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Smart Sensing System for Detection and Forecasting Forest Fire in Riau Province, Indonesia

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Abstract. Indonesian is one of the countries in a tropical region, in the summer season normally high temperature and hot environmental then land and forest fire happened. This is because most of the land in Indonesia is peatland and forestry area, especially in Sumatera and Kalimantan island. Worst when it has a huge impact on the local economy, environment, flora, fauna and human health. As reported, millions of people have suffered from respiratory problems, which some have died and in serious health conditions. This research aims to prevent more casualties, providing an early warning and forecasting on fires as alert to the community and representative institution. Furthermore, the research focus on developing a smart sensing system for the ground level to do monitoring and forecasting. Several types of sensor used based on fire basic parameters such as temperature, humidity, gasses and carbon sensor to measure value in the open environment. Arduino microcontroller and algorithm introduce to the system to achieve smart monitoring system and filtering noise data from the sensor mathematical model and analysis using Autoregressive Integrated Moving Average (ARIMA) applied in this system to do forecasting for the future and estimate number of hotspots in the area of Riau Province. The information based on sensing and analysis as well as forecast data forward to the institution or government agency for further action.

Keywords: Smart Sensing, Forest Fire, Detection, Forecasting, Riau Indonesia.

1 Introduction

Riau Province is located at Sumatera Island in Indonesian, as a tropical country was suffering from bad haze due to land and forest fires that happen almost every year. The location of Indonesia at equatorial causes this country to have longer dry season spans from July to October. This disaster is not only affecting the community in Indonesia but also to the neighbouring countries such as Singapore, Malaysia and Thailand. Worst when it has a huge impact on the local economy, environment, flora, fauna and human health. Elderly people and children are severely affected due to haze. As reported, millions of people have suffered from respiratory problems, which some have died and in serious health conditions. To prevent more casualties, providing an early indication of fires is vital and crucial. Therefore, in this research discussed developing a smart monitoring system to detect and monitor the environmental behaviour in term of temperature, humidity, gasses and climate change to do forecasting on a forest fire. The technology used in this smart monitoring is a wireless data communication with long-range (LoRa) and internet of things (IoT) technology. The integration of sensors with LoRa technology would not only save the environment and people's lives. Furthermore, the sensor would also have forecasting and could access the information through developed real-time database anywhere and anytime. This ground level detection method deployed in regions and states in Indonesia. It is anticipated to be a quicker and cheaper solution than to satellite data acquisition and this would be beneficial to social welfare and economy development in Indonesia. Figure 1 shows forest fire hotspot scattering in Indonesia region and most of it in Riau Province in Sumatera Island. Riau province is located in the centre and middle of Sumatra Island which most of the is peatland type that easily to get fire when dry season.

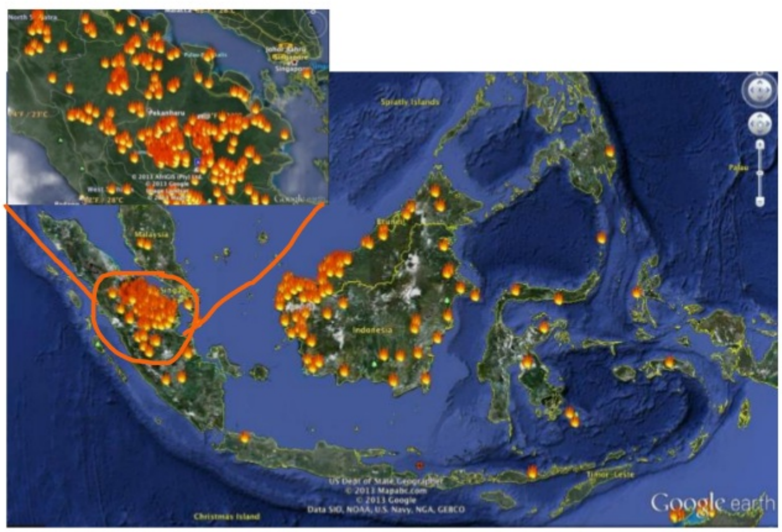

Fig. 1. Forest fire hotspot scattered in Indonesia and Riau Province.

The detailed objective of this research is to develop a ground level of sensing and collect information on the environment that can be done on analysis as data collection. There basic parameter and closely related to the impact of forest fire such as temperature, humidity, gasses, and carbon from the environmental changing for land and forest. This can be achieved by designing a smart sensor network using LoRa-IoT technology and analysis the data for the forecasting.

Forest fire data in Indonesia, especially in the summer season, become the increasing number of hotspots because of dry environment, many places in Indonesia with rising temperature in summer then easy to get fire on land and forest area. In Sumatera dan Kalimantan Island, a forest fire is a disaster because of the peatland area and easy to get fire and even no one fired the land. Table 1 shows the data of forest fire in Indonesia based on province, where Riau province is one of the high and very often getting forest fire.

Table 1. Forest fire data in Indonesia year 2014-2019.

No	Province	2014	2015	2016	2017	2018	2019	Total (ha)
1	Aceh	155.66	913.27	9,158.45	3,865.16	1,284.70	141.78	15519.02
2	Bali	30	373.46	-	370.8	206.54	-	980.8
3	Bangka Belitung	-	19,770.81	-	-	2,055.67	-	21826.48
4	Banten	2	250.02	-	-	-	-	252.02
5	Bengkulu	5.25	931.76	1,000.39	131.04	8.82	1.47	2078.73
6	DKI Jakarta	-	-	-	-	-	-	0
7	Gorontalo	-	5,225.89	737.91	-	158.65	27.7	6150.15
8	Jambi	3,470.61	115,634.34	8,281.25	109.17	1,390.90	4.18	128890.45
9	Jawa Barat	552.69	2,886.03	-	648.11	4,104.51	-	8191.34
10	Jawa Tengah	159.76	2,471.70	-	6,028.48	331.67	-	8991.61
11	Jawa Timur	4,975.32	7.966,79	-	5.116,43	7.279,76	-	4975.32
12	Kalimantan Barat	3.556,10	93,515.80	9,174.19	7,467.33	68,311.06	2,273.97	180742.35
13	Kalimantan Selatan	341	196,516.77	2,331.96	8,290.34	98,637.99	52.53	306170.59
14	Kalimantan Tengah	4.022,85	583.833,44	6.148,42	1.743,82	41.521,31	27,00	0
15	Kalimantan Timur	325.19	69,352.96	43,136.78	676.38	26,605.57	5,153.07	145249.95
16	Kalimantan Utara	-	14,506.20	2,107.21	82.22	625.82	792.11	18113.56
17	Kepulauan Riau	-	-	67.36	19.61	320.96	4,969.85	5377.78
18	Lampung	22.8	71,326.49	3,201.24	6,177.79	14,963.87	-	95692.19
19	Maluku	179,83	43,281.45	7,834.54	3,918.12	14,131.33	180.03	69345.47
20	Maluku Utara	6.5	13,261.10	103.1	31.1	69.54	56.79	13528.13
21	Nusa Tengara Barat	3.977,55	2.565,71	706,07	33.120,81	14.352,26	29,10	0
22	Nusa Tengara Timur	980.87	85,430.86	8,968.09	38,326.09	55,207.64	99.13	189012.68
23	Papua	300	350,005.30	186,571.60	28,767.38	87,676.88	-	653321.16
24	Papua Barat	-	7,964.41	542.09	1,156.03	120.63	58.36	9841.52
25	Riau	6,301.10	183,808.59	85,219.51	6,866.09	37,220.74	27,683.47	347099.5
26	Sulawesi Barat	-	4,989.38	4,133.98	188.13	978.38	56.77	10346.64
27	Sulawesi Selatan	483.1	10,074.32	438.4	1,035.51	1,741.27	441.07	14213.67
28	Sulawesi Tengah	70.73	31,679.88	11,744.40	1,310.19	3,890.95	215.92	48912.07
29	Sulawesi Tenggara	2,410.86	31,763.54	72.42	3,313.68	8,121.35	16.42	45698.27
30	Sulawesi Utara	236,06	4.861,31	2.240,47	103,04	125,07	9,98	0
31	Sumatera Barat	120.5	3,940.14	2,629.82	2,227.43	2,421.90	60.68	11400.47
32	Sumatera Selatan	8,504.86	646,298.80	8,784.91	3,625.66	13,019.68	236.49	680470.4
33	Sumatera Utara	3,219.90	6,010.92	33,028.62	767.98	3,678.79	152.55	46858.76
34	Yogyakarta	0.27	-	-	-	-	-	0.27
	TOTAL (ha)	**32,438.97**	**2,012,184.19**	**429,268.22**	**125,399.82**	**447,285.81**	**42,674.34**	**3,089,251.35**

2 Related Work

Research on the forest fire and wildfire have been done by some others researcher, there is a gap for the previous research required o fulfil and improve to become better solution and action. Previous research has been done as discussed in (1)(2)(3)(4), the researchers used satellite images to collect data for wildfire in India region, the use of images and analysis for prediction. Modelling and detection of forest fire for prediction of number hotspot in future have been done, the data used is series data with mathematical analysis and computer simulation.

The other literature review on previous works as discussed on Enhanced Bidirectional Long Short-Term Memory Network (ABi-LSTM) for video-based forest fire smoke recognition. The ABi-LSTM consists of the spatial features extraction network, the Bidirectional Long Short-Term Memory Network(LSTM), and the temporal attention subnetwork, which can not only capture discriminative spatiotemporal features from image patch sequences but also pay different levels of attention to different patches (5)(6)(7)(8) design a sequential Monte Carlo estimation approach of the time-varying frequency in the proposed nonlinear model using the particle filter (PF). the design of the sensor is addressed, underlining the key technologies that allow the required performance to be attained at low industrial costs. Experimental characterization of the developed radiometer is reported focusing on both accuracy and sensitivity issues.

In (9)(10)(11) discuss on the processing method of the essentially different from the traditional signal. assessing the number of days per month with the forest fire risk based on monthly mean values of air temperature, relative humidity, and the amount of precipitation. Obtained are the quantitative estimates of the contribution of each of the above meteorological parameters to the linear regression equation. The multi-sensor system information fusion can be merged at different levels. The use of Wi-Fi system to detect fire is applied in (12) but the application for indoor as a Wi-Fi signal with the analysis used the fuzzy logic system. The used of Wireless Sensor Network (WSN) system to easily reconfigure its topology in the communication of data. The system applies several numbers of sensor such as temperature, gas concentration, and visibility. The adaptive method based on a multilayer perceptron for the processing of measurement results in a multi-sensor system (13). The development of the multi-sensor system in the detection of fire apply the algorithms to increase the sensitivity in the detection of fire and some devices implement to reduce nuisance alarms (14).

Wireless multi-sensors for fire detection in WSN node and algorithm is implemented to determine the probability of fire. Fire detection is formed of the low-power electrochemical carbon monoxide sensor, photoelectric smoke detector, and semiconductor temperature sensor. Algorithm for the program in an embedded system is applied as samples of the algorithm were used to derive from the fire detection standard room of the State Key Laboratory of Fire Science of China (15)(16). Furthermore, a research conducted by the previous researcher is the detection of forest fire in prediction model based on two-stage adaptive duty, then the results obtained be able to detect but some of spot inaccurate. The discussion on the used Internet of Things (IoT) technology in the detection of forest fire as elaborate in (17), this section applies IoT as alerts and broadcast information through IoT system that currently widely used (18). As well as discussed in this paper (19) geographic information system (GIS), in combination with other geoinformation technologies such as remote sensing and computer modeling, for all aspects of wild land fire management. Identifying areas that have a high probability of burning is an important component of fire management planning. The development of spatially explicit GIS models has greatly facilitated this process by allowing managers to map and analyze variables contributing to fire occurrence across large, unique geographic units.

3 Forest Fire Detection and Monitoring System

The number of hotspot detection and monitoring is based data received by the ground sensor system installed a dedicated area that potential go get fire. Data captured by sensor send to the central database which is at the backend system in the Islamic University of Riau for analysis. In this case, the station installed in most of region or location potentially to become a hotspot based on the survey have been done before installation. Figure 2 shows the map of Riau Province Indonesia, where the location of the ground sensor installed and scattered at the point of the area which becomes potentially to get fire, especially in the peatland area.

Fig. 2. Location of ground sensor installed in Riau Province, Indonesia.

Wireless Sensor Network (WSN) technology is applied in this sensing system, for the detection environmental parameter and monitoring the changes of the basic parameter as indicating the potential to become fire. The parameters such as temperature, humidity, carbon dioxide, haze, and smoke. These parameters can be analyzed and become the main reference to determine either the environmental potential for the fire or just normal condition. Figure 3 shows a block diagram for the detection of basic parameters used for analysis and determine the potential of the forest fire. There is a different sensor used, each sensor working asset to detect the parameters set in the system. Data detected from all the sensor collected in an internal memory system in sensor node then forward to the WSNs gateway system for a large capacity of data memory. In the gateway system data filtering for unused data is done to minimize a large number of data to be sent to the backend system.

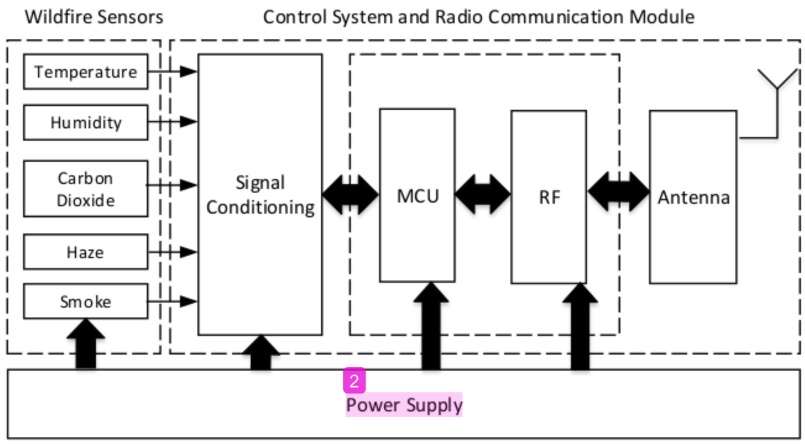

Fig. 3. Block diagram of a sensor system for detection environmental parameters.

In actual condition, the fore in the forest may have a different scenario, in someplace have many numbers of hotspot and closer, while other places may have a few numbers of the hotspot. To determine the number of hotspots in a geographical area, can do estimation using formula (1) with assuming the number of sensors deployed in the area with the function of coverage P is given as (1).

$$P = f\,(x, y, t) = \{(\mathrm{x}_1, \mathrm{y}_1)\ \ldots\ (\mathrm{x}_n, \mathrm{y}_n)\},$$
$$(\mathrm{x}_k, \mathrm{y}_k) = f(t), k = 1,2,3,..n \tag{1}$$

(x, y) is representing coordinate of the sensor deploys in the area or region to be monitor, the larger area to cover than more sensor to deploy. In this research used scenario of the sensor with the static position, while the sensing system expected to read more data from the environmental as well as multi parameters then coverage area indicates by IP. In this case, assume the IP is coverage area that can define by a scalar value refer to the amount of percentage area coverage by the sensor and with the specific time can be calculated IP as in formula (2). The number of sensors deploy will determine the IP, more sensor installed will get more accuracy in data collection.

$$IP = \frac{\text{area covered with sensors}}{\text{the total area of the surveillance region}}\,.100\% \tag{2}$$

4 Results and Discussion

The data captured and recorded by the sensor deploy in the area within Riau Province provide information number of hotspots of forest fire during the time. Table 2 shows a series data number of hotspots recorded started from January 2014 to December 2019.

Table 2. Forest fire data in Riau Province, Indonesia year 2014-2019.

Year	Month	No. of fire hotspots	Year	Month	No. of fire hotspots
2014	January	15	2017	January	25
	February	66		February	11
	March	122		March	18
	April	21		April	20
	May	5		May	24
	June	15		June	15
	July	11		July	55
	August	20		August	16
	September	40		September	30
	October	10		October	19
	November	10		November	10
	December	10		December	25
2015	January	11	2018	January	24
	February	75		February	48
	March	21		March	28
	April	65		April	30
	May	15		May	11
	June	44		June	16
	July	16		July	43
	August	26		August	13
	September	52		September	12
	October	16		October	10
	November	30		November	10
	December	28		December	20
2016	January	41	2019	January	35
	February	74		February	35
	March	22		March	27
	April	20		April	33
	May	26		May	88
	June	36		June	40
	July	32		July	32
	August	11		August	30
	September	42		September	15
	October	13		October	21
	November	20		November	16
	December	12		December	12

Initial data to investigate with simple data were chosen to recognize the basic parameters of the time series method and to identify any abnormal characteristic in the existing cases. The investigation was conducted by creating a simple time-series data plot as shown in figure 4 and then fitting a linear trend. However, the series does not indicate the presence of seasonal effects that could be construed as irregular effects, although significantly large values at the time point March 2014 and May 2019 were observed.

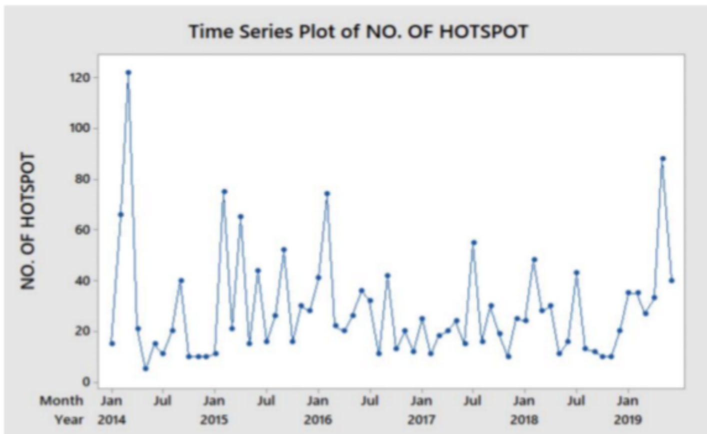

Fig. 4. Time plot number of hotspots in series timeline.

Table 3 show the summary of the Portmanteau Test for the four ARIMA models ARIMA (2,1,2), ARIMA (2,1,1), ARIMA (1,1,1) and ARIMA (1,1,0). From the table, several characteristics can be measured to select the best ARIMA model for the temporal predictions of the appearance of hotspots in Bengkalis, Riau. In this step, the values of Calculated Qs are checked and compared against the tabulated values, and it is shown that two out of four ARIMA models, ARIMA (2,1,2) and ARIMA (1,1,1), accept the null hypothesis, which indicates that the errors are random because the value of Calculated Q is less than Tabulated Q; values were 3.21<14.06 and 3.28<16.91, respectively. Therefore, the conclusions are that these two models are well specified and adequate. In contrast, ARIMA (2,1,1) and ARIMA (1,1,0) are not well-specified models since both models have Calculated Q values greater than the Tabulated Q, that is, 28.89>15.50 and 21.45>18.30, respectively. To choose the best model among ARIMA (2,1,2) and ARIMA (1,1,1), measurement of the smallest Q statistics was conducted. Based on this measurement, ARIMA (2,1,2) was chosen as the best model. However, to make sure that the above choice is true for further analysis, MSEs were used for verification. According to the smaller value of MSE, the results again point towards ARIMA (2,1,2). In contrast, by introducing the concept of parsimony, ARIMA (1,1,1), although having marginally greater MSE values and calculated Q than ARIMA (2,1,2), will be the obvious choice.

Table 3. Summary of portmanteau test.

Statistics	ARIMA (2,1,2)	ARIMA (2,1,1)	ARIMA (1,1,1)	ARIMA (1,1,0)
Calculated Q	3.21	28.89	3.28	21.45
DF	7	8	9	10
Tabulated Q	14.06	15.50	16.91	18.30
Decision (5% of sig, level)	Accept H_0	Accept H_1	Accept H_0	Accept H_1
Conclusion	The error are white noise	The error are not white noise	The error are white noise	The error are not white noise
MSE	9540.088	11377.10	9979.31	12530.90

ARIMA (2,1,2) was selected as the best model with the smallest Mean Square Error (MSE) and was used to predict the appearance of the fire hotspots in Riau Province, Indonesia. Table 4 shows a forecast value of the appearance of fire hotspots for 5 months ahead. The analysis and forecasting data have been done based on series data collected by the sensor system.

Table 4. Forecasting number of forest fire hotspots in Riau Province in 5 months.

Months	Appearance of number fire hotspots
1	25
2	31
3	26
4	30
5	27

The final number of forest fire hotspot based on analysis is the results of forecasting in the next few coming months. Based on the data then authority or representative institution can do preparation on the disaster of land and forest fire including the location or region that potentially to become get fire. The decision and analysis give the values with the high accuracy, the data collected is based on real environmental and from the sensor deployed. Finally, the detection and monitoring system for forest fire get benefit to the authority and community to prevent forest fire in the summer season with the dry environmental.

5 Conclusion

Forest fire hotspots detection and forecasting based on sensor data collection and analysis with mathematical analysis and modelling have been done. Data obtain refer to sensor deployed in many areas that potentially become fire and strategic location. Series data achieved for the 5 years with the number of hotspots, the data collected with Riau Province. A model which ARIMA (2,1,2) was selected and could be used for monthly data modelling of hotspots for 5 months ahead since it fulfilled all the criteria in the Portmanteau Test. The measurement of errors, ARIMA (2,1,2) had the smallest Mean Square Error (MSE) compared with the other model. The results also show that the model was well specified and could be used for predicting the number of hotspots in Riau province because the model accepted the hypothesis that the error is random or white noise. This is explained by the value of Q being calculated as smaller than Q in the tabulation, that is, 3.21 is less than 14.06. By using the best selected ARIMA (2,1,2) model, the predictions of the appearance of hotspots for 5 months ahead were thus 25, 31, 26, 30 and 27.

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