Adapting PLUM: Earthquake Early Warning with Node-Level Processing in New Zealand

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ABSTRACT:

Is running the Propagation of Local Undamped Motion (PLUM) algorithm in a community-engaged earthquake early warning (EEW) network feasible, and can it function effectively at the node level without centralised processing units? This study investigates the practicality of deploying the PLUM algorithm within a node-level architecture, shifting away from traditional centralised seismic data processing methods. The study uses cost-effective MEMS-based seismographs to decentralise EEW. The preliminary phase of the research included the deployment of sensors and the establishment of a two-tiered Primary-Secondary node structure for node-level intensity prediction and alert generation, with the sensors functioning as independent prediction points. Future work includes threshold calibration for optimal alert issuance, and network expansion to reduce blind spots. This work-in-progress paper discusses progress towards a scalable, efficient EEW system that could serve as a replicable model for earthquake-prone regions globally, aiming for operational readiness that empowers communities against the threat of earthquakes.

Keywords

Earthquake Early Warning (EEW), Node-Level Processing, PLUM Algorithm, Citizen Seismology, Low-cost sensors

INTRODUCTION

Earthquake Early Warning System (EEWS) has been recognised as a vital advancement towards mitigating the impacts of seismic events (Allen & Melgar, 2019; Chandrakumar et al., 2022). The evolution of EEWS has been propelled by technological advancements and research breakthroughs, resulting in the implementation of systems across various regions and countries (Chandrakumar et al., 2022; Cremen & Galasso, 2020; McBride et al., 2022). These systems are designed to provide advanced alerts, enabling individuals and authorities to take preventive measures to safeguard lives and infrastructure. The effectiveness of EEWS in reducing damages and injuries associated with seismic activities has been well documented globally (e.g., Fujinawa & Noda, 2013; Nakayachi et al., 2019; Suárez et al., 2009).

Despite the pronounced seismic hazard in Aotearoa New Zealand (NZ), the country lacks an official national EEWS, a critical gap in preparedness underscored by Becker et al. in their 2020 study. The country relies predominantly on the GeoNet programme, managed by GNS Science, for rapid earthquake information. GeoNet provides earthquake source parameters and ground-shaking data through a website and mobile app but lacks dedicated Earthquake Early Warning (EEW) capabilities (GeoNet, 2017).

The absence of an official EEWS in NZ is primarily due to various technical and non-technical challenges, with the high cost of advanced systems representing a considerable obstacle (Brooks et al., 2021; Prasanna et al., 2022). For cost-effective earthquake preparedness solutions, there has been a marked global trend towards adopting low-cost alternatives. Micro-electromechanical systems (MEMS) based ground motion sensors have gained prominence among these. Demonstrating a successful track record in seismic applications since the early 1990s, MEMS-based ground motion sensors have been effectively integrated into EEWS in various regions, facilitating real-time public alerting systems (Anthony et al., 2019; Holland, 2003).

In pursuing a cost-effective EEWS in NZ, Prasanna et al. (2022) have initiated and deployed an experimental, community-engaged network in the Greater Wellington region. As depicted in Figure 1, this innovative system leverages Raspberry Shake 4D (RS4D) seismographs equipped with MEMS-based accelerometers, signifying a pivotal development in earthquake detection and alert technology. This network adopts a node-level processing approach to analyse and process ground motion data, diverging from the centralised processing approaches predominant in established EEWS globally. The experimental network uses the propagation of local undamped motion (PLUM) algorithm (Kodera et al., 2018) for its EEW capabilities, optimised for low-cost sensors with limited computational resources, to facilitate this node-level processing.

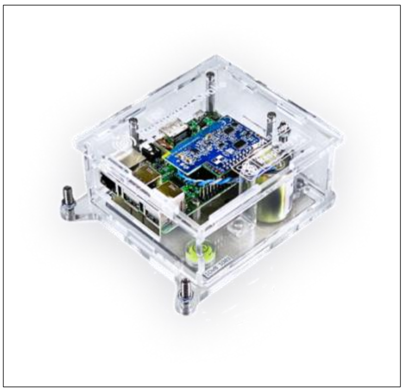

Figure 1: The RS4D Seismograph.

The effectiveness of node-level processing has been compared to conventional centralised approaches. This assessment was conducted by applying the PLUM algorithm to a selected array of sensors within a simulated environment (Prasanna et al., 2022). Chandrakumar et al. (2023) have also validated this approach's earthquake detection capabilities within a community-engaged network, focusing on a particular earthquake event. This work-in-progress paper builds on past research and addresses the ongoing progression and practical application of the PLUM algorithm within a real-life operational context, including adaptation processes of the original PLUM algorithm for node-level processing.

The article is structured as follows: The Background section outlines the node-level processing architecture and PLUM algorithm. The Work-in-Progress section details the ongoing adaptation of the PLUM algorithm to a node-level processing architecture within the community-engaged EEWS. Finally, the Discussion section presents the insights from the preliminary findings, outlines future research work, and concludes by highlighting the importance and potential impact of this research.

BACKGROUND

Node-Level Processing Architecture

Two principal methodologies dominate the landscape in data processing: centralised and node-level processing (Xi, 2020). Centralised processing gathers data from diverse sources into a unified, centralised facility undergoing analysis and processing. Conversely, node-level processing adopts a decentralised approach, wherein individual nodes or sensors independently execute data analysis and processing tasks (Santamaria et al., 2019). This distinction primarily revolves around allocating computational responsibilities; centralised systems centralise data processing in a singular hub, whereas node-level systems distribute these tasks across each node within the network, potentially augmenting the system's responsiveness and robustness against widespread failures.

Most EEWS operates on a centralised model, where a central facility receives and processes seismic data. While this centralised approach offers superior control and consistency in data handling, it is susceptible to critical delays and communication failures, particularly when major seismic events compromise infrastructure (Prasanna et al., 2022).

Recent technological advances have led to the enhancement of low-cost, MEMS-based sensors with in-built processing capabilities. These advancements enable data processing directly at the sensor nodes, allowing a transition from centralised to node-level processing (Chandrakumar et al., 2022). Node-level processing empowers the system to analyse seismic information and issue alerts where the data is collected, utilising the built-in computational power of the sensors. Aside from Prasanna et al.' (2022) publication on community-engaged EEW network, there is minimal documentation of node-level processing for EEW.

The shift toward node-level processing is motivated by multiple benefits. It reduces the time to issue alerts by removing the necessity for data to travel to a central server, allowing the system to provide a longer warning window for the end users. It also strengthens the resilience of the EEWS against central system failures caused by earthquakes. Furthermore, processing at the node level can decrease the operational costs associated with the upkeep of sophisticated central processing systems (Fischer et al., 2012; Prasanna et al., 2022).

The PLUM Algorithm

Over the past three decades, significant advancements have been made in EEWSs (Chen et al., 2015; Clinton et al., 2016). These advancements have primarily focused on network-based[1] approaches, utilising source-based[2] models to estimate earthquake parameters like hypocentre locations and magnitudes (Kuyuk et al., 2014; Satriano et al., 2011). Traditional EEW systems analyse seismic data, including P-wave onsets and maximum displacement amplitudes (Meier et al., 2015; Noda et al., 2016). However, the accuracy of these predictions heavily depends on the precision of the estimated parameters, which poses challenges, particularly during complex seismic events like large magnitude earthquakes and simultaneous aftershocks (Hoshiba, 2013; Hoshiba et al., 2011).

Recognising these limitations, Kodera et al. (2018) introduced an alternative approach known as the PLUM method. Based on Hoshiba (2013) work, this method offers a more direct ground motion estimation approach, emphasising cost-effectiveness and ease of implementation.

The PLUM algorithm operates by forecasting seismic intensity using real-time ground motion data. Its operation involves collecting pseudo-seismic intensities from observation stations within a predefined radius around a target station. The forecasted seismic intensity is then determined based on the highest value among these real-time observations. This method assumes that ground motion, responsible for significant seismic intensity, travels within the specified radius without notable attenuation. Figure 2 illustrates the PLUM algorithm's operation, demonstrating the intensity prediction at a prediction point using intensity data from surrounding observation stations.

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[1] A network-based approach in EEWS involves deploying a network of sensors across various locations within a geographical area. Earthquake detection is achieved by collectively processing the data gathered from this interconnected sensor network.

[2] Source-based EEWS models are designed to detect earthquakes and alert stakeholders, providing detailed information about the seismic event.

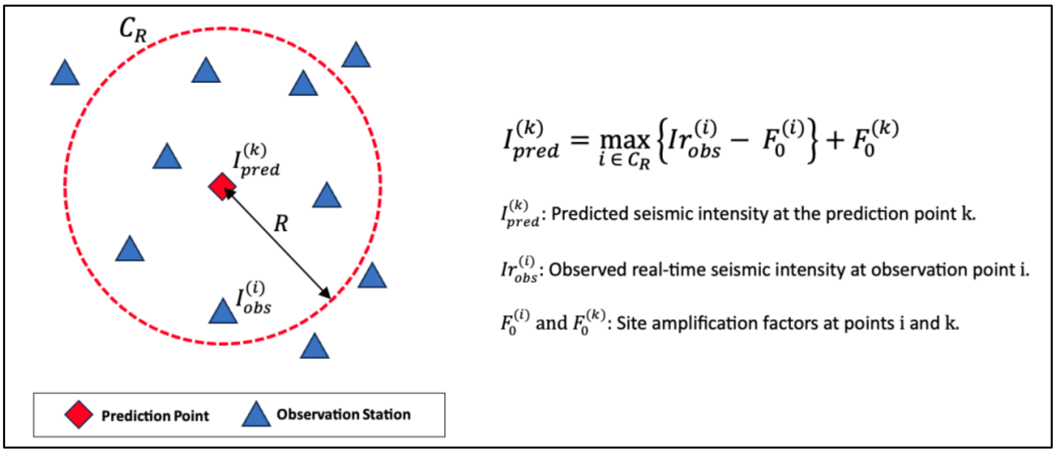

Figure 2: Illustration of the PLUM Algorithm's Operation, Demonstrating Intensity Prediction at a Target Station Based on Observations from Peripheral Stations (Adapted from Kodera, 2018).

A key component in the operation of the PLUM method is monitoring the observed intensity at each observation station. The PLUM method triggers an EEW alert when the real-time ground motion predictions from two or more monitoring stations exceed a specified threshold. This alert is generated explicitly for the region surrounding the target station, ensuring timely warning dissemination.

The PLUM method's distinct advantage lies in its ability to continuously monitor ground motion distribution in real-time, addressing the overprediction issues and false alarms prevalent in traditional ground-motion-based systems. This was particularly evident following the Mw 9.0 Tohoku earthquake, where PLUM issued more reliable early warnings (Hoshiba, 2021). Further validation with the 2016 Kumamoto earthquake data reinforced PLUM's superiority, consistently providing earlier warnings and effectively reducing blind zones (Kodera et al., 2016).

Moreover, the PLUM method has shown resilience in handling multiple simultaneous earthquakes and predicting strong motion by monitoring real-time seismic intensities. This capability sidesteps technical issues associated with source-based models and suggests a potential for further improvements with denser seismic networks, including low-cost sensors (Kodera et al., 2016).

Despite its advantages, the PLUM method has limitations. Its effectiveness is contingent upon a dense observational network, as it is limited by the short prediction radius and site amplification factors that significantly influence seismic ground motion (Kodera et al., 2016). Additionally, the PLUM algorithm tends to provide shorter warning durations than source-based methods. While it excels in predicting ground motion in complex seismic scenarios, the maximum warning time it offers is limited by the radius of observation.

WORK IN PROGRESS

This section highlights the work-in-progress of this study's implementation of an EEWS with node-level processing for the PLUM algorithm.

Installation of Seismic Sensors and Validation of Ground Motion Data

The initial phase of seismic sensor installation was carried out in 2020 and 2021, utilising MEMS-based RS4D sensors for their affordability, accuracy, and processing power, aligning with the objectives of a community-engaged EEWS (Prasanna et al., 2022). Community participants were recruited to host these ground motion sensors within their households. An workshop was conducted to gain insights into user perspectives and to develop strategies for distributing sensors to the general public, promoting a citizen seismology approach (Tan et al., 2021).

Following that, the network expansion in 2023 aimed to increase sensor density, leveraging social media campaigns to gather community interest in hosting additional RS4D sensors. The campaign resulted in 80 expressions of interest, informing the strategic selection of sensor locations through geographical data analysis. By mapping the geographical spread of these responses, 25 locations were identified from the pool to install additional sensors. This expansion strategy aligns with insights from a recent study, which explores the necessity of a comprehensive approach to developing a community-engaged EEWS for NZ, addressing the technological, societal, and cultural challenges (Tan et al., 2023). The criteria for site selection encompassed algorithm coverage, seismic activity, proximity to fault lines, population density, and other technical and environmental considerations. This careful selection has contributed to a network comprising approximately 60 ground motion sensors across NZ, with a significant concentration of around 45 sensors within the Greater Wellington area.

The performance of the community-engaged EEW network was evaluated through a dedicated study focusing on P-wave detection capabilities utilising the collected ground motion data (Chandrakumar et al., 2023). This evaluation centred on data obtained within 48 hours surrounding a magnitude 5.8 earthquake on 22 September 2022. The analysis involved a detailed assessment of recorded seismic data by the stations, specifically focusing on identifying any false detections or missed detections of seismic events within the dataset. The findings from this investigation underscore the effectiveness of a citizen seismology-based EEWS in identifying seismic occurrences relevant to early warning objectives.

These results affirm the operational capability of the newly implemented network, demonstrating its potential to contribute meaningfully to earthquake early warning efforts.

Adaptation of PLUM for Node-Level Architecture

Reason for Choosing PLUM for Node-level Processing.

In developing the node-level architecture for EEWS, the crucial task was to select an algorithm that conforms to the computational limits of the RS4D sensor nodes. These nodes are limited by their processing capabilities, necessitating an EEW algorithm that is both lightweight and effective. Through benchmarking existing EEW algorithms, the PLUM algorithm stood out as the optimal solution with its robustness, lightweight design, and ease of implementation (Prasanna et al., 2022). Its successful deployment in Japan's EEWS and validation across various global contexts affirm its appropriateness (Kodera et al., 2018). With its proven effectiveness with EEWSs worldwide, the PLUM algorithm was chosen for node-level operation for this study.

Processing Method of the Original PLUM Algorithm

The PLUM method predicts seismic intensities at designated prediction points, distributed across various areas based on seismic risk. For each area, the predicted seismic intensity is computed as the highest forecasted value among all its prediction points. This computation involves selecting the maximum observed real-time seismic intensity within a radius R from each prediction point, incorporating site effect corrections with a continuous one-second update interval (Kodera et al., 2018).

Real-time ground motion data processing in PLUM is centralised; observation stations transmit their data to a central unit, which issues intensity predictions to the target sites. This system has pre-programmed prediction points and corresponding observation stations for streamlined processing (Kodera et al., 2018). However, the adaptation to node-level processing necessitates a fundamental reconfiguration. In this architecture, each sensor node assumes the role of processing, effectively rejecting the need for a centralised processing unit. This shift ensures that the PLUM algorithm's calculations are conducted within the individual sensor nodes, thus fully embracing the decentralised nature of node-level architecture.

Defining Prediction Points for Node-level Architecture

The next objective focused on enabling the functionality of the PLUM algorithm at the node level. Defining prediction points is a foundational step in the methodology for adapting the PLUM algorithm to node-level architecture. The current implemented EEW network is depicted in Figure 3. In the original implementation of the PLUM method, authorities selected prediction points based on regional seismic activity to disseminate alerts to those areas (Kodera et al., 2018). These regions had various prediction points, reflecting the seismic activities observed.

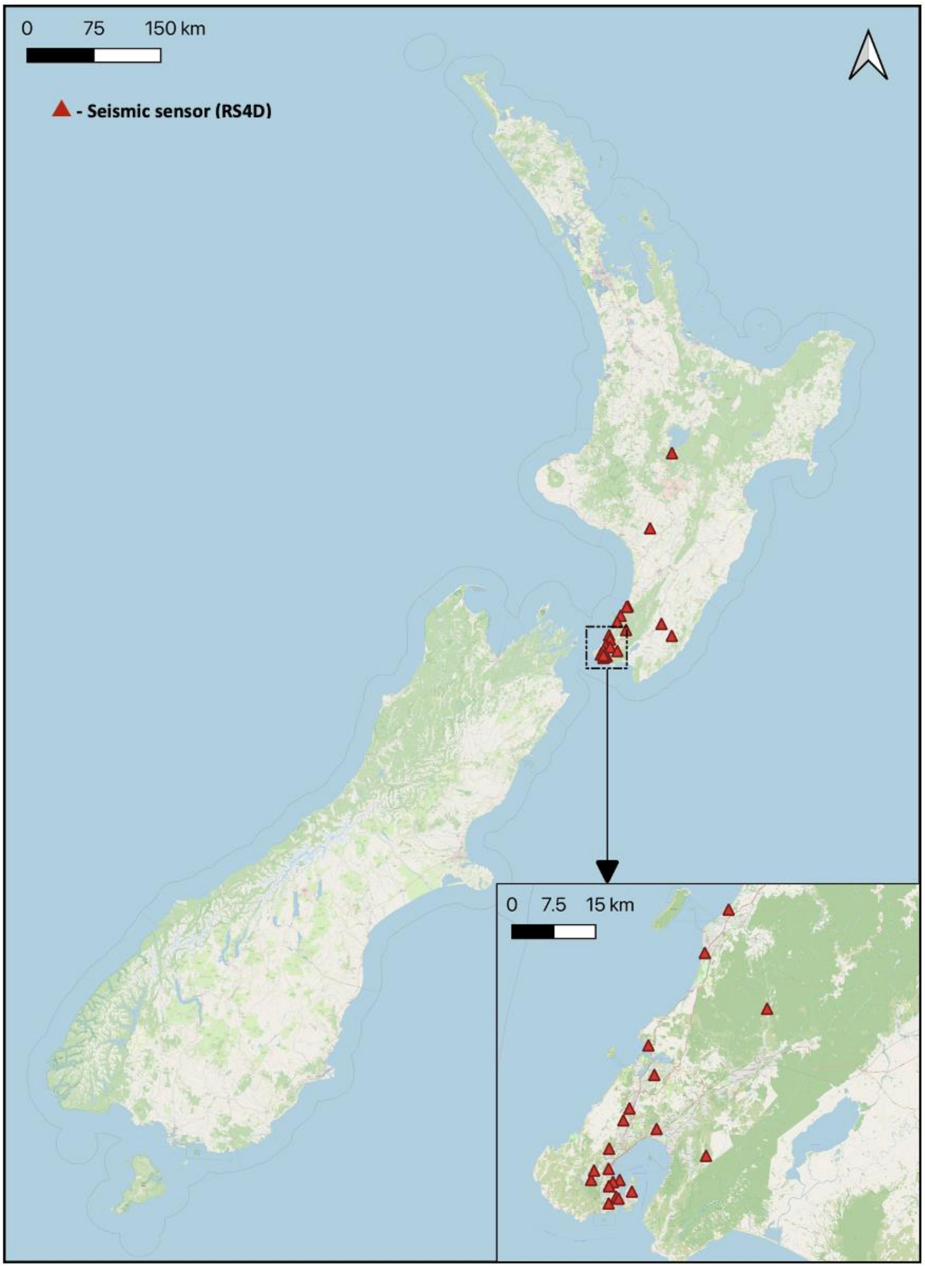

Figure 3: Overview of the EEW Network Deployed by the CRISiSLab Team.

Compared to the original PLUM implementation, our approach differs by designating the sensors as prediction points. Figure 4 presents four different prediction points as an example; each sensor marked in red represents a prediction point with a 30 km prediction radius consistent with the original PLUM specifications. Sensors within this radius serve as observation stations around the prediction point and are responsible for predicting the seismic intensity at the prediction point. Currently, our focus is not on issuing EEW alerts for broader regions but on generating alerts specifically for the prediction point - the RS4D sensor. This strategy is rooted in the concept of a community-engaged EEW network, ensuring that each sensor host receives EEW alerts directly through their installed RS4D sensor. However, it is essential to note that, in future, the network has the potential to be augmented with additional passive nodes. These nodes would also function as prediction points but receive alerts without estimating the intensity, enhancing the system's reach and effectiveness.

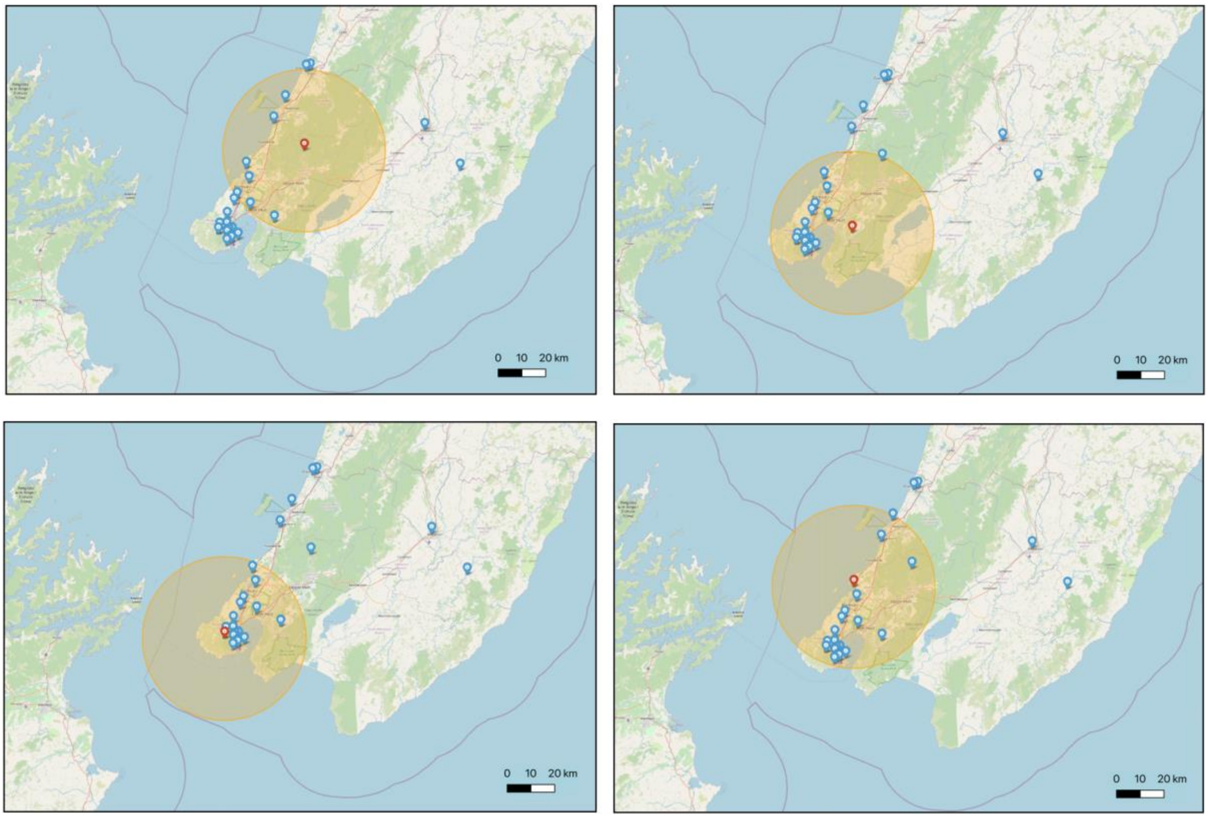

Figure 4: Illustration of Four Prediction Points with 30 km Prediction Radii, Highlighting Sensors in Red as Designated Prediction Points.

Implementing Node-Level Processing in the EEWS

Upon designating prediction points within the EEWS, the node-level implementation of the PLUM algorithm was initiated, establishing a dual-tiered structure of RS4D sensors: Primary and Secondary. Each prediction point, with a 30 km radius, is approached as a distinct scenario where one RS4D sensor is appointed as the Primary sensor, entrusted with two key functionalities: **intensity prediction** and **alert generation** for its specific prediction site. Concurrently, the surrounding sensors, classified as Secondary sensors within the same radius, are tasked with transmitting real-time intensity data to the Primary sensor for analysis. It is essential to highlight that a single sensor may serve multiple roles, acting as a Primary sensor for one prediction point while simultaneously functioning as a Secondary sensor for another, especially in areas where prediction radii overlap. The selection of a Primary sensor is strategically based on its current processing load, favouring sensors with minimal existing commitments to other prediction points. This strategic allocation and distribution of processing responsibilities ensure the efficiency and effectiveness of the node-level processing within our EEWS. Figure 5 illustrates how node-level processing utilises the PLUM algorithm, showcasing a prediction radius (Orange circle) scenario and the prediction point (Red icon), Primary (Purple icon) and Secondary stations (Blue icons).

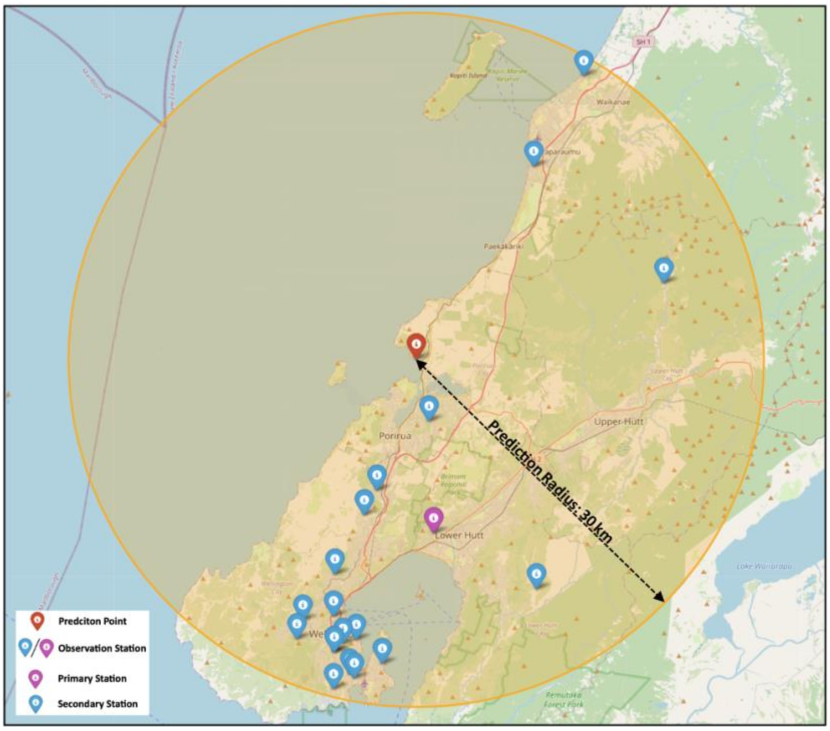

Figure 5: An Illustration of the PLUM Algorithm Adopted for Node-level processing, Featuring a Prediction Point, Primary Station, and Secondary Stations within a Specified Prediction Radius.

To address the potential failure of a Primary sensor, our system allocates at least three sensors to the Primary sensor role - one serves as the active Primary sensor, while the other two are on standby as backups. These backups also function as Secondary sensors, springing into action as the Primary sensor should the main one fail. This redundancy is crucial for maintaining continuous and uninterrupted seismic intensity predictions at each prediction point.

In contrast to the original PLUM methodology, which requires that all observation stations within the prediction radius update their real-time intensity to a centralised processing unit each second, our approach modifies the interaction between Secondary and Primary sensors. In our system, Secondary sensors independently process initial data, forwarding intensity updates to the Primary sensor only upon surpassing an internal threshold. Each sensor within our network is programmed to estimate real-time intensity, including Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and Peak Ground Displacement (PGD) on a second-by-second basis, assessing whether the PGA exceeds a specified internal threshold.

The Primary sensor undertakes the task of predicting the intensity at the prediction point solely under two conditions: if its internal threshold is exceeded or if it receives an intensity update from any Secondary sensor within the prediction radius that has surpassed the internal threshold. Secondary sensors are programmed to transmit real-time intensity data (PGA, PGV, and PGD) to the Primary sensor only after crossing this pre-determined internal threshold; the specifics of determining the internal threshold are detailed in a separate subsection. This strategic introduction of an internal threshold diverges from the original PLUM's approach by aiming to minimise the processing load on the Primary sensor. By reducing the influx of data packets during PLUM operation, this internal threshold mechanism ensures the Primary sensor maintains optimal performance, marking a significant adaptation in our node-level implementation to streamline processing and enhance efficiency. Figures 6 illustrates the overall working flow of Primary sensor in terms of predicting the intensity to a given prediction point according to our PLUM approach adopted for node-level processing. The comprehensive operation of the Primary sensor's alert generation is detailed in the next section.

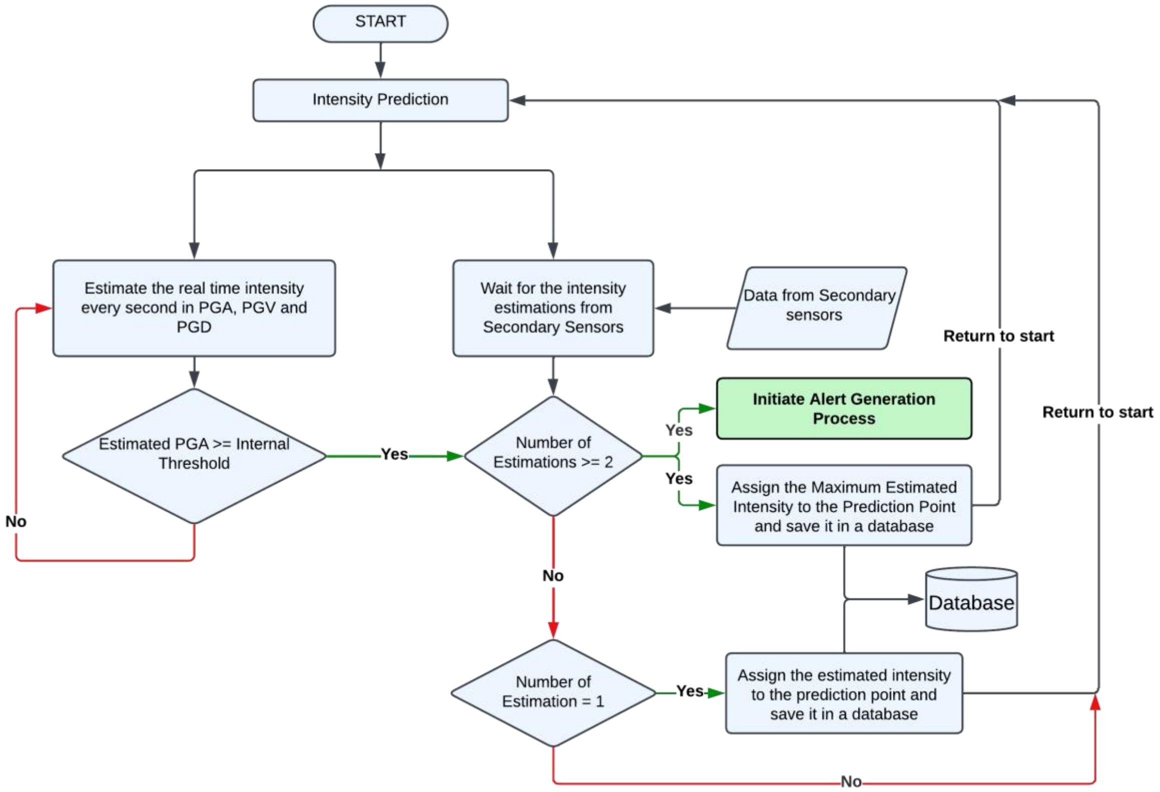

Figure 6: Flow Chart Explains the Intensity Prediction Flow of the Primary Sensor for the Assigned Prediction Point.

Defining the Internal Threshold for Secondary-Primary Communication

An internal threshold mechanism has been introduced to streamline communication between Secondary and Primary sensors, thereby reducing the processing load on the Primary sensor. This threshold determines when Secondary sensors should transmit real-time intensity updates. The formulation of this internal threshold began with establishing a specific Modified Mercalli Intensity[3] (MMI) range that effectively signals the necessity for an update without indicating considerable ground shaking.

The selection of an appropriate MMI range was based on the descriptions provided by GeoNet (Dowrick, 1996; GeoNet, n.d.). This choice ensures that our system's criteria for triggering intensity updates are well-tuned to the regional seismic activity profiles, thereby maintaining the system's accuracy and relevance. After careful consideration, MMI 3 was selected as the internal threshold. MMI 3 is characterised by indoor light vibrations, where hanging objects might sway slightly. This level of intensity serves as a pragmatic threshold, allowing Secondary sensors to initiate communication with the Primary sensor early in the event of significant seismic activity or at the onset of a large earthquake, thereby optimising the timing of alert dissemination.

Following the selection of MMI 3 as the internal threshold, the challenge was addressed by translating this MMI value into measurable parameters for the sensors, specifically PGA, PGV, and PGD. Since our sensors estimate intensity through these physical measures every second, determining an equivalent PGA value for MMI 3 was essential. To accomplish this, Ground Motion Intensity Conversion Equations (GMICEs), as outlined by Moratalla et al. (2020), were utilised. Figure 7 visually illustrates the correlation between MMI levels and PGA values, as defined by the GMICEs. In the figure, the MMI threshold of 3 or above is marked with a green vertical line, setting a clear benchmark for triggering communication from Secondary to Primary sensors based on real-time seismic data.

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[3] The Modified Mercalli Intensity scale is a qualitative tool used to describe the intensity and effects of an earthquake on the Earth's surface, structures, and inhabitants. It ranges from I (imperceptible) to XII (destruction), describing the impact on structures, the environment, and human perception and response.

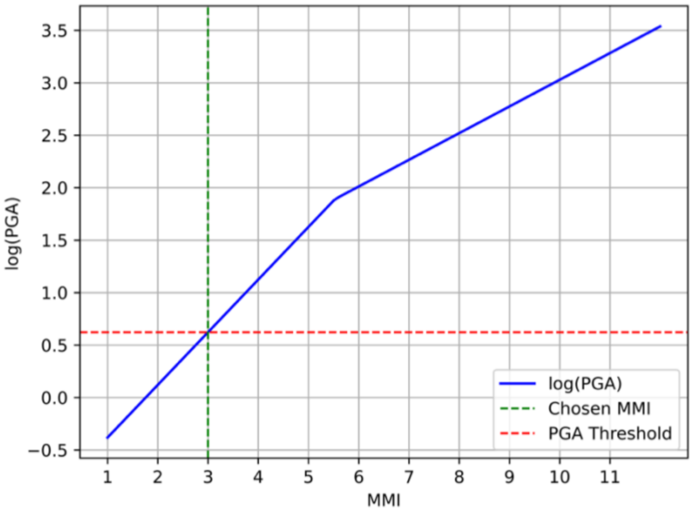

Figure 7: Correlation Between MMI Levels and PGA Values as Defined by GMICEs, Featuring a Green Vertical Line to Indicate the MMI Threshold of 3 and a Horizontal Red Dotted Line Representing the log(PGA) Threshold for Transferring Intensity Estimations from Secondary to Primary Sensor

Subsequently, the log(PGA) threshold was identified by analysing the intersection point depicted in Figure 7. The chosen log(PGA) value, serving as the internal threshold for Secondary sensors, was identified as 0.62, as represented by a red dashed horizontal line within the figure. After converting the logarithmic value to its original scale, the PGA internal threshold was determined to be 4.2 cm/s².

Alert Generation

In our EEWS, the generation of alerts for a specific prediction point, typically another RS4D sensor installed in a household, is managed by the Primary sensor designated for that point. The key requirement for a Primary sensor to trigger an alert is the reception of at least two intensity predictions that surpass a predefined threshold. These predictions can originate from the Primary sensor and one or more Secondary stations or exclusively from Secondary stations. The surpassing of this threshold by the predictions is critical, as it indicates a level of seismic intensity warranting generating an alert.

In the experimental network designed for testing, an intensity threshold of MMI level 5 has been provisionally selected. According to the GeoNet MMI descriptions, this intensity level corresponds to shaking typically felt outside, capable of awakening most sleepers and causing alarm among a few people indoors. However, establishing an ideal alert activation threshold requires carefully evaluating societal impacts and technical capabilities. Determining such a threshold is part of a broader, ongoing conversation to formulate a comprehensive set of guidelines specific to NZ's unique needs and circumstances.

The MMI 5 was translated into a PGA value of 42.3 cm/s² to quantify this threshold, utilising the same method for establishing the internal threshold for Primary-Secondary sensor communication. Therefore, if the predicted intensity from two or more observation stations within a prediction radius exceeds this PGA threshold of 42.3 cm/s², the Primary station will initiate an alert to the prediction point.

DISCUSSION

Launching a node-level EEWS using the PLUM algorithm in NZ seismically varied landscape represents a significant shift from conventional centralised models. Table 1 summarises the key differences between the traditional PLUM methodology and this research's approach. This proposed approach has optimised the processing capability of RS4D sensors for real-time seismic intensity prediction and alert dissemination. Transitioning to a decentralised architecture enhances the resilience of the EEWS by minimising the risks associated with a single point of failure, a potential issue in centralised systems.

Table 1: Comparative Overview of Traditional Plum Approach Versus Node-Level PLUM Adaptation Proposed in this Study.

Characteristics	Traditional PLUM implementation	Experimental Node-Level PLUM adaptation
Processing Approach	Centralised processing	Node-level processing with a two-tiered Primary-Secondary structure
Prediction Point Determination	Selected based on areas of interest reflecting observed seismic activities	Sensors themselves are used as prediction points
Data Handling Method	All observations within a prediction radius are sent to a centralised unit in real time.	Secondary sensors process data independently, sending updates to a Primary sensor only if internal threshold is surpassed.
Intensity Predicting Method	Observations are collected and processed at a central location to predict the intensity at prediction points.	The Primary sensor is responsible for predicting the intensity when its threshold is exceeded or upon receiving data from Secondary sensors.
Alert Generation	Centralised system issues alerts to the prediction points.	The Primary sensor issues an alert for its prediction point.

Adapting the PLUM algorithm for node-level application showcases the system's adaptability and the algorithm's suitability for environments with limited resources, particularly with the constraints of RS4D sensors. Identifying sensors as prediction points facilitates a community-centric warning system, ensuring swift alert delivery directly where needed. The classification of sensors into Primary and Secondary roles optimises task distribution, streamlining the network's operation.

A key focus for this proposed architecture was to minimise network traffic coming from the frequent intensity updates from Secondary sensors. Implementing an internal threshold curtails unnecessary data transfers, minimising the processing burden on Primary sensors. This threshold, determined by NZ's specific MMI scale and GMICEs, enhances network efficiency.

The MMI scale was utilised for alert generation, with MMI level 5 selected as an illustrative threshold to demonstrate the alerting process. However, establishing a definitive threshold needs further research for both societal impacts and technical capabilities, underscoring the need for a comprehensive discussion on this topic.

Future Work

In the next phase of our research, we will concentrate on a sequence of strategic undertakings designed to strengthen the capabilities of an operational node-level processing EEWS:

1. **Pilot Implementation and Performance Assessment:** The proposed concept will be piloted by integrating it into several RS4D sensors. We will focus on investigating the PLUM algorithm's performance at the node level, with particular attention to the accuracy of intensity estimations. Data collected from these sensors will be stored in a dedicated database for subsequent analysis to evaluate the system's performance metrics thoroughly.
2. **Network-Wide Implementation:** Upon completing the initial tests and refinements, the algorithm will be rolled out across the entirety of the operational network (45 sensors in the Wellington Region). This crucial step will mark the transition from a controlled testing environment to a real-world application, setting the stage for comprehensive system evaluation.
3. **Alert generation and threshold calibration:** Research efforts will be directed toward fine-tuning the parameters that trigger alert generation. This task will entail a deep dive into alerts' societal impact and the technical nuances associated with threshold calibration, tailored to NZ's unique seismic profile.

4. **Communication Technology Exploration:** Pursuing alternative communication methodologies, such as LoRa, is essential, particularly as an alternative strategy to ensure network operability during traditional communication infrastructure failures.

The conceptual framework detailed in this work-in-progress paper will undergo operational testing, refinement, and expansion. Future results from the experimental network are planned for journal publication to validate the system's effectiveness and provide guidance for similar deployments in seismically active areas.

CONCLUSION

This work represents a notable contribution to EEWSs by integrating node-level processing with the PLUM algorithm. The system's design, emphasising redundancy, cost-efficiency, and reduced latency, addresses the critical need for resilient seismic warning capabilities. Furthermore, the node-level approach emerges as a viable solution following significant earthquakes, where standard communication networks may fail. The potential for sensors to utilise alternative communication methods, such as LoRa, highlights a forward-looking strategy for ensuring continuous alert delivery during aftershocks, enhancing community safety and preparedness. In conclusion, our endeavour to develop a community-engaged node-level EEWS in NZ signifies a step forward in seismic risk management.

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