Slope stability monitoring system based on the ORLPStarNET IoT platform

A promising system for mining industries is deemed as a slope monitoring system (SMS). Additional benefits are possessed by the progression of wireless sensor network (WSN) along with Internet of Things (IoT) for real-time SMS. For observing slope failure (SF) in opencast mines (OCM), a low power, long-range (LoRa), along with an energy-effective solution are suitable. The mine officials along with workers become poorer as they could not have an enhanced smart mine monitoring system owing to severe environmental conditions of mines. For overcoming the existing challenge, a slope stability (SS) monitoring system is created by the work centered on the optimal routing low power star topology networking (ORLPStarNet) IoT platform. Optimal nodes are chosen by the work in a heterogeneous environment utilizing the prediction interval based Woodpecker Mating Algorithm (PI-WMA) technique for avoiding high energy consumption, storage limitation, regular disconnections, and limited bandwidth to gather the slope data. High throughput is attained with the selection of nodes followed by ORLPStarNet gateway networking. Then, the optimal routing of the path is performed utilizing balanced vector sparrow search algorithm (BVSSA) for data transfer. The problems linked with coverage, routing, cost, and loss of data are overcome by the developed gateway networking. Lastly, the data is saved into the IoT Cloud server. As of the server, the data is accessed by the mine officers, and the SS is monitored by them. For detecting slope collapse, the proposed framework system assists in examining the continual monitoring of the deformation, deformation rate (DR), along with inverse-velocity trends as revealed by the experimental analysis. Concerning throughput, the proposed one stays better when analogized to prevailing methods.

Keywords: Slope stability, internet of things, opencast mine, sensor node, prediction interval based woodpecker mating algorithm (PI-WMA), optimal routing low power star topology networking (ORLPStarNet), balanced vector sparrow search algorithm (BVSSA).

Mr. Banda Srikanth, Assistant Professor, University College of Engineering, Kakatiya University, Kothagudem, Telangana State, India. Email: bsrikanthiitkgp@gmail.com.

1.0 Introduction

A major problem in OCM is SS. For avoiding the loss of human life, mining equipment, and vehicles, SS should be observed in real-time [1, 2]. Shear strength along with tension governs the SS. The slope is more prone to failure or collapse when there is some movement or shifts, which could manifest as a natural disaster both locally and globally [3, 4]. Slope steepness, slope water content (which adds extra weight to the slope with decreased cohesive force), human activities namely riding heavy mine vehicles, slope surface fissures, blasting activities, uneven pit design, etc are the major factors that contribute to slope instability along with collapse [5]. More wireless systems are being created with the growing evolution of wireless communication [6, 7]. The growth of huge-scale deployment of traditional cellular networks namely 4G and also 5G (to be launched by 2020), ZigBee, Bluetooth, along with Wi-Fi has been compelled by the urge to connect more gadgets within the IoT [8]. Besides, IoT has been interrupted by these prevailing low-power LoRa wireless technologies namely LoRa, Sigfox, low power wide area networks (LPWAN), LTE-M, along with NB-IoT [9]. However, cost constraints are faced by these existing technologies for set-up and it requires complex infrastructure installation [10]. For conquering the existing problem, a SS monitoring system is generated by the work centered on the ORLPStarNet IoT platform to monitor SS via IoT.

This paper is systematized as: Section 2 explores the associated works regarding the proposed work. Section 3 proffers the proposed work's brief elucidation. Section 4, proffers the experimental result. Section 5 exhibits the conclusion.

2.0 Literature survey

Devendra Kumar Yadav et al. [11] offered a LoRa framework for the IoT which had attracted sample consideration as of the society recently. Low power, LoRa, along with an energy-effective solution was offered by LoRa for monitoring SF in OCM. Therefore, the LoRa's coverage range and the capacity in open space were concentrated by LoRa. The results attained revealed that for delivering the mining sector's needs, LoRa could be deemed as a suitable solution. An SMS was created which proved to be effective for the mining industry centered upon LoRa's flagship features. However, one node failure highly impacted the Mesh network approach.

Marc Elmouttie et al. [12] proffered a systems engineering approach for designing the SMS. The rock engineering systems approach was utilized by the methodology for geotechnical engineering issues. The system theoretic process analysis approach's application was followed that modelled the control system for monitoring the system and recognizing along with mitigating sub-optimal configurations. For designing along with applying SMS, the approach was practical to apply and support transparent along with defensible decisions. The approach was better; however, it did not focus upon the coverage issue.

Devendra Kumar Yadav et al. [13] stated that the WSN was a creative tool for observing the tangible environmental structures that sensed the differences, processed the raw data, as well as communicated the outcome to the web. As of the web, it could well be suggested for researches along with predicting mechanisms. For communicating the sensed along with processed data as of the sensors towards the application, IoT was helpful. Here, the data could well be further examined. Furthermore, a more organized, robust, energy-effective, cost-efficient real-time monitoring scheme was created by the combined operation of WSN with IoT for detecting SF. However, for climatic disorders, the approach was not much robust.

3.0 Proposed slope stability monitoring system via IoT

Utilizing ORLPStarNet, a real-time slope monitoring architecture is proffered as exhibited in Fig.1.

3.1. Sensor node data collection

Using a sensor located at the mining location, the data centered on the SS is gathered.

3.2. Node selection

Over numerous networks, the traffic in the IoT has been routed. Every node is connected to the Internet by the IoT through physical items combined with different kinds of intelligent sensors. Huge amounts of data are created by a considerable number of IoT nodes that make daily living easier, helps in making hard decisions, and offer helpful services to consumers. Probably, one among the most popular networking technologies is IoT. It has the capability of offering numerous benefits. Message delivery latency stays a vital measure that must be decreased as the nodes in the networks are often delay-tolerant. The algorithm began by choosing nodes using a PI-WMA for addressing the current difficulties. The search space is ameliorated by the devised node selection approach via balancing the exploration along with exploitation phases. The lower and upper bounds of Random running away are assessed by the suggested approach and it adjusts the balancing rate utilizing prediction intervals. Centered on a meta heuristic algorithm, the node selection is done that imitates the woodpecker mating behaviour. It is enthused by the intensity of the drumming sound. Centered on numerous characteristics of the sample population of woodpeckers, the selection is done. Residual energy of the nodes (N_{res}), proximity (N_{prox}), distance to the base station (N_{db}), cost (N_{cost}), along with node centrality or coverage (N_{cov}), etc. are the features utilized. The node is selected by taking a weighted sum approach ($\Re_i$) for disparate features and creating into one scalar objective function, which is presented as:

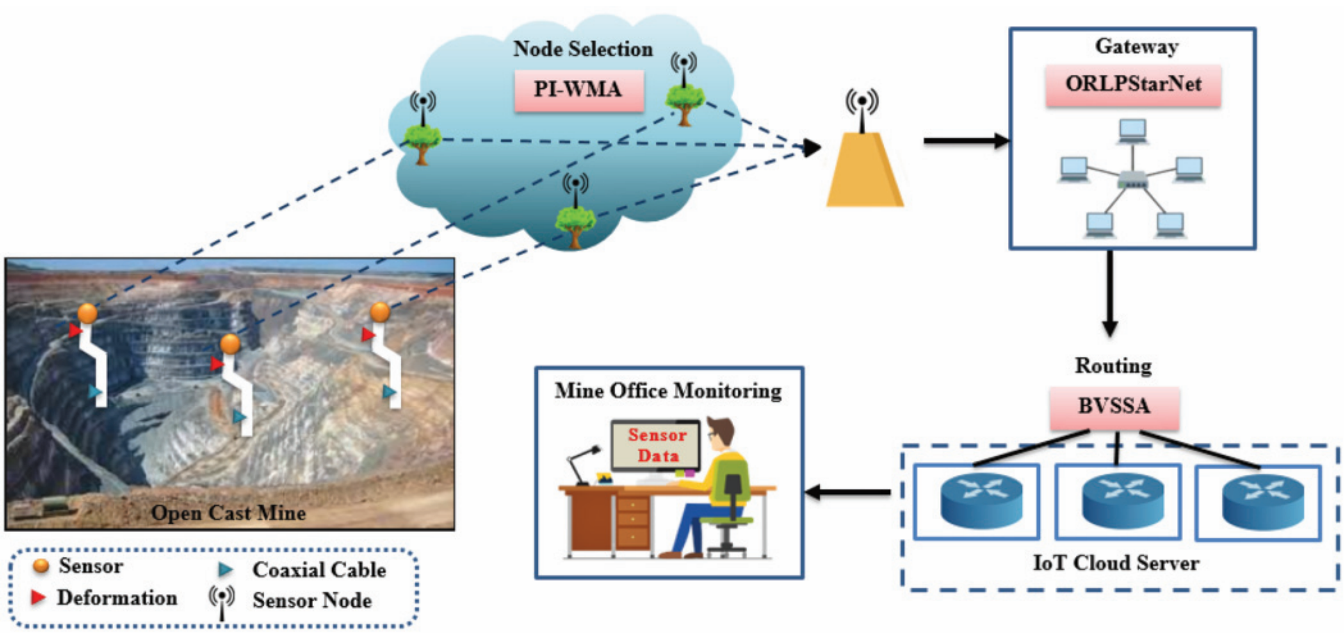

Fig.1: Proposed slope stability monitoring system via IoT

$$O_{fitness} = \Re_1 \times \mathrm{N}_{prox} + \Re_2 \times \mathrm{N}_{\cos t} + \Re_3 \times \mathrm{N}_{res} + \Re_4 \times \mathrm{N}_{\mathrm{cov}} + \Re_5 \times \mathrm{N}_{db} \quad \text{... (1)}$$

i.e.,

$$O_{fitness} = \Re_1 \times \frac{1}{N_T}\sum_{i=1}^{N} P_{prox}(N_i) + \Re_2 \times \frac{1}{N_T}\sum_{i=1}^{N} N_{\cos t}(N_i) + \Re_3 \times \sum_{i=1}^{N}\frac{1}{N_T} + \Re_4 \times \frac{1}{N_T}\sum_{i=1}^{N}\frac{\sqrt{d_{db}(S_i, N_i)}}{network\ \mathrm{dim}ension} + \Re_5 \times \frac{1}{N_T}\sum_{i=1}^{N} d_{db}(S_i, N_i) \quad \text{... (2)}$$

Wherein, $\Re_1+\Re_2+\Re_3+\Re_4+\Re_5=1$. Maximizing the value of the fitness is the PI-WMA's objective.

$$\chi_{objective} : Maximize\ O_{fitness} \quad \text{... (3)}$$

The position of each wood pecker is calculated utilizing,

$$N_i^{t+1} = N_i^t + r * \frac{\Im_i^t * \left(\beta_{pop} * \left(N_{pop}^t - N_i^t\right) + \beta_{mj} * \left(N_{mj}^t - N_i^t\right)\right)}{2} \quad \text{... (4)}$$

Wherein, N_i^{t+1} and N_i^t implies the updated and previous position of the woodpecker, r signifies the random value, $\Im_i^t$ indicates the random coefficient for the i^{th} feature in t^{th} iteration, β_{pop} and N^t_{pop} implies the populace of woodpeckers and best solution amongst the population, N^t_{mj} signifies the male woodpecker's position at t^{th} iteration.

As the number of iterations augments, the populace of male woodpeckers in the algorithm's iteration cycle reduces linearly. A minimum population of one woodpecker is possessed by the male woodpeckers, which is the β_{pop}.

$$N_i^{t+1} = N_i^t + r * \Im_i^t * \left(\beta_{pop} * \left(N_{pop}^t - N_i^t\right)\right) \quad \text{... (5)}$$

Due to sound overlap, the attraction of female woodpeckers is improper. The global search space is increased by the search space which changes arbitrarily. This results in a high convergence rate. For addressing this issue, prediction intervals are utilized by the method centered on runway running away (RRA). Initially, for female woodpeckers, the threshold is decided.

$$\begin{aligned}
T_\beta &= 0.8 * \frac{\sum_1^{n-1} \beta_{pop}^i}{n-1} \\
\beta_{pop}^i &= \frac{1}{1 + sI_j^i} \\
N_{RRA}^i &= l_b - (l_b - u_b) * r \\
l_b &= \eta - z\sigma \\
u_b &= \eta + z\sigma
\end{aligned} \quad \text{... (6)}$$

Where, T_β implies the threshold for the β_{pop} sound intensity, sI^i_j denotes the sound intensity of the target woodpecker (j), β^i_{pop} indicates the probability attraction of male woodpecker j for woodpecker i, N^i_{RRA} signifies the position of a new element attained as of RRA on the i^{th} woodpecker l_b, and u_b denotes the lower bound and upper bound of variables, η implies the mean for the population, z and σ indicates the standard score and variance.

Now, GRA (β_{pop} running away) is assessed that is controlled by:

$$\Gamma_{GRA} = \wp * \left(1 - \frac{t}{t_{\max}}\right) \quad \text{... (7)}$$

Where, Γ_{GRA} implies RA probability, and $\wp$ denotes RA coefficient.

Lastly, the new position of the female woodpecker sits at any random point betwixt the β_{pop} positions and the random woodpecker.

$$N_{GRA}^i = N_t^i + GRA_{bit} * \left\{\left(N_{pop}^t - N_r\right) * R\right\} \quad \text{... (8)}$$

Where, N^i_{GRA} implies the position of a new element attained from RA on the ith woodpecker, $GRA_{bit} = \begin{cases} 1 & if\ r \le \Gamma_{GRA} \\ 0 & else \end{cases}$, illustrates the best member's position (β_{pop}, the best male) in t^{th} iteration, N_r implies the position of a random woodpecker i, R indicates a random number of a uniform distribution selected as of [–1, 1].

Thus, utilizing the objective function, the fitness of N^i_{GRA} or N^i_{RRA} is decided at the end of this operator (running away function). If the fitness value is larger than N^i_t, then the fitness gets replaced. If not, then the element created by the RA operator is rejected. For attaining the goal, i.e. finding the best node, the optimal fitness is obtained.

3.3. Gateway

The gathered slope data node is transmitted by the gateway. Routing the data packets in the network as of end devices to the main server via a black-haul interface, radio link, and 3G or 4G connections is the gateway's primary responsibility. However, the monitoring of the slope suffers significantly owing to high power communication, coverage issues, poor routing, high cost, along with data loss. For addressing this issue, an ORLPStarNet is created by the researchers for transporting data.

The detection of situations is enabled by the created gateway network where the network is likely to be linked. The coverage radius (i.e. critical radius) or the number of nodes could determine the connection criteria. Centered on the nodes that are randomly distributed as per a homogeneous Poisson Point Process (PPP), the following critical radius might be computed.

$$r_c = \sqrt{\frac{\log(N_i) + 2(k-1)\log\log(N) +}{\pi N}}$$

$$\vartheta = \begin{cases} -2\log\left(\sqrt{e^{-c} + \left(\frac{\pi}{4}\right)^2} - \frac{\pi}{4}\right) + \varsigma & k = 1 \\ 2\log\left(\frac{\pi}{2^k k!}\right) + 2c + \varsigma & k > 1 \end{cases} \quad \text{... (9)}$$

Where, ϑ implies the connectivity degree of a node for some constant $c>0$, and N denotes the number of nodes, ς indicates the routing. Here, n sensors are assumed to deploy that depends on m extra relay nodes for filling the connectivity gaps, so that $N=n+m$. It is vital to note that sensor data are not created by relay nodes, but it transmits packets on the sensor's behalf. Using the BVSSA, optimized routing is performed for reducing excessive power consumption, traffic congestion, and higher cost. A balanced search capability is maintained by the suggested route selection approach that assists in detecting the ideal path for transferring data with little loss and a quick response rate. The suggested approach is centered only on the goal function, i.e.

$$\Phi_{objective}(\hat{\Im}) = [\Phi_1(\varsigma_1) + \Phi_2(\varsigma_2) + \ldots + \Phi_n(\varsigma_n)] \quad \ldots (10)$$

Where, $[\Phi_1, \Phi_2, \Phi_3, \ldots \Phi_n]$ denotes the objective constantthat states the best path.

The population of the sparrow is initialized that is provided as $\Phi_{i,j} = \Phi_{i,j} - \Phi_{min} / (\Phi_{max} - \Phi_{min})$ where $\Phi_{i,j}$ implies the i^{th} sparrow in the j^{th} dimension of the search space, Φ_{min} and Φ_{max} signifies the minimum and maximum value of the j^{th} dimension. A matrix represents the sparrow's position, and the fitness values are allotted to the individual's sparrow. Superior fitness values are possessed by the producers. For attaining a global solution that is better than the best local solution, the producer should hunt for food in a huge area. For acquiring the optimum global solution, the updation of the producer's location is done.

$$\Phi_{i,j}^{t+1} = \begin{cases} \Phi_{i,j}^{t} * \exp\left(\dfrac{-i}{\hbar}\right) & if(B < AL) \\ \Phi_{i,j}^{t} + \Psi * \lambda & If(B \geq AL) \end{cases} \quad \ldots (11)$$

$$\hbar = 2e^{-\left(\frac{\Delta t}{t_{\max}}\right)}$$

where, $\Phi^t_{i,j}$ exhibits the current position of the producer, $\hbar$ implies a significant coefficient that balances the local along with global, t_{max} indicates the maximum number of iterations, $\Psi \in [0,1]$ implies a random number which obeys normal distribution, λ implies a $1 \times$ dim matrix along with its every element is 1, B and AL denotes the alarm along with safety threshold value, correspondingly. No predators as well as producers could globally look for food sources when $B<AL$. Otherwise, some sparrows identify the predators. When the chirping alarm takes place, the whole population rapidly flies to others afeareas.

Centered on the location of thescroungers, the fitness value obtained is offered forthescroungers. It is presented by:

$$\Phi_{i,j}^{t+1} = \begin{cases} \Psi * \exp\left(\dfrac{\Phi_{worst}^{t} - \Phi_{i,j}^{t}}{i^2}\right) & if(i > n/2) \\ \Phi_{p}^{t+1} + \left|\Phi_{i,j}^{t} - \Phi_{p}^{t+1}\right| * \hbar * \lambda & If(B \geq AL) \end{cases} \quad \ldots (12)$$

where, Φ^t_{worst} implies the existing global worst position, Φ_p indicates the optimal position that is occupied by the producer, B implies a $1\times dim$ matrix along with its every element is randomly allotted 1 or-1.

For demonstrating lower energy reserve and starvation, a unique condition is utilized. If, $(i>n/2$ then the current location is left and relocated to a new place in search of food; otherwise, the sparrows migrate towards the producers for competing with what they have found. If the sparrows win, then the losers will be replaced by the sparrows as new producers. Thus, until the whole population turns into a producer, the global best solution is updated in each iteration. For avoiding data traffic, an optimum path is generated by substituting the global best solution in the objective function.

3.4. Cloud server

End-to-end service is offered by the IoT cloud server and it stores all the data of the SS. The data is securely stored by the cloud platform and it offers access to the legal user. It also maintains data confidentiality, privacy, along with availability.

3.5. Monitoring

The SS data is monitored by the user for OCM by accessing a cloud server. Then, it takes a decision centered on the monitoring outcome.

4.0 Results and discussion

Centered on measured surface deformation of the slope, the proposed framework for SS monitoring in opencast mining via IoT platform is examined. Deformation and inverse velocity trends are calculated and examined for observing the time of failure centered on the measured value. The onset of acceleration (OOA), trend update (TU), and SF sites are graphically characterized by the work on cumulative deformation, DR, along with inverse velocity against time graphs. At the conclusion of the progressive (or accelerating) deformation stage, the SF point is found. It concludes the failure points with a huge acceleration event where the slope's integrity is lost and transitioned to regressive (or stable) levels. Slope collapse happens when the material is physically detached as of the slope. When contrasted to the time of SF, the time of slope collapse might not be the same relying upon the kind of rock mass (brittle or ductile).

The opencast SF's deformation, DR, along with inverse velocity trends (filtered across short along with long time periods) are exhibited in Fig.2. For every dataset, only one TU point was selected. In this case, data noise was decreased. It should be perceived that for allowing greater comparisons of findings, different TU points may have been selected. The inverse velocity trends attained from the collected data are exhibited in Figs.2(a) and 2(b). It is revealed that SF could be predicted by the proposed framework up to the first partial collapse and it does not predict future collapse occurrences. To assure that the area is kept clean and no workers re-enter until all following slope collapses occur, the deformation, DR, along with inverse-velocity trends should be monitored constantly after recognizing the occurrence of a staged

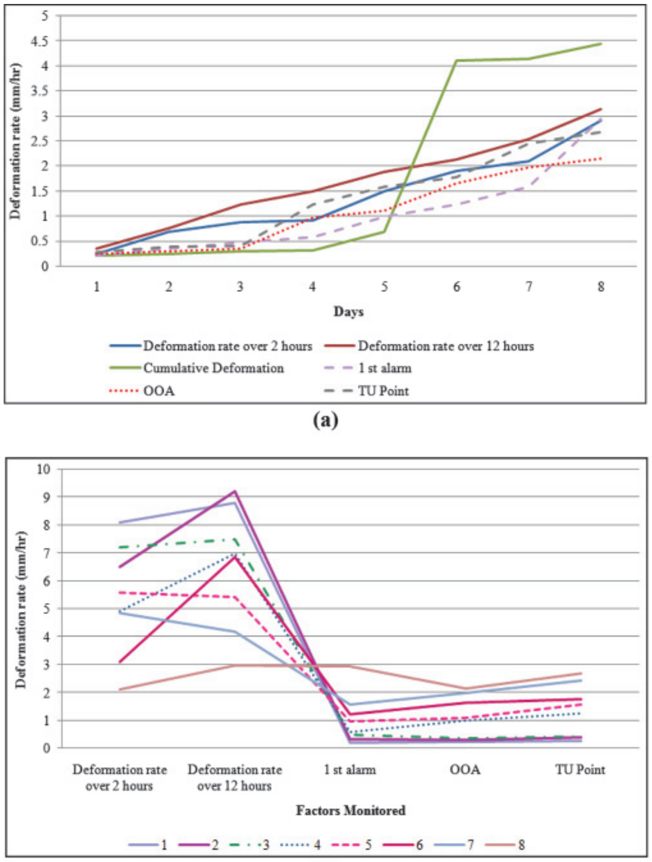

Fig.2: Demonstration of opencast mine slope stability based on (a) Deformation rate (b) Inverse velocity trends

TABLE1: EVALUATION OF PROPOSED ORLPSTARNET WITH VARIOUS METRICS

Metrics/ techniques	LoRa	Mesh topology	Star topology	Proposed ORLPStarNet
Throughput	65	59	74	86
PDR	64	61	76	88
Goodput	56	52	65	85

collapse event. Thus, constant monitoring and quicker data sharing are allowed by the suggested architecture for taking action in the case of a slope breakdown.

Centered on throughput, PDR, along with goodput metrics, the proposed ORLPStarNet gateway network is authenticated in Table 1. The validation exhibits that the proposed work performs better data transfer with less informative data loss when analogized to prevailing methods, namely LoRa, Mesh topology, and Star topology. It could be stated that less data loss is attained by the proposed one as it evades data traffic, consumes low power for transferring the data, and avoids node failure. Thus, a throughput of 865, PDR of 88%, and goodput of 85% are obtained by the proposed one, while a metrics value ranging between 52% and 76% is attained by the existent methods, which is comparatively less as analogized to the proposed one.

5.0 Conclusions

A great risk of failure is encompassed by the excavation of slopes in open pit mines to the steepest feasible angle for maximum profits. For monitoring slopes, the IoT's growth has become highly effective. However, SMS is impacted by certain challenges utilizing the IoT platform. For overcoming the challenges, a SS monitoring system is formed by the work centered on the ORLPStarNet IoT platform. The slopes along with movements occurring in that slope are monitored by the proposed framework. Energy efficiency, cost-effectiveness, ease of set up, and long-range data transmission with optimal routing are the features of the framework. Without any data loss, the data transmission occurs and it takes low computational time. Lastly, stable communication is offered by the framework amongst the network layer and it attains efficient slope monitoring. Experimental results revealed that a high range of data transmission is obtained by the proposed work with minimum data loss. It also attains a throughput of 86%, goodput of 85%, and PDR of 88%. For observing slope, the result stays more stable when analogized to prevailing methods.

6.0 References

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