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Enhanced Flood Forecasting using Quantitative Precipitation Forecast from Weather Research Forecast-Artificial Neural Network (WRF-ANN) Model Post Processing

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Abstract: Flood forecasting accuracy is crucial for authorities so that they can make better plans. There are many variables involved to provide accurate flood forecasting. The case study area is at Kelantan River Basin, where it experiences the northeast monsoon. QPF from the NWP model was process, evaluate, and use as an alternative to traditional rain gauge systems for input into an integrated hydrometeorological flood forecasting system. The direct QPF outputs from the WRF model with a horizontal resolution of 4 km x 4 km were validate using gauged rainfall measurements. The findings indicates that the WRF model produces QPF for rainfall forecasting. However, the accuracy is not very satisfactory. ANN model was used which integrates several WRF model products to increase the accuracy. After the post-processing using ANN, the accuracy of the QPF had greatly improved. After ANN post-processing, the best r value increased from 0.79 (direct QPF) to 0.99. The enhanced QPF model served as an alternate input for a rainfall-runoff model (HEC-HMS). The NSE value for HEC-HMS with rain gauge rainfall is 0.752 and after calibration is 0.932. The NSE value for the HEC-HMS with WRF-ANN QPF rainfall data is 0.489 and after calibration, 0.764. Even though the NSE value is lower than the NSE using rain gauges as input, but it is still acceptable and may be used to improve rain gauge data to predict floods. The WRF-ANN QPF can forecast rainfall hours of the gauge input, which is a clear benefit. In conclusion, WRF-ANN-based rainfall can predict future floods and help Search and Rescue (SAR) authorities in the decision-making process.

Keywords: Quantitative Precipitation Forecast, Numerical Weather Prediction Model, Weather Research Forecast Model,Artificial Neural Network Model, Flood Forecasting

1. Introduction

Malaysia is an equatorial region which has high temperature and humidity throughout the year and influenced by the northeast and southwest monsoons. The climate in Malaysia is characterized by two monsoons namely Southwest Monsoon from late May to September, and the Northeast Monsoon from November to March. The northeast monsoon brings heavy rainfall (as much as 600 mm in 24-hour extreme cases) occurs during the month of November to February to the east coast of Peninsular Malaysia and to Sabah and Sarawak. Southwest monsoon also brings rain from April to September but generally less than during northeast monsoon. Therefore, the climate of Malaysia is dominated by the northeast monsoon where flooding on the eastern coast of Peninsular Malaysia is commonly corresponds to the monsoon.

The uneven rainfall distribution throughout the year has caused 60 percent of annual rainfall to fall in the month between November to January. The seasonal distribution and variation of rainfall have caused some areas in the country to face floods, especially in low-lying areas while several regions of the country have a problem with the water shortage (Chan, 2006). It is estimated that the areas that are prone to flooding are about 29,800 km2 or 9 percent of the total area in the country which affect 2.7 million people (DID, 2007).

Flood occurs when surface water inundates the land or when water overflows normal confinements (Junk, 1997; Mays, 2010). The process of flooding involves hydrological and meteorological factors. Flood events can occur for a few hours to days or even longer periods. There are many factors that lead to the occurrence of flood including natural factors such as heavy monsoon rain and intensive convective rain combine with human factors such as inefficient drainage systems and an increase in impervious surfaces (Wardah et al., 2011). Floods are known to be hazardous because it has the ability to cause massive damage to the environment (Pradhan

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and Youssef, 2011; Suliman et al., 2013). Floods are common in Malaysia, but the monsoon flood from December 2014 to January 2015 was considered as one of the most devastating floods to hit Malaysia in recent decades, with over 100,000 flood victims evacuated from their homes (Reuters 2014). This has created a huge loss to the country.

Many researchers have proven that floods are damaging to human and properties. Study by Juneng et al., (2010) has indicated that flood episodes occur during monsoon periods can cause severe loss of public infrastructure, crop yield and loss of lives especially in low lying areas in the eastern coast of Peninsular Malaysia. This was supported by Tangang et al., (2008) who discussed that flood events had caused huge economic losses. For example, in between December 2006 and January 2007, extreme flood event occurred in the southern Peninsular Malaysia had caused evacuation of more than 200 000 people, 16 deaths and economic losses of 500 million U.S dollars.

The river Kelantan is among the most crucial rivers in Malaysia because it is subject to the most severe monsoon flood in Malaysia (DID,2004). Kelantan faces many flood events every year due to the monsoonal season. The major flood events reported that occur starting from year 1886, 1967, 1981, 1984, 1988, 2001, 2004, 2007, 2012 and the massive event in year 2014. Flooding has increased along the river in terms of frequency and magnitude (Sooryanarayana, 1988; MMD, 2007) and causes significant management problems. For example, in the year 2002, the intense and prolonged precipitation caused floods in total area of 1,640 km2 and affected the total population of 714,287. In the year 2004, again a flood occurred and the frequency increase to twice per year in 2006 where it occurred on 12 February and 19 December and 2007, the event occurred on 08 January and 13 December.

There are numerous research that has identified the hydrological factors that affect the flood, and it is important to quantify these changes in precipitation and the answer will determine the future planning policy for flood management and decisions. Currently, the authority in Malaysia is implementing the National Flood Forecasting and Warning System (NaFFWS) for Malaysian river basins. The system adopts the hydrodynamic basin model integrated with radar and Numerical Weather Prediction (NWP) Weather Research Forecast (WRF) model (Azad et al., 2019; Wardah et al., 2022).

The post-processing approaches can significantly enhance the forecasting ability of WRF model. Study by Frnda et al., (2019), indicate that the neural network- based model outperformed the "traditional" NWP ECMWF (European Centre for Medium-Range Weather Forecasts) model in terms of accuracy. The model is able to pinpoint crucial model inputs, which improved the precision of predicted outputs. The outcomes served as proof of concept, highlighting the practical applicability of the fundamental hypothesis on the use of neural networks for the development of weather forecasts. This research suggests a forecasting approach based on sensor data processing and machine learning. This method's innovation is concentrated on enhancing the ECMWF global numerical model's forecast accuracy. The application is simple to use by both experts and average end users, and it can offer outputs (in the form of a more accurate ECMWF prediction in real-time.

According to Frnda et al., (2022), a calibration model based on a neural network is suggested for the post-processing of two critical meteorological data, namely the near-surface air temperature (2 m) and the 24-hour accumulation of precipitation. This study's major goal is to enhance forecasts provided by the worldwide NWP model ECMWF for the short term (up to three days). The ECMWF offers a forecast of the meteorological phenomena around the world as opposed to the current local weather models, which typically offer weather forecasts for certain geographic areas (for example, inside one country, but they are more accurate).

This global NWP model also has the crucial advantage of ensuring forecasts are available for free via several well-known internet applications, unlike local models, whose outputs are frequently sold for a fee. Raw ECMWF data and other input parameters discovered as helpful for estimating ECMWF error and subsequent correction are combined in the suggested ECMWF-enhancing model. Real observations from weather stations situated in 10 cities across two European countries consist of the ground truth data used for the model's training phase.

The parametric model performs better than a typical ECMWF prediction and approaches the forecast precision of the regional NWP models, according to the cross- validation data. This research suggests DL-based ECMWF model calibration. The innovative aspect of this approach is the increase in prediction accuracy for daily precipitation and 2m air temperature over a three-day period. The model's performance examination revealed a 13 percent error (RMSE) decrease for 2m air temperature and a 45 percent error reduction for 24 hours of precipitation, respectively. The global model ECMWF is more appealing to both experts and novice users since it provides forecasts without geographic limits, in contrast to localized NWP models. It's also important to note that this strategy might make supercomputer purchases less expensive.

Study by Jabbari and Bae (2018) indicated the importance of improving the accuracy of the forecasting that use raw WRF data by applying Artificial Neural Network (ANN) model as the post- processing technique. This technique had reduced the bias, therefore it resulted in the enhancement of the real-time precipitation forecast accuracy. The research of ANN application related to water studies is widely studied, however the studies still lacking in the improvement of the coupled hydrometeorological model accuracy which use ANN for bias correction of the precipitation data (Jabbari & Bae, 2018).

The ANN has the ability to model complex relations behavior between input and output data. ANN was applied in rainfall forecasting decades ago. The research of ANN application related to water studies is widely studied across the world. The application of it was described in numerous studies [(Bodri and Cermak, 2000; Cigizoglou and Alp, 2004; Kia et al., 2012 ; Jabbari and Bae, (2018)].

There are other studies that had used ANNs in forecasting extreme precipitation events (Nastos et al., 2014). Study by Nastos et al., (2014) indicate there is satisfactory relationship between forecasted and observed rainfall for maximum daily precipitation total for one year ahead when tested the model reliability. Study by Paul (2014), that use ANN to do flood prediction by predicting the water level at Manu River Basin in India. The model is trained and tested using approximately 200000 datasets of real time rainfall and river water level data from gauging stations along the Manu River Basin in the Meghna basin. The input and output parameters were obtained from The Flood Forecasting and Warning Centre, Bangladesh Water Development Boar. In this research, the Feed Forward (FF) and Back Propagation (BP) technique of the Multi Linear Perceptron (MLP) based ANN is used to predict flood. Statistics demonstrate that the data fit the model effectively. This research compares the projected water level to the actual water level using simulation results. Results demonstrate that the model accurately forecasts the flood water level 24 hours in advance.

2.0 Methodology

2.1 Case study of Kelantan River Basin

In this research, Kelantan River Basin has been selected as the case study. Kelantan River basin is situated in the district of Kelantan Darul Naim at the North- eastern part of Peninsular Malaysia with latitude of 4° 40' to 6° 12' North and longitude of 101° 20' to 102° 20' East (Fig 1). The length of the river is about 248 km long and it occupies 85 percent of the Kelantan state. The river basin receives annual rainfall of about 2700 mm during the northeast monsoon between October and January. There are two main tributaries which are Lebir River (2,430 km^2) and Galas River (7,770 km^2) and six sub-basins in Kelantan River basin namely Galas, Nenggiri, Pergau, Guillemard Bridge, Kuala Krai and Lebir. The River Galas has two other main tributaries which are River Nenggiri and River Pergau. Both rivers contribute around 8,000 km^2 or 54 percent from the total Kelantan catchment. The entire basin contains large areas of tropical forested mountains, lowland forest, and limestone hills. Kelantan River system flows northward passing through major towns such as Kuala Krai, Tanah Merah, Pasir Mas and Kota Bharu, before finally discharging into the South China Sea. Kelantan River has average width between 180 to 300 m.

Kelantan has faced many flood episodes including disastrous events occurred in 2009 and 2014. The flood episodes occurred in 2014 had resulted in huge damage to the country. It has been reported by the DID that flooding area is 13,088 km which is 86 percent from the total area of the Kelantan District. The total damage is estimated to be RM94 million for 1640 km^2 total area and affected 714,281 people.

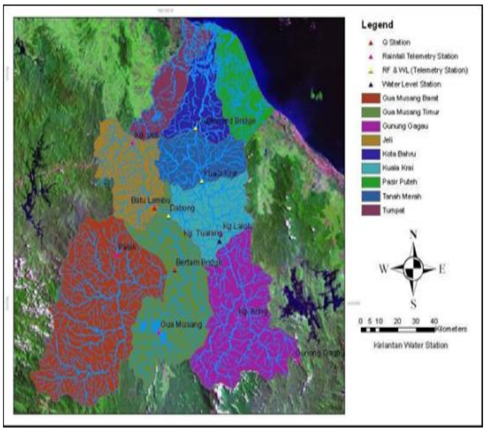

Fig 1- Location of Kelantan River Basin

2.2 Data collection and processing

Data collecting was crucial to this investigation. Multiple data are obtained from the Weather Research Forecast (WRF) model and observation data. The hydrology model predicts floods using the diverse data. WRF model products (rainfall, humidity, and temperature data) in metadata format were received from the Malaysian Meteorological Department (MMD), while hydrological data such rain gauge data and discharge were collected from the Department of Irrigation and Drainage. The study used GrADS, ArcGIS, Matlab, and HEC-HMS for data gathering, processing, and analysis. WRF-ANN rainfall is produced after Artificial Neural Network (ANN) post-processing using WRF model input variables such as WRF rainfall, WRF temperature and WRF relative humidity. Hydrological model HEC-HMS simulates flow in integration with flood forecasting model.

2.2.1 Rainfall Data

Rainfall recorded data was collected from eight rain gauge stations located in the Kelantan River Basin. hydrological data such as rainfall, river streamflow and water levels were obtained from the Hydrology Division, DID. In this study, hourly rainfall data from DID were used for time period from January 2013 until December 2013. The rainfall stations used in this study are listed in Table 1 and their locations are demonstrated in Fig 2. Three categories of rainfall have been included: low rainfall (< 10mm/hour), medium rainfall (>10mm/hour but <30mm/hour) and heavy rainfall (> 30 mm/hour). In year 2013, there were about 85 recorded heavy rainfall events (more than 30 mm/hour) occurred in Kelantan. For statistical measurement requirement, all rainfall data are taken and evaluated against the WRF data sets which consists of about 8760 data sets per year.

Table 1-List of rainfall stations for Kelantan River Basin.

No.	Station ID	Station Name	Latitude	Longitude
1	4819027	Gua Musang	4.88	101.97
2	5017001	Gemala	5.09	101.97
3	5120001	Bertam	5.15	102.05
4	5216001	Gob	5.25	101.66
5	5320038	Dabong	5.38	102.02
6	5322044	Kg. Laloh	5.31	102.28
7	5422046	Ldg. Lepan Kabu	5.46	102.23
8	5722057	Jps Machang	5.79	102.22

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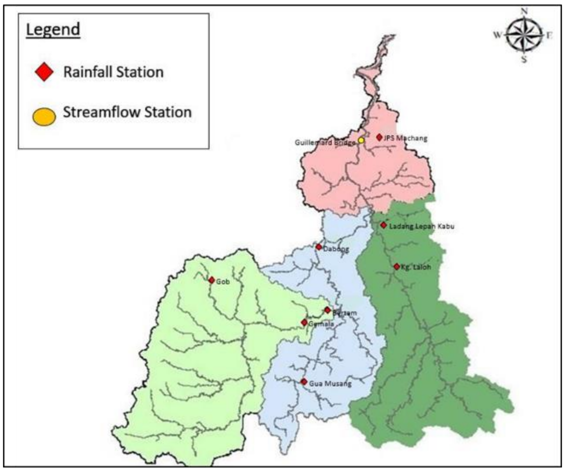

Fig 2- Location of rainfall and streamflow station (Rain Gauge).

2.3 **Development of the Hydro-Meteorological Flood Forecasting Model**

The development of the hydro-meteorological flood forecasting model for the Kelantan River Basin by using HEC-HMS model is illustrated in Fig 3. The process begins with the preparation of the input data to be used into the HEC-HMS model. In this research, the input data is from the ANN model which is WRF based ANN rainfall input into the hydrological or rainfall-runoff model as described in previous section. The rainfall-runoff model for the Kelantan River Basin catchment was developed using the HEC-HMS model which begins with watershed delineation. The model calibration, validation and simulation were conducted based on event scenario where only selected duration period was used in this study.

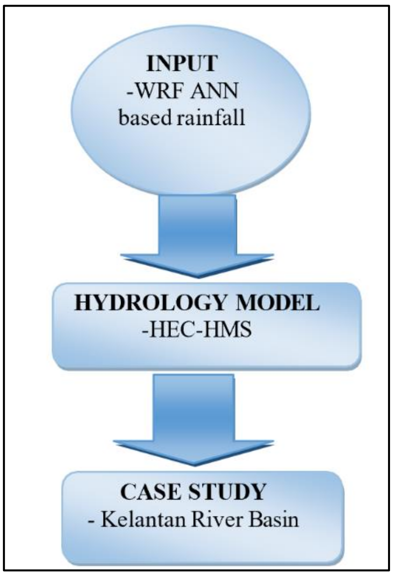

Fig 3-Hydro-meteorological Flood Forecasting System Flowchart.

2.4 **Model Performance-Nash-Sutcliffe coefficient (NSE)**

The Nash-Sutcliffe model efficiency coefficient (NSE) is commonly used to assess the predictive power of hydrological discharge models. However, it can also be used to quantitatively describe the accuracy of model outputs for other things than discharge (such as nutrient loadings, temperature, concentrations etc.). It is defined as:

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{n}(X_{o,t} - X_{m,t})^2}{\sum_{t=1}^{n}(X_{o,t} - \overline{X}_o)^2}$$

Where:

- $X_{o,t}$: Observed value at time t
- $X_{m,t}$: Modeled (simulated) value at time t
- $\bar{X}_o$: Mean of the observed values
- n: Total number of time steps

Nash-Sutcliffe efficiencies can range from -∞ to 1. An efficiency of 1 (E = 1) corresponds to a perfect match between model and observations. An efficiency of 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero ($-\infty < E < 0$) occurs when the observed mean is a better predictor than the model. Essentially, the closer the model efficiency to one, the more accurate the model.

3.0 **Results and Discussion**

3.1 **Statistical Verification of WRF-ANN rainfall model (period of 92 days-wet season).**

The most crucial element in rainfall forecasting is data accuracy. High error data can lead to misleading forecasts, which can have an impact on flood forecasting. The accurate forecasting of WRF model products with adequate lead time would, in turn, aid in disaster management systems, reducing the loss of lives and property damage. Forecast verification can assist in the monitoring and improvement of forecast data. The verification process begins with a matched set of forecasts and observations for identical locations and times based on rainfall amount. The verification method is crucial for ensuring the accuracy of the forecast data. This statistical verification covers the 92-day period from October to December 2013. Generally, during this period, it was the wettest months in comparison to the other months.

Table 2-Correlation, r for all stations

		r, correlation	
Time (UTC)	**Hour**	**Before ANN**	**After ANN**
1100	Hour 3	0.64	0.99
1400	Hour 6	0.8	0.94
1700	Hour 9	0.49	0.89
2000	Hour 12	0.52	0.84
2400	Hour 16	0.53	0.84
800	Hour 24	0.39	0.9

The correlation coefficient r quantifies the strength of a linear relationship between two quantitative variables. The value of correlation, r for all stations was summarized as in Table 2. A strong correlation exists when the r value is greater than 0.7. According to the results of the ANN model, hour 6 had the highest correlation compared to the other hour intervals. The longer forecast lead time affects rainfall forecasting accuracy and thus the correlation between WRF-ANN Rainfall and observed rainfall, which could cause the low value of correlation, r before ANN post- processing. As the lead time increases, so does the accuracy of the WRF QPF, as well as the ability to forecast floods (Li et al., 2017).

There is an improvement in the correlation for forecasted rainfall (WRF rainfall) after ANN post-processing (WRF-ANN rainfall), with better correlation where all correlation is higher. This is consistent with the findings of Benavides Cesar et al., (2022), who discovered that combining multiple data sources can improve the forecast model accuracy. Therefore, it can be concluded that ANN post-processing does improve the accuracy of the forecasted data.

3.2 **Rainfall Runoff Model Development for Kelantan River Basin using HEC-HMS model.**

A rainfall-runoff model for the Kelantan River Basin catchment area was successfully developed during this research. The model was constructed with HEC- HMS 4.9 via integration with the GIS application software ArcGIS to create a basin model from DEM data. The basin characteristics were exported into the HEC-HMS model, and the pre-processing of the basin model. The rainfall input was selected based on wet period time series rainfall data. It is essential to ensure that the selection of the rainfall event is not taken lightly. The magnitude of rainfall intensity, the duration of the rainfall, and the spatial variability are all factors to consider in selecting the event-based rainfall.

The rainfall runoff model was successfully run and optimized for simulation period between 28th November 2013 until 8th December 2013 with an hourly time interval. During this time period, a large flood event had occurred in the Kelantan River Basin. The following sections discuss the simulation results by using the rainfall input from gauge stations and from the newly formulated WRF-ANN based rainfall.

3.2.1 **Using Rainfall from Rain Gauge**

The results of the simulation are presented in Fig 4. The blue line represents the flow generated by the rainfall runoff model that was successfully simulated. The black line represents the observed data from the Guillemard Bridge streamflow (SF5721442). For the streamflow station, the observed data flow was smooth due to the availability of the peak flow data. Therefore, the observed data can be used for flood analysis observation. As a result, it is also possible to conclude that the simulation of flow using this rainfall runoff model is clearly successfully delivered. Fig 5 displays the results of the test simulation. The computed peak flow is 4894.6 m^3/s, which is greater than the observed peak flow of 5516.5 m^3/s. The Nash-Sutcliffe Efficiency Coefficient (NSE) of 0.752 is considered as an acceptable agreement with a value near to one. The error percentage is 32.03%, which is still considered high. Thus, a calibration (optimization) and validation procedure were used to enhance the accuracy of the simulation results as shown in the following sub- section.

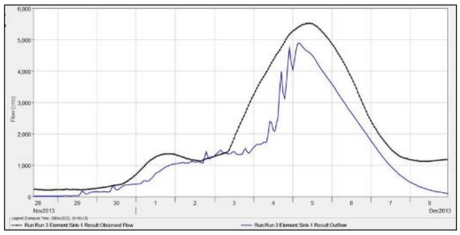

Fig 4-HEC-HMS simulation result using rain gauge rainfall.

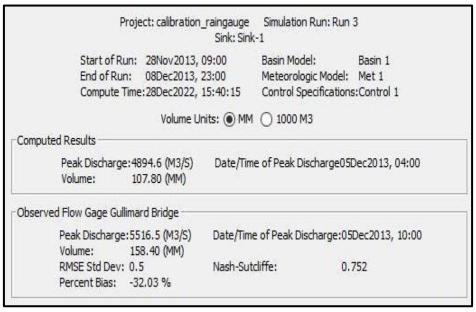

Fig 5-Summary result for calibration of HEC-HMS using rain gauge.

3.2.1.1 **Model Optimization (Calibration)**

Model optimization (calibration) is the process of adjusting model parameter values in order to obtain the best fit or acceptable simulated hydrograph in contrast to an observed hydrograph (Feldman, 2000). Calibration and validation are methodologies that concentrate on the accuracy of the simulated peak flow and time peak at the confluence of the Kelantan River Basin. The calibration process in this study was done manually using the optimization tools, and the parameters were adjusted during the calibration process. The validation process was then carried out to ensure the best fit model's efficiency. Nash-Sutcliffe Efficiency (NSE) was chosen as the model performance criteria for the calibration method used in this research.

According to (Gupta et al., 2009; Bardossy, 2007; Krause and Bronstert, 2007). The NSE is broadly used in hydrological models for flood forecasting analysis or research because it is sensitive to the hydrographs' peak flow. As a result, the NSE was an appropriate model efficiency criterion for assessing the performance of the model. Calibration could be carried out manually or through an optimization process. Manual calibration is based on the user's understanding of physical properties. The optimization calibration process entails iteration and model parameter adjustments until the value of the selected objective function is minimized (Cunderlik and Simonovic, 2007). The calibration process in this research was conducted by using optimization calibration.

The selection of rainfall events for model calibration and verification in hydrological models is a crucial component according to Chu and Steinman, (2009). This is affirmed by (Krause et. al, 2007), as there are numerous factors to consider, such as rainfall characteristics, magnitude, and intensity. Moreover, the duration of the storm and the spatial distribution of rainfall impacts the characteristics of the

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rainfall-runoff process. As a result, the rainfall event used in the calibration and validation process was selected depending on the rainfall duration and magnitude. Intense rainfall events were selected as calibration events since the goal of this study is to incorporate the hydrological element into the meteorological aspects in order to forecast flood.

The plot for simulated and observed hydrographs are presented as in Fig 6. According to Fig 7, the observed hydrograph volume was 158.40 MM for the whole duration, and the observed peak discharge was 5516.5 m^3/s. The hydrograph patterns indicate how well both observed and simulated hydrographs. The falling shape of the hydrograph was assumed to have no effect on the overall performance of the model because the model performance was evaluated using the rising limb and peak flow of the runoff. The computed volume was 154.50 MM which is very close to the observed volume (158.40 MM) and the computed peak discharge from the calibration run was 6376.3 m^3/s, which is greater than the observed peak discharge of with an accepted percent error of 2.59. Meanwhile, the NSE for model efficiency was 0.932, indicating it is a satisfactory agreement of the rainfall runoff model.

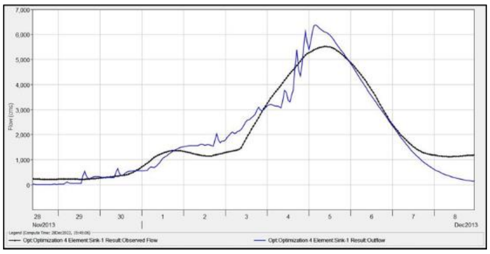
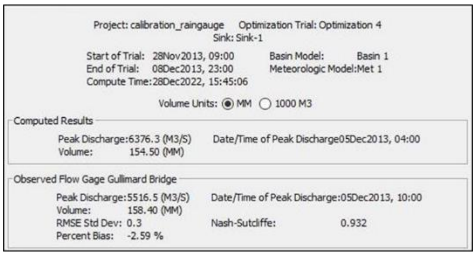


Fig 6-Calibration of HEC-HMS.



Project: calibration_raingauge Optimization Trial: Optimization 4
Sink: Sink-1
Start of Trial: 28Nov2013, 09:00 Basin Model: Basin 1
End of Trial: 08Dec2013, 23:00 Meteorologic Model: Met 1
Compute Time: 28Dec2022, 15:45:06
Volume Units: MM 1000 M3
Computed Results
Peak Discharge: 6376.3 (M3/S) Date/Time of Peak Discharge 05Dec2013, 04:00
Volume: 154.50 (MM)
Observed Flow Gage Gullimard Bridge
Peak Discharge: 5516.5 (M3/S) Date/Time of Peak Discharge: 05Dec2013, 10:00
Volume: 158.40 (MM)
RMSE Std Dev: 0.3 Nash-Sutcliffe: 0.932
Percent Bias: -2.59 %

Fig 7-Summary result for calibration of HEC-HMS

3.2.2 Using WRF-ANN based Rainfall

Once the rainfall-runoff model for Kelantan River basin was created and calibrated, it is now ready to be applied for the newly formulated WRF-ANN based rainfall (QPF) input. The simulation results using WRF-ANN based rainfall are presented in Fig 8. The blue line represents the flow generated by the successfully simulated rainfall runoff model. The observed data from the Guillemard Bridge streamflow is represented by the black line (SF5721442). The observed data flow for the streamflow station was smooth due to the availability of peak flow data. As a result, the observed data can be used to observe floods.

The simulated results from the WRF-ANN rainfall model were shown in Fig 9. The computed peak flow of m3/s exceeds the observed peak flow of 5516.5 m^3/s. 0.489 is the Nash-Sutcliffe Efficiency Coefficient (NSE) and the percent error is 29.60. Therefore, the model will be calibrated and validated using the optimization computation in the HEC-HMS model as illustrated in the following sub- section.

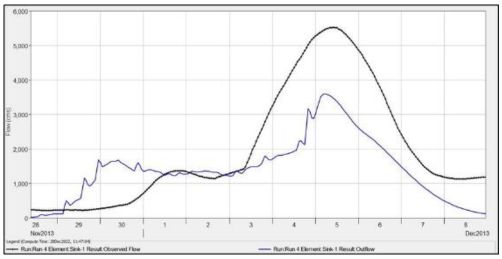
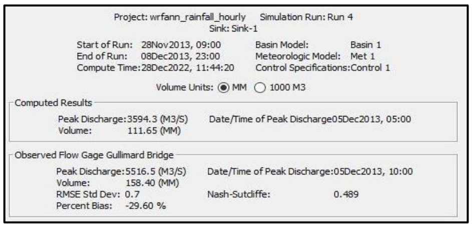


Fig 8- HEC-HMS simulation result using WRF-ANN rainfall.



Project: wrfann_rainfall_hourly Simulation Run: Run 4
Sink: Sink-1
Start of Run: 28Nov2013, 09:00 Basin Model: Basin 1
End of Run: 08Dec2013, 23:00 Meteorologic Model: Met 1
Compute Time: 28Dec2022, 11:44:20 Control Specifications: Control 1
Volume Units: MM 1000 M3
Computed Results
Peak Discharge: 3594.3 (M3/S) Date/Time of Peak Discharge 05Dec2013, 05:00
Volume: 111.65 (MM)
Observed Flow Gage Gullimard Bridge
Peak Discharge: 5516.5 (M3/S) Date/Time of Peak Discharge: 05Dec2013, 10:00
Volume: 158.40 (MM)
RMSE Std Dev: 0.7 Nash-Sutcliffe: 0.489
Percent Bias: -29.60 %

Fig 9-Summary result for simulation of HEC-HMS WRF-ANN rainfall.

3.2.2.1 Model Optimization (Calibration)

In most modelling studies, a sensitivity analysis is performed (Azam et. al, 2017, Tassew et.al, 2019). Identifying the key parameters and parameter precision required for calibration is a necessary process. The most basic sensitivity analysis technique makes use of partial differentiation, whereas the simplest method involves changing parameter values one at a time. A sensitivity analysis was performed to determine the most influential parameter in the simulation. Fig 10 demonstrates the plot for simulated and observed hydrographs. The observed runoff hydrograph volume was 158.40 MM for the whole selected duration and the peak discharge was 5516.5 m^3/s. The calibration process successfully improved the results. According to Fig 11. The hydrograph observations indicate how well both observed and simulated hydrographs perform. The computed volume was 165.38 MM, 4.4% higher than the observed runoff hydrograph volume of 158.40 MM and the computed peak discharge from the calibration run was 6147.2 m^3/s, which was greater than the observed peak discharge by 4.28 %.

Meanwhile, the NSE for model efficiency was 0.764, indicating that the rainfall runoff model is in satisfactory agreement. The peak flow and total volume of all events are very close to the observations after optimization, with less than 5 % error in peak and volume, The results revealed from the sensitivity analysis that the curve number is the most sensitive parameter, followed by the lag time. Based on the selected loss, transform, and flow routing methods, the overall performance of the HEC-HMS model was very good in terms of relative error functions and Nash-Sutcliffe Efficiency. As a

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result, it is possible to propose that the calibrated parameters be applied to other catchments in the basin and nearby basins where the areas have similar geomorphologic conditions with the case study area.

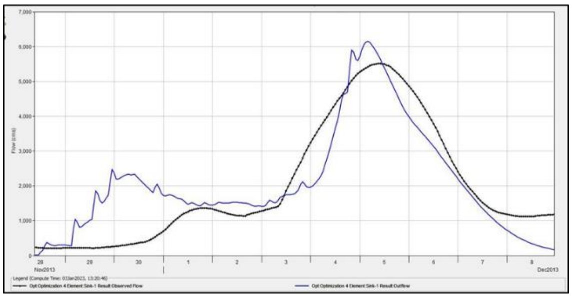
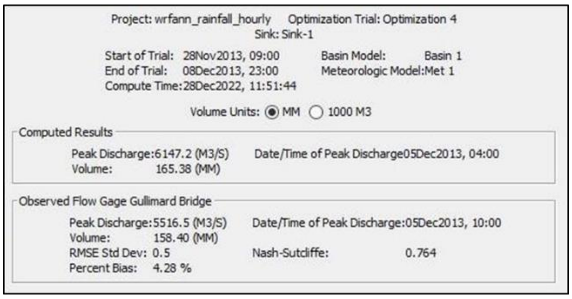


Fig 10-Calibration HEC-HMS result using WRF-ANN rainfall.



Project: wrfann_rainfall_hourly Optimization Trial: Optimization 4
Sink: Sink-1

Start of Trial: 28Nov2013, 09:00 Basin Model: Basin 1
End of Trial: 08Dec2013, 23:00 Meteorologic Model: Met 1
Compute Time: 28Dec2022, 11:51:44

Volume Units: MM 1000 M3

Computed Results

Peak Discharge: 6147.2 (M3/S) Date/Time of Peak Discharge 05Dec2013, 04:00
Volume: 165.38 (MM)

Observed Flow Gage Gullimard Bridge

Peak Discharge: 5516.5 (M3/S) Date/Time of Peak Discharge: 05Dec2013, 10:00
Volume: 158.40 (MM)
RMSE Std Dev: 0.5 Nash-Sutcliffe: 0.764
Percent Bias: 4.28 %

Fig 11- Summary result for calibration of HEC-HMS WRF-ANN rain.

4.0 **Conclusion**

In overall, the adoption of the Artificial Neural Network (ANN) model into the post-processing process had improved the accuracy of the Weather Research Forecast (WRF) model products i.e., rainfall with incorporation of other data namely the relative humidity and temperature. This research was carried out with a large size catchment: the Kelantan River Basin, which is in the state of Kelantan, northeast of Peninsular Malaysia where this area does experience the northeast monsoon. The Quantitative Precipitation Forecast (QPF) can provide valuable information and guidance to hydrologists when issuing flood watches and warnings, especially when several storms must be analyzed at the same time. The implementation of hydrometeorological flood forecasting by integration using the HEC-HMS model for flood prediction in the Kelantan River Basin is recommended for more accurate flood prediction. The newly developed WRF-ANN based rainfall (WRF-ANN QPF) is coupled with a rainfall runoff model (HEC-HMS) in an integrated hydro-meteorological flood forecasting system for Kelantan River basin case study. Results indicate that the WRF-ANN based rainfall is able to represent gauge rainfall as input to flood forecasting model. Thus, it can provide a more accurate flood forecast and would assist in the development of a better rainfall runoff model setup. The advantage of the WRF-ANN QPF is its ability to be able to forecast up to 24 hours ahead. As a result, it can provide longer lead time in flood forecasting.

A rainfall-runoff model for the Kelantan River Basin catchment area was successfully developed during this research. NSE was chosen as the model performance criteria for the calibration method used in this research. Nash-Sutcliffe Efficiency (NSE) indicates there is a satisfactory agreement of the rainfall runoff model. The calibration process in this research was conducted by using optimization calibration. The results revealed from the sensitivity analysis that the curve number is the most sensitive parameter, followed by the lag time.

Based on the selected loss, transform, and flow routing methods, the overall performance of the HEC-HMS model was very good in terms of relative error functions. As a result, it is possible to propose that the calibrated parameters be applied to other catchments in the basin and nearby basins where the areas have similar geomorphologic conditions with the case study area. The results indicate that the NSE value for HEC-HMS using rainfall from rain gauge as an input into the model is 0.752 and the NSE value after calibration is 0.932. While the NSE value for the HEC-HMS using WRF-ANN rainfall as data input to the model is 0.489 and after calibration, the NSE value is 0.764. Even though the NSE value is lower than the NSE using rain gauge as input, the result is still considered satisfactory where the value of NSE is near one, and it can be used to support the rain gauge data as for purpose to forecast flood. The obvious advantage is the WRF-ANN QPF can provide rainfall forecast hours ahead compared to the traditional gauge rainfall input. As an outcome, WRF-ANN-based rainfall can provide an early warning system by forecasting future floods and providing assistance to Search and Rescue (SAR) authorities in the decision-making process.

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