Decision support system for predicting tsunami characteristics along coastline areas based on database modelling development
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ABSTRACT
Tsunamis are extraordinary occurrences that are difficult to identify; most of the incidents have no recorded predictions and tsunamis are generally infrequent events with poor data acquisition. The development of a tsunami database system has become important for improving the management of information with regard to a tsunami early warning system for vulnerable communities along coastline areas. Numerical modelling is usually employed to simulate the wave height and travel time of a wave arriving at a coastline area. However, numerical modelling for tsunami prediction is too time-consuming to be useful as an early warning system for the mitigation of tsunami-related damage and loss. Therefore, this model was used to develop a tsunami database system, based on hypothetical data, in order to develop a recognition pattern for a neural network learning process that will improve the speed and accuracy of tsunami prediction. To improve the accuracy of numerical modelling and observation, an adjustment was established for an advanced training process which used a generalised regression neural network. In other words, the training and testing datasets were obtained by correcting near-field tsunami numerical models from hypothetical earthquakes. The case study was performed on part of the Southern Pangandaran coastline in West Java, Indonesia.

Key words | correction factor, generalised regression neural network, hard and soft computing, tsunami database

INTRODUCTION
One and a half years after the 2004 Indian Ocean tsunami, a tsunami struck Indonesia again on the south coast of West Java Province triggered by an earthquake of 7.7 MW located at 9.295 S and 107.347 E (Muhari et al. 2008). The yield of essential impacts on the disaster strategy in that part of the southern Java coastline was due to this being not only the first local experience of a tsunami but also the most destructive tragedy in this part of the southern Java coastline in recorded history. This earthquake prompted a series of tsunamis and devastated many communities over hundreds of miles of exposed coastline area. It is ranked as the most catastrophic event in recent times in Indonesia after Aceh, the earthquake and subsequent tsunamis causing significant damages to the tourism business. In addition, Srivichai et al. (2008) specified that the lack of any effective tsunami early warning system or tsunami education in the region exacerbated the degree of losses.

Lack of experience or capability regarding a tsunami early warning system is one of the major reasons for this disaster. In this case, the government is concerned with the lack of capability in carrying out tsunami watch information and in issuing an early warning for a tsunami in the region. The objective of the present study was to develop a model of tsunami warning database system for improving decision-making in the issuance of an early warning based on hard and soft computing techniques, i.e. numerical and neural...
computation, respectively. Tsunami events are infrequent, with most incidents passing with poor or no data acquisition. Therefore, it is necessary to develop a database system to analyse tsunami behaviour to obtain more accurate predictions.

The recently developed technique of soft computing has been applied to learning tsunami behaviour from several potential hypothetical earthquakes. The proposed technique was also examined based on historical tsunami events. In this case, numerical methods were established to develop a database management system after calibration and adjustment based on observations. The numerical modelling developed is the basis for generating potential tsunami events from numerous hypothetical earthquakes and to simulate tsunami wave height and arrival time from the earthquake source to the coastline area. Because numerical modelling is too time-consuming to act as a tsunami warning system, neural network modelling was applied to learning tsunami behaviour using a database developed from the numerical modelling data. This study is specifically related to tsunami events at 30 locations in the southern Java coastline area of Indonesia.

CASE STUDY

The holiday cape of Pangandaran on the southern coast of west Java became the worst disaster area, experiencing the highest recorded tsunami wave (7 m above mean sea level). In Cimerak, near Pangandaran, the maximum inundation of tsunami waves reached 1 km from the coastline. The tsunami disaster killed 378 people, damaged 904 houses and hotel buildings, and caused additional damage along the southern coast of Java. Unfortunately, people felt nothing to indicate an impending tsunami in spite of tremors due to an earthquake that occurred 178 km from southwest Pangandaran (Pribadi et al. 2006) (see Figure 1). The Meteorological and Geophysical Agency of Indonesia (2006) in cooperation with teams from Japan and Korea were responsible for investigating the disaster. A field survey of the southern Java earthquake tsunami was conducted during 18–22 July 2006 and 4–8 August 2006 along the southern part of Java Island.

As indicated in Figure 2, the earthquake was followed by a tsunami that had a maximum run-up height of 8.5 m, which swept most of the coastal villages along the south coast of West Java Province and Central Java Province (Figure 2), causing more than 668 casualties and a financial loss of $44.7 million up to July 2006. This financial loss is still increasing because of the collapse of tourism that was the primary economic sector of local economic development (Muhari et al. 2008) (see Figures 3 and 4).

HARD COMPUTING TECHNIQUE WITHIN TSUNAMI NUMERICAL MODELLING

For emergency units, tsunami prediction as an operational guideline is critical for decision-making. An early warning
A decision support system for tsunamis provides for immediate action through regional authorities to mitigate the damage from a predicted major wave or flood in a coastal area. Effective action can be taken immediately and accurately to save more lives if the warning system sends information regarding the characteristics of a tsunami as promptly as possible. Currently, the warning system related to tsunami issues is limited due to imperfect and vague data. The initial decisions of the warning system derived from seismic waves are based on indirect measurements of coastal tide gauges due to tsunami generation and confirmation. However, this common method may cause the warning to arrive too late for evacuation measures and result in an ineffective local response to the tsunami (Srivichai et al. 2008). The most needed information for emergency units responding to tsunami events is wave height and travel time from the source (earthquake) to the coastline area.

The current development of a hard computing method using numerical modelling of tsunami dynamics will create a higher-standard research instrument for tsunami assessment. Modelling methods have robust performance and have demonstrated highly precise simulations of past tsunami events based on field and instrumental data (Srivichai et al. 2008). Latief & Imamura (1998) applied numerical modelling as hard computing for the tsunami event in East Java, Indonesia. In addition, Latief et al. (2006) also applied numerical modelling and simulation to a tsunami in West Java.

**TUNAMI-N2 for developing database modelling**

In this study, the hard computing model used for developing the tsunami database is based on tsunami modelling developed by Tohoku University, Japan, called TUNAMI-N2 (Tohoku University’s Numerical Analysis Model for Investigation of Near-field Tsunamis, No. 2). The governing equation used for the prediction of tsunami propagation consists of a two-dimensional long-wave hydrodynamic model (called the shallow water theory). The continuity equation for the long wave as described in Imamura et al. (2006) is

\[
\frac{\partial \eta}{\partial t} + \frac{\partial M}{\partial x} + \frac{\partial N}{\partial y} = 0
\]

and the momentum equations for the \(x\) and \(y\) directions are

\[
\frac{\partial M}{\partial t} + \frac{\partial}{\partial x} \left( \frac{M^2}{D} \right) + \frac{\partial}{\partial y} \left( \frac{MN}{D} \right) + gD \frac{\partial \eta}{\partial x} + \tau_x = A \left( \frac{\partial^2 M}{\partial x^2} + \frac{\partial^2 M}{\partial y^2} \right)
\]

\[
\frac{\partial N}{\partial t} + \frac{\partial}{\partial x} \left( \frac{MN}{D} \right) + \frac{\partial}{\partial y} \left( \frac{N^2}{D} \right) + gD \frac{\partial \eta}{\partial y} + \tau_y = A \left( \frac{\partial^2 N}{\partial x^2} + \frac{\partial^2 N}{\partial y^2} \right)
\]
where $D$ is the total water depth specified by $h + \eta$; $\tau_x$ and $\tau_y$ are the bottom frictions in the $x$ and $y$ directions; $A$ is the horizontal eddy viscosity, that is assumed to be constant in space; and the shear stress on a surface wave is neglected. $M$ and $N$ are the discharge fluxes in the $x$ and $y$ directions, provided by

$$M = \int_{-h}^{\eta} udz = \nu(h + \eta) = uD$$

and

$$N = \int_{-h}^{\eta} vdz = \nu(h + \eta) = vD$$

respectively. In addition, the bottom friction is commonly suggested analogously to the uniform flow for the $x$ and $y$ directions, respectively, as

$$\frac{\tau_x}{\rho} = \frac{fn^2}{D^{7/3}} M\sqrt{M^2 + N^2}$$

and

$$\frac{\tau_y}{\rho} = \frac{fn^2}{D^{7/3}} N\sqrt{M^2 + N^2}$$

for the $x$ and $y$ directions, respectively. Numerical methods were used in solving these equations.

**Numerical solution**

The aforementioned depth-integrated continuity and momentum equations are solved by the finite-difference method with the staggered leapfrog scheme (Goto & Ogawa 1992). Figure 5 illustrates the points of computation for calculating the leapfrog numerical scheme.

**Initial and boundary condition**

The current program is intended only for tsunamis, excluding wind waves and tides. The height of still water is given by the tide levels and is assumed to be constant when the tsunamis are calculated. As a consequence, no motion is assumed up to time $n - 1$. Because the duration of a tsunami is between 1 and 2 hours, at sea, $\eta_{i+1/2,j+1/2} = 0$ and $M_{i,j}, N_{i,j} = 0$. For the boundary between the land and the sea, a hard-wall boundary condition was set up; to terminate the computational domain, a transparent boundary condition for the open sea was implemented (Imamura et al. 2006).
Static source (bottom deformation due to the fault motion)

To produce a seabed deformation, the magnitude of the earthquake should be large ($M_w > 6$), and its hypocenter should be shallow ($d < 60 \text{ km}$). The relationship between a seismic moment and deformation is formulated as follows (Latief 2009):

$$M_w = \frac{2}{3} (\log_{10} M_o - 16.1)$$

(4)

$$M_o = \mu A_f D_d$$

(5)

where $M_w$ is the moment magnitude, $M_o$ is the seismic moment, $\mu$ is the rigidity, $A_f$ is the fault area and $D_d$ is the deformation.

SOFT COMPUTING TECHNIQUE WITHIN NEURAL NETWORK MODELLING

The application of the artificial neural network (ANN) technique to solve problems in civil engineering began in the late 1980s (Flood & Kartam 1994). Their application to simulating and forecasting problems in water resources is relatively recent (French et al. 1992; Hsu et al. 1995; Thirumalai & Deo 1998; Campolo et al. 1999; Hu et al. 2001). The ANN modelling technique is used to solve problems without any prior assumptions. As long as enough data are available, a neural network will extract any regularities or patterns that may exist and use them to form a relationship between input and output. Additional benefits include data error tolerance and the characteristic of being data-driven, thereby providing a capacity to learn and generalise a pattern in noisy and ambiguous input data. There has been wide application of neural networks to civil engineering problems. Hadihardaja & Sutikno (2007) applied a neural network for rainfall–runoff modelling using back propagation and the reduced gradient method for obtaining the optimal weights.

However, Cigizoglu (2005) developed an ANN algorithm using the generalised regression neural network (GRNN) for intermittent river flow forecasting and estimation and concluded that GRNN simulations were superior to Feedforward Back Propagation (FFBP) in terms of the selected performance criteria. In addition, the GRNN simulations do not face the frequently encountered local minimum problem encountered in FFBP applications, and GRNN does not generate physically implausible forecasts or estimates. Other studies related to GRNN were also used for daily river flow and suspended sediment relationship at Juniata Catchment in the USA. The suspended sediment estimations provided by two ANN algorithms were compared with a conventional sediment rating curve and multi-linear regression method results (Cigizoglu & Alp 2006). In addition, Srivichai et al. (2008) initiated the use of numerical and GRNN methods for developing the forecasted tsunami database for the Andaman coastline, Thailand.

Generalised regression neural network for learning database modelling

In this study, the learning algorithm for the neural network system uses a Generalised Regression Neural Network (GRNN) and was developed using Delphi 7.0 as the compiler of GRNN-ITB 2008. The GRNN, first developed by Specht (1991), is a neural network architecture capable of solving any problem in estimating a probability distribution function. According to Srivichai et al. (2008), the neural learning process corresponds to obtaining a surface in a multidimensional space, which is up to the standard of some statistical parameters. The closer projected state is weighted heavier than the further projected state in the phase space, which is a reasonable approximation, provides fast learning and converges to the optimum regression surface. Therefore, the GRNN is also used in this study.

In this section, Amrouche & Rouvaen (2006) explained the basic theory of the generalised regression for a learning algorithm of the neural network. The regression function performed on an independent variable $X$ calculated nearly all feasible values of the dependent variable $Y$ based on a finite set of observations of $X$ and the associated values of $Y$. Sample values $X^i$ and $Y^i$ of the random variables $x$ and $y$, a good choice for the probability estimator, as in Specht (1991, 1995), is provided by the following equation:

$$\hat{f}(X, Y) = \left[ \frac{1}{(2\pi)^{p+1/2} \sigma^{p+1}} \right] 
\times \frac{1}{n} \sum_{i=1}^{n} \exp \left( -\frac{(X - X^i)^2}{2\sigma^2} \right) \exp \left( -\frac{(Y - Y^i)^2}{2\sigma^2} \right)$$

(6)
where \( p \) is the dimension of the vector variable \( x \), \( n \) is the number of observations \( \sigma \) is the width (spread) of the estimating scalar output and \( Y^i \) is the desired output corresponding to the input training vector \( x_i \) and the \( J \)th output, then the equations can be written as follows:

\[
y_j = \frac{\sum_{i=1}^{n} w_{ji} h_i}{\sum_{i=1}^{n} h_i}
\]

\[
h_i = \exp\left[-\frac{D_i^2}{2\sigma^2}\right].
\]

Based on Equations (11) and (12), the topology of a GRNN is illustrated in Figure 6 and consists of the following elements:

1. Input layer (input nodes) that is completely linked to the pattern layer.
2. Pattern layer with one neuron for every pattern, calculating the pattern functions \( h_i(\sigma, C_i) \) as written in Equation (11) applying the centre \( C_i \).
3. The summation layer, which has two units \( N \) and \( D \).

Firstly, the unit has input weights equal to \( X^i \) and calculates the numerator \( \sum h_i \) and the denominator \( \sum h_i \) according to its Euclidean distance from \( X \) (Specht (1991) in Amrouche & Rouvaen (2006)).

### Neural architecture

Specht (1991, 1995) and Amrouche & Rouvaen (2006) proposed and described, respectively, the implementation of a general regression neural network. If \( w_j \) is the target output, then the equations can be written as follows:

\[
y_j = \frac{\sum_{i=1}^{n} w_{ji} h_i}{\sum_{i=1}^{n} h_i}
\]

\[
h_i = \exp\left[-\frac{D_i^2}{2\sigma^2}\right].
\]

In the effort to examine the performance of the network, Srivichai et al. 2008 mentioned two common statistics, i.e. root mean square error (RMSE) and efficiency index (EI), that are used in the following two equations:

\[
\text{RMSE} = \sqrt{\frac{\sum_{p=1}^{P} (t_p - H_p)^2}{P}}
\]

\[
\text{EI} = 1 - \frac{\sum_{p=1}^{P} (t_p - H_p)^2}{\sum_{p=1}^{P} t_p - H_p^2}
\]

where \( P \) is the total number of input–output data patterns, \( t_p \) is the target output, \( H_p \) is the predicted output and \( t \) is the mean value of the target output.
exponential terms multiplied by the $Y_i$ associated with $X_i$. Secondly, the unit has input weights equal to 1 and the denominator $D$ is the summation of exponential terms alone.

4. The output unit divides $N$ by $D$ to provide the prediction outcome.

The selection of the smoothing factor is very important, especially when $\sigma$ is small, only a few samples are part of the cause. On the other hand, if it is large, even distant neighbours have an effect on the estimate at $X_i$, leading to a very smooth estimate. In an extreme case, when $\sigma$ approaches infinity, $\hat{Y}(X)$ is the average of $Y_i$, which is independent of the input (Specht 1991).

**Model input adjustment and correction factor**

In numerical modelling, the tsunami source and tsunami propagation were used to generate the tsunami wave and the time of travel. The input of the tsunami source included the depth, position (longitude and latitude) and magnitude of the earthquake, as well as the dip, slip, strike, length, width and dislocation of the fault. The length, width and dislocation were adjusted to obtain the magnitude of the earthquake (from observation) as calibration of the tsunami source model. Dip, slip and strike of the fault were based on measurement data from www.seismology.harvard.edu.

In addition, the input of tsunami propagation was related to water vertical displacement resulting from the tsunami source model and bathymetry. The optimal values of dip, slip and strike provided the minimum deviation of tsunami height between the numerical model and observation.

In GRNN modelling, the input is a state space denoted by $X$ (epicentres, which are the longitude and latitude of earthquake source coordinates, moment magnitude and earthquake depth). The estimated, or target, value $\hat{Y}(X)$ is the number of observation points along the coastline (50 points). The input parameters vary according to Table 1.

The total data for neural network training are the combination of input numbers and targets. Therefore, there are 45,560 rows of data, with 90% and 10% of the combinations used for neural network training and testing, respectively.

Because the observation data is very limited, i.e. a single observation event in this case, and the numerical result may over- or under-estimate the value compared to the observation, it is necessary to adjust the results by applying a correction factor. This correction factor was developed in order to close the deviation between the numerical model and the observation at each location point when the observation data is accurately measured and considered. The correction factor for enhancing the numerical modelling results related to the tsunami height can be presented as follows:

$$K = \frac{H_o}{\kappa}$$

where $K$ is the ratio between field observation and simulation results, $\kappa$ is the correction factor, $H_o$ is the maximum tsunami height based on field observation and $H_m$ is the maximum tsunami height based on the numerical model. In this case, $K$ is expected to be unity to close the deviation between field observation and the numerical model. Then, by linear assumption based on the location point, these values are used for the GRNN learning algorithm to predict the adjusted tsunami height. The correction factors based on specific locations are only used for tsunami height.

The scenario for training and testing is introduced such that 90% and 10% of data are used for training and testing, respectively; the scenario was intended to evaluate the performance and capability of the GRNN during learning from the numerical model. The 10% of data for testing is applied to obtain an optimal smoothing factor. Furthermore, by using input from the actual earthquake

<table>
<thead>
<tr>
<th>Inputs for GRNN</th>
<th>Number</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothetical earthquake sources</td>
<td>24</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Moment magnitude (MW)</td>
<td>9</td>
<td>6.3</td>
<td>8.7</td>
<td>0.3</td>
</tr>
<tr>
<td>Depth (km)</td>
<td>7</td>
<td>10</td>
<td>70</td>
<td>10</td>
</tr>
</tbody>
</table>
observations, the tsunami height predicted by the numerical model is corrected by applying a linear correction (using Equation (13)) for each location along the coastline area. After the correction factors for each location are found, the tsunami height database (based on numerical modelling generated from hypothetical sources) is corrected to produce a new database. Subsequently, the new database is learned by GRNN (corrected GRNN), but only for the hypothetical sources of the tsunami, with the single actual source and its resulting observed tsunami height excluded from the database. In other words, the GRNN does not learn the input of the actual earthquake source and the output of the tsunami height based on observation. Thus, the single actual source is used as the input for GRNN to predict the tsunami height along the selected 30 area points, and the final results are compared to the actual tsunami height observations.

### RESULTS AND DISCUSSION

A database system was developed using a numerical model generated in this study based on hypothetical sources of tsunami, which were necessary to meet the size and number
of data points required for the database. This limitation is a significant constraint because database system development generally needs a great deal of observational data for accuracy. In addition, the numerical model for expanding the database system cannot give satisfactory results and needs to be adjusted. Therefore, testing procedures were established to conveniently verify that the neural network can perform with acceptable results.

Database of tsunami wave height and time of arrival

Numerical modelling has been developed for predicting tsunami characteristics at 30 points along the designated Southern Java coastal line. The neural network performs satisfactorily, with coefficient determination, efficiency index and RMSE equal to 0.862 (high correlation when approaching 1), 0.81 (high performance when approaching 1).
Figure 11 | Time series of tsunami wave at selected locations, before and after corrected numerical modelling.

Figure 12 | (a) Four hypothetical sources of earthquake location and (b) tsunami wave heights between observation and uncorrected numerical modelling.
and 2.89 (no error when equal to zero), respectively, after learning the wave height pattern generated by numerical modelling (Figure 7(a)). In addition, the linear trend line gives a gradient value of 0.788, approaching unity, as presented in Figure 7(b).

The time of arrival of the tsunami from the actual earthquake source to the designated point of observation along the coastline is learnt by the neural network solely by using the numerical modelling database. The time of tsunami propagation from the source to the coastline, calculated using numerical modelling, is around 20–60 min (Figure 8). In addition, the execution time required by the numerical modelling simulation is 20–30 min. In contrast, the neural modelling needs only 1 s for execution of the model. This is understandable because the numerical model computes tsunami properties in every grid for the entire model domain, while GRNN does so only at specific areas along the coastline. The estimated arrival time learned by the neural model is relatively accurate, with the coefficient of determination, efficiency index and RMSE of 0.999, 0.997 and 0.22, respectively. In addition, the linear trend line has a gradient value of 0.995, approaching unity, as presented in Figure 8(b).

Because there are no observations near the arrival time, no correction factors are applied in this case, and Figure 8 indicates that the GRNN results show high-quality performance in learning the arrival time purely from the numerical model.

![Figure 13](https://iwaponline.com/jh/article-pdf/13/1/96/386523/96.pdf)

Figure 13 | (a)–(d) Evaluation of four hypothetical earthquakes: tsunami wave heights between GRNN correction and uncorrected numerical modelling at locations 1–4, respectively.
Corrected tsunami wave height for improving database modelling

The use of modelling based on hard computing is required because there is only one recorded incident based on observations in the field during a tsunami. Based on the previous discussion, the neural network can satisfactorily perform the database system generated by numerical modelling. However, the numerical method provides under-estimated results compared to the observation of the actual tsunami event (based on the report of the Meteorological and Geophysical Agency of Indonesia (2006)), as indicated in Figure 9(a). In addition, in Figure 9(b), the plot between the numerical modelling and the neural network indicates relatively small correlations with observations. Therefore, it is necessary to adjust the numerical modelling results using a reasonable method to obtain values close to the observed ones. If the numerical results can be adjusted to approach the actual value of observation, the neural network can perform more accurate predictions in support of the warning system.

In other words, corrected numerical modelling results for the tsunami database generator will promote more reasonable database results for the learning process of the neural network. The correction is established based on each of the 30 locations. Every location has a specific correction value for the numerical model (Figure 10(a)). These corrections are applied to the previous database generated by numerical modelling using hypothetical sources and excluding the actual tsunami source or the real tsunami event. The neural network then learns the

![Graphs showing corrected numerical modelling results](https://iwaponline.com/jh/article-pdf/13/1/96/386523/96.pdf)

**Figure 14** (a)–(d) Evaluation of four hypothetical earthquakes: tsunami wave heights between GRNN correction and corrected numerical modelling at locations 1–4, respectively.
corrected numerical results. To evaluate the performance of the network, the neural network is then given the actual input of a real tsunami source to obtain a predicted value along the coastline area and compare it to the observational data. Figure 10(b) illustrates the comparison between the tsunami observation, the original numerical modelling before correction and the neural network results after learning the adjusted database. These show that improving the prediction using a neural network based on the adjusted database is completely acceptable.

The time series plots for the selected location are presented to illustrate the difference between uncorrected and corrected numerical models for developing the database. In addition, the maximum height of the tsunami wave is identified for the basis data of the early warning system (Figure 11).

**Tsunami wave height evaluation**

The numerical model under-estimates the value of the tsunami height in its predictions based on the observations used in this study. Therefore, the numerical model is corrected to improve the predicted value for developing the database system. In addition, to verify that this correction provides more accuracy in predicting the wave height, it is necessary to evaluate the predicted wave height between the GRNN (after correction) and the numerical model. This is used for evaluating the gradient for both the observation (Figure 12(a)) and GRNN (Figure 12(b)) versus numerical modelling. If the gradients of the regression line are identical, then the neural network can learn effectively. This technique is performed because the observational data are extremely limited, i.e. only a single event of tsunami observation is available in this case. Therefore, the corrected values at each location are very important and offer improved reliability of the database system for the neural network learning process.

**Figure 13** shows the ability of GRNN to learn an uncorrected numerical model with acceptable results. Here, the GRNN provides forecasted values and the linear trend line for four hypothetical source locations shows similar patterns.

**CONCLUSION**

The study indicates the possibility of predicting the tsunami characteristics of wave height and arrival time along a coastline area in an accurate and timely fashion by developing a tsunami database model and associated neural network. It also describes the development of an easily applicable soft computing model that predicts the tsunami wave height and arrival time. The prediction depends on the accuracy of the hard computing model that is specifically related to the numerical model, its calibration and its correction factor.

The proposed model has several advantageous characteristics, such as fast learning capability and robustness, with regard to developing a tsunami early warning system for the at-risk communities along the coastline areas. GRNN is a successful alternative to a database system, developed by using hard computing modelling for the advantageous characteristics, although the extrapolation technique requires further research when the earthquake sources occur at the outer domain of the model regarding their scale and location.

It is necessary to have observations of the arrival time of tsunamis and their propagation to the coastline area to compare between a real-time numerically based model and actual tsunami arrival times. The correction factor for the arrival time can then be formulated, as the correction factor used in this study is only for tsunami height. In order to minimise the correction factor for numerical modelling, more sophisticated and advanced numerical modelling must be applied, leading to more time-consuming execution in the developing database system. This requires more work, and advanced computers may be better in developing a database system in terms of hard computing and execution time for obtaining a more accurate database for the GRNN learning process. In addition, the correction factors may be adjusted based on future tsunami event observations to increase the accuracy of the model.
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First received 17 January 2009; accepted in revised form 10 July 2009. Available online 22 April 2010