst case model based parameter value.

programmed to get activated during an emergency shut off enabled condition. This DO2 digital output relay directly makes the interfaced pump to an off state by disabling the local intelligence functioning at the field station.

5. Performance analysis of LQR-PID controller with scada in pressure and flow control

In the fluid transport system, the flow rate and pressure are maintained by adjusting the opening and closing of the control valve. Hence to develop the mathematical model of the fluid transport system, a transient response curve is recorded by regulating the control valve opening to acquire the equivalent pressure and flow rate changes on the pipeline in the open-loop structure. The open-loop test run is carried out by linearly adjusting the percentage of control valve opening (i.e. from 10% to 100% opening of the control valve) [8]. This open-loop experimentation reveals the pressure of the fluid is at a maximum rate with minimum flow rate when the opening of the control valve is around 10% of the overall opening and vice versa when the control valve opening reaches its full stretch of 100%. It is inferred that the initial flow rate of 179 lph and pressure of 2.2 kg/cm^2 is obtained during a 10% opening of the control valve and continuous readings were documented which is given in Table 2. The result reveals that for 100% control valve opening the maximum flow rate and pressure accomplished are 1792 lph and 0.22 kg/cm^2. The real-time open-loop readings of pressure and flow were noted for the percentage of control valve opening through the CENTUM VP platform is displayed in Fig. 6. From Table 2, the first-order model considerations (process gain k_p and process time constant τ_p) of the fluid transport system parameters of pressure and flow rate are given in Table 3.

From Table 4, the worst-case model with the leading process gain and lowest time constant are selected to represent the process model. Since it shows the parameter variations holding non-linear characteristics, First Order Plus Time Delay (FOPTD) transfer

Table 4
ZN-PID controller tuning parameters with values.

Tuning Rules	Tuning Parameters for pressure					Tuning Parameters for flow rate				
	k_c	τ_i (s)	τ_d (s)	k_i= (k_c/τ_i)	k_d= (k_c*τ_d)	k_c	τ_i (s)	τ_d (s)	k_i= (k_c/τ_i)	k_d= (k_c*τ_d)
$k_c = \frac{a\tau p}{\theta Kp}$; a∈ [1.2,2] $\tau_i = 2\theta$ and $\tau_d = 0.5\theta$	1.896	1.263	0.159	1.501	0.303	1.849	3.771	1.421	0.4903	2.629

Where k_c is controller gain and τ_i, τ_d indicates the integral and derivative gain.

Table 5
IMC-PID controller parameters.

Controller	Tuning Parameters for pressure					Tuning Parameters for flow rate				
	k_c	τ_i (s)	τ_d (s)	k_i= (k_c/τ_i)	k_d= (k_c*τ_d)	k_c	τ_i (s)	τ_d (s)	k_i= (k_c/τ_i)	k_d= (k_c*τ_d)
IMC-PID controller	1.765	12.73	0.448	0.1385	0.791	1.896	3.468	2.377	0.5466	4.508

function ($G(s) = \frac{Kp}{\tau pS+1}e^{-\theta s}$) model is used to represent the pressure and flow rate maintenance of fluid transport system, wherek_p = process gain, τ_p = time constant and θ = process delay. The identified FOPTD model for the flow control loop from Table 4 is represented as,

$$G(s) = \frac{0.914}{8.317s + 1}e^{-5.16s} \tag{1}$$

Similarly, the FOPTD model for the pressure control loop from table 4 is exemplified as,

$$G(s) = \frac{1.681}{4.026s + 1}e^{-13.58s} \tag{2}$$

The system model identification is developed from the real-time experimental data obtained from the fluid transport system in open-loop performance analysis by varying the control valve opening [9].

5.1. Robust controller design

The PID controller serves as one of the popular and extensively applied controllers in the industrial sector due to its simplicity, robustness and wide applicability to near-optimal performance. Even though innovative control techniques can deliver substantial improvements, a well-tuned PID controller has been determined to be suitable for an enormous quantity of engineering control loops [10]. A PID type controller is used to optimize the performance of the control valve to regulate and uphold the pressure and flow rate of the fluids being transported in the pipeline system.

5.1.1. Ziegler–Nichols PID (ZN-PID) Controller

The Ziegler–Nichols PID (ZN-PID) Controller is the most commonly used heuristic method of tuning a PID controller in all the industrial feedback control applications. The ability to predict future errors in the process is possible in the PID controller, meanwhile, it can eliminate oscillations and can decrease the rise time in the performance. Since the process is modeled as FOPDT (First Order process with Dead Time), hence the implementation of the ZN-PID controller is the benchmark of conventional techniques used for the comparative purpose [11]. The parameters of the ZN-PID controller are shown in Table 4.

5.1.2. Internal mode control PID (IMC-PID) controller

The effectiveness of the internal model control (IMC) design principle has made it attractive in the process industries, where the Direct Synthesis for the disturbance (DS-d) method proposed by Edgar and Seborg, by obtaining the PI/PID controller parameters by computing the ideal feedback controller which gives a predefined desired closed-loop response. This closed-loop tuning method overcomes the shortcoming of the well-known Ziegler Nichols continuous cycling method and gives consistently better performance and robustness for a broad class of the process [12]. The resulting tuning rules for the PID controller based on Internal Mode controller design criteria is given as,

$$k_c = \frac{\alpha}{k_p(2\tau_i - \alpha + \theta)}; \tau_i = \alpha; \tau_d = \tau_2 \tag{3}$$

Where k_c is controller gain,τ_i is integral time and τ_d is derivative time. The value of α (non-minimum phase element) is selected so that it cancels out the pole at s=−1/τ and the value of α is obtained as

$$\alpha = \tau\left\{1 - \left(1 - \frac{\tau c}{\tau}\right)^2 e^{-\frac{\theta}{\tau}}; \quad \tau_c = 2\theta\right. \tag{4}$$

By using this tuning, it is possible to get the enhanced disturbance rejection performance by adjusting the single tuning parameter of

Table 6
LQR-PID controller parameters.

Controller	Tuning Parameters for pressure			Tuning Parameters for flow rate		
	k_c	k_i= (k_c/τ_i)	k_d= $(k_c{*}\tau_d)$	k_c	k_i=(k_c/τ_i)	k_d= $(k_c{*}\tau_d)$
LQR-PID controller	0.841	0.602	1.024	4.934	1.567	2.641

the controller [13]. The important feature of this controller is that it deals with the nonlinear and stable process in a unified way. The parameters of the IMC-PID controller are shown in Table 5.

5.2. Linear quadratic regulator (LQR-PID) controller

Linear Quadratic Regulator (LQR) control theory is well recognized for the modern optimal control with assured robustness property. The LQR method is an efficient procedure for creating controllers for a complex process plant having tedious control requirements that seek to catch the optimal controller that reduces a plant cost function [14]. Consider the first-order model of the validating fluid transport system as in the form

$$\mathrm{G(s)} = \frac{b}{\mathrm{cs+a}}e^{-\mathrm{Ls}} = \frac{0.914}{8.317\mathrm{s}+1}e^{-5.16\mathrm{s}}(\text{for flow}) \tag{5a}$$

$$\mathrm{G(s)} = \frac{b}{\mathrm{cs+a}}e^{-\mathrm{Ls}} = \frac{1.681}{4.026\mathrm{s}+1}\mathrm{e}^{-13.58\mathrm{s}}(\text{for pressure}) \tag{5b}$$

From the developed transfer function for pressure and flow, the corresponding values to the coefficients of a, b and c can be obtained from equation 5a &5b. A PID controller can be represented as

$$u(t) = K_p\left(e(t) + \frac{1}{T_i}\int e(t)dt + \tau_d\ d(e(t))\,/\,dt\right) = K_P e(t) + K_i\int e(t)dt + K_d de(t)/dt \tag{6}$$

When$t \geq L$, this flow and pressure control system has a possible non zero input signal. Here L becomes system time delay. Where A, B, C are the specified matrices with suitable dimension, $Q \geq 0$ and$R > 0$ with F is a gain matrix for pressure and flow control loop [15]. The closed-loop system matrix A_c for DCS fluid transport system becomes to obtain gain values of PID the controller is

$$A_c = A - BF = \begin{bmatrix} 0 & a^2 + \left(R^{-1}c^2q_3 + p_{21}q_2b\right)p_{12}c \\ -\dfrac{b^2\left(ac^2 + R^{-1}bc + p_{21}p_{22}a^2c\right)}{b^2c} & -R^{-2}a^2p_{11} \end{bmatrix} = \begin{bmatrix} 0 & d_1 \\ d_2 & d_3 \end{bmatrix} \tag{7}$$

To obtain feedback gain, its necessity to calculate exp(Act) using inverse Laplace transformation [51,52] hence

$$\exp(\mathrm{Ac}\ t) = l^{-1}(sI - \mathrm{Ac}\ )^{-1} \tag{8}$$

After calculating exp(Act) and then multiplying with corresponding gain matrix F of flowrate and pressure, the corresponding LQR optimal tuning value k_p, k_i and k_d for PID controller when$t \geq L$ is calculated using Eq. 7

$$\begin{aligned} &K_p(t) = R^{(-1)}(b+c)/d_1d_3], K_i(t) = R^{(-1)}c^2d_2, \\ &K_d(t) = R^{(-1)}\frac{c}{ba}\left(\frac{d_1d_2}{d_3}d_1\right), \end{aligned} \tag{9}$$

Then the final form of the PID controller structure as given in Eq. 8 with gain values attained from Eq. 9 is

$$u(t) = 0.841e(t) + 0.602\int e(t)dt + 1.024de(t)/dt\,\textit{for the pressure control loop}, \tag{10}$$

$$u(t) = 4.934e(t) + 1.567\int e(t)dt + 2.641de(t)/dt\,\textit{for the flowrate control loop} \tag{11}$$

The corresponding values of k_c,k_i and k_d are determined for a flow and pressure control of a fluid transport system of DCS plant obtained from Eq. 10 and 11 are given in Table 6.

5.3. Real-time experimental analysis in a DCS plant

The LQR-PID controller performance is experimentally validated in real-time on a lab-scale experimental set up of the fluid transport system by comparing with IMC, ZN-PID controllers. The resultant tuning values of the PID controller using the LQR technique are confirmed through simulation and are put on to the created operator interface tune window using CENTUM VP. The DCS plant is

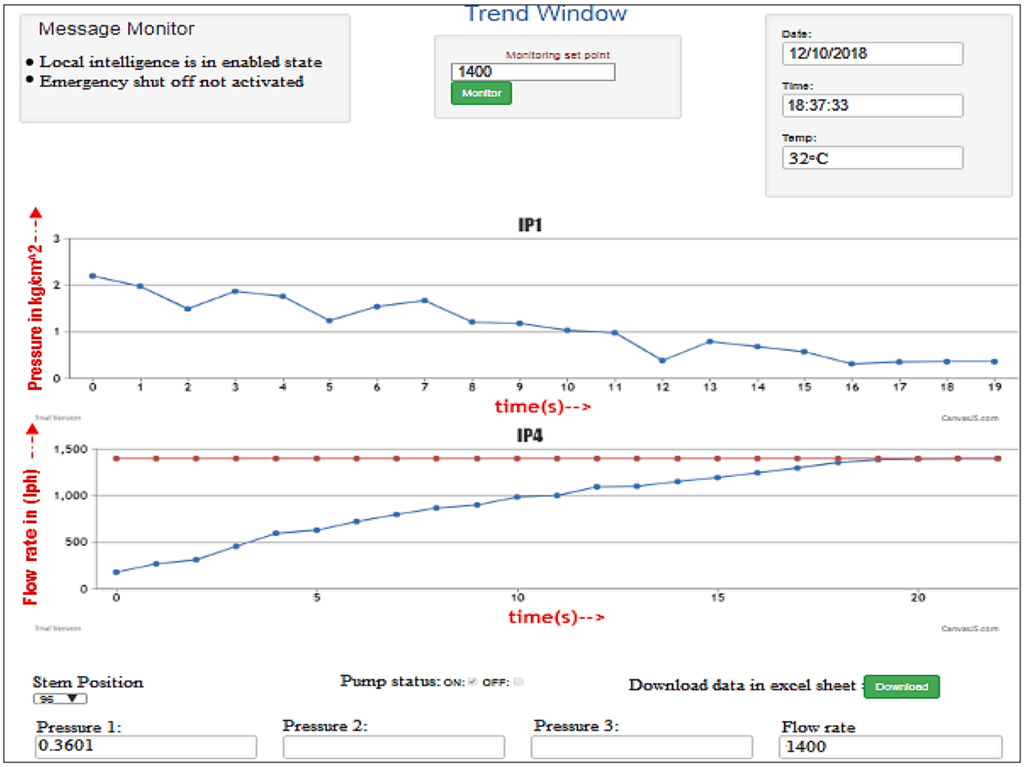

Fig. 7. Real-time monitoring and control of pressure and flow using a Local Intelligence at a field control station.

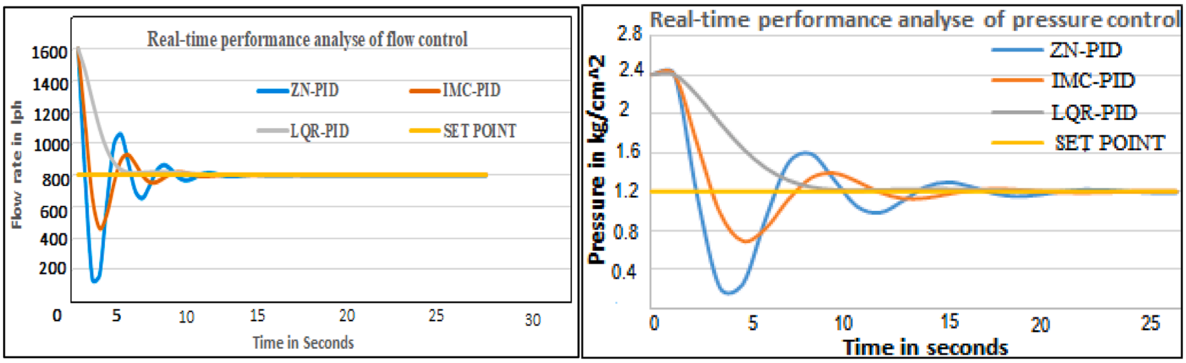

Fig. 8. Real-time performance analyses of pressure and flow rate using ZN, IMC and LQR-PID controller.

put to run by enabling the auto mode initiated by the operator when the setpoint for pressure and flow rate is given in the corresponding pressure and flow rate faceplate present in the SCADA front end panel.

After fixing the required operating range, the pump will be on track to run which is enabled by an operator remotely. The real-time successive data of both pressure and flow rate parameters of the fluid being transported is displayed continuously in the created trend view window in PIC100.PV/ FIC100.PV tag tab is present below the trend graph and these data can be exported to excel by enabling the local utility data box option as shown in Fig. 7. The real-time performance analyses by ZN, IMC and LQR-PID controller on monitoring and control of pressure and flow rate in the DCS plant of the fluid transport system are conducted by fixing the setpoint of pressure and the flow rate is given as 1.2 kg/cm^2 and 800 lph respectively. The validated controller performances readings are taken along with controller output signals are shown in Fig.s 8, 9 and its corresponding time integral performance criteria are tabulated as seen in Table 7.

Based on the operating setpoint of pressure and flow rate, the implemented controller running on the back end of the SCADA adjusts the feedback signal going from the remote master control panel to the I/P converter incorporated with a corresponding control valve to regulate its opening and closing installed on the process plant control loops.

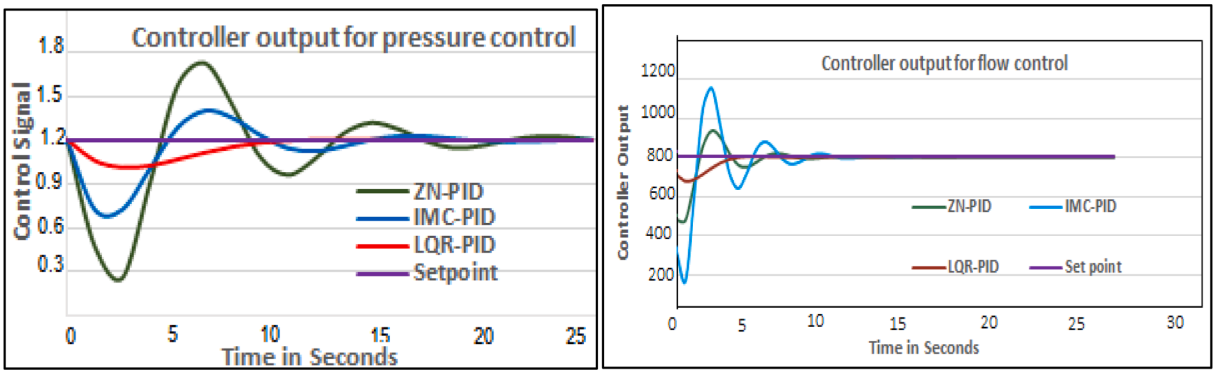

Fig. 9. Controllers output signals for pressure and flow control in the DCS fluid transportation system.

Table 7
Performance measures at the operating point of pressure at 1.2 kg/cm^2 and flow rate at 800 lph.

Performance Measures	Pressure ZN-PID	IMC-PID	LQR-PID	Flow rate LQR-PID	IMC-PID	ZN-PID
ISE	0.0923	0.0798	0.0374	0.02347	0.0521	0.0752
IAE	0.0725	0.0427	0.0249	0.0193	0.0296	0.0341
ITAE	0.03114	0.0275	0.0136	0.00952	0.018	0.0127
t_r (s)	5.34	4.057	2.01	4.871	6.32	8.34
t_s (s)	24.02	19	12	10.27	12.621	18.241
%M_p	21.03	15.68	Nil	Nil	12.38	19.937

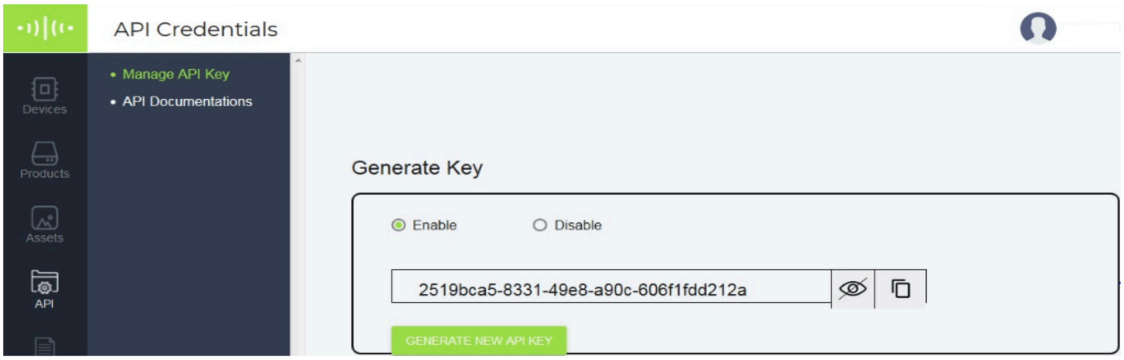

Fig. 10. The API key for used Bolt IoT Wi-Fi device in the smart IoT module.

The real-time experimentation discloses that the LQR-PID controller accomplishes better results by its settling time of 12 seconds (for pressure loop) and 10.27 seconds (flow loop) than ZN, IMC-PID controller by comparing error indices in regulating the control valve to maintain pressure and flow rate. When the percentage of control valve opening gets increased, the field parameters such as pressure and flow rate of the fluids passing through the pipelines get decreases and increases consistently. The developed LQR-PID controllers confirm the enhanced performance of 26.2% by its connectivity and interoperability possessing minimum error indices and highest robustness. But, the SCADA with the LQR-PID controller cannot offer timely control action when the pressure and flow rate undergoes sudden rise or drop due to fault occurrences. This is because the SCADA could not able to process numerous sensor data on the database management resulting in delayed data communication [16]. This causes time delay to activate the emergency shut off during crack or leakages in the oil pipeline. The existing SCADA system can able to handle the field control action only when the monitoring parameters subjects to minor deviations from the threshold point of ±0.65 variations. To sort out these issues, SCADA with IoT application is proposed in which the same data are simultaneously sent to the cloud through the NB-IoT module as proposed in section 4. During abnormal changes of pressure and flow rate caused by cracks and leaks in the transportation system, the IoT module associated with the IoT operator interface handles the decision-making functions.

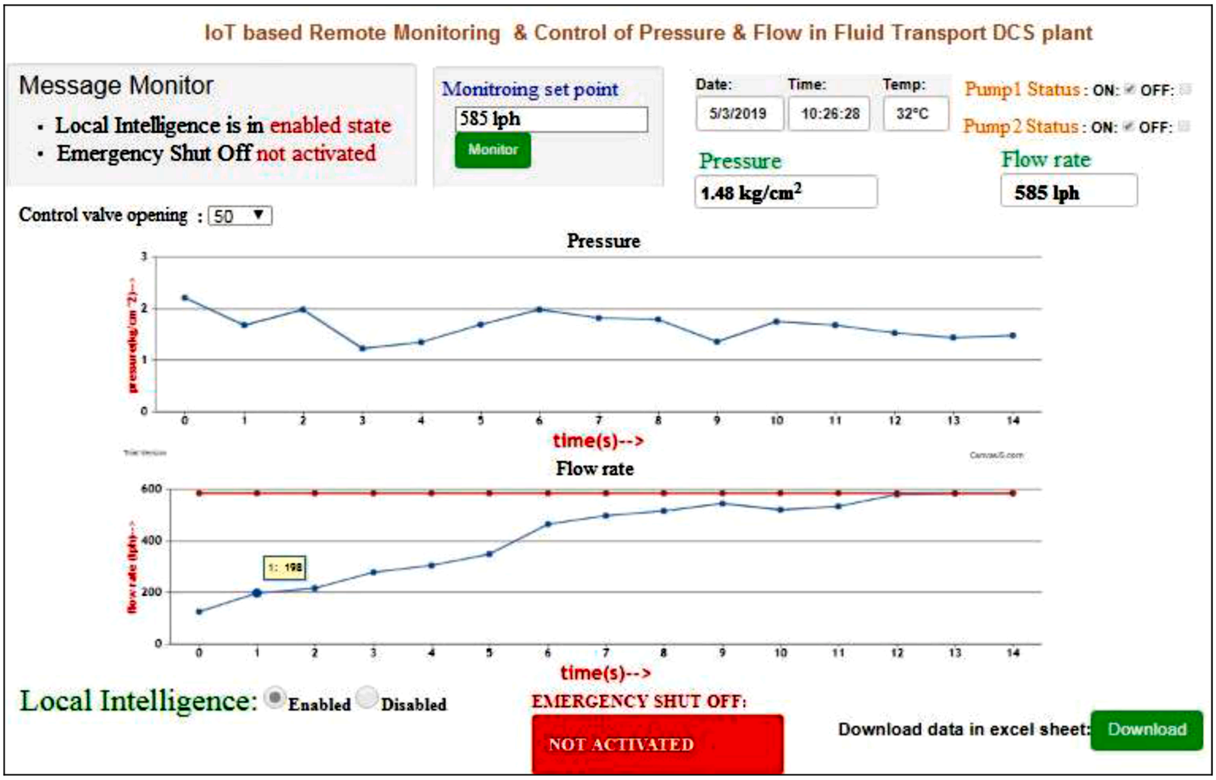

Fig. 11. IoT front end panel to monitor and control pressure and flow rate remotely.

Table 8
Configuration of pressure and flow rate variable in IoT operator interface.

Fluid transport pipeline station Manipulating parameters	Pressure	Flow rate
Upper limit	2.35 kg/cm^2	-
Lower limit	0.15 kg/cm^2	-
Label notation in IoT front end	IP1	IP4
Input port configuration in IoT module	AC1	AC4
Emergency shutoff activating output port in IoT module	DO2	

6. Performance evaluation of IoT application in fluid transport system

The developed IoT architecture application layer exhibits the data analysis with monitoring and control applications. It is accomplished by designing SCADA with the PID controller as local intelligence and cloud server as a centralized database along with cloud computing techniques to proactively decide and react promptly.

The data processing algorithms like K-means clustering running on stored cloud data will perform online control actions (fire alerts, shut down of different equipment, identifying the exact location and rectifying the fault, operator alerts) against risk events like oil pipeline crack, bursts, etc., [17]. Figs. 10 and 11 shows the created IoT front interface for DCS fluid transport plant comprising of trend visualizing the real-time parameters' values along with pump status for each pressure and flow rate control loop using API key. Table 8 gives the limit for manipulating pressure variable acquired during crack and leak in the pipeline done manually to observe maximum and minimum ranges along with its notation on the IoT interface of input and output ports. Since pressure is the main attribute taken for data analysis, its threshold limit values alone are given in the configuration table.

The main emergency shut off control is provided in this cloud server gets activated by stopping the pumps when the local intelligence fails to respond at the appropriate time during crack or leakage or burst in the pipeline during fluid transportation. The message monitor displays the enabled and disabled status of emergency shutoff and local intelligence associated with the DCS plant. Through the incorporation of IoT with the validated local intelligence (LQR-PID controller with SCADA), hardware configuration gets synchronized with the flexibility of software customized application to the DCS plant to provide monitoring and control capabilities online from a remote location [6].

To compare the performance of SCADA with the LQR-PID controller and IoT with local intelligence, the Cumulocity software

Table 9
Performance comparison of SCADA with LQR-PID and IoT with local intelligence.

Parameters	Local intelligence without IoT	local intelligence with IoT
Time is taken to transmit received data to the processing station	69µs (microseconds)	24 µs(microseconds)
Time is taken to identify the abnormality	≥ 84µs (microseconds)	≤ 13µs (microseconds)
Time is taken to activate the shutoff	17µs (microseconds)	9µs (microseconds)
Data storing time	11µs (microseconds)	5µs (microseconds)
Control signal initiating time	≤ 19µs (microseconds)	≤ 6µs (microseconds)

Table 10
Final cluster centers information regarding pressure attributes during normal condition.

Pipeline station	Final Cluster		Distance between final cluster centers	
	Cluster 1	Cluster 2	Cluster 1	Cluster 2
pressure	1.8572	.4689	0.096	0.096

Table 11
Final cluster centers information regarding pressure attributes during abnormal condition.

Pipeline station	Final Cluster		Distance between final cluster centers	
	1	2	Cluster 1	Cluster 2
pressure	2.1572	0.1886	1.982	0.237

testing platform is utilized. By interfacing each data processing execution flow chart to compute the time taken to complete the task is given in Table 9. The obtained results show that proposed research on IoT with SCADA has taken only 24µs (microseconds) to process each acquired data with fast activation of alert signals with a duration of 17µs (microseconds) respectively.

6.1. K-means clustering machine learning to identify abnormal pressure variations in the cloud stored data

In the cloud storage, to identify abnormal pressure rise and drop caused by the fault in the fluid pipeline system, the K-means clustering machine learning technique is implemented. K-means clustering belongs to hard or exclusive clustering in which each data point be appropriate to precisely one cluster with no more uncertainty in the orientation of cluster membership formulation [18–21]. Each data item in the evaluating database is allotted to only the cluster which possesses the maximum priority of similarity. The optimization model of K-means which incorporates intra-cluster compactness points to the statistics of dispersions and inter-cluster separation gives the distances between different clusters is summarized as

$$P(U,W,Z)=\sum_{p=1}^{K}\sum_{q=1}^{K}\sum_{j=1}^{m}w_{p,q,j}D_{p,q,j}+\gamma\sum_{p=1}^{K}\sum_{q=1}^{K}\sum_{j=1}^{m}w_{p,q,j}\log\left(w_{p,q,j}\right) \tag{12}$$

$$D_{p,q,j}=\sum_{i=1}^{n}u_{i,p}\left[\left(x_{i,j}-z_{p,j}\right)^{2}-\beta\left(z_{p,j}-z_{q,j}\right)^{2}\right] \tag{13}$$

$$\text{Subject to}\begin{cases}\sum_{p=1}^{k}u_{i,p}=1,u_{i,p}\ \in\{0,\ 1\}\\ \sum_{j=1}^{m}w_{p,q,j}=1,0\leq w_{p,q,j}\leq 1.\end{cases} \tag{14}$$

Where X={X_1, X_2,.......X_n} be an input of n data set, Z= {Z_1,...Z_K} is a group of k vector, $w_{p,q,\ j}$ is the weight of the features, γ - features weight optimizing parameter, β -intra-cluster firmness and inter-cluster separation are contributing parameter, p, q represent cluster groups [22].

X={X_1,X_2,.......X_n} be an input of n data set characterized by X_i={$x_{i,1}$,$x_{i,2,...,}$$x_{i,m}$}with m features. u is a membership matrix of n × k with $u_{i,p}=1$by denoting the feature assigned to cluster p otherwise it will not be grouped to cluster p. Z= {Z_1 ...Z_K} is a group of k vector indicating the centroid of k clusters and $w_{p,q,\ j}$ is the weight of the features j in cluster p while comparing cluster p with q, as always p≠q. The parameter γ is to optimize the allocation of features weight in each cluster and parameter β regulates the scheme of intra-cluster firmness and inter-cluster separation [23–25]. The software computing K-means includes the method of clustering data groups with minimum intra-cluster firmness and maximum inter-cluster segregation to enhance the strength of forming clusters on the implied data. Table 10 gives the pressure range statistical analysis during fluid transported in the pipeline showing normal performance.

Table 10 provides the final cluster center points by showing the maximum rate optimal value where cluster formation terminated.

Table 12
ANOVA table for designed clusters based on pressure attributes in first-month data.

ANOVA- Oil Station	Cluster Mean Square	df	Error Mean Square	Df	F	Sig.
Pressure 4	55157.067	1	0.092	19017	59991.962	0.000

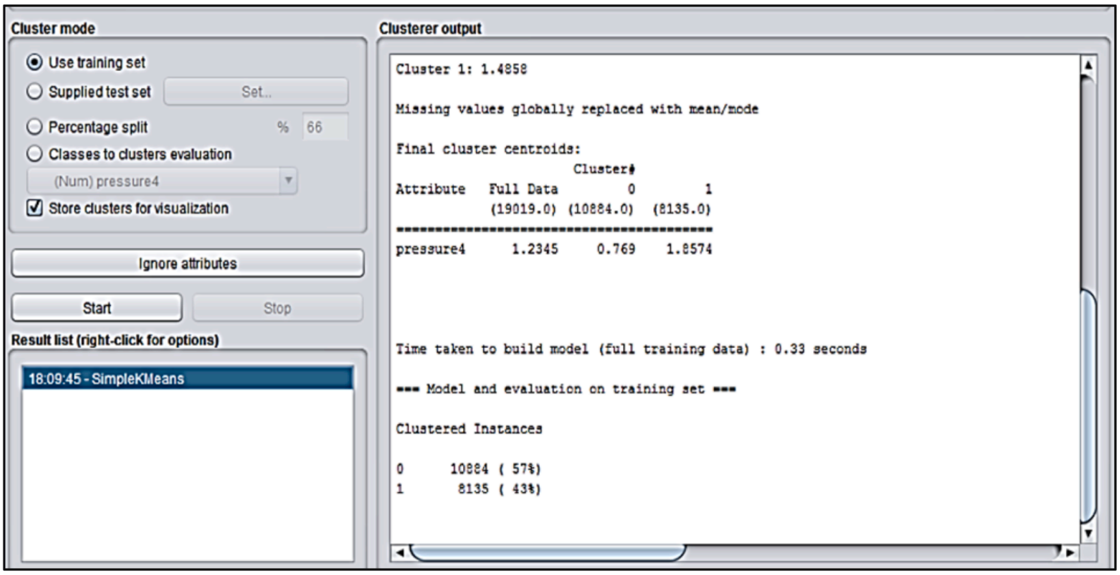

Fig. 12. Executing the K-means algorithm on pressure 4 attributes for first-month datasets of the oil station.

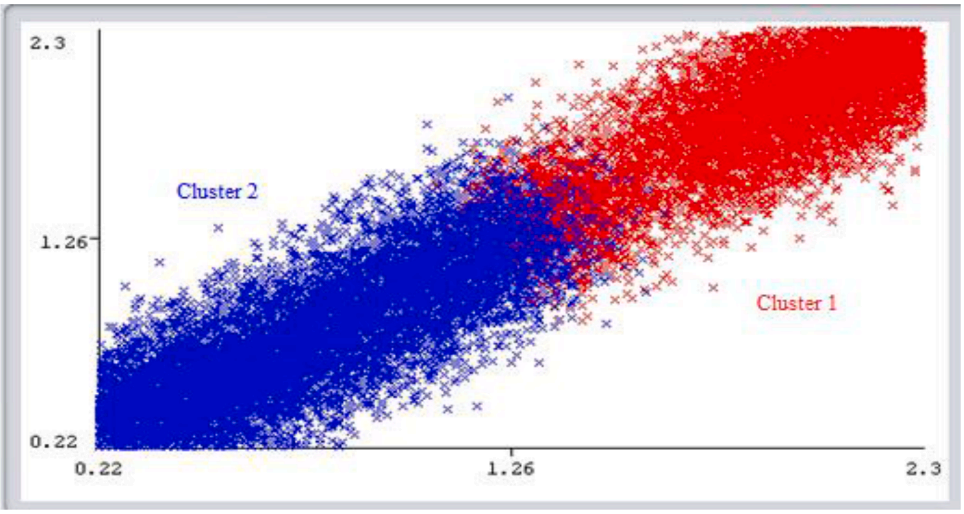

Fig. 13. Cluster formation for pressure during the normal performance (X & Y-axes are in kg/cm^2).

The final cluster centers conclude 1.8572–0.4689 kg/cm^2 for pressure correspondingly. Hence by this final cluster center data, the inspection engineer observes the pressure range variations to estimate normal and abnormal performance. In the obtained results of final cluster centers, all attributes are within the normal threshold limit pointing not the existence of any risk occurrence in the evaluated performance. Similarly, Table 11 gives the analysis result regarding pressure variation due to abnormality in the pipeline caused by leak during the long run passage. The obtained analysis inference confirms that the inspection engineer identifies that the pressure goes beyond the desired limit. Further, it ensures that the experimental run data of pressure data obtained during normal operating conditions summarized in Tables 2 and 3 coincides with the final cluster centers range. The ANOVA result shown in Table 12

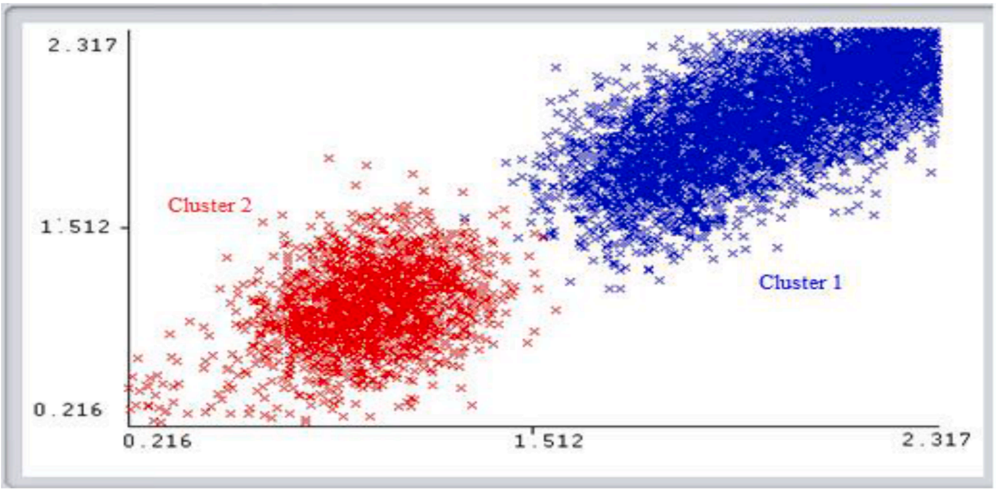

Fig. 14. Cluster formation for pressure during the abnormal performance (X & Y-axes are in kg/cm^2).

indicates the most prominent attributes constituting more contribution for the cluster solution can be identified by the cluster-based mean square value. Regarding the predominant contribution in sub-stations, only one parameter is considered to holds the mean square value of 55157.06 for pressure four labels. Meanwhile, the attribute with the uppermost F (F-statistics) value offers maximum separation between the cluster formations. In ANOVA table on pipeline station incorporates all the undertaken attribute holds maximum F value pointing the clusters well-oriented with more similarity data between the designed clusters with the rate of around 59991 for oil station.

The descriptive statistic summary output of the K-means clustering algorithm on a different bimonthly real-time database of pressure variables acquired from stations 1 and 2 is further validated by this software platform. In this platform, once the execution of K-means clustering has been completed on the given datasets, it is feasible to visualize clusters by utilizing the visualize cluster assignments option available in the results list as shown in Fig. 12. Figs. 13 and 14 shows the visualization of the final cluster result of Tables 10 and 11 showing the cluster assignment structure during the normal and abnormal performance by analyzing the pressure data using WEKA software.

Fig. 14 shows that two cluster groups have not coincided whereas most of the datasets accumulated in cluster 1 indicating regular operating performance whereas cluster 2 with minimum datasets figuring out the appearance of unusual sudden pressure drops occurred during transportation in the fluid pipelines. It can be concluded that if the processing historical pressure datasets are lying within the safer threshold limit, two clusters get overlapped pointing to normal transportation performance as seen in Fig. 13. In another case, if the pressure range were out of the threshold fit range indicates two clusters without overlap pointing to abnormal performance during transportation as shown in Fig. 14. On identifying occurred abnormal performance by K-means clustering algorithm, between the two separated clusters, the cluster with minimum datasets infers the abnormal pressure rises or drops existed during transportation. Hence by implementing K-means clustering on the historical datasets holding multiple pressure variables, it will be possible to identify the occurred pressure rises or drops at the early stage by proactively making a decision rather than before it leads to great losses in the surrounding circumstances.

7. Conclusion and future scope

The proposed SCADA architecture with the LQR-PID controller and IoT application provides better improvement in online monitoring and control of field parameters by overcoming the drawbacks of the SCADA system. The conducted experimental results of the NB-IoT module proves its excellent signal strength of data transmission with maximum throughput having SNR value > -60 dBm range. The real-time validation of the LQR-PID controller with the SCADA system offers better control action only when the field parameters show deviation with ±0.65 range of threshold range. But when the risk occurrences like crack and blockages exist in the pipeline, it undergoes abnormal deviation by exceeding the ±0.65 range of the threshold range. The designed local intelligence fails to act instantly which leads to great damage to human life and the environment. The incorporated IoT with local intelligence provides timely monitoring and control action by executing the k-means clustering machine learning technique to analyze the pressure abnormality. The performance comparison of SCADA with the LQR-PID controller and IoT with local intelligence using the Cumulocity software platform shows that the proposed architecture has taken only 24μs (microseconds) to process each acquired data with fast activation of alert signals with a duration of 17μs (microseconds) respectively. Further, the final cluster assignment statistical result of normal and abnormal pressure range of data analysis gets matched with the real-time threshold limit decided for a smooth transportation over a long distance.

Regarding the future work, the present experimented LQR-PID controller with SCADA as a local intelligence in an Internet of Things (IoT) based reliable monitoring and control modular architecture will be implied in real-time in the industrial oil pipeline system.

Advanced deep learning algorithms will be applied for data analysis to identify risk occurrences on the process plant.

Declaration of Competing Interest

All the contributors in this research work have no clashes of attention to announce and publishing this article.

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Priyanka E.B. received a doctorate in Mechanical Engineering from Anna University, Chennai, India. Currently she is an assistant professor in the department of Automobile Engineering, Kongu Engineering College, Erode. Her research interests are in the areas of IoT, Machine learning and data analytics.

Maheswari C. received her doctorate from Anna University, Chennai, India. Currently she is an associate professor in the department of Mechatronics, Kongu Engineering College, Erode. She has 12 years of experience in teaching. Her research interests are in the areas of PLC and Microcontroller.

Thangavel S. received his master's in Mechatronics from Kongu Engineering College, India. Currently he is an assistant professor in the department of Mechatronics, Kongu Engineering College, Erode. He has 6 years of experience in teaching. His research interests are in the areas of PLC, MEMS and IoT.

Ponnibala M. received her doctorate from Anna University, Chennai, India. Currently she is an associate professor in the department of Electronics & Instrumentation, Kongu Engineering College, Erode. She has 14 years of experience in teaching. Her research interests are in the areas of Biomedical and Instrumentation control.

Kalavathidevi T received her doctorate from Anna University, Chennai, India. Currently she is an associate professor in the department of Electronics & Instrumentation, Kongu Engineering College, Erode. She has 14 years of experience in teaching. Her research interests are in the areas of VLSI and Embedded system.

Sivakumar N.S. received his master's in Production Engineering from PSG college of Engineering, India. Currently he is an assistant professor in the department of Mechatronics, Tishk International University, Erbil. He has 10 years of experience in teaching. His research interests are in the areas of thermodynamics and IoT.