FORECASTING EMERGENCY TROLLEY DRUG UTILISATION USING ARMA AND SVR WITH EXTERNAL FACTORS

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DEDICATION

This thesis is dedicated to all people who didn't give up on me to finish my master degree. Especially to my love ones who at least did their part to help me finish it. A great achievement after being delayed for few semesters.

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ABSTRACT

Adequate stock management in emergency trolleys is important to ensure that every process requiring medication specifically in hospitals, runs smoothly in any given situation. Stock management based on the value of means (or average usage) is not adequate to account for unpredictable situations that may result in disruptions in drug utilisation and supply. In this study, an investigation to identify possible factors that correlate with the fluctuation of terbutaline injection drug utilisation used in emergency trolleys, using univariate forecasting methods, machine learning (ML), and hybrid models capable of predicting future usage was undertaken. Based on an experimental dataset, it was found that the mean temperature in Mersing, Johor, has the highest negative correlation with terbutaline injection utilisation, at a correlation coefficient value of -0.27 (*p*-value = 0.0068). Three univariate models and three univariate models with exogenous variables were constructed and compared. All advanced models show better performance than the naive baseline model that served as a benchmark for model building. The univariate models in the analysis consisted of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) models. Also, the ML models considered in this study including Support Vector Regression (SVR), used the lagged values of terbutaline injection as its input variables. The Autoregressive Moving Average (ARMA) (4,4) model performed better than the ML models, with a Mean Absolute Error (MAE) of 8.9524 and a Root Mean Square Error (RMSE) of 11.4518 in the validation data set. To incorporate the effects of exogenous variables, significant lags of emergency admission and climate variables were used to construct a predictive model from ARMA (4,4). The hybrid model of ARMA-ANN outperformed all other models, with MAE and RMSE values of 8.8571 and 10.8496 respectively. It can also be summarized that models utilising ANN are far better than SVR models due to a variety of factors, including the type of data input and the optimization techniques used to build the SVR models. Future studies should focus on modelling different types of medication used in emergency trolleys. The application of other ML algorithms and optimisation strategies can also be explored for different patterns of data.

ABSTRAK

Pengurusan stok yang mencukupi dalam troli kecemasan penting bagi memastikan setiap proses yang memerlukan ubat, terutama di hospital, sentiasa berjalan lancar. Pengurusan stok berdasarkan nilai min (atau purata penggunaan) tidak mencukupi dalam keadaan sukar diramal dan boleh menyebabkan gangguan dalam penggunaan dan bekalan ubat. Kajian ini melakukan siasatan bagi mengenalpasti faktor turun naik penggunaan ubat suntikan terbutalin yang digunakan dalam troli kecemasan menggunakan kaedah ramalan univariat, mesin pembelajaran (ML) dan model hibrid yang mampu meramalkan penggunaan masa depan. Data eksperimen mendapati purata suhu di Mersing, Johor mempunyai korelasi negatif tertinggi dengan penggunaan suntikan terbutalin pada nilai -0.27 (nilai p = 0.0068). Tiga model univariat dan tiga model univariat dengan pemboleh ubah eksogenus telah dibina dan dibandingkan. Semua model canggih menunjukkan prestasi lebih baik berbanding model dasar naif yang berfungsi sebagai penanda aras untuk pembinaan model. Model univariat dalam analisis ini terdiri daripada model Purata Pergerakan Bersepadu Autoregresif (ARIMA) dan Rangkaian Neural Buatan (ANN). Selain itu, model ML yang dipertimbangkan dalam kajian ini termasuklah Regresi Vektor Sokongan (SVR) menggunakan nilai terdahulu bagi suntikan terbutalin sebagai nilai input. Model Purata Pergerakan Autoregresif (ARMA) (4,4) berprestasi lebih baik daripada model ML dengan nilai Min Ralat Mutlak (MAE) 8.9524 dan nilai Punca Ralat Min Kuasa Dua (RMSE) 11.4518 dalam set data pengesahan. Bagi menggabungkan kesan pemboleh ubah eksogenus, nilai signifikan terdahulu bagi kemasukan kecemasan dan pemboleh ubah iklim telah digunakan untuk membina model ramalan daripada ARMA (4,4). Model hibrid ARMA-ANN mengatasi semua model lain dengan nilai MAE dan RMSE sebanyak 8.8571 dan 10.8496. Kesimpulannya, model yang menggunakan ANN mempunyai prestasi lebih baik berbanding model SVR kerana pelbagai factor, termasuk jenis input data dan teknik pengoptimuman yang digunakan untuk membina model SVR. Kajian masa depan harus fokus pada pemodelan pelbagai jenis ubat lain dalam troli kecemasan. Aplikasi menggunakan algoritma ML dan strategi pengoptimuman model yang berbeza juga boleh diterokai bagi corak data berlainan.

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INTRODUCTION

1.1 Background

Emergency trolley is crucial for the survival of patients in critical and life-threatening situations. Any delay in delivering the appropriate response in emergency cases due to medication stock-outs will increase the mortality rate among the patients of the said facility. Medication stock-out and shortage happen when the supply chain management is disrupted. This is mainly due to the inability to predict sufficient stock of medications in the facility especially when tight government funding which can affect the procurement of medications. Presently, most medical institutions tend to stock up their medication supply by observing the trend of medication usage rather than forecasting the future trends that may affect drug utilisation. Hence a more systematic and structured method of predicting the required medication stock is needed for an optimized stock-up process.

The method of retrospectively observing past values and utilisation of medication alone would not be effective in accommodating the future increase in demands and in predicting outbreaks that may occur in a seasonal or cyclic manner. The use of an average value to predict future utilisation will soften the effect of fluctuations on medication usage. Fluctuations will further cause damage due to sudden surge in demands, consequently causing disruptions in the supply of the required medications.. Expert judgement in the other hand is considered to non-objective as it is based on instinct rather than an evidence-based approach to solve a problem.

To predict future drug utilisation, forecasting strategies should be implemented. Presently, there are multiple types of forecasting methods available including qualitative method, time series analysis method and causal methods.

Qualitative method uses expert judgement, experience and knowledge to predict the outcome while time series analysis focuses entirely on patterns over a period of time. For causal method, it uses single or multiple factors that influences that outcome during forecasting (Chambers et al., 2014). Besides that, the effect of external factors that influence drug utilisation can be identified and analysed. External variables may either negatively or positively influence the medication usage trends and this will later be beneficial in providing the “why” behind medication fluctuations.

To approach the stated problems, this study proposes to employ the use of univariate time series analysis with external factors to forecast future drug utilisation. The ultimate aim of the study is to produce a statistical model that can be used to predict the usage of emergency trolley medication to ensure that and adequate stock for the related drug is always available. The ability to scientifically predict the demand of drugs by means of statistical analysis is beneficial in aiding decision making process for procurement of these lifesaving medication. This in turn will reduce the mortality rate of patients that could be contributed by stock inadequacy especially when prudent spending is encouraged due to tight budget allocated by the government.

1.2 Problem Statement

Emergency trolley is crucial for the survival of patients that are admitted during dire and critical situations that needs immediate resuscitation. Any delay in the appropriate response to the emergency cases due to medication stock-out and medication shortage can cause lethal consequences. To date, the existing research involving stocking of medication tends to focus more on the descriptive statistics. In normal practice, stocks are kept based on the value of means which does not account for fluctuating utilisation over the period of observation. Moreover, long-term forecasting is not usually carried out. Without forecasting data, medication stock-out is bound to occur as the demand for the medication constantly varies. In general, the usage of medication is influenced by the number of patients and climate variables. Hence, it is important to support these claims by implementing appropriate statistical method and/ or machine learning to account for stock fluctuations and to explore the relationship between patient admissions and weather variables towards medication utilisation. ARMA models are better suited for the linear relationships found in the given data. In contrast, non-linear relationships between data can be modelled using Machine Learning (ML) models like ANN and SVR. ARMA has an advantage over ANN and SVR models because, in contrast to ANN and SVR models, the relationship between past and future predictions can be explained through the equation formed. ANN and SVR have the advantage over ARMA model due to its ability to handle big volume of data. When used separately, these limitations and advantages of the models could not be optimised or corrected. Many studies have started to develop hybrid models to fully utilised the specific advantages of ARMA, ANN and SVR models. Current studies however, that used hybrid models such as ARMA-ANN and/ or ARMA-SVR, used its own residuals from the initial ARMA model, to build the hybrid model. Exogenous variables were often implemented into ARMA models using a statistical model (e.g the use of linear regression and develop ARMAX model). With this, it is safe to say that currently, there is no or there is lacking in studies, that models ARMA-ANN and ARMA-SVR, using input variables and external factors. Besides, it is important to explore the ability to construct a forecasting model that could help in both descriptive and inferential decision making. Comparison between these two methods could then be explored to find the most efficient method for forecasting medication utilisation.

1.3 Research Questions

1. What factors influence the outbreaks in the drugs usage?

2. How to overcome the fluctuation in the usage of drugs?

3. How to produce a hybrid of ARMAX, ARMA-ANN and ARMA-SVR with incorporation of external factors to forecast for stock replenishment?

4. What is the best way to quantify the performance of the proposed ARMA, Machine Learning (ANN) and Hybrid Models (ARMAX, ARMA-ANN and ARMA-SVR)?

1.4 Objectives

The objectives of the research are listed as follows:

1. To identify the possible factors that correlate with the fluctuation of medication usage in the emergency trolley using correlation testing.

2. To develop emergency medication model by employing the use ARMA and ANN Models.

3. To incorporate external factors that could influence the model using ARMAX, ARMA-ANN and ARMA-SVR models.

4. To validate and compare the proposed model efficiency using MAE & RMSE.

1.5 Hypothesis

1. External factors found to be correlated to the fluctuation of medication usage is able to allow the exogenous variable to be included into the ARMAX, ARMA-ANN and ARMA-SVR models.

2. ARMAX, ARMA-ANN and ARMA-SVR model is able to reduce the volatility error due to the fluctuation in the univariate data.

3. ARMAX, ARMA-ANN and ARMA-SVR model is able to produce a coherent value and estimate as to when the stocks should be replenished.

4. The simulation is able to produce a good reflection of the data and the performance of ARMAX, ARMA-ANN and ARMA-SVR model is able to minimise errors.

1.6 Significance of Study

Adequate stock management is important to ensure that every process requiring medication specifically in hospitals run smoothly in any given situations. Stock management depending on the value of means (or average usage) is not adequate to account for unpredictable situations that may cause fluctuations in drug utilisation. By identifying the variables that influence the fluctuations in drug usage, decision making process can be done in a more rationalised manner. In future, drug procurement can be done by considering the presence of variables caused by fluctuations in the drug usage. In addition, drug utilisation trends must be identified, analysed and carefully monitored from time to time to prepare for future scenarios.

To date, studies that investigate the trends that are affecting the drug usage are still scarce. Studies that focus on the relationship between covariates or exogenous variables with drug utilisation is hoped to reduce the incidence of drug shortages within a healthcare facility. It can also assist the facilities to prepare adequate stocks of medication as one of the means of preventive action and proactive approach.

The findings expected from this study would be beneficial and can be an eye opener in bringing the issues concerning stock usage fluctuations forward. The results would be useful to aid in the decision-making process of medication procurement by the pharmacists and to avoid the practice of just relying on the average usage of medication.

1.7 Scope of Limitation of The Study

In this study, the data from the usage of emergency medication from the year 2006 to 2019 from Hospital Mersing, Mersing, Johor was used. These primary data was obtained from the unit supplying the medication which is the Unit Farmasi Pesakit Dalam, Unit Farmasi dan Bekalan, Hospital Mersing. Each transaction of the medication was recorded when supplied to the unit using KEW-PS 4. The data were collected using the recorded transactions on KEW-PS 4. The type of medication selected for the purpose of this research was specifically related to respiratory emergency management that is Terbutaline 0.5 mg/ ml injection. Some limitations have been identified in the process of obtaining this data. One of the assumptions of the data was that each of the medication utilisation was recorded into kad kawalan stok and that each transaction was used for clinical management for the patients.

Meteorological data were the secondary data and it was obtained from the Malaysian Meteorological Department (MMD) while daily emergency admission were obtained from the Unit Rekod of Hospital Mersing. The daily data for both admission and meteorological data were from January 2015 to 2019. Both data were recorded on a daily basis. In the study, the analysis for the drug use and meteorological data included descriptive statistics, Mann Kendall trend test and Pearson correlation coefficients. Autoregressive techniques were applied to model the association between medication use, emergency admission and weather conditions while Akaike's Information Criterion (AIC) was used to select the best model. Among the limitations of the model developed was that it could not be generalised towards other healthcare facility. Local data must be obtained and developed for the forecasting of medication utilisation for other facility.

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