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STUDY OF HYBRID FLOOD FORECASTING APPROACH COMBINING MULTIPLICATE SEASONAL ARIMA AND HYBRID-NEURO FUZZY BASED ON LONG-TERM TIME SERIES

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Abstract

This research proposes a modern hybrid method to forecast the flood employing an approach combining Multiplicative Seasonal Autoregressive Moving Average (MSARIMA) and Hybrid-Neuro Fuzzy Inference System (HN-FIS) based on long-term time series. This proposed method is called Hybrid Flood Forecasting System Technology (Hybrid-FFST). This research aims to improve three previous types of research on flood forecasts, such as flood prediction using HN-FIS and flood forecasting using MSARIMA and rainfall prediction using Multiplicative Seasonal Autoregressive Moving Average Subsequence Aggregate (MSARIMASA). This research has taken place in Bandung West Java Province, Indonesia. The performance of flood event forecasting improving by using the hybrid approaches method using both MSARIMA and two levels of HN-FIS. This proposed method employs six parameters: rainfall, temperature, population density, large watershed, the altitude of the area, and slop of the land to predict the flood event. The performance of this method is generated and fitting well using the Hybrid-FFST approach and the verified by Mean Absolute Percentage Error (MAPE), Root Means Square Percentage Error (RMSPE), and Mean Forecast Error (MFE) to identify the best-fitted model of the proposed model. The proposed model's performance is compared using MAPE, RMSPE, and MFE with MSARIMA, HN-FIS, and MSARIMASA model. The confidence performance of the proposed method obtains more significant than 97% according to the MAPE, RMSE, and MFE values. The proposed model results indicate better performance than the MSARIMA, HN-FIS, and MSARIMASA models to forecast the flood event. The impact of this research is the flood can be predicted before occurred in someplace.

Keywords: Flood forecasting system, Flood, Hybrid approach, Prediction.

1. Introduction

Rainfall is the primary variable of the climate in Indonesia, especially in Bandung, West Java Province. The rainfall is linked with the monsoon as the extreme variation caused by the flood event in Indonesia (according to Indonesia-Climate-Country Studies) [1]. The previous research on meteorological forecasting was aimed to assess the disaster impact in some regions. Asklany et al. [2] proposed the probabilistic prediction using two skills scores as the Friction and Brier Score. They demonstrate that is the prediction of rainfall events could be a success only in zero when no rainfall at the time. Otherwise, the fuzzy inference system output preceded the recorded maximum data in six previous hours before the rain. Nhita and Adiwijaya [3] have discussed the Genetic Algorithm (GA) to produce higher accuracy of the rainfall forecast system. Alfin and Sarno [4] were analysed agricultural irrigation control used fuzzy methods to determine water quantity quantitatively. Fallah-Ghalhary et al. [5] studied Mamdani FIS to predict the Khorasan region's rainfall events. Tanzouak et al. [6] predicted flood events with improving the accuracy of Numerical Weather Prediction (NWP). Sahagun et al. [7] studied mainly predicted by the water level in the high-risk area of Masantol, Pampanga employs Artificial Neural Network. Research in Sumitra and Supatmi [8] studied how to forecast the flood using a three-parameter of the Mamdani fuzzy model. Supatmi et al. [9] proposed MSARIMA to predict the occurrence of flooding in Bandung, West Java, Indonesia. Supatmi et al. [10] proposed the hybrid neuro-fuzzy inference system (HN-FIS) to predict the flood event. Supatmi et al. [11] studied the rainfall prediction employing MSARIMASA.

The idea of flood event forecasting is based on the previous data according to Badan Meteorologi Bandung [12]. Many researchers working on flood forecasting employing different models but still obtained a significant error. In this study, the proposed new model approach obtains better accuracy than other models. The new model is hybrid flood forecasting combining Multiplicative Seasonal ARIMA (MSARIMA) and Hybrid-Neuro Fuzzy Inference System (HN-FIS).

2. Method

The design system consists of the proposed flood forecasting approach, MSARIMA multi-step and two-level HN-FIS architecture. The steps of the method could work and how to apply this system to the environment.

Figure 1 presents the main structure of the proposed Hybrid approach. The structure comprises MSARIMA and Hybrid-Neuro fuzzy models arranged in series, together with Principal Component Analysis and Balancing (PCA+BAL) procedures. The major stages for the proposed flood forecasting approach are as follows:

- A large database is created with historical data records of meteorological data, and then the observed variables selected are performed. The data divided into training and test.
- MSARIMA model in first used as an auxiliary linear predictor to predict future values of the observed variables.
- Principal component analysis and balancing (PCA+BAL) procedures aim to reduce the dimension of the output data.

- A first Hybrid-neuro fuzzy inference system (FH-NFIS) is used to reach the forecasted variable to catch nonlinear relations between data. To guarantee generalization capacity, it is necessary to reduce the dimension of input data again.
- The second Hybrid-Neuro FIS (SH-NFIS) is used to forecast flood event series based on past values of flood events and data from the previous step.

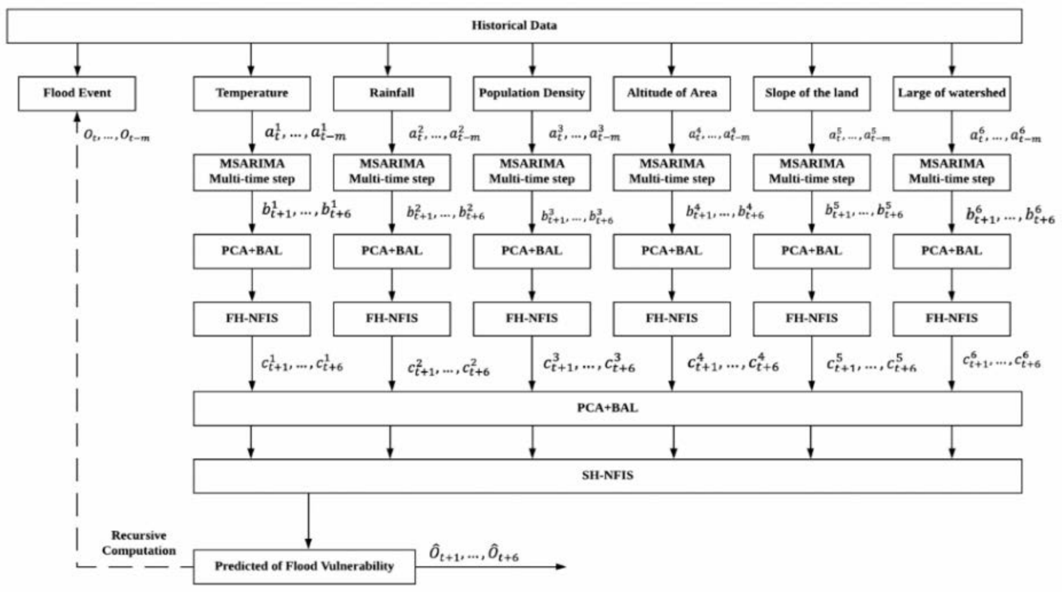

Fig. 1. The architecture of the proposed hybrid flood forecasting approach.

Table 1 shows the best MSARIMA model obtained for each inventory datasets variable. First HN-FIS (FHN-FIS) aims to process the output from the MSARIMA model became the input for the next step.

Table 1. MSARIMA model to the inventory datasets variables.

Variable	MSARIMA Model MSARIMA (*p*,*d*,q) *x* (*P*,*D*,*Q*)$_s$
Population density	MSARIMA (0,0,0) *x* $(0,1,1)_{12}$
Large of watershed	MSARIMA (0,0,0) *x* $(1,1,1,)_{12}$
Slope of the land	MSARIMA (0,1,0) *x* $(1,1,1)_{12}$
Altitude of area	MSARIMA (0,0,0) *x* $(2,1,1)_{12}$
Temperature	MSARIMA (0,1,0) *x* $(0,1,1)_{12}$
Rainfall	MSARIMA (0,1,0) *x* $(2,1,1)_{12}$

The rules of FHN-FIS model denoted as below:

- Rule-1 (r_1): if P is P_1 and A is A_1 and R is R_1 and S is S_1 and T is T_1 and L is L_1, then Z=B_1.
- Rule-2 (r_2): if P is P_2 and A is A_2 and R is R_2 and S is S_2 and T is T_2 and L is L_2, then Z=B_2.
- Rule-n (r_n): if P is P_n and A is A_n and R_f is R_{fn} and S is S_n and T is T_n and L is L_n, then Z=B_n.

P, *A*, *R*, *S*, *T*, *L* presents the input, which is population density, the altitude of the area, rainfall, the slope of land, temperature, and size of the watershed. P_1, P_2, P_3, P_4 presents the membership functions of population density. A_1, A_2, A_3 presents the membership functions of the altitude of the area. R_1, R_2, R_3, R_4 presents the membership functions of rainfall. S_1, S_2, S_3, S_4, S_5 presents the membership functions of the slope of the land. T_1, T_2, T_3 presents the membership functions of temperature. L_1, L_2, L_3, L_4, L_5 presents the membership functions of the large watershed. The firing strength denotes as w_1, w_2, …, w_n. B_1, B_2, …, B_n presents the consequent parameters which need to adjust. The output from FHN-FIS is processed as the input for the last step employing the second HN-FIS (SHN-FIS) model. The rules of the SHN-FIS model denoted as below:

- Rule-1(r_1): if *PF* is PF_1 and *FF* is FF_1, then $Z=B_1$
- Rule-2 (r_2): if *PF* is PF_2 and *FF* is FF_2, then $\underline{Z}=B_2$
- Rule-n(r_n): if *PF* is PF_n and *FF* is FF_n then $Z=B_n$

PF, *FF* presents the input, which is the previous flood event, forecasted flood event. PF_1, PF_2, PF_3 presents the membership functions of the previous flood event. FF_1, FF_2, FF_3 presents the membership functions of the forecasted flood event from the HN-FIS1 outputs. The firing strength denotes as w_1, w_2, …, w_n. g_1, g_2, …, g_n presents the consequent parameters which need to adjust. The result of the proposed model presented on the performance measurement using MAPE, MFE, and RMSPE is described in section 3.

Measurement performance using mean absolute percentage error (MAPE), mean forecast error (MFE), root mean square percentage error (RMSPE). The absolute error *Et* denoted as *Et* = *Pt* - *Ft*, where the *Pt* is the previous values, and *Ft* is the forecasted values. The equation formulas for MAPE, RMSPE, and MFE are formulated as Eqs. (1) to (3). Where *n* is the number of both real value and predicted value

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|E_t|\ x\ 100\ \% \tag{1}$$

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {E_t}^2}\ x\ 100\% \tag{2}$$

$$\mathrm{MFE} = \frac{1}{n}\sum_{t=1}^{n} E_t \tag{3}$$

3. Results and Discussion

The results were obtained with the proposed Hybrid FFST approach based on MSARIMA-HNFIS models for flood vulnerability forecasting. Thirty areas in Bandung city in West Java province of Indonesia were considered, and different prediction time horizons were analysed: one-step-ahead (12 years) and multi-step-ahead forecasting (up to 42 years). The results are presented as follows.

In the first step, all the inventory datasets parameter forecasted using MSARIMA. The result is based on the best model of the MSARIMA model shows in Tables 2 to 7. Based on the design of the proposed model in Fig. 1, obtained six best models MSARIMA to predict the inventory dataset of flood vulnerability factors. The best performance of rainfall obtained inMSARIMA (0,1,0) *x* $(2,1,1)_{12}$ with MAPE, RMSPE, and MFE respectively 0.146, 0.271, 0.11. The best model of temperature is MSARIMA (0,1,0) *x* $(0,1,1)_{12}$ with MAPE, RMSPE, and MFE respectively 0.112, 1.134, 0.301. The best model of large watershed obtained in

MSARIMA (0,0,0) *x* $(1,1,1)_{12}$ with the MAPE, RMSPE, MFE respectively 0.0007, 0.0089, 0.0000006. The altitude of the area obtains best MAPE, RMSPE, and MFE in model MSARIMA (0,0,0) *x* $(2,1,1)_{12}$ with the values respectively 0.011, 0.083, 0.0087. The slope of the land obtains the best RMSE, MAPE, MFE (0.038, 0.194, 0.002) in model MSARIMA (0,1,0) *x* $(1,1,1)_{12}$. The population density obtains the best RMSE, MAPE, MFE (0.42, 0.61, 0.56) in MSARIMA (0,0,0) *x* $(0,1,1)_{12}$. Those results have shown the good performance of the MSARIMA model to predict the parameters for flood vulnerability occurrence. In addition, based on the result the lowest parameter may or may not be unconsidered on the next flood vulnerability forecast employing FHN-FIS (shown in Tables 2 to 7).

Table 2. MSARIMA models criteria for the yearly rainfall forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) *x* $(0,1,1)_{12}$	0.160	0.321	0.15
MSARIMA (0,0,0) *x* $(1,1,1,)_{12}$	0.187	0.432	0.18
MSARIMA (0,1,0) *x* $(1,1,1)_{12}$	0.159	0.51	0.14
MSARIMA (0,0,0) *x* $(2,1,1)_{12}$	0.174	0.387	0.17
MSARIMA (0,1,0) *x* $(0,1,1)_{12}$	0.136	0.268	0.12
MSARIMA (0,1,0) *x* $(2,1,1)_{12}$	0.146	0.271	0.11

Table 3. MSARIMA models criteria for the yearly temperature forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) *x* $(0,1,1)_{12}$	0.104	1.46	0.27
MSARIMA (0,0,0) *x* $(1,1,1,)_{12}$	0.109	1.53	0.87
MSARIMA (0,1,0) *x* $(1,1,1)_{12}$	0.143	1.63	0.56
MSARIMA (0,0,0) *x* $(2,1,1)_{12}$	0.132	1.045	0.420
MSARIMA (0,1,0) *x* $(0,1,1)_{12}$	0.102	1.021	0.241
MSARIMA (0,1,0) *x* $(2,1,1)_{12}$	0.112	1.134	0.301

Table 4. MSARIMA models criteria for the yearly population density forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) *x* $(0,1,1)_{12}$	0.42	0.61	0.56
MSARIMA (0,0,0) *x* $(1,1,1,)_{12}$	0.83	0.92	0.76
MSARIMA (0,1,0) *x* $(1,1,1)_{12}$	0.78	0.86	0.94
MSARIMA (0,0,0) *x* $(2,1,1)_{12}$	0.80	0.91	0.61
MSARIMA (0,1,0) *x* $(0,1,1)_{12}$	0.51	0.71	0.59
MSARIMA (0,1,0) *x* $(2,1,1)_{12}$	0.79	0.86	0.82

Table 5. MSARIMA models criteria for the yearly large of watershed forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) *x* $(0,1,1)_{12}$	0.0012	0.0112	0.0000016
MSARIMA (0,0,0) *x* $(1,1,1,)_{12}$	0.0007	0.0089	0.0000006
MSARIMA (0,1,0) *x* $(1,1,1)_{12}$	0.0009	0.0136	0.0000018
MSARIMA (0,0,0) *x* $(2,1,1)_{12}$	0.0034	0.0230	0.0000023
MSARIMA (0,1,0) *x* $(0,1,1)_{12}$	0.0008	0.0091	0.0000009
MSARIMA (0,1,0) *x* $(2,1,1)_{12}$	0.0034	0.0350	0.0000016

Table 6. MSARIMA models criteria for the yearly altitude of area forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) x $(0,1,1)_{12}$	0.164	0.199	0.0768
MSARIMA (0,0,0) x $(1,1,1,)_{12}$	0.072	0.113	0.0187
MSARIMA (0,1,0) x $(1,1,1)_{12}$	0.089	0.102	0.0212
MSARIMA (0,0,0) x $(2,1,1)_{12}$	0.011	0.083	0.0087
MSARIMA (0,1,0) x $(0,1,1)_{12}$	0.124	0.163	0.0136
MSARIMA (0,1,0) x $(2,1,1)_{12}$	0.036	0.096	0.0096

Table 7. MSARIMA models criteria for the yearly slope of the land forecasting.

MSARIMA Models	MAPE (%)	RMSPE (%)	MFE
MSARIMA (0,0,0) x $(0,1,1)_{12}$	0.123	0.243	0.018
MSARIMA (0,0,0) x $(1,1,1,)_{12}$	0.045	0.209	0.003
MSARIMA (0,1,0) x $(1,1,1)_{12}$	0.038	0.194	0.002
MSARIMA (0,0,0) x $(2,1,1)_{12}$	0.088	0.336	0.045
MSARIMA (0,1,0) x $(0,1,1)_{12}$	0.065	0.242	0.034
MSARIMA (0,1,0) x $(2,1,1)_{12}$	0.098	0.216	0.093

In the next step, the result from MSARIMA became the input for the next model (FHN-FIS) shows in Tables 7 to 9. According to research, most flood-prone areas are the areas with the lowest slope of the land, the lowest altitude of the area, and the lowest watershed size, and high rainfall.

In this study, the more slope of the land, the more of the watershed's size, the more of the altitude of the area, the more of population density, the more of temperature and the lowest rainfall intensity effect to lower of flooding probability. In fact, in the residential area, rainfall would increase with a decrease in the area's altitude. However, a flood occurs at a lower altitude of the area, lower of the land's slope, lower of the size of the watershed, and higher rainfall intensity [13-16].

Table 7 summarizes the performance of all models developed throughout this work for one-step forecasting: MSARIMA, HNFIS, MSARIMASA, and Hybrid FFST. The MAPE of the Hybrid FFST model is 0.0203%, while it is similar to 0.0236% for the MSARIMA model. The RMSE is improving from 1.17% to 0.0273%, and for MFE also improving from 0.67 to 0.077. Based on the better RMSE value of MSARIMA and HN-FIS than MSARIMASA, in this study, the proposed model combining two models: MSARIMA and HN-FIS, namely Hybrid FFST model.

Table 12 also shows combining MSARIMA and HN-FIS obtains the best performance. Tables 8 to 11 show the proposed model's performance on multi-step ahead forecasting. Those tables also showed the proposed model obtain the best performance (MAPE, RMSPE, MFE) to forecast the flood vulnerability in Bandung, West Java Province in Indonesia.

Table 11 shows the proposed model performance for testing and training datasets. The RMSE values is 0.077%, RMSPE is 0.504%, and MFE is 0.159%. It means that the proposed models can be forecasted the flood vulnerability with a confidence interval greater than 97%.

Table 8. One-step-ahead forecasting errors

Error	MSARIMA [9]	HN-FIS [10]	MSARIMASA [11]	Proposed Model Hybrid FFST
MAPE (%)	0.0236	1.256		0.0203
RMSPE (%)	0.0818	0.0371	1.17	0.0273
MFE			0.67	0.077

Table 9. Multi-step ahead (24 years) forecasting errors

Error	MSARIMA [9]	HN-FIS [10]	MSARIMASA [11]	Proposed Model Hybrid FFST
MAPE (%)	0.0348	1.356		0.0303
RMSPE (%)	0.0918	0.0571	1.87	0.0296
MFE			0.87	0.086

Table 10. Multi-step ahead (36 years) forecasting errors

Error	MSARIMA [9]	HN-FIS [10]	MSARIMASA [11]	Proposed Model Hybrid FFST
MAPE (%)	0.0465	1.656		0.0412
RMSPE (%)	0.0938	0.0371	2.17	0.0291
MFE			0.97	0.087

Table 11. Multi-step ahead (42 years) forecasting errors

Error	MSARIMA [9]	HN-FIS [10]	MSARIMASA [11]	Proposed Model Hybrid FFST
MAPE (%)	0.0512	1.256		0.0461
RMSPE (%)	0.123	0.0491	2.37	0.0301
MFE			1.07	0.088

Table 12 describes the performance of hybrid-FFST for the training dataset and testing dataset and shown that the testing dataset results better than the training dataset result for MAPE, RSMPE, and MFE.

Table 13 describes the comparison of real flood vulnerability and forecasted flood vulnerability; it also showed that the proposed model has excellent performance to predict the future of flood. It employs all inventory datasets in this study. The confidence performance more significant than 97% according to the MAPE, RMSE, and MFE values.

Table 12. Performance of proposed model (Hybrid FFST)

Error	Training dataset	Testing dataset
MAPE (%)	0.097	0.077
RMSPE (%)	0.513	0.504
MFE	0.166	0.159

Table 13. Comparing real vs forecasted of flood vulnerability status

No.	Areas	The real status of flood vulnerability	The result of the proposed model	Forecasted Flood vulnerability status for the proposed model
1	Andir	Extreme danger	399	Extreme danger
2	Antapani	Danger	300	Danger
3	Arcamanik	Danger	320	Danger
4	Astana Anyar	Less danger	230	Danger
5	Babakan Ciparay	Extreme danger	380	Extreme danger
6	Bandung Kidul	Danger	333	Danger
7	Bandung Kulon	Danger	350	Danger
8	Bandung Wetan	Danger	366	Danger
9	Batununggal	Danger	352	Danger
10	Bojong Loa Kaler	Danger	267	Danger
11	Bojong Loa Kidul	Danger	277	Danger
12	Buah Batu	Extreme danger	400	Extreme danger
13	Cibeunying Kaler	Danger	287	Danger
14	Cibeunying Kidul	Danger	287	Danger
15	Cibiru	Less danger	219	Less danger
16	Cicendo	Less danger	189	Less danger
17	Cidadap	Danger	250	Danger
18	Cinambo	Danger	350	Danger
19	Coblong	Danger	345	Danger
20	Gede Bage	Extreme Danger	401	Extreme Danger
21	Kiara Condong	Danger	370	Danger
22	Lengkong	Extreme danger	381	Extreme danger
23	Mandalajati	Extreme danger	389	Extreme danger
24	Panyileukan	Danger	366	Danger
25	Rancasari	Less danger	199	Less danger
26	Regol	Less danger	187	Less danger
27	Sukajadi	Danger	367	Danger
28	Sukasari	Danger	289	Danger
29	Sumur Bandung	Less danger	200	Less danger
30	Ujung Berung	Extreme danger	399	Extreme danger

The proposed method's performance is better than MSARIMA in studies [9] and HN-FIS in studies [10] employing MAPE. The proposed method also obtains the best performance than research in [9-11] on flood prediction employing RMSPE.

4. Conclusion

The proposed model has an excellent performance on flood forecasting in Bandung, West Java Province, Indonesia. This study compares the three models in predicting flood events to obtain the best method for prediction. The results have shown that the proposed model (Hybrid-FFST) is the best model on flood forecasting on one-step and multi-step ahead with average MAPE, RMSPE, and MFE, respectively 0.22%, 0.20%, and 0.08%. The researchers employing various models in hybrid approaches to give the best contribution to flood warnings were presented in this study. It can be useful for the flood warning system and disaster prevention. Hybrid approaches can combine more than two algorithms to better forecast values forecasting values through other AI, NN, and FIS models as the multi-hybrid model. It employs more parameters to generate better results in decision making for the flood vulnerability in some areas, provides better SMS service to avoid the failure of broadcasting the information about flood status in some areas.

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