Developing Accurate Predictive Model Using Computational Intelligence for Optimal Inventory Management

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***Abstract* — People are all currently living in the world where data has changed how company think, act and plan. Data, if used correctly, might be able to become a company's sharpest weapon in fighting the competition with other companies. Inventory cost is one of the most burdening costs in the food and beverage industry with the items like degradable raw materials or fresh ingredients. If not managed correctly might become a waste causing loss to the company. Degraded ingredients also might lower the overall food quality which might result in unsatisfied customers. Managing inventory, however, is not as easy as it seems, especially with the traditional method. This paper focuses on development of accurate predictive model using computational intelligence for optimal inventory management with a case study of restaurant ingredient management. Several machine learning algorithms like linear regression, multi-layer perceptron, random tree, random forest, and model trees were utilized to build accurate predictive models from time series data of the restaurant inventory. With good prediction system using computational intelligence, the inventory cost and wasted ingredients can be significantly reduced, which this eventually maximizes the profit.**

Keywords—machine learning algorithm, time series forecasting, inventory optimization and control

I. INTRODUCTION

In the current era of information, data has greatly changed the world we live in today. The combination of data science and machine learning has earned the ability to predict the future [1, 2]. Nowadays, a lot of big companies are data driven, they are utilizing the data to improve themselves even more, to gain advantage over their competitor, to efficiently manage their resources, to reduce unnecessary cost, etc. With the utilization of the data, there are unlimited potential of how one company can improve [3]. Food and beverage are one of the sectors that is quite interesting. Despite seemingly countless number of restaurants out there, which also mean tight competition, there are a lot of things that can be done in order to win in the fierce competition. One of the examples is to keep the total expenses low, allowing the restaurant to generate higher revenue [4]. And to do this, what the company can do is to control the restaurant food cost . One of the methods to control the food cost is by buying the fresh ingredients needed by the restaurant in bulk. As we all might have already known, buying ingredients in bulk can help us to save inventory costs. The main advantage of buying in bulk is cheaper price per unit. Another advantage of buying in bulk is less trip to or from the supplier, which mean less delivery cost [5]. However, despite the advantages of buying in bulk, it also comes with disadvantages [6]. For example, buying in bulk requires in-depth planning especially when it comes to fresh ingredients. Buying in bulk mean the company need to consider the inventory carrying cost. Ultimately, the company need to decide the exact amount of the inventory they want to buy. This is also called Economic Order Quantity or EOQ [7]. When deciding the EOQ, there are a lot of factors that need to be considered by the company. For example, fresh ingredients have deterioration rate which need to be carefully taken into consideration. Another example is demand spike or drop due to various reason such as weekends and holidays, unforeseen event, promotion etc. This mean that the company needs to be able to utilize its past data and numbers to predict the upcoming trends and demands. To do this, the company needs to analyze the previous data, process it into meaningful information and then eventually draw a decision based on it.

Similar research regarding demand forecasting in restaurant using machine learning have been conducted [8-10]. In the previous research, the research was conducted using a different methodology. In their research, the algorithm used to predict the trend was Bayesian linear regression, boosted decision tree regression, decision forest regression, and stepwise method. Their target data was also different as the research was trying to predict the number of customers visiting the restaurant.

Predicting the number of customers visiting the restaurant only gives a vague idea to the business owner. Knowing how many customers are coming on a certain day does not let the business owner know how many ingredients the restaurant would need to prepare in order to avoid problems such as running out of ingredients or having too much supply which end up being food wastage. This research aims to gives the business owner a better idea and better preparation when preparing for the upcoming days. Therefore, the research aims to predict the number of ingredients required for a certain day, not the number of customers coming. The reason why this research is aiming to predict the number of ingredients required is because it would give a better insight, considering they know how much ingredients they would need to prepare, not just how many customers are coming.

This study will use the data gathered from various sources as a study case. As explained above, this kind of business model rely heavily on its inventory management as a way to gain profit. However, since each business model, or company even has its own unique process, EOQ formula need to be modified based on accordingly. Therefore, this study will be focusing on finding the most optimized EOQ for this study case with the help of machine learning algorithm prediction. This study utilized real restaurant data sets representing food and beverage business model. The sample data used in this research is limited in term of quantity.

The main goals of this study are to help both existing and upcoming all-you-can-eat restaurant business model in some ways which are: (1) to find which machine learning algorithm that can produce the best prediction result, (2) to build accurate predictive models using computational intelligence [11-13] associated with the optimal inventory management in a restaurant, like predicting number of visitors and quantities of ingredients for a certain day, and (3) to optimize the overall revenue, the ingredients waste and inventory cost [14-17]. With the help of this study, the company is expected to be able to manage its own inventory better than before and therefore will receive benefits such as:

a) Improved order accuracy

A better management of inventory also mean one thing: improved order accuracy. With higher accuracy, the company would be able predict which menu will be ordered during specific hours or days. This will also assist the company to be able to stock up enough ingredients to make sure there isn't any ingredients shortage.

b) Forecast trends

By using the method offered by this study, the company would be able to forecast the upcoming trend and revenue. By doing comparison between past data with the current one, the company would be able to foresee where the company would be in the future. And with this information, the company could develop a strategy to help the business to achieve its target.

c) Reduce food waste

When developing a menu, it is crucial for a company owner to know the amount of ingredients needed to prepare the menu. A better inventory management would be able to assist the company to check the past and present inventory levels. This will help the company to minimize the food waste by buying the exact amount required at the right time and therefore reduce the overall food cost.

d) Better planning

Lastly, better inventory management aid the company to prepare for future shifts by foretelling customer trends and business peak time.

II. Theoritical Foundation

A. Restaurant Inventory Management

In restaurant cases, there's also restaurant inventory management. Restaurant inventory management is the process of tracking ingredients in and out of the restaurant. This process regulate the number of menu ordered, everything that came out the kitchen, and the amount of ingredients left afterward. It also includes the product allocation between stores. measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. It also includes the product allocation between stores. This process is a bit tricky to do especially since ingredients will go stale over time. According to assetinfinity.com, proper restaurant inventory management can be achieved by having features such as: cloud-based system, instant billing, stock management, raw material management, recipe management costing, menu updates, central kitchen management, roles and permission, analytics and reporting, shelf-life management, marketing and CRM module, centralization, scalability, integrations, ease of use, quick support, theft control, security, mobility, and payment integration [18].

B. Data Science and Machine Learning

Data science is the domain of study that deals with vast volumes of data using modern tools and techniques to find unseen patterns, derive meaningful information, and make business decisions. Machine learning, as explained above is the machine's ability to learn something new, by itself. This is the core of the data science [19].

Fig. 2. Restaurant Chain Management

III. Methodology

A. Data Science Project Lifecycles

According to simplilearn.com, data science project usually follows the same pattern which are:

a) Concept Study

The first step of data science project is the concept study. The purpose of this phase is to comprehend the setback by understanding the business model.

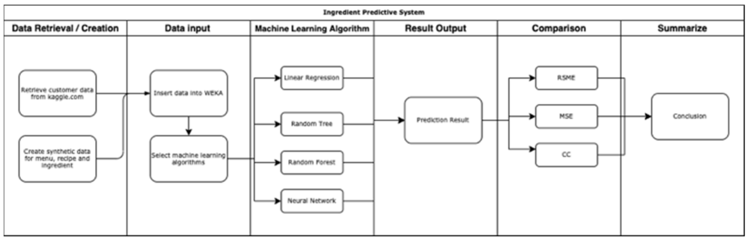

Fig. 1. Data Science Phases

b) Data Preparation

As raw data might not be utilizable, data preparation is required to arrange the data into meaningful information. To do this, the data need to be separated to know which data can be used a sample data for mining. In this research, the data science project is divided into a few phases which are data retrieval, data input, applying machine learning algorithm, result output, result comparison, conclusion.

B. Data Description

For the research, one dataset will be used as the main dataset. The dataset contains number of orders of a cafe and has more data ten thousand data instance and starts from July 2020 to July 2020. However, since the dataset itself mostly contains number of menus sold over half the year, the researcher chose a menu as a sample and tried to predict amount of the ingredients required. The dataset was retrieved from one of the cafés in Indonesia.

IV. System Analysis and Proposed Design

A. *Visitor, Dish, and Ingredient Management*

There are a few entities that have to be included in a restaurant's information system. Those entities are order, menu, recipe, and ingredient and visitor. In order to predict the number of ingredients required, the record of how many numbers of menu or dishes ordered every day are needed. The number of menu or dishes ordered every day determine the final number of ingredients required on that day. Those data will then be used as the main independent variable when building the predictive model. Another factor such as number of customers ordering the order can also be used as the independent variable to increase the accuracy of the predictive model. The required entities are shown in Fig. 4.

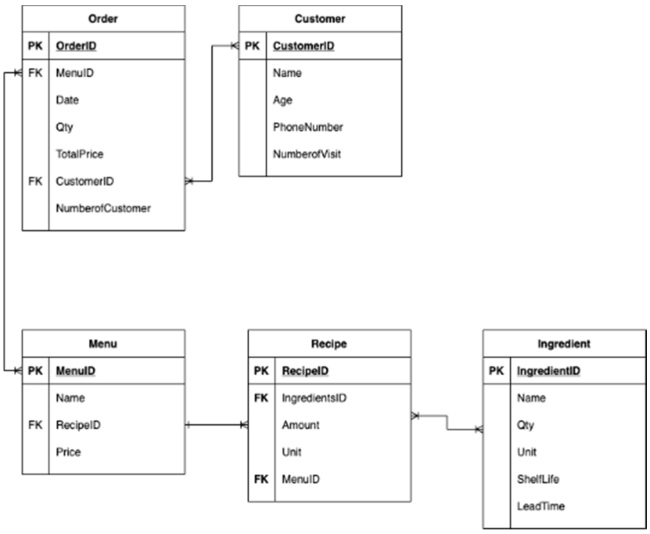

Fig. 4. Entity Relationship Diagram for Visitor, Dish, and Ingredient Management

B. *Processes in Building Predictive Model*

There are several steps that should be followed in order to build the predictive model for this research. Those steps can be categorized into data preparation and cleaning first, data transformation processes, significant variable identification and selection, data de-transformation processes and predictive model performance and selection, as schematized in Fig. 3.

The file was originally retrieved from 3rd party source in a pdf form. The pdf form was then converted to csv file in order to make it readable by WEKA. The original data has lots of redundant and missing data, therefore the researcher had to cleanse the data to make it mineable. The researcher then selected one of the ingredient to be used as a sample data. The data was afterward improved with several methods. First the data was checked to see whether it contains any anomality. If the data had anomality, the researcher would have to remove the anomality. The data was then tested if it requires interpolation, and box-cox transformation. After that, the researcher created a time series for the it from i_{t-1}, i_{t-2}, to i_{t-12}. The time series was tested with CC to see which one has the CC over 0.1. The time series that have CC over 0.1 will be used as independent variable to increase the accuracy of the prediction. If the data is a large number data type, it will be divided by a 100 to make it easier for the machine learning to mine the data. The next step was building the predictive model. WEKA will then do the prediction and produce the prediction result. Afterward, the result was multiplied by 100 if it was divided by a 100 before, and box-cox de transformed if it was transformed before. The result will then be analyzed by checking the previously stated measurement method.

V. Design Implementation

A. *Data Preparation*

As explained above, data preparation is the step where the data scientist or the researcher prepare the data to be processed into useful information. The first step in this phase is to gather the data. Data can be gathered from a lot of

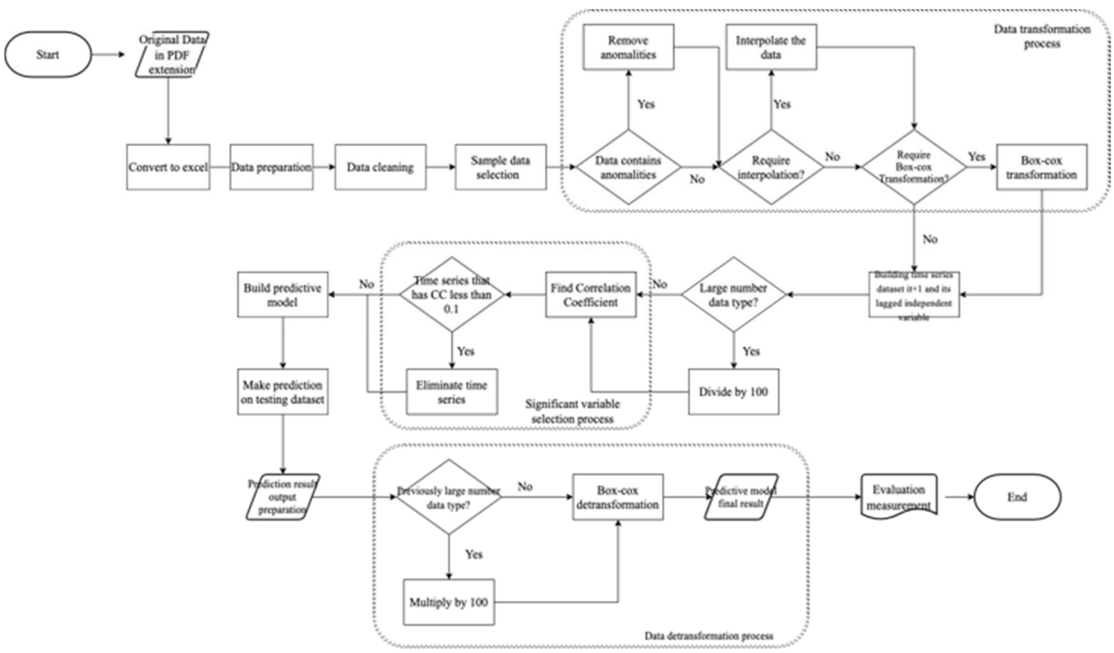

Fig. 3. Predictive Model Building Process Diagram

sources depending on the company.

B. Ingredients Data

This research will use data set consists of ingredient data as our main data. The data set later on will contain examples of menu available in the restaurant and ingredients required to produce the menu. The dataset itself is retrieved from an existing restaurant and consists of half year worth of data starting from July 2020 to December 2020. One fresh ingredient will be selected to be used as a sample data to be datamined, as depicted in Fig. 5.

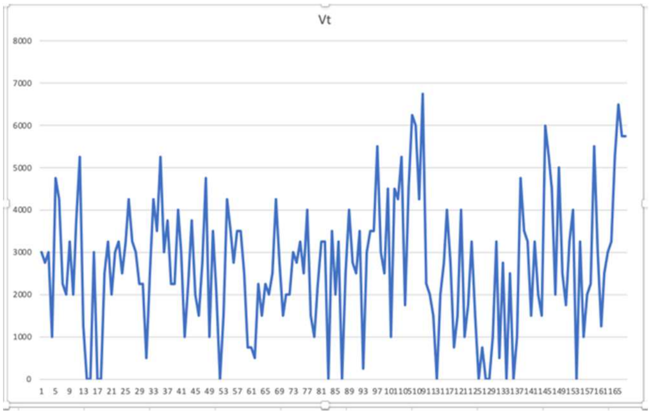

Fig. 5. Fresh Milk Ingredients Data Graph

C. Dish Data

Another data that will be used in this research is the dish data. The data is retrieved from the same resource as the ingredient data. The data will later be used as another independent variable to make multivariate data in order to improve the accuracy of the ingredient prediction, as shown in Fig. 6.

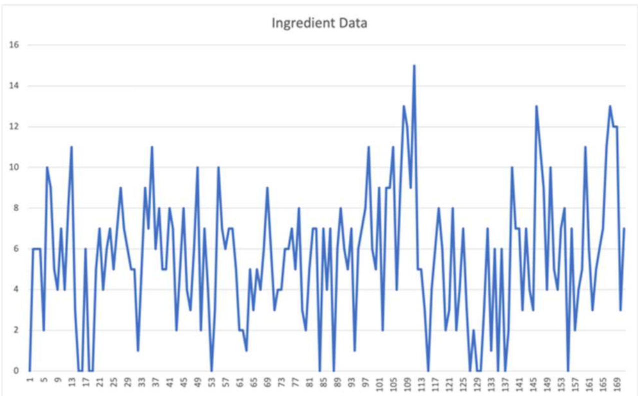

Fig. 6. Number of Dishes Ordered with Fresh Milk Ingredient

D. Time Series Prediction Analysis

To gain the expected result, Machine learning algorithms mentioned above such as linear regression, random tree, random forest and neural network will be used. The tool used to achieve this is called Weka. According to Wikipedia, Weka or Waikato Environment for Knowledge Analysis is a collection of machine learning algorithms for data mining tasks. Weka provide tools for a lot of tasks such as data pre-processing, classification, regression, clustering, association rules and visualization that help people to execute machine learning tasks without having to code. The ingredient data, as can be seen in figure above, will be separated into time series, which consists of V_t, V_{t+1}, and V_{t-1}, V_{t-2}, …, V_{t-12}. The formula that will be used to test the data is $V_{t+1} = f\ (V_t, \ldots, V_{t-n})$ with V_{t+1} being a dependent variable while V_t and V_{t-1} to V_{t-12} being independent variables. These independent variables, as also referred to features, are the inputs for some processes being analyzed. The dependent variables are the outputs of the process.

VI. Building Predictive Models Using Machine Learning Algorithms

As mentioned in section before, the ingredient data was retrieved from a real restaurant data. The data mining process of ingredients data will be divided into six phases, with three being univariate data, and another three being multivariate data. The first one is building the predictive model with the original data. The second one is the building of the predictive model with the interpolated version of the original data. The third one is building the predictive model with the box-cox transformed version of the data.

A. Original Univariate Fresh Milk Data

The first phase is mining the original univariate fresh milk data. The time series predictive model for ingredient can be formulated as $i_{t+1} = f_M\ (i_t, i_{t-1}, i_{t-2}, i_{t-3}, i_{t-6}, i_{t-7})$, where the i_{t+1} is the ingredient required for the next day t+1; and the independent variables of i_t, i_{t-1}, i_{t-2}, i_{t-3}, i_{t-6}, i_{t-7} are historical ingredients consumed on the days of t-1, t-2, t-3, t-6, t-7, and f_M is the predictive model using machine learning algorithms M.

Table I shows the result comparisons of all machine learning algorithms. The best one result is highlighted in bold. As for the observed and predicted result comparison can be seen in Fig. 7.

TABLE I. Original Univariate data predictive model result comparison

Original Univariate Fresh Milk Data				
Test Option	***Algorithm***	***CC***	***RMSE***	***MAE***
Percentage split / Cross-validation	Linear Regression	**0.314**	**1174.08**	**1502.14**
	Neural Network	0.0728	1554.39	2056.40
	M5P	**0.314**	**1174.08**	**1502.14**
	Random Tree	0.0839	1747.02	2176.03
	Random Forest	0.17	1254.64	1567.96
Supplied test set 70% 30%	Linear Regression	**0.1385**	**1002.479**	**1217.8018**
	Neural Network	-0.0881	1311.7974	1728.8617
	M5P	**0.1385**	**1002.479**	**1217.8018**
	Random Tree	0.036	1054.6569	1313.888
	Random Forest	-0.1413	1544.1176	2016.1724

The result is pretty decent as can be seen from Fig. 7, the prediction manages to predict the rise and fall of the original data although still missed the exact number. Aside from the result shown above, another test is conducted in order to produce a different result. The test used another test option, which is the supplied test set option in WEKA. Supplied test set prediction result is not randomized and is sorted based on the time series. This gives out a better insight compared to the random result given by cross-fold validation and split test option. The supplied test set option is also splitting the data based on percentage. In this scenario, the dataset is split to 70% training and 30% testing. The best prediction result of original univariate data with supplied test set is linear regression and M5P with CC at 0.1385 and MAE RMSE a little over thousand. The result is not good since it has low CC. From the graph we can see the prediction also missed every time which make it a bad prediction.

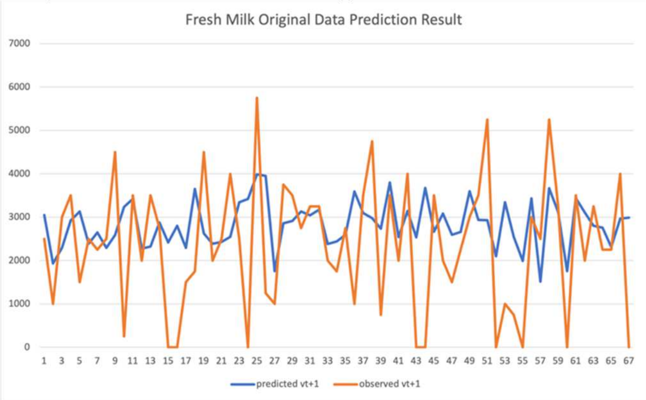

Fig. 7. Original Univariate Fresh Milk Linear Regression Predicted and Observed Result Comparison

B. *Interpolated Box-Cox Transformed Univariate Fresh Milk Data*

The third phase is mining the interpolated box-cox transformed univariate fresh milk data. The time series predictive model for this data can be formulated as $i_{t+1} = f_M(i_t, i_{t-1}, i_{t-2}, i_{t-3}, i_{t-7}, i_{t-8})$.

In the Table III, it can be seen the linear regression and M5P yield the same result, and both are the best one out of all five algorithms for the percentage split / cross-validation. While for the supplied test set 70% 30% random forest has the highest score.

TABLE II. INTERPOLATED BOX-COX TRANSFORMED UNIVARIATE DATA PREDICTIVE MODEL RESULT COMPARISON

Interpolated Box-Cox Transformed Univariate Fresh Milk Data				
Test Option	***Algorithm***	***CC***	***RMSE***	***MAE***
Percentage split / Cross-validation	Linear Regression	**0.1934**	**21.14**	**26.36**
	Neural Network	0.0673	31.996	21.14
	M5P	**0.1934**	**21.14**	**26.36**
	Random Tree	0.0265	31.46	40.64
	Random Forest	0.1225	22.67	27.54
Supplied test set 70% 30%	Linear Regression	0.1464	28.7856	23.4404
	Neural Network	-0.0451	24.8428	28.7569
	M5P	0.0016	18.8075	24.4025
	Random Tree	0.1357	24.5686	29.984
	Random Forest	**0.3258**	**17.1852**	**23.4075**

This time, instead of using the split test option, the cross-validation test option was used. Just like the previous results, this prediction also has yet to be able to predict the sharp rise and fall of the original data. Compared to the other result tested with supplied test set option, it is the best result out of all. The prediction manages to predict some correctly although the majority is still a miss prediction.

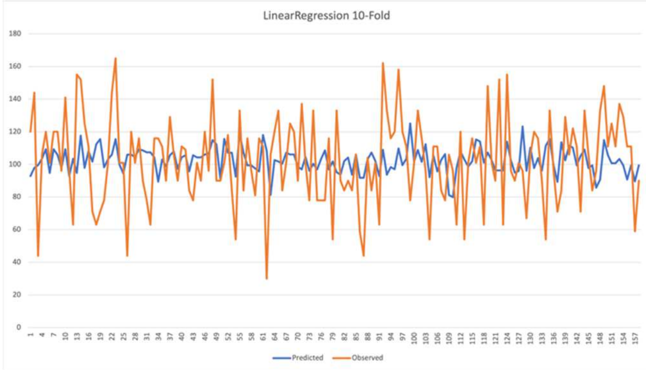

Fig. 8. Interpolated and Box-cox transformed Univariate Fresh Milk Linear Regression Predicted and Observed Result Comparison

C. *Interpolated and Box Cox Transformation for Multivariate Fresh Milk Prediction*

The fourth phase is mining the original multivariate fresh milk data. The time series predictive model for this data can be formulated as $i_{t+1} = f_M(i_t, d_t, i_{t-1}, d_{t-1}, i_{t-2}, d_{t-2}, i_{t-3}, d_{t-3}, d_{t-4}, i_{t-6}, i_{t-7}, d_{t-7}, i_{t-11}, i_{t-12}, d_{t-12})$.

Similar to the previous result, the random tree model also came out as the best model in the sixth phase tested with 60% 40% supplied test set, while for the supplied test set 70% 30%, random forest has the highest score. The difference is that the sixth phase have a much higher CC compared to the previous result.

The machine learning prediction manages to predict some of the sharp rise and fall. While it has also managed to miss some prediction. Overall, it has achieved a pretty satisfying result.

TABLE III. INTERPOLATED MULTIVARIATE PREDICTIVE MODEL RESULT COMPARISON FOR FRESH MILK DATA

Interpolated Multivariate Fresh Milk Data				
Test Option	***Algorithm***	***CC***	***RMSE***	***MAE***
Supplied test set 60% 40%	Linear Regression	0.0568	25.92	31.47
	Neural Network	0.1383	58.69	84.07
	M5P	0.0568	25.92	31.47
	Random Tree	**0.3217**	**25.61**	**33.35**
	Random Forest	0.292	24.42	30.36
Supplied test set 70% 30%	Linear Regression	-0.0276	18.1621	25.1716
	Neural Network	0.0486	25.9726	32.128
	M5P	0.1801	18.5798	24.2158
	Random Tree	0.1928	26.7059	33.094
	Random Forest	**0.2456**	**17.7131**	**24.1641**

The best algorithm for the interpolated box-cox transformation data with supplied test set is random forest with CC 0.2456 and MAE RMSE of 17.7131 and 24.1641 respectively, as listed in Table VII. The result has improved compared to the other 70% 30% supplied test set option since the prediction has managed to predict some of the sharp rise correctly, as depicted in Fig. 9.

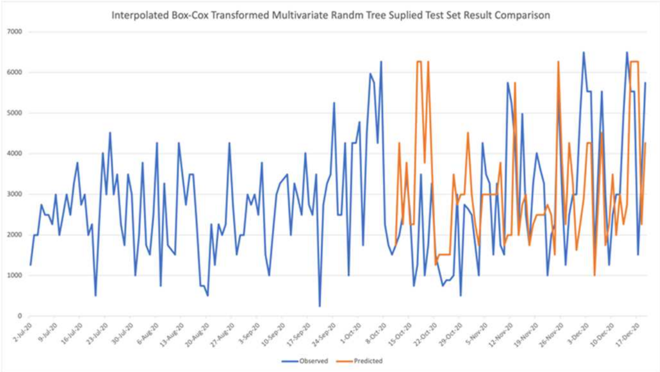

Fig. 9. Interpolated Box-Cox Transformed Multivariate Fresh Milk Random Forest Predicted and Observed Comparison Result

VII. CONCLUSION

Considering six phases of data mining processes, every single result has showed an improvement compared to the previous result. The end result, which is interpolated box-cox transformed multivariate fresh milk data has showed a significant improvement compared to the first phase of data mining result. The result has managed to reach CC 0.32, RMSE 25.61, and MAE 33.35. From Figure 5.8 it can be seen that the prediction itself has managed to predict correctly at some points even though the original data have a lot of sharp rise and fall. However, the result itself is still far from perfection. There are some constraints that lower the overall result of the data mining, such as time, data quality, etc. All in all, while there are still a lot of rooms for improvement, the research has achieved a satisfying result. It has managed to achieve the initial aims which are:

- Finding the best machine learning algorithm that produce the best prediction result for this study case
- Building accurate predictive models using computational intelligence associated with the optimal inventory management in a restaurant, like predicting number of visitors and quantities of ingredients for a certain day.
- By having an accurate predictive model for ingredients and visitors the optimal stock management and ingredients waste reduction could be well managed. Not directly but receive impact in the future.

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