A forecast modelling and decision support system for vaccine demand Decision Making

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Abstract

The objective of this research aims to propose a computer-based forecast and decision support system to forecast and allocate the annual vaccine demand for specific vaccines of Taiwan so that the governmental immunization authority can take this result to make a better decision for budgeting and purchasing for these annual vaccine requirement.

The research firstly uses the models of ARIMA and Neural Network, respectively to forecast the relative variables for these specific vaccines. The results generated by these two models are then further use to compute the estimation of annual workload and the number of vaccine demand, so that the more suitable and reasonable demand is selected for decision making and vaccine allocation.

1. Introduction

Nowadays, medical computer science was a field of study involved in the application of computer science based algorithms, methodologies, and design processes into medical-based research and clinical practice. Medical informatics is not just the application of computers into the medical field; mostly it involves the integration of computers into medicine. The collection of structured and unstructured data had to be stored in databases and should be available to health professionals for the purpose of best patient care and support better decision, without the loss of confidentiality or security of information. Information technologies (IT) and computer-based decision support system may be a strategic tool to improve the quality of decision and patient safety, and so forth.

Many countries have already devoted to develop forecast models of vaccine and put in many resources including human and capital. A medical research team concluding Longini etc.(2004)built a simulation model to simulate the condition of flu virus, and this model can suggest executive how many antiviral agents you must prepare for your population. In Europe many countries adopt this research result and prepare their strategic resources against H5N1. Another team concluding Viboud etc.(2003) use a method of analogues to predict the incidence of FLU spread. This method is to use a time series as input and compute the similarity with past data to determine the incidence of current period. These medical research teams can predict trend of epidemic basic on computer science objective information. It can make the quality of decision better and reduce the mistakes of insufficient of data.

Until now, the immunization affair of Taiwan's Center for Disease Control (CDC) hasn't yet adopted a computer-based model and method to determine its annual demand of national immunization vaccines. Instead, they take an experience rule by referring to the previous supplied volume and current population growing rate to estimate the demand for its variety of vaccines. In this research, we firstly build a decision model to forecast the demand for DPT and OPV vaccines by applying the forecast models built on ARIMA and Neural Network, respectively. Next, we apply these values and the calculation formula of annual vaccine demand released by World Health Organization (WHO) to calculate the annual demands for each vaccine to provide a better information for the decision making of government's immunization authority of Taiwan to conduct its annual vaccine purchasing. By the aids of these decision models to estimate the volume of annual vaccine demand and to conduct the vaccine allocation, we expect the annual cost of expenditures for purchasing vaccines can be under well controlled and the waste of vaccines can be reduced as well.

2. Literature Reviews and Research Adoption

2.1. Impact Factors of Vaccine Demand

Regarding to the research of vaccine demand for the national immunization program of Taiwan's government, in the past only Chen (2003) brought up an optimal purchasing forecast model for the national vaccine demand. Chen (2003) indicated that the impact factors of determining vaccine demand could be referred from Alexander (2002) who used the factors to estimate vaccine usage in the Republic of Ukraine. These factors are vaccine-preventable disease trends, public commitment to infectious disease control and prevention, national immunization schedule and mandated coverage, target vaccine-inoculation population size, vaccine wastage rates, and so on. Chen established his significant impact factors used for conducting the forecast by using a group appraisal and decision method. He not only considered the factors mentioned in Alexander's research but also added the net migration of population and actual vaccine usage over the past four or more years to help to forecast the annual vaccine purchase volume. Chiu and Kuo (2006) further adopted these decision factors and added birth cohort, vaccine wastage rate, vaccination complete rate, and so on to conduct the forecast for the annual demand of Diphtheria Tetanus Pertussis (DTP), Measles Vaccine (MV) and Oral Poliovirus (OPV). The variable used are further classified into vaccine demand relative variables and population growth relative variables. The results of forecast generated were better than Chen(2003).

To choose and decide the sufficient and necessary decision factors to build a forecasting model is always a prior issue of carrying on modeling a decision. In this research, we increase two parts of construct to support our forecast. The one is the construct of population including the birth of infant, the migration of population and the total population. These demographic variables can affect the demand of vaccine so this research would take these data to assist analysis. The other construct is psychology including the level of education, conjugal condition and the number of contract hospital. Zimmerman(2003) indicate that the relationship between level of education and whether inoculated is positive. Nexoe, Kragstup & Sogaard(1999) found that the relationship between whether live with family and whether inoculated is positive. As to number of contract hospital, if the distance to hospital is shorter, the willing to be inoculated is stronger. Base on above reasons, this research try to add these variables to improve the preciseness of forecast

2.2 Method of Estimating Vaccine Demand

World Health Organization (WHO, 2002) announced the estimation model of total vaccine demand which could be computed as Formula 1.

$$N = \frac{B \times I \times D \times (1 + R)}{1 - W} - S \qquad (1)$$

where,

N = the total amount of vaccine demand in doses for next year.

B = the number of annual birth rate for next year.

I = the expected immunization coverage rate in percentage for next year.

R = the reserve stock in percentage for next year.

W = the wastage rate in percentage for current year.

S = the number of vaccine doses in stock for current year.

As we see from Formula 1, if there is no stock on hand in the first year's estimation, then the value of S is 0. Because the vaccine we discuss here is the immunization vaccine under current statutory policy, we must put the S into consideration. To determine vaccine demand, we must also consider the expected immunization volume for a period. Furthermore, we must also consider vaccine wastage rate from the past to supplement the vaccine volume which is caused by damage. Lastly it needs to add reservation stock into consideration in case an abnormally unpredictable requirement such a sudden infectious disease outbreak.

Instead of using a fixed I×B×D×(1-C) to calculate the total number of inoculation, in this research we can also use a forecast variable J to substitute I×B×D×(1-C) in Formula 1 so that we may obtain a new formula which is shown in Formula 2. Hence, the variable J refers to the demand of total number of inoculation for the next year. The value of Variable J is obtained by forecast mainly on the basis of the forecast values of B and I. To deserve to mentioned, C is be added to accept formula into our immunization conditions. Because the life in Taiwan become better, more people are willing to pay money for inoculation by them self in hospital. So replace rate of vaccine at one's won expense (C) is more and more high and must be considered as a factor in demand formula.

$$J = I \times B \times D \times (1 - C) \qquad (2)$$

Then, we can use formula 2 to compute the total amount of vaccine demand in doses for next year (N). J can be estimated by forecasting directly or derived from I×B×D×(1-C). We can choose a better estimation and take it into formula 3. Formula 3 can computer the demand of vaccine according to the reserve stock in percentage for next year (R), the wastage rate in percentage for current year (W) and the number of vaccine doses in stock for current year (S).

$$N = \frac{J \times (1 + R)}{1 - W} - S \qquad (3)$$

J = the amount of inoculation in doses in DHC

C= replace rate of vaccine at one's won expense.

2.3. Forecasting Modeling

There are two modeling methods which are applied for modeling the forecast model of this research. One is the method of time series. The other one is neural networks. The two methods are very often used by the researchers and practitioners to conduct the forecast which are closely related to the time changes of the historical data in the past. Because our intentions to the forecasts of the annual new baby birth, the expected immunization coverage rate, and so on are all related to the time changes, therefore we decide choose these two methods. However, we also desire to select a better result from results generated by these two methods to compute the final volume of annual vaccine demand.

2.3.1. Auto-Regressive Integrated Moving Average

Time series model have been develop into many different types. In this research, we adopt the Auto-Regressive Integrated Moving Average (ARIMA) model which was introduced by Box and Jenkins in 1976 and 1994 [Box and Jenkins, 1976; Box, et al., 1994). As we understand, ARIMA is also the most commonly used so far among many types of time series models.

The ARIMA is generally referred as auto-regressive integrated moving average model of (p, d, q) which is shorted as ARIMA (p, d, q) for short. The word of "Integrated" refers to if the raw series of data is not stationary, it can use the differencing method to make the data series stationary and then use the stationary data series to build the ARIMA (p, d, q) model.

In this research, we use multiple-variant ARIMA to build the forecast model for vaccines of DPT and OPV. For adding time series variable X to assist subscribing time series Y, Box-Jenkins in 1977 issued transfer function. ARIMA with transfer function can not only deal with the data set of predict variable and input variables but also subscribe their relationship. It can make ARIMA adapt more condition with flexibility to forecast. In the practice of inoculation, the number of inoculation is almost a stationary series that suitable to fit an ARIMA model for predicting, so this research would use ARIMA with its transfer function to build a forecast model to improve the quality of decision for vaccine decision making.

As we can see from formula 4, ARIMA original only subscribes the change of y_i and fits it as ARMA(p,q). ARIMA with transfer function(ARIMAT) can subscribe the change of y_i and x_{ki}, and series of x_{ki} can explain the part of variation of y_i. So we can see that after y_i was differentiated and subtracted by u, the value can be distribution by x_{ki} and residual of y_i.

$$(1-B)^d y_t - u = \sum_{k=1}^{k=K} \frac{\omega_{kl}(B)B^b}{\delta_{kr}(B)}(1-B)^d x_{kt} + \frac{\theta_q(B)}{\phi_p(B)} e_t \tag{3}$$

ω_{kl} = the parameter of limited lag

δ_{kr} = the parameter of limitless lag

b = the level of lag

2.3.1. Neural Network

A generic model of neural network mode consists of three types of layers, which are input, hidden, and output layers which are illustrated as Figure 1 (Negnevisky, 2002). Each layer may consist of many artificial neurons or viewed as processing elements. Each processing element is designed to emulate the function analogous to a biological neuron in human brain. The number of neurons in each layer can be as many as tens, hundreds, even thousands depending upon the problem. Again, each neuron can have several different inputs and may send its output to many other neurons. As it is shown in Figure 1, a neuron may be connected by weighted links passing signals from one neuron to another. The output signal is transmitted through the neuron's outgoing connection. The outgoing connection splits into a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections of other neurons in the network. Hence, neurons are wired up in a 3-dimensional pattern. The features of each layer are briefly described as follows:

(1) Input Layer: The initial inputs are presented to this layers. The number of processing elements depends on the problem.
(2) Hidden Layers: It shows the interaction among processing elements. There is no standard rule to decide the number of processing elements. In order to find out the best number of elements used in the neural network model, we need to verify each network is generated by repeatedly testing. The neural network can have not only more than one hidden layer but also none of hidden layer.
(3) Output Layer: It shows the output variables which are decided when the network is in convergent state through a number of simulation run. The number of processing element of output also depends on the problem.

Commercial neural networks incorporate three and sometimes four layers, including one or two hidden layers. Each layer can contain from ten to thousand neurons. Experimental neural networks may have five or even six layers, including three or four hidden layers, and utilise millions of neurons.

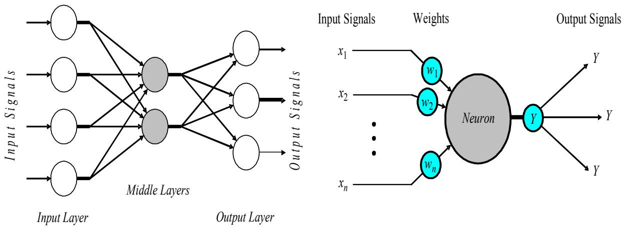

Figure 1. A Generic Model of Back Propagation Neural Network

Neural network model also has many different forms (Fish et al., 1995). Among these forms, researchers and practitioners (Lippmann, 1987; Fish et al., 1995) agreed that nowadays the back propagation neural network (BPNN) is the most representative and universal model in many different models of Neural Networks. BPNN is the part of supervised learning network which is commonly used to build decision model for diagnosing and forecasting. Lippmann (1987) presented a proof that the forecast results by using BPNN are better than using traditional statistics analysis by applying it in several forecasts of real cases.

Neural networks have been used in wide areas such as investment analysis, signature analysis, process control, monitoring, marketing, and various kinds of trend analysis. In this research, we intend to use the Back Propagation neural network model predict the related variable values of forecasting the vaccine demand is a type of trend analysis as time changes of the historical data in the past.

3. Research Framework

In this section, we will discuss the framework of this research from the aspects of research method, the decisive variables selected for forecasting, and forecast model and procedure of the research so that the readers can comprehensively understand the process of this research.

3.1 Research Method and Process

3.1.1. Research Method

This research takes forecast models to predict the determining related factors with vaccine demand. In addition, it uses ARIMAT predicting the "total number of inoculation" for next year and uses BPNN predicting the "coverage rate of inoculation".

As we discuss in the prior sections, the Multi-variant ARIMA model of time series is adopted to build the forecast model to forecast the total doses of demand for certain vaccine in the next year by inputting one variable "the number of baby-birth".

The workload of immunization in current year is used as a referential value to decide the amount of vaccine demand they purchase. So, this research uses several variables to increase the accuracy of the forecast of workload of immunization in the next year. It obtains great results in many single variable statistic methods (Shieh, 2001).

In order to obtain a better result of forecast, we attempt to combine the advantage of ARIMA and BPNN. BPNN can also accept multiple factors of influencing vaccine demand as the input variables. Lippmann (1987) has shown that the great forecast results by using BPNN with multivariable inputs. And ARIMA can handle single number list great. So we can build a integrate forecast model and base on the property of variables we use different mode to predict to get a better accuracy.

3.1.2. Research Process

We establish single/multiple-dose vaccine demand forecast and optimal allocation model through 4 stages of process, the detail research architecture and procedure are illustrated in Figure 2.

The first stage we use ARIMA, ARIMAT and BPNN models to forecast all related variables about vaccine demand. In ARIMA, we use models to forecast "the numbers of baby-birth" and "replace rate of vaccine". The result of "the numbers of baby-birth" can be used to build a transfer function to assist ARIMAT to predict "the number of inoculation". In BPNN, this research intends to use "conjugal condition" and "the number of migration" to be input variables. Then we train BPNN to predict "coverage rate of inoculation". These predictions will be use to computer the vaccine demand.

The second stage then takes the value generated from the first stage and take into formula 1 and 2. We can obtain two estimations of the amount of inoculation in doses in district health centre(DHC) (J). These two estimations will be compare to actual value and take one that has a smaller error to vaccine demand formula. After that, We can compute the vaccine demand in next year (N).

The third stage then takes the workload of inoculation of DHC in the past year to get the vaccine demand of DHC (Z_i), and each DHC can use his Z_i to compute the volume of his own vaccine demand next year.

The fourth stage will take vaccine demand forecast result from third stage to compute the vaccine amount of allocation for each DHC and the cost for each centre's allocation and the total cost for the entire nation for this vaccine demand under some specified constraints which is regulated by the rules defined by CDC's immunization management operating authority. The constraints and rules are shown in Figure 2.

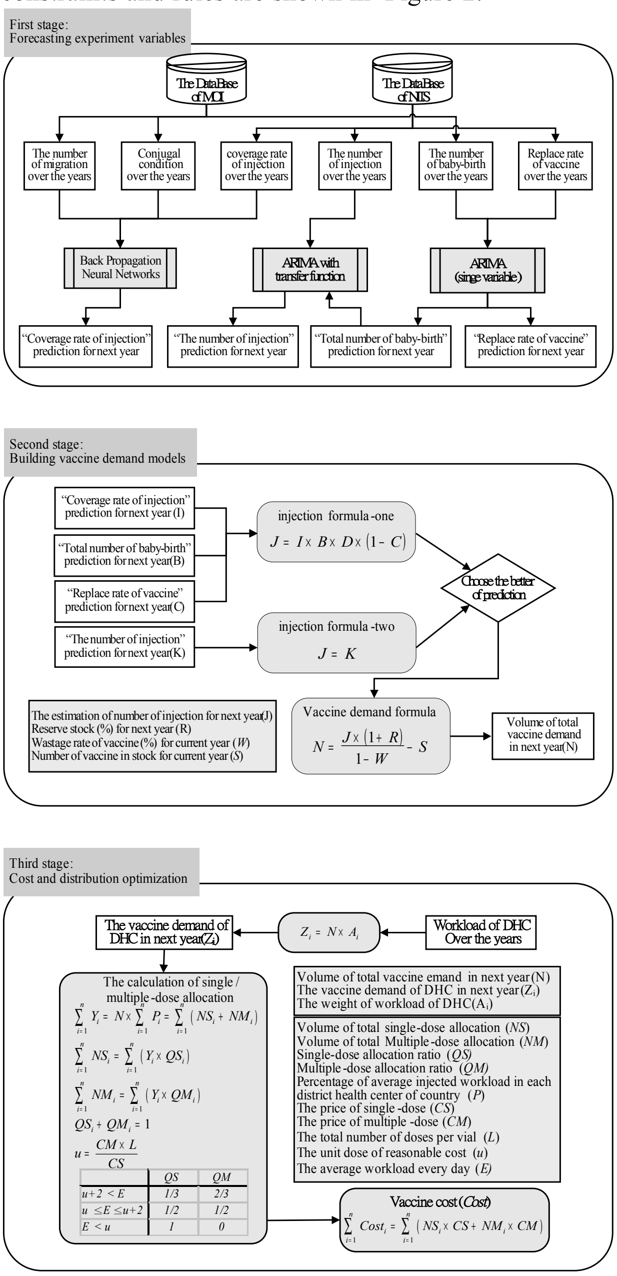

Figure 2. Forecast model and procedure for this research

3.2 Decision Variables

This research initially obtains many considerable impact variables which may impact the decision of vaccine demand through initially investigating from various reports and literatures (Alexander, 2002; Chen, 2003; WHO, 2002). This research classified these input variables for forecasting model into major categories which include the people relative factors and the psychology relative factors. These factors are shown and described in Table 1. The predict variable is “the number of inoculation”, these input variables must be filtered before they can be used as the true factors for forecasting. In addition, there are simulation variables used to adjust the number of vaccine purchased base on the vaccine demand of local unit. Each local unit can set these simulate variables including reserved stock, wastage rate and the number of vaccine in stock. It can let local health centers to obtain proper demand based on their individual demands and situations.

We only take the data from the Taipei county, which is the largest one county and also has most population in Taipei. Taipei County not only it is the most populated county in Taiwan but also its geographical environment may be thought as a window of Taiwan which includes the densely populated city areas, thinly populated country areas, and far-reaching mountain areas. It contains twenty-seven district health centres which are dispersedly located around the entire county. We firstly build the model to forecast the demand for each district health centers, and then sum them up to estimate the demand for the entire county. We think if the model can correctly estimate the need of Taipei county, the results shall be able to be further applied for the entire country. Consequently we choose the most populated Taipei County to be the research target to be the experimental county. The data sources relative to the population growth relative factors described in Table 1 used to forecast vaccine demand are extracted from the entire 29 local district health centres in the data base of National Immunization Information System (NIIS) of Taipei County. The relative data of population factors for the past years are solicited from the Ministry of the Interior (MOI) of Taiwan’s government. The time period of data sampling is from 1993 to 2004. We use the data from 1992 to 2003 as the training data to the forecasting model and the data of 2004 as the proofing data.

At first, we investigated the trend of the workload of immunization operation for each vaccine from every local district health centers in Taipei County over the time period from 1993 to 2002. We attempt to find if they have a trend that can be followed so that the forecast can properly be applied. Interestingly, we discovered a very similar trend for different vaccines throughout the twelve months of different years. Among these investigations, we found three vaccines having a stable presentation of workload trend in which are Measles-Mumps-Rubella (MMR). It should belong to the forecast of historic data trend for the vaccine demand. Hence, in this research we firstly select MMR to be the experimental vaccine to conduct the demand forecast. In our mind, if we can fine a proper forecast model to accurately forecast the demand of total number of inoculation of MMR, then we can apply it to forecast other two kinds of vaccines.

According to our understanding, the MMR normally inoculates only 1 dose for a new-born baby during his/her one year old period. Whereas in each year there exists some makeup MMR inoculation for other ages of children (usually in his/her 1^{st} grade of elementary school) who missed the normal inoculation during his/her must-be immunization period and for the other special cases like women at childbearing age. Because these cases of makeup inoculation are few and data collection are not precisely, therefore although the government do not take into account of these inoculators for the annual vaccine immunization coverage rate but we still put them into the consideration of the input sources of annual total number of inoculation estimate the workload of immunization. This is the reason why we set the forecast target on “total number of inoculation” but not “the number of already-inoculated-people” that may be taken from the vaccine immunization coverage database is that especially consider non-new-born baby or other public immunization demand to be more close to the condition of real demand.

	Decisive Variables	Explanations and Data Sources
Vaccine demand relative variables	Total number of inoculation	It also means workload of vaccine inoculation. The value is obtained from NIIS database and is also verified against the data obtained the workload of vaccine inoculation each month over the years in Taipei country.
	Immunization coverage rate	The value is assumed to be constant. According to the average immunization coverage rate released from the CDC immunization administration office of Taipei country in the last three years, the average coverage rate of DTP vaccine is about 95.62%.
	Vaccine wastage rate	The value is thought to be constant. Because there is no related records in NIIS database, so we adopt 25% as the general wastage rate of DTP according to WHO’s reports.
	The number of vaccine in stock	The value will be the surplus stock in the end of every year, but NIIS is just installed in operation in 2003, so it has no actual record of vaccine in stock before the years of 2002.
	Vaccine reserve stock	The value is thought to be constant. Because the policy of Taiwan stipulates it must maintain the stock for being used for three-month period so the percentage of vaccine reserve stock is set to be 25%.
	The number of doses per fully immunized child	The value is thought to be constant. A new-born baby must inoculate DTP total four doses which come to 2, 4, 6, 18 months to inoculate one dose per each after being born.
	The price of single/multiple dose	The value is thought to be constant. Because the price of vaccine is different every year, so the value will be obtained through CDC of Taiwan to obtain the purchase price of DTP in 2002.
Population growth relative variables	The number of baby-birth	The value may be obtained form ministry of interior
	Conjugal condition	The value may be obtained form ministry of interior
	The number of migration	The value may be obtained form ministry of interior

Table 1. The Decisive Variables and Explanations

4. Experimental Result Analysis and Estimation

Through different model predict different variables, we can obtain the result showed table 2. We use ARIMA model to predict "the number of baby-birth" and get a prediction 31202. it has a error rate 4.52%. this is a small error rate for predicting. Moreover, we use "the number of baby-birth" building a transfer function to add the accuracy of ARIMAT of "the amount of inoculation" and take 31202 as input variable to model. The result of predicting of "the amount of inoculation" is 30568 and has error rate 9.42%.

We also use ARIMA model to predict "replace rate". The result of predicting is 90.56% and has error rate 4.45%. Besides, the variable "coverage rate" use BPNN model to forecast. The BPNN model use two input variables to forecast including "conjugal condition" and "the number of migration". The result of prediction is 93.47% and has error rate 2.85%. These result can be used to compute the vaccine demand of Taipei county.

variable	prediction	error rate	model
baby-birth	31202	4.52%	ARIMA
inoculation	30568	9.42%	ARIMAT
replace rate	90.56%	4.45%	ARIMA
coverage rate	93.47%	2.85%	BPNN

Table 2. the result of forecasting of related variables

Using above prediction we can estimate the number of workload of DHC in next year. By formula-one, we can compute the estimation 26,411 and has error rate 5.46% with actual workload in 2004.

$$J = 93.47\% \times 31202 \times 1 \times 90.56\% = 26411$$

In formula-two, we can use the prediction of "the number of inoculation" as our estimation, so the estimation is 30568 and has error rate 9.42%. we can take small error rate, 26411, into our demand formula.

	formula-one	formula-two
estimation	26411	30568
error rate	5.46%	9.42%

Table 3. the comparison of estimation of formula

$$N = \frac{26411 \times 1.8333}{1 - 0.4} - 21547 = 59152$$

Finally, we compute the vaccine demand in Taipei county in 2004 and the number is 59,152.

When we get the number of vaccine demand, we can distribute the quantity to each DHC according to their workload over the years. Moreover, following single/multi dose vaccine principle as Figure 2, we can get the distribution of single/multi dose listed table 4. The table includes the cost of single/multi dose vaccine. Cost of single dose vaccine is 3,736,128; Cost of multi dose vaccine is 2,145,459; Total cost is 5,881,587.

	price	amount	cost	total cost
single-dose vaccine	116	32,208	3,736,128	5,881,587
multi-dose vaccine	79.6	26,953	2,145,459	

Table 4. The Result of vaccine distribution

5 Conclusion and Suggestion

In chapter 4 the Experimental Result shows that the error rate of "baby-birth", "replace rate" and "coverage rate" are under 5%, those are good predictions and have a great accuracy. A great prediction is important for vaccine demand model because accurate prediction can derive effective estimation.

After building the forecasting model to predict the relative variables with vaccine demand, we begin to estimate the annual workload of DHC. The result of research shows the combination of forecast models has a better performance than single forecast model. So formula-one combines three predictions and has a smaller error rate 5.46%. Using the estimation of formula-one can get a vaccine demand 26,411. the number can be used to advice by decision maker.

Finally, this research presented a "single/multi dose vaccine principles" for CDC to decide the distribution of single/multi dose vaccine, which can reduce the wastage of vaccine and optimizing the distribution. Using it, we can compute the cost of vaccine and the total cost of MMR vaccine in Taipei county in 2004 is 5,881,587. This result can be an advice number for CDC.

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