Using Local Weather and Machine Learning to Forecast Market's Demand and Supply: A Pilot Study (November 2019)

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USING LOCAL WEATHER AND MACHINE LEARNING TO FORECAST MARKET'S DEMAND AND SUPPLY: A PILOT STUDY (November 2019)

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Abstract

The study explored Long-Short-Term-Memory (LSTM) neural networks (ANN) to predict local Small and Medium Scale Entrepreneurs' (SMEs') goods purchases quantities, buying and selling prices. The independent variables included low and high temperatures. The study was exploring the impact of using ANN models in forecasting local goods' quantity purchase, buying prices, and the goods selling prices, from the day-to-day local weather conditions, on the local SMEs. The weather was the independent variable for forecasting. The study's SMEs included marketers trading in household edible commodities, like bread, mealie-meal, cooking oil, green vegetables and sugar. LSTM modular was employed to forecast the daily goods' quantity purchase, buying and selling prices. It was observed that ANN can use the weather to forecast demand and supply parameters for market traded goods. The study used the weather in the LSTM ANN model to forecast demand and supply to establish the feasibility to build an application embedded with ANN model which can be used by the local SMEs for insisting into their businesses' future. This will help SMEs plan for their localised markets, to combat unprecedented demand-and-supply fluctuations, inflation adversities, price instability, excess inventory, etc.

The IMPACT STATEMENT

SMEs suffer from price instability, the inventory carrying costs, excess inventory, wrong decision making, lack of accurate monitoring of stock levels, lack of correct supplier lead-times information, etc. This study seeks to give them an insist into their business future, by seeking and developing a reliable technology for predicting local goods' quantity purchase, buying and selling prices. Most economic and market forecasting models fail to keep up, because of the exclusive of weather elements as parameters for forecasting economic forces. As supported by Carabello F. (2019), weather influences every sector of the economy and using it to forecast by artificial neural networks would yield results more reliable than results from current forecasting models. The purpose of this document is to establish that fact, and to open research for the same, to help the local SMEs, have a tool to forecast their local markets forces more cheaply and reliably.

1 INTRODUCTION

The study sought to explore the impact of machine learning's artificial neural networks on demand and supply forecasting in small and medium scale enterprises (SMEs) using the local weather as the main independent variable and to understand how local weather impacts local market's demand and supply forces. It also aimed at establishing if a relationship between past market's forces and past weather historical data, exists. The study decided to use local weather elements (which comprised of high and low temperatures) as the independent main variables and machine learning in forecasting traits of local household and Small and Medium Scale Entrepreneurs' (SMEs') local- market's demand and supply indicators so as pave a means that will give the local small and medium scale entrepreneurs' (SMEs') businesses a comparative advantage through the forecasts of the days' sales, profits and/or losses of their products and produce, and generally the days' local market's forces of demand and supply forecasts. Enabling the SMEs and households to individually make a forecast of local market's forces of demand and supply from their local weather will allow them to make personalised proactive business decisions, as they will be able to identify the business risks in-real-time, allowing them to take pre-emptive actions to avoid the adverse effects of bad market's forces.

Artificial neural networks models are designed to mimic the biological neural networks, as such, they behave similarly to biological neural networks when they are exposed to data. Most biological organisms develop intuitions, and in the same manner, artificial neural networks are also able to develop an 'instinctive' mathematical model (a similar human feeling) of an outcome (in a numerical sense) using historical data, and not explicitly from reasoning capabilities. Because of this, ANNs are better candidates for market demand and supply forecasting for the SMEs', than ordinally mathematical-statistical methods, especially when a variable which is the weather is incorporated which almost every economist never includes during an economic forecast.

Weather plays a major role in impacting production and influencing human behaviour. According to Carabello F. (2019), in the United States of America's alone, more than 20% of the economy is directly affected by the weather, and the profitability and revenues of virtually every industry which includes agriculture, energy, entertainment, construction, travel, and others, largely depend onto a great extent on the vagaries of temperature, rainfall, and storms. Risks which individual enterprises and markets face due to weather are usually unique. And Carabello F. (2019), said: "there is growing awareness and signs of potential growth in the trading of weather futures among agricultural firms, restaurants, and companies involved in tourism and travel." Which implies that they are currently no potential usage of weather variants among agricultural firms, perishable market traders, restaurants, to mention but a few, least using weather as a variable in market forces forecasting or predicting tools, just like in Zambia. [1]

2 RESEARCH PROBLEM

The study chose to use weather factors of low and high temperatures for forecasting and predicting goods and services demand and supply because most forecasting models don't include weather as a factor. The lack of using weather as a factor in forecasting obscures seasonal variations in the popularity of certain items goods and services which results in over-stocking or outages, leading to obsolescence and missed order deadlines. [1] [2]

The other problem which warranted the study is lack of models that can forecast and predict the local household and small and medium scale entrepreneurs' (SMEs') market's demand and supply of goods and services (through goods availability and cash-flow) more accurately. Duncan, et al (2018), said: most research focused on the challenges of inflation, local goods and services demand and supply traits forecasting during the last few decades in advanced economies, and yet less attention was paid to emerging market economies (EMEs). And from Duncan, et al (2018), findings, this study was motivated to look for alternative ways to model demand and supply among the SMEs by SMEs. [3]

Zambia is faced with adverse economic and price instabilities, which has affected how the house and SMEs financially plan. According to Mester (2016), price stability is the Holy Grail for a monetary policymaker, as it ensures over the long run term plans, and price forecasting tools can ensure price stability over the short term and the long run. While price stability and monetary policy are intimately linked, setting monetary policy to achieve price stability is not trivial, according to Mester (2016), it requires being able to forecast and predict market's goods supply and demand forces, as well as inflation so that persons can know how far they are from their goals. This study seeks to use ANNs models to mitigate the economic and price instabilities by forecast the market's demand and supply forces from another variable, weather. [4]

Most small and medium scale enterprises (SMEs) lack the necessary new technological advances which can advise on balancing incoming supplies with outgoing orders. This has given rise to the imbalance between incoming supplies and outgoing orders for most SMEs. The Zambian SMEs have no forecasting system and most accounting institutional offices equally lack these tools. As Kelber (2020), puts it, a spreadsheet, a calculator, and some speculation are not a solid demand and supply forecasting toolset. This lack of forecasting tools among SMEs has given rise to spiralling cost overruns, underproduction of in-demand items and much more. Kelber (2020) said: "If you're still relying on these outmoded methods of supply chain forecasting, it's time to upgrade to a Strategic Cost Management Solutions (SCMS) solution that integrates the advanced analytics you need to gain a foothold in today's market." [2]

Another factor which prompted the study is lack of up-to-date accurate cheap monitoring stock-keeping units (SKUs) tools and stock levels for SMEs among Zambian and some other parts of the world. Fritsch (2015), puts it out that "traditional methods of stocktaking can be inaccurate and the data is often out of date". As such, demand and supply forecasting become difficult leading to poor planning, with high stock levels which become difficult to monitor. Due to lack of proper and easy access to stock level reports, most SMEs' businesses quickly build up unnecessary excess stock levels and at times end up with the complete opposite-stock outages when the demands for specific products are spiked. [5]

Chibwe (2014), said that economic factors which can include demand, inflation and supply are difficult to control. He continued to mention that the exact relationship between various economic factors remains unidentified through empirical studies, despite having several statistical methods that can forecast and predict demand, inflation and supply factors. Couple with what Carabello F. (2019) discussed, the problem seems to be that weather is not included when they are studying economic variables, and Zambia, in particular, has had little studies concerning the relationships between economic factors and climatic factors which can help device new methods for controlling and mitigating demand, inflation and supply adverse market valedictions. [6] [7]

3 PURPOSE OF THE STUDY

The purpose of the study was to explorer the impact of using machine learning artificial neural networks to forecast and predict the local small and medium scale entrepreneurs (SMEs) local goods and services demand and supply from local weather traits, and thus to establish if a relationship exists between local-weather factors (low and high temperatures), and goods and services demand and supply, economic factors.

To achieve the objective, the study sought to:

- forecast and predict local goods and services demand and supply traits using selected local-weather attributes, which included low and high temperatures.
- explore the impact of predicting the seasonal traffic variations of demand and supply for various products traded-in, by using local weather and artificial neural networks on the local small and medium scale entrepreneurs (SMEs).
- establish the relationship between local-weather and local goods and services demand and supply traits using machine learning artificial neural networks forecasted data and actual collected data.

In summary, all the benefits which will enumerate from exploring how machine learning models' forecasts goods' quantity purchase, buying prices, and goods selling prices, from a day local weather conditions of low and high temperatures, will benefit local small and medium scale entrepreneurs' (SMEs') in short term and also in a long time. All the expected benefits of the study's inclusion of seasonal variations in forecasting will include new methods of mitigating adverse financial and price instability, changing production policies, effectively deciding production capacity, forming of new commerce policies, balancing incoming supplies and outgoing orders, knowing lead-time for order fulfilment, new forecasting technological advances, planning long term activities and new tools for monitoring stock-keeping.

4 STUDY DESIGN AND METHODOLOGY

1. Hypotheses

- **H_1**: Artificial neural networks cannot determine day-to-day local small and medium scale entrepreneurs' (SMEs') local-market demand and supply traits from interpolated day-to-day local-weather low and high temperatures as the weather does not affect markets.
- **H_0**: Artificial neural networks can determine day-to-day local-market demand and supply traits for local SMEs from interpolated day-to-day local-weather low and high temperatures as weather affects markets.
- **H_1**: Artificial neural networks' local weather-forecasted local-market demand and supply traits cannot be used to facilitate planning and preparations by SMEs against local-inflation adversities.
- **H_0**: Artificial neural networks' local weather-forecasted local-market demand and supply traits can be used to facilitate planning and preparations by SMEs against adverse inflation traits.

2. Sample Size

The study employed a purposive sample of 10 participants, from Chiwempala market. The participants provided samples data for items' quantities they bought for a day, items' quantity buying price and items' selling prices. Items whose sample data was collected included cooking oil, bread, sugar, tomatoes, onion and green vegetables. The data was collected from 01 November 2019 to 30 November 2019 in evenly spread 12 days. Which gave a collective (cooking oil, bread, sugar, tomatoes, onion and green vegetables) total of 144 sample records for quantities, 144 sample records for buying prices and 96 sample records for selling prices collected. For each sampled record, 24 sample data were for cooking oil, 24 sample data for bread, 24 sample data for sugar, 24 sample data for tomatoes, 24 sample data for onion and 24 sample data for green vegetable quantities bought for a day and quantity buying price as well were collected. The same numbers were collected for each item selling price, with an exception on tomatoes and onion, of whose prices were not recorded. Low and high temperatures for the very 12 days when the sample data was collected, were recorded.

3. Statistical Analysis

For each day, the averages were computed from the data collected, which were used for the forecasts. The study forecasts and predictions were conducted using an encoder-decoder Long-Short-Term-Memory (LSTM) Multi-step neural network model. The model forecasted and predicted future market behaviour using the collected market products' quantities, buying and selling prices behavioural data. The neural network model was compared for accuracy, the proximity of the predicted data to the actual data using statistical analysis, and was used to forecast the rest of the data which was used for statistical analysis as well.

The predicted data from the encoder-decoder LSTM Multi-step neural network model was compared with actual daily historical collected data using the Statistical Package for Social Science application (SPSS) version 26 for independence. An Independent-Samples Mann-Whitney U Test was conducted using SPSS, the data consisted of the day's averages for the small and medium entrepreneurs (SMEs) items' quantities bought, buying and selling prices. The data was later analysed for normality in SPSS v26, using Kolmogorov-Smirnov test and the Shapiro-Wilk tests, seeing that each sampled item provided a total of not more than 12 average sampled data (which is very little data to assume it had a normal distribution) for each day, for either the items' quantities bought, buying and selling prices of actual data, and 8 of the predicted sampled data, for either of the items' quantities bought, buying and selling prices.

4. Software Requirements

The study employed several application-software from the onset to the conclusion of the study. Data collected was stored in a spreadsheet application, called Microsoft Excel version 2019 using to excel 2007 (.XSLX) file format and the excel comma delimited (.CSV) file format. The data stored in CSV format was used to model the neural networks model, and for making forecasts. The Neural Networks were designed using the python language. Thus, the software requirements for the Neural Networks model included:

- Python (3.7): It is an interpreted, high-level, general-purpose scripted programming language
- Anaconda 3 64bit: Provide several python libraries and the Integrated Development Environments
- Spyder 3.3.4: An Integrated Development Environments, which is a software application that provided comprehensive facilities for the software development, and it consists of a source code editor, build automation tools and a debugging tool
- Microsoft Excel 2019: A spreadsheet application, which was used to store the data collected
- The following libraries in Table 1 were employed, as shown below:

SN	Python Libraries	Type	Description
	NumPy	Numerical Operations	Supports scientific computing that is high-level mathematical functions over large, multi-dimensional arrays and matrices
	Pandas	Data Analysis	Contributes high-performance operations and data structures for time series and numerical tables manipulation
	Keras	Deep Learning	Providing quick computing of numerical data through deep neural networks. Efficiently handling mathematical expressions, particularly matrix values

Table 1: Python Machine Learning Libraries Used

5. The Software System Script Design

The modular implements the necessary command-queries with stored in a spreadsheet to design a model needed for forecasting data. The modular was an 'Encoder-Decoder Long Short-Term Memory (LSTM) Neural Network, shown below:

```
#data for training
X = array(tran[:,4:6])
y = array(tran[:,:-3])
# input data for prediction
XpreQ=array(preQ3[:,4:6])
# data for comparing prediction
YpreQ=array(preQ[:,:-3])
# reshape from [samples,timesteps] into [samples,timesteps,features]
X = X.reshape((X.shape[0],X.shape[1],1))
y = y.reshape((y.shape[0],y.shape[1],1))
# define model
model = Sequential()
model.add(LSTM(100,activation='relu',input_shape=(2,1)))
model.add(RepeatVector(4))
model.add(LSTM(100,activation='relu',return_sequences=True))
model.add(TimeDistributed(Dense(1)))
model.compile(optimizer='adam',loss='mse')
# fit model
model.fit(X,y,epochs=100,verbose=1)
# demonstrating forecasting
x_input = array(XpreQ)
x_input = x_input.reshape((3,2,1))
predict = model.predict(x_input,verbose=1)
#print the forecast
print(predict).
```

The model used had a two-dimensional input, with a three-dimensional output, which is shaped using the Encoder-Decoder model. The number of input time steps was set to 1 and the number of features was set to 2 via the input shape argument on the first hidden layer. The LSTM encoder reads and encodes the input sequences of 1-time step. The encoded sequence was repeated four times by the model using a Repeat Vector layer. This fed to a decoder LSTM layer before using a Dense output layer wrapped in a Time Distributed layer that produces one output for each step in the output sequence. The model used the efficient Adam version of stochastic gradient descent and optimizes the mean squared error (‘MSE‘) loss function. The model was trained using the collected data and then after used to make forecasts.

5 FINDINGS

The study aimed at assessing whether ‘Offsetting Small and Medium Scale Entrepreneurs’ local-market demand and supply traits adversities using artificial neural networks’ and daily local weather forecasts’, is possible. This study intended to use local-weather to predict local-market demand and supply traits, for which the forecasts are to be used to facilitate the small and medium scale entrepreneurs to plan their daily business activities to minimize loses and wastage of resources, thus increasing savings and profits. The independent variables for the study were daily low and high temperatures because the two are the main driving forces of weather. While the dependent variables were the quantities of products ordered for a day, the cost of the products being ordered, and selling price for the products for that day.

The results of the study are presented in this chapter. This chapter is divided into three sections, namely: Outcomes and Estimation, Statistical Analysis of Data using Independent-Samples Mann-Whitney U Test and Normal Distribution Tests.

The data recorded and computed is presented using tables of numerations, frequencies, and percentages. The views expressed in this report are a representation of the facts collected and generated by the study for the main research study.

The records for the original and predicted sample were independent of each other because they did not overlap: every record was either original or predicted data, never both. However, some values of original and predicted records had quite different means, which may suggest that the original and predicted means weren't equal after all (i.e.: the original and predicted records are independent of each other). Thus, an Independent-Samples Mann-Whitney U Test can confirm if the differences between the original and predicted records’ means are large enough to conclude that there are independent of each other.

The first records computed consisted of the quantity’s bought for cooking oil, bread, sugar and vegetables, and their statistics are shown in Table 2.

		N	Mean	Std. Deviation	Std. Error Mean
Cooking Oil	Original Record	8	12.562	6.945	2.455
	Predicted Record	8	11.976	1.250	0.442
Bread	Original Record	8	13.312	2.235	0.790
	Predicted Record	8	15.319	1.715	0.606
Sugar	Original Record	8	25.187	11.692	4.133
	Predicted Record	8	24.621	1.829	0.646
Vegetables	Original Record	8	25.437	6.899	2.439
	Predicted Record	8	27.984	3.024	1.069

Table 2: Group statistics for Quantities

From Table 2, there are visible small differences between the sampled means. To begin with, the largest variation is of the vegetable's quantities' sample, for the original record and predicted data are of 25.43 and 27.98 respectively, with the smallest variation of the sugar's quantities' samples, for the original and predicted records as 25.19 and 24.62 respectively.

When an Independent-Samples Mann-Whitney U Test was computed for the quantity's bought records, the following were the outcomes, shown in Table 3.

	Oil	Bread	Sugar	Vegetable
Total N	20	20	20	20
Mann-Whitney U	52	48	42	34
Wilcoxon W	88	84	78	70
Test Statistic	52	48	42	34
Standard Error	12.96	12.686	12.952	12.947
Standardized Test Statistic	0.309	0	-0.463	-1.081
Asymptotic Sig.(2-sided test)	0.758	1	0.643	0.28
Exact Sig.(2-sided test)	0.792	1	0.678	0.305

Table 3: Independent-Samples Mann-Whitney U Test for the Quantity's Bought

From table 3:

- The distribution of oil was the same across categories of the original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.792.
- The distribution of bread was the same across categories of the original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 1.000.
- The distribution of sugar was the same across categories of original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.678.
- The distribution of vegetables was the same across categories of original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.305.

As such, there is enough evidence to conclude that the sampled quantity's original and predicted records are highly related. Implying that ANN can determine the day-to-day local demand and supply quantities for local SMEs using the local weather's low and high temperatures.

The second records computed were of the products' buying prices for cooking oil, bread, sugar and vegetables, and their statistics are shown in Table 4.

		N	Mean	Std. Deviation	Std. Error Mean
Cooking Oil	Original Record	8	286.437	119.587	42.280
	Predicted Record	8	268.094	35.530	12.562
Bread	Original Record	8	114.250	31.208	11.034
	Predicted Record	8	123.459	14.515	5.132
Sugar	Original Record	8	234.562	39.904	14.108
	Predicted Record	8	228.301	31.804	11.244
Vegetables	Original Record	8	11.381	3.302	1.167
	Predicted Record	8	11.399	3.133	1.107

Table 4 Products' Buying Price Group Statistics

From Table 4, it is evident a small mean difference (0.0185) exists between the sampled means of the original and predicted vegetables' buying prices. With the largest variation of means (18.3426) between cooking oil's buying prices' samples of the original record and predicted records.

When an Independent-Samples Mann-Whitney U Test was computed for the products' buying prices records, to see if there were statistically significant differences between means for the original and predicted records, the results which followed are shown in Table 5.

	Oil	Bread	Sugar	Vegetables
Total N	20	20	20	20
Mann-Whitney U	66	66	50	59
Wilcoxon W	102	102	86	95
Test Statistic	66	66	50	59
Standard Error	12.79	12.686	12.932	12.932
Standardized Test Statistic	1.407	1.419	0.155	0.851
Asymptotic Sig.(2-sided test)	0.159	0.156	0.877	0.395
Exact Sig.(2-sided test)	0.181	0.181	0.91	0.427

Table 5: Independent-Samples Mann-Whitney U Test for the Products' Buying Price

From Table 5,

- The distribution of oil was the same across categories of the original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.181.
- The distribution of bread was the same across categories of the original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.181.
- The distribution of sugar was the same across categories of original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.910.
- The distribution of vegetables was the same across categories of original data and the forecasted data, as the Independent-Samples Mann-Whitney U Test exact significance was 0.427.

Since the level of the significance level is for all products is above 0.050, we retain the null hypothesis as they are statistical evidence the two samples are related. Thus, ANN can determine the day-to-day local demand and supply cost for local SMEs using the local weather's low and high temperatures.

Normal Distribution Tests

The study could not assume that the data collected was normally distributed, which is an underlying factor in statistical parametric testing. For this fact, there was a need for an assessment of normality of data, which is a prerequisite for any statistical test. This study thus used normal distribution statistical tests, which has the advantage of making objective judgements of normality, unlike graphical methods which lack objectivity. Graphical interpretations on the other hand, also give good interpretative judgements of normality in situations where numerical tests are over or under-sensitive.

For the statistical tests for normal distribution, the Kolmogorov-Smirnov test and the Shapiro-Wilk tests were performed using the Statistical Package for Social Sciences application (SPSS v.26), due to the descriptive statistics shown in Table 2 and 4. Table 6 and 7 show the results from the two tests for normality, namely the Kolmogorov-Smirnov Test and the Shapiro-Wilk Test. The Shapiro-Wilk Test is more appropriate for small sample sizes (< 50 samples), which the study used for assessing the numerical means for normality. Where the significant (sig.) value of the Shapiro-Wilk Test is greater than 0.05, the data is normally distributed, unlike if it is below 0.05, the data has significantly deviated from a normal distribution.

Table 6, displays the test for normality performed for the quantity's bought the results. Cooking oil's significant level (sig.) was 0.019 for the original data, implying that it was not normally distributed, unlike the predicted data (0.510), which was normally distributed. For bread, sig. was 0.021 for the original data, implying that it was not normally distributed, unlike the predicted data (0.472), which was normally distributed as well. With sugar, the sig. was 0.342 for the original data, implying that it was normally distributed, which also goes for the predicted data (0.193), which was also normally distributed. And for the vegetables, the sig. was 0.014 for the original data, implying that it was not normally distributed, and the predicted data (0.012) was also not normally distributed.

Items		**Kolmogorov-Smirnov[a]**			**Shapiro-Wilk**		
		Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Cooking Oil	Original data	0.321	8	0.015	0.783	8	0.019
	Predicted data	0.200	8	0.200*	0.929	8	0.510
Bread	Original data	0.275	8	0.076	0.787	8	0.021
	Predicted data	0.196	8	0.200*	0.925	8	0.472
Sugar	Original data	0.171	8	0.200*	0.908	8	0.342
	Predicted data	0.259	8	0.122	0.881	8	0.193
Vegetables	Original data	0.290	8	0.047	0.771	8	0.014
	Predicted data	0.315	8	0.019	0.766	8	0.012

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 6: Quantity's Bought Tests of Normality

Table 7 shows the test for normality performed for the products' buying price results, and cooking oil's significant level (sig.) was 0.668 for the original data, implying that it was normally distributed, same for the predicted data (0.564), which was normally distributed. For bread, sig. was 0.008 for the original data, implying that it was not normally distributed, unlike the predicted data (0.549), which was normally distributed. For sugar, the sig. was 0.000 for the original data, implying that it was not normally distributed, unlike the predicted data (0.657), which was normally distributed. And for the vegetables, the sig. was 0.677 for the original data, implying that it was normally distributed, just like the predicted data (0.829) which was also normally distributed.

Item		**Kolmogorov-Smirnov[a]**			**Shapiro-Wilk**		
		Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Cooking Oil	Original data	0.212	8	0.200*	0.946	8	0.668
	Predicted data	0.177	8	0.200*	0.935	8	0.564
Bread	Original data	0.272	8	0.084	0.751	8	0.008
	Predicted data	0.174	8	0.200*	0.934	8	0.549
Sugar	Original data	0.488	8	0.000	0.479	8	0.000
	Predicted data	0.158	8	0.200*	0.945	8	0.657
Vegetables	Original data	0.213	8	0.200*	0.947	8	0.677
	Predicted data	0.167	8	0.200*	0.962	8	0.829

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 7: Products' Buying Price Tests of Normality

6 INTERPRETATION

The propose of the study was to determine if it is feasible to conduct a research study using artificial neural networks to determine if a relationship exists between local-weather factors (low and high temperatures) and local demand and supply forces, economic factors and if artificial neural networks can forecast local small and medium scale entrepreneurs (SMEs) demand and supply forces, from local weather traits. The research study will further seek to find the best machine learning artificial neural network model which can be used for forecasting the local-inflation indicators using local-weather attributes (low and high temperatures), to help the SMEs improve their business and economic planning.

Thus, to achieve our current objectives, the study sought to predict local demand and supply traits using selected local-weather attributes, which included low and high temperatures. And to predict the traffic of demand and supply for the product(s) that local small and medium scale entrepreneurs (SMEs) traded-in by using local-weather which can be a better variable to use to improve the forecasting accuracy of the day-to-day selling and buying of products by SMEs. The other study's objective was to seek to identify the day-to-day emerging risk conditions for small businesses and possible pre-emptive actions for SMEs by monitoring day-to-day goods quantity and sales traffic using neural networks forecasts from the local-weather variables. To help achieve the first two objectives, a null hypothesis indicating that artificial neural networks cannot determine day-to-day local SMEs' products demand and supply forces, from interpolated day-to-day low and high temperatures were derived, with the alternative hypothesis assuming that 'artificial neural networks can determine day-to-day local-market demand and supply traits for local SMEs from interpolated day-to-day local-weather low and high temperatures. To test the null and alternative hypothesis, an Independent-Samples Mann-Whitney U Test was conducted for the quantity's bought-records and the quantities' buying price. It was statistically observed for the quantity's bought-records, that the original and the predicted records' means were not independent of each other, as their p(sig.) values were greater than 0.05. Entailing that the original records mean and the predicted records mean were dependent on each other. An Independent-Samples Mann-Whitney U Test conducted for the sampled quantities' buying original and predicted records prices means, also suggested that all the means were dependent on each other because the levels of significance (p values) were greater than 0.05, implying that the means for original and predicted data were dependent on each other. This further implies that the artificial neural networks are capable of forecasting the local-economic indicators using local-weather attributes as the main independent variables.

From the independent sample test conducted, the other null hypothesis that artificial neural networks' weather-forecasted economic data cannot be used to facilitate planning and preparations by SMEs against local-inflation adversities, is rejected in favour of the alternative hypothesis, that artificial neural networks' weather-forecasted local-market demand and supply traits data can be used to facilitate planning and preparations by SMEs against local-economic adversities.

The other objective for the study was to predict the traffic of demand and supply for the product(s) that local small and medium scale entrepreneurs (SMEs) traded, using weather to improve the forecasting accuracy of the day-to-day selling and buying by SMEs. This objective was attained because of the statistical evidence from the analysis of Independent-Samples Mann-Whitney U Test from SPSS v.26, which showed that the ANN models can forecast the volumes of the products to be bought for a day, and it could also forecast the products-volume buying prices. As it forecasted the demand and supply traffic for the items the local small and medium scale entrepreneurs (SMEs) traded, using local-weather as the independent variable.

7 GENERALIZABILITY

The results for this need to be generic for any market. For this reason, a normality test for the data was performed to test which data was normally distributed between the original data and the predicted data, which can be generalised. Normally distributed data can be generalised. It was, however, discovered from the results, that the artificial neural networks can forecast and predict local-market of demand and supply forces using local-weather.

From the results of the normality test performed for the quantity's bought, the cooking oil's original data were not normally distributed, unlike the predicted data which were normally distributed. For bread, the original data was not normally distributed, unlike the predicted data which was normally distributed. With sugar, the original data were normally distributed, which also goes for the predicted data which was also normally distributed. And for the vegetables, the original data was not normally distributed, as well as the predicted data, which was also not normally distributed.

From the test for normality performed for the products' buying price, the cooking oil's original data was normally distributed, same for the predicted data which was also normally distributed. For bread, the original data was not normally distributed, unlike the predicted data which was normally distributed. For sugar, the original data was not normally distributed, unlike the predicted data which was normally distributed. And for the vegetables, for the original data was normally distributed, just like the predicted data which was also normally distributed.

From this, it is deduced that the artificial neural networks results, for the predicted and forecasted the local-market demand and supply indicators from local-weather attributes (low and high temperatures), can be generalised for any scenario, and any market. However, the data for the quantity's bought, the cooking oil's original data were not normally distributed, thus cannot be generalised, same goes for bread's original data, and for the vegetables' original data which cannot be generalised, as well as the predicted data as well. The products' buying price for bread's original data cannot be generalised, same as for sugar's original data since it was not normally distributed.

8 OVERALL EVIDENCE OF FEASIBILITY

It is statistically evident, that weather can be used to forecast the quantity's buying volume, and the quantities' buying prices, using the artificial neural networks. The study was able to forecast the local demand and supply for the SMEs from local-weather attributes (low and high temperatures). And from the statistical evidence of the relationship between the raw data and the tabulated results, the study can be generalizable for any weather scenario and any market condition.

The reason for conducting the pilot study was to deduce the possibility of using weather as a variable for forecasting market forces using artificial neural networks. And it has been proved to be possible to predict local-market forces of demand and supply from local-weather attributes, despite the limited data and resources. The main independent variables of the study were low and high temperatures, and the dependent variables were the daily bought quantities and daily sales by the small enterprises. From the study, it is evident that it is necessary to adjust the dependent variables to include other parametric qualities and quantities and to have included a unit automatic converting model for the quantities to a standard of either volume and weights bought, and the standard prices for the same. The other factor which needs to be adjusted is the period for which data was collected, the study collected data in a space of one month, which can be extended to several months, and to increase the number of participants.

9 CONCLUSIONS

From the study results, it is feasible to conduct the research study on offsetting Small and Medium Scale Entrepreneurs' local market-forces' adversities using artificial neural networks' and daily local weather forecasts. It is also evident to forecast local-market of demand and supply indicators from local-weather attributes, given limited data and resources on any given scale. From the study's statistical evidence, artificial neural networks can use local-weather to predict local-market forces of demand and supply indicators, which has never been attempted before. It is for this reason, applications embedded with artificial intelligent neural networks, offered to local SMEs to forecast their local traits of household edible and non-edible local-market forces of demand and supply traits using local-weather conditions (low and high temperatures), can change their lives. They can help them to prepare to confront and counteract the economic 'weather' adversities, as warnings of low sales, shortage supplies and high purchase prices, will be generated right on their hands. Greatly giving them the advantage to plan for local economic depressions and plan measures on reducing overspending, what products may give them profits, and avoid the products which may give them economic loses.

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