ISSN: 2157-7420

# Modeling National Trends on Health in the Philippines Using ARIMA

#### Florence Jean B Talirongan\*, Hidear Talirongan and Markdy Y Orong

Misamis University, Ozamiz City, Philippines

#### Abstract

Health is a very important prerequisite in people's well-being and happiness. Several studies were more focused on presenting the occurrence on specific disease like forecasting the number of dengue and malaria cases. This paper utilized the time series data for trend analysis and data forecasting using ARIMA model to visualize the trends of health data on the ten leading causes of deaths, leading cause of morbidity and leading cause of infants' deaths particularly in the Philippines presented in a tabular data. Figures for each disease trend are presented individually with the use of the GRETL software. Forecasting results of the leading causes of death showed that Diseases of the heart, vascular system, accidents, Chronic lower respiratory diseases and Chronic Tuberculosis (all forms) showed a slight changed of the forecasted data, Malignant neoplasms showed unstable behavior of the forecasted data, and Pneumonia, diabetes mellitus, Nephritis, nephrotic syndrome and nephrosis and certain conditions originating in perinatal showed a decreasing patterns based on the forecasted data. In terms of the predicted health disease on leading causes of infant's deaths, it is evident that all causes of death, pneumonia of newborn, Neonatal aspiration syndromes and other congenital malformations showed a slight decrease of prediction patter. Further, Bacterial sepsis of newborn, the respiratory distress of newborn, Disorder related to short gestation and low birth weight, not elsewhere classified, congenital pneumonia and Diarrhea and gastroenteritis of presumed infectious origin showed an increasing pattern of prediction sutilizing another algorithm for trend analysis and forecasting.

Keywords: ARIMA • Health • Diseases • Forecasting • Trend analysis

## Introduction

People weigh high value on health since it is a core element in people's well-being and happiness [1] to the extent of setting it as a priority in the governmental and societal agenda [2]. Health is considered as an important prerequisite in reaching person's goals and aspirations, and contributory factor to development of societal undertakings [1,3,4].

The World Health Organization (WHO) battled underfunded diseases like AIDS/HIV and tuberculosis and issued International Health Regulations to make medical standards consistent and stop epidemics in their tracks [5]. In the United States, leading causes of infant, neonatal and postneonatal death in rank order which include diseases of heart; malignant neoplasms; chronic lower respiratory diseases; cerebrovascular diseases; accidents (unintentional injuries); alzheimer's disease; diabetes mellitus; influenza and pneumonia; nephritis, nephrotic syndrome and nephrosis; and intentional self-harm (suicide) [6]. In Asia Pacific regions like Thailand and China account for a significant burden of global poverty and disease. Indeed, approximately one-third of the world's intestinal helminthiases, most of the food-borne trematode infections, one-half of the active trachoma infections and a significant number of cases of lymphatic filariasis (LF), schistosomiasis and arboviral infections occur in the region [7]. Urban healths in developing countries were taken care of by WHO in terms of global overview on health and the cities, policies and health status and health environment [4,5,8]. However, it was an extraordinary opportunity to create a sustained global movement against premature death and preventable morbidity and disability from NCDs, mainly heart disease, stroke, cancer, diabetes, and chronic respiratory disease. The increasing global crisis in NCDs is a barrier to development goals including health [8,9].

\*Address for Correspondence: Florence Jean B Talirongan, Misamis University, Ozamiz City, Philippines, Tel: +09054137874, E-mail: badilles.fj@gmail.com

**Copyright:** © 2020 Talirongan FJB. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Received 22 November 2019; Accepted 24 December 2019; Published 15 January 2020

Reflecting the information that is most readily available in the Philippines have placed on diseases like diabetes, tropical diseases, gastroduodenal diseases, dengue, lung disease, foot and mouth disease and allergenic rhinitis [10-13].

It was observed that several studies were more focused on the trend of individual disease however no further studies concentrated on the trends of health data. The objective of this research is to visualize the national trends of health data particularly in the Philippines. This motivates the researcher to identify the most and least vulnerable disease in the country. The trend analysis utilized time series and data forecasting using autoregressive integrated moving average (ARIMA).

#### **Theoretical framework**

Review of related literature: Several literature and studies support the use of ARIMA model as a forecasting tool in predicting diseases. Li et al., [14] applied ARIMA in the incidence of hemorrhagic fever with renal Syndrome (HFRS) in China during 1986 to 2009 which fit to the given study and can be applied to future forecasting on prevention and control. Yu et al., [15] constructed ARIMA model to forecast the number of HIV infections from 2013 to 2017 in Korea. Research done by Midekisa et al., [16] and Zhang et al., [17] in Ethiopia and China used ARIMA to quantify the relationship between malaria cases. Another study of Naiman et al., [18] used ARIMA model to test the relation between smoking bans and admission rates that lead to cardiovascular and respiratory conditions. Baker-Austin et al., [19] illustrated associations between environmental changes to the emergence of vibrio infections and forecasted the risk of infections. Time series analysis of dengue incidence was studied by Gharbi et al., [20] in Guadeloupe, French West Indies. ARIMA model was used to predict the occurrence of dengue epidemics which was also studied Wongkoon [21] in Thailand and Johansson et al., [22] in Mexico. The impact of climate change on dengue transmission in the Asia-Pacific region was also examined by Banu [23]. Soebiyanto [24] analyzed the role of climatic variables as input series on influenza transmission in two regions: Hong Kong (China) and Maricopa County (Arizona, USA) where the influenza cases depend on its past values and error signal. Razvodovsky [25] found out that alcohol is an important contributor to the liver cirrhosis mortality rate in Russia.

# **Materials and Methods**

#### Materials

The data used in the study are the statistical data taken from the Philippines in Figures of the Philippine Statistics Authority (PSA) from the year 2012 up to 2016. There were several areas presented in the statistics but this study will highlight the Health comprising three areas of data on ten leading causes of death, leading causes of morbidity and leading causes of infant's deaths. These data were taken from the sources like PSA, Family Planning Survey, National Demographic and Health Survey, Department of Health and Department of Social Welfare and Development. The data were taken from the books of Philippines in Figures 2017 to 2018. However, the book only reflected data from 2012 up to 2016 which will be used for trend analysis and data forecasting on the three areas.

#### Methods

The study utilized Autoregressive Integrated Moving Average (ARIMA) model employed in many fields to construct models for forecasting time series [14,26]. ARIMA (p,d,q) algorithm is used to forecast the data pattern of diseases for the next fourteen years. Time series predictions are based on changes over time in historical data sets and can produce mathematical models by using statistical data that can be extrapolated [27,28]. The ARIMA (p,d,q) model is defined as follows:

$$Xt = \Phi \mathbf{1} X_{t-1} + \dots + \Phi_p X_{t-p} + a_t - \Theta_1 a_{t-1} - \dots - \Theta_n a_{t-q}$$
(1)

Where,  $\Phi$ 's (phis) represents the autoregressive parameters to be estimated,  $\Theta$ 's (thetas) are the moving average parameters to be determined, the original series is represented by X's, and the a's are the unknown random errors which are assumed to follow the normal probability distribution.

Three steps were performed to predict the incidence of leading causes of death, morbidity and infants by using the ARIMA-related modules. Model identification used autocorrelation analysis and partial autocorrelation analysis methods to analyze any random, stationary, and seasonal effects on the time series data. The researcher prepared a stationary time series by considering the differences and then determined plausible models on the basis of an autocorrelogram and a partial autocorrelogram. Lastly, the parameter estimation and model testing were used to compare the plausible models obtained, and we selected the most appropriate model. Finally, we conducted predictive analysis. The study used GRETL (Gnu Regression, Econometrics and Time-series Library) software for plotting the graphs and analysis of the data sets. Figure 1 presents the architectural design in predicting incidences of leading causes of death, morbidity and infant's death.

## **Results and Discussion**

In trend analysis of the three areas of data on ten leading causes of death, leading causes of morbidity and leading causes of infant's deaths, the GRETL software was utilized. Tables 1-3 present the raw data on causes of death covering year 2012 until 2016.

#### Forecasting

ARIMA model was used to forecast the occurrences of each health disease. The study will forecast for the next fourteen years using the available historical data. Figures 2-4 show the graph of the predicted health disease on ten leading causes of death from 2017 to 2030 having 95% interval.

It is evident that the predicted cause of death which is the diseases of the heart from 2017 to 2030 showed a very slight change forecasted data pattern. Result signifies that heart diseases cases in the country are not stable in terms of its occurrences based on the forecasted data. This result is still true with disease with the vascular system, accidents, chronic lower respiratory diseases and Chronic Tuberculosis (all forms). Hence, a continuous mitigation strategy by the Department of Health should be conducted to mitigate the occurrence of the identified disease in the country.

It is evident that the predicted cause of death which is malignant neoplasms from 2017 to 2030 showed unstable behavior of data pattern. Result signifies that there will be years in the future that the number of occurrence of the disease will increase and it will eventually decrease. Hence, regular monitoring of its occurrence and regular conduct of mitigation plans should be observed by the concerned agency in the country.

The predicted cause of death which is the pneumonia from 2017 to 2030 showed a slight decreasing pattern based from the historical data. The result showed similarity with diabetes mellitus, Nephritis, nephrotic syndrome and nephrosis and certain conditions originating in perinatal. A result signifies that the existing intervention plans of the Department of Health in mitigating the occurrence of the diseases are effective. A continuous support to the health agency from the government should be in place at all times to continually lessen the occurrences.

Based on the identified causes of death, it is evident that the heart diseases were the leading among others and it was found out that certain conditions originating in perinatal period as one of the causes of death was found as the least cause of death based on the data. Results were supported in the reported causes of most death in the Philippines showed in the health data organization website (healthdata.org, 2019) [29].



Figures 4-8 show the graph of the predicted health disease on leading causes of morbidity from 2017 to 2030.

Figure 1. Predicting diseases trends.

#### Table 1. Raw data on ten leading causes of death.

Ten Leading Causes of Death	Year						
	2012	2013	2014	2015	2016		
Diseases of the heart	112581	118740	125906	68572	74134		
Diseases of the vascular system	68826	68325	69913	58715	60470		
malignant neoplasms	50507	53601	56219	49595	57809		
pneumonia	50144	53101	54877	58310	56938		
accidents	36375	40071	43853	34506	33452		
diabetes mellitus	22910	27064	31687	34050	33295		
chronic lower respiratory diseases	24275	23867	52114	31729	28641		
tuberculosis, all forms	22693	23216	24929	24644	24642		
nephritis, nephrotic syndrome and nephrosis	13555	14954	15359	23760	24365		
certain conditions originating in perinatal period	11374	10436	10174	18061	19759		

#### Table 2. Raw data on leading causes of morbidity.

Leading Causes of Morbidity	Year				
	2012	2013	2014	2015	2016
Acute respiratory infection	2793066	2174740	1445320	2115018	3080343
ALTRI and pneumonia	569122	674597	488415	474406	786085
Hypertension	512604	410432	475693	601173	886203
Bronchitis	338789	249173	204086	202343	200176
Influenza	232584	149777	172683	147400	216074
Urinary tract infection	276442	235446	213666	298200	288588
Acute watery diarrhea	235110	74876	91202	130246	139700
TB respiratory	93094	70053	32335	62396	87422
Acute febrile illness	85471			55759	
Dengue fever	44172	53750	26077	69532	56487
TB other forms		30971	25727		

Table 3. Raw data on leading causes of infant's deaths.

Leading Causes of Infant's Death	Year					
	2012	2013	2014	2015	2016	
All causes	22283	22254	21992	20750	21874	
Bacterial sepsis of new-born	3669	3156	2731	2157	2136	
Pneumonia	2792	2738	3146	2370	2885	
Respiratory distress of new-born	2414	2497	2347	2276	2263	
Congenital malformation of the heart	1452	1356	1383	1398	1407	
Disorder related to short gestation and low birth weight, not elsewhere classified	1455	1422	1466	1278	1202	
Congenital pneumonia	1115	989	728	625	734	
Neonatal aspiration syndromes	1104	994	969	1036	1196	
Intrauterine hypoxia and birth asphyxia	906	871	838	802	832	
Other congenital malformations	883	896	895	1030	1000	
Diarrhea and gastroenteritis of presumed infectious origin	911	843	901	824	1328	
All other causes	5582	6492	6588	6954	6891	

The predicted cause of morbidity which is the acute respiratory infection from 2017 to 2030 showed a lightly decreasing pattern. The prediction result signifies that the forecasted data still on range based on the historical data. The result is similar with ALTRI and pneumonia and Hypertension.

The predicted cause of morbidity which is the bronchitis from 2017 to 2030 showed an increasing pattern. Further, other results showed similarity with bronchitis such as the TB other forms and TB respiratory. The prediction results signify that there was an on-going increase of the occurrences of bronchitis in the Philippines.

The predicted cause of morbidity which is the influenza from 2017 to 2030 showed unstable pattern of the case from the year 2016 to 2020. On the other hand, there is a stable prediction pattern of the case from the year 2023 to 2030.

The predicted cause of morbidity which is the urinary tract infection from 2017 to 2030 showed a stable number of forecasted cases based on the pattern presented on the graph. Further, the result is similar with the dengue fever. The prediction signifies that the forecasted data reach the maximum number of occurrences in the Philippines.

The predicted cause of morbidity which is the acute watery diarrhea from 2017 to 2030 showed a lightly decreasing pattern similar with the acute febrile illness. The prediction signifies that the forecasted data reach the maximum number of occurrences in the Philippines. Figures 9-11 show the graph of the predicted health disease on leading causes of infant's deaths from 2017 to 2030.

The predicted cause of infant's deaths which is the all causes from 2017 to 2030 showed a lightly decreased pattern which is similar with the



Figure 2. Forecasted ten leading causes of death - Diseases of the heart from 2017 to 2030.



Figure 3. Forecasted ten leading causes of death - Malignant neoplasms from 2017 to 2030.



Figure 4. Forecasted ten leading causes of death - Pneumonia from 2017 to 2030.

results of Pneumonia of newborn, Neonatal aspiration syndromes, other congenital malformations and all other causes of death. The prediction results of the mentioned causes signify that the forecasted data reach the maximum number of occurrences in the Philippines.



Figure 5. Forecasted leading causes of morbidity - Bronchitis from 2017 to 2030.



Figure 6. Forecasted leading causes of morbidity - Influenza from 2017 to 2030.



Figure 7. Forecasted leading causes of morbidity – Urinary tract infection from 2017 to 2030.

The predicted cause of infant's deaths which is the bacterial sepsis from 2017 to 2030 showed a gradual increase of the forecasted data based on the pattern showed in the graph similar with the results of the respiratory distress of newborn, Disorder related to short gestation and low



Figure 8. Forecasted leading causes of morbidity - Acute watery diarrhea from 2017 to 2030.



Figure 9. Forecasted leading causes of infant's deaths - all causes from 2017 to 2030.



Figure 10. Forecasted leading causes of infant's deaths- Bacterial sepsis of newborn from 2017 to 2030.

birth weight, not elsewhere classified, congenital pneumonia and Diarrhea and gastroenteritis of presumed infectious origin. Hence, intervention plans are needed to be in place by the Department of Health to mitigate the future occurrences of the identified diseases.



Figure 11. Forecasted leading causes of infant's deaths - Congenital malformation of the heart from 2017 to 2030.

The predicted cause of infant's deaths which is the congenital malformation of the heart from 2017 to 2020 showed an unstable pattern similar with the result of Intrauterine hypoxia and birth asphyxia. Moreover, it is evident that there was a stable behavior of data based on the forecast from 2021 to 2030.

# **Conclusion and Recommendations**

Having trend analysis and forecasting on each disease per area is very useful in foreseeing future incidences. Moreover, predicting its occurrences can give insights to the health administration in designing preventive measures against the possible spread of diseases. In the study, ARIMA (1,0,1) model helps in predicting the increasing and decreasing pattern of diseases in the community.

In the ten leading causes of death, heart disease was found as leading among others in terms of its forecasted data. On the other hand, in terms of morbidity, the acute respiratory infection was found as leading disease. Further, in the cause of disease of infant it is evident that all identified causes were found as the possible reasons of infant's death.

Future research work will focus on the measles and chickenpox trends and predictions utilizing another algorithm for trend analysis and forecasting.

### References

- Leppo, Kimmo, Eeva Ollila, Sebastián Peña, and Matthias Wismar, et al. "Seizing Opportunities, Implementing Policies. Helsinki." Finland: Ministry of Social Affairs and Health, 2013.
- Kickbusch Ilona, and David Gleicher. "Governance for Health in the 21st Century." Geneva: World Health Organization, 2012.
- Elena, Mogilyansky, and Isidore Rigoutsos. "The miR-17/92 Cluster: A Comprehensive Update on its Genomics, Genetics, Functions and Increasingly Important and Numerous Roles in Health and Disease." Cell Death & Differentiation 20 (2013): 1603-1614.
- Tanner, Marcel, and Trudy Harpham. "Urban Health in Developing Countries: Progress and Prospects." Routledge, 2014.
- Reisman, David A. "Health tourism: Social welfare through international trade." Edward Elgar Publishing, 2010.
- Heron, Melonie. "Deaths: Leading Causes for 2008." National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System 60 (2012): 1-94.
- Hotez, Peter J, and John, P Ehrenberg. "Escalating the Global Fight against Neglected Tropical Diseases through Interventions in the Asia Pacific Region." Advances in Parasitology 72 (2010): 31-53.

- Beaglehole, Robert, Ruth Bonita, Richard Horton, and Cary Adams, et al. "Priority Actions for the Non-Communicable Disease Crisis." *The Lancet*, 377 (2011): 1438-1447.
- Alwan, Ala, David R Maclean, Leanne M Riley LM, and Colin Douglas Mathers, et al. "Monitoring and Surveillance of Chronic Non-Communicable Diseases: Progress and Capacity in High-Burden Countries." *The Lancet* 376 (2010): 1861-1868.
- Higuchi, Michiyo. "Access to diabetes care and medicines in the Philippines." Asia Pac J Public Health 22 (2010): 96S-102S.
- 11. Idolor, Luisito F, Teresita S. De Guia, Norberto A. Francisco, and Camilo C. Roa, et al. "Burden of Obstructive Lung Disease in A Rural Setting in the Philippines". *Respirology* 16 (2011): 1111-1118.
- 12. Gaw, Albert C, Byron Lee, Giselle Gervacio-Domingo, and Charles Antzelevitch, et al. "Unraveling the Enigma of Bangungut: Is Sudden Unexplained Nocturnal Death Syndrome (SUNDS) in the Philippines a Disease Allelic to the Brugada Syndrome?" *Philipp J Intern Med* 49 (2011): 165-176.
- Windsor, Peter Andrew, Freeman Paul, R Abila, and Carolyn Benigno. "Foot-and-Mouth Disease Control and Eradication in the Bicol Surveillance Buffer Zone of the Philippines." Transbound Emerg Dis 58 (2011): 421-433.
- 14. Li, Qi, Na-Na Guo, Zhan-Ying Han, and Yan-Bo Zhang, et al. "Application of an Autoregressive Integrated Moving Average Model for Predicting the Incidence of Hemorrhagic Fever with Renal Syndrome." Am J Trop Med Hyg 87 (2012): 364-370.
- 15. Yu, Hye-Kyung, Na-Young Kim, Sung Soon Kim, and Chaeshin Chu, et al. "Forecasting the Number of Human Immunodeficiency Virus Infections in the Korean Population Using the Autoregressive Integrated Moving Average Model." Osong Public Health and Research Perspectives 4 (2013): 358-362.
- 16. Midekisa, Alemayehu, Gabriel Senay, Geoffrey M Henebry, and Paulos Semuniguse. "Remote Sensing-Based Time Series Models for Malaria Early Warning in the Highlands of Ethiopia." *Malar J* 11 (2012): 165.
- 17. Zhang, Ying, Peng Bi, and Janet Hiller. "Meteorological Variables and Malaria in a Chinese Temperate City: A Twenty-Year Time-Series Data Analysis." *Environ Int* 36 (2010): 439-445.
- Naiman, Alisa, Richard H. Glazier and Rahim Moineddin. "Association of Anti-Smoking Legislation with Rates of Hospital Admission for Cardiovascular and Respiratory Conditions." CMAJ 182 (2010): 761-767.
- Baker-Austin, Craig, Joaquin A Trinanes, Nick G. H. Taylor, and Rachel Hartnell, et al. "Emerging Vibrio risk at high latitudes in response to ocean warming." *Nature Climate Change* 3 (2013): 73-77.

- 20. Gharbi, Myriam, Philippe Quénel, Joël Gustave, and Sylvie Cassadou, et al. Time Series Analysis of Dengue Incidence in Guadeloupe, French West Indies: Forecasting Models Using Climate Variables as Predictors. BMC Infect Dis 11 (2011): 166.
- Wongkoon, Siriwan, Mullica Jaroensutasinee, and Krisanadej Jaroensutasinee. "Assessing the Temporal Modelling for Prediction of Dengue Infection in Northern and Northeastern, Thailand." *Tropical Biomed* 29 (2012): 339-348.
- 22. Johansson, Michael, Nicholas G Reich, Aditi Hota, and John S Brownstein, et al. "Evaluating the Performance of Infectious Disease Forecasts: A Comparison of Climate-Driven and Seasonal Dengue Forecasts For Mexico". Scientific Reports, 2016.
- Banu, Shahera. Examining the impact of climate change on dengue transmission in the Asia-Pacific region (Doctoral dissertation, Queensland University of Technology), 2013.
- Soebiyanto, Radina P, Farida Adimi, and Richard K. Kiang. "Modeling and Predicting Seasonal Influenza Transmission in Warm Regions Using Climatological Parameters." *PloS One* 5 (2010): e9450.
- Razvodovsky, Yury, Evgeny. "Alcohol Consumption and Liver Cirrhosis Mortality in Russia." J Alcohol Drug Depend 2 (2014): 152.
- 26. Lee, Yi-Shian, and Tong Lee-Ing. "Forecasting Time Series Using A Methodology Based on Autoregressive Integrated Moving Average and Genetic Programming." *Knowledge-Based Systems* 24 (2011): 66-72.
- Kayacan, Erdal, Baris Ulutas, and Okyay Kaynak. "Grey System Theory-Based Models in Time Series Prediction." *Expert Systems with Applications* 37 (2010): 1784-1789.
- Orong, Markdy Y, Ariel M Sison, and Alexander A Hernandez. "Mitigating Vulnerabilities through Forecasting and Crime Trend Analysis". 2018 5th International Conference on Business and Industrial Research (ICBIR) (2018): 57-62.
- 29. Institute for Health Metrics and Evaluation (IHME). "Global Burden of Disease Data on the Philippines." Retrieved on November 15, 2019. Available from: http://www.healthdata.org/philippines.

**How to cite this article:** Florence Jean B Talirongan, Hidear Talirongan and Markdy Y Orong. Modeling National Trends on Health in the Philippines Using ARIMA. J Health Med Informat 11 (2020) doi: 10.37421/jhmi.2020.11.342