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Research Article

Using Time Series Models in Product Based Order Forecasting

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Abstract

Production systems play a vital role in maximizing consumer satisfaction by efficiently transforming inputs such as labour, raw materials, and capital into products or services aligned with consumer demands. An order-based production takes place in poultry meat and meat products production facilities, which face various difficulties in meeting changing customer demands and managing the supply of raw materials. To optimize production and increase customer loyalty, these facilities use strategic scheduling, considering their daily production capacity and fluctuating customer orders. In this study, estimating which customer and product type the future order quantities will come from for the relevant facilities, increasing customer satisfaction by facilitating order processes and minimizing storage costs are discussed. With this study, the number of orders was estimated, and it was aimed to meet the orders in the most accurate way. In the estimations, the order data of a poultry meat and meat products production facility between 2013 and 2021 were used. Since the order figures will change every year in cases such as the customer working with the facility, growing, or shrinking, better results have been tried to be obtained with the arrangements made on the data set used and three different data sets have been obtained. Estimation processes were performed for these three data sets using LSTM and Prophet algorithms. While the RMSE value was 7.07 in the LSTM model in experimental studies, this value was obtained as 10.96 for Prophet. In the results obtained, it was observed that the arrangements made on the data set positively affected the accuracy of the estimations and the LSTM algorithm produced better results than the Prophet algorithm.

Keywords: Production optimization, Poultry production system, Time Series, LSTM, Prophet.

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1. Introduction

The change in the management approach of the enterprises has also caused a change in the structure of the companies. To meet their needs, companies must adopt different approaches in their structures and management styles, but they also must use the developing modern production systems. A system within the enterprise may have many subsystems. However, this system can also constitute a subsystem of a larger-scale system. While marketing, management, accounting and finance, sales and human resources constitute the sub-systems within an enterprise, the enterprise constitutes the sub-system of the country's economy. In summary, production systems, which constitute the whole of activities that create value for the environment, constitute the subsystem of an enterprise.

Production systems are one of the important subsystems within a business or organization. A production system is a system in which products or services are produced by going through a certain transformation process of various inputs such as labour, raw materials, data, energy, and capital [1]. The main purpose of these systems is to maximize consumer satisfaction by providing the production of products or services in accordance with consumer demands. Production systems are classified into four different types: continuous, intermittent, mixed, and project-based [2].

In order-based production systems, which are a subclass of discrete production systems, the characteristics and quantity of the products to be produced are determined by order in line with the demands of the customers. From this point of view, order-based production is carried out in poultry meat and meat products production facilities. In these facilities, it is of great importance to meet the demands of the customers completely. However, to meet these demands, difficulties are encountered such as meeting the daily raw material supply from the poultry grown and obtaining only a certain amount of raw material from each product. Another challenge for poultry meat and meat products production facilities is that the animals that have reached sufficient maturity come to the slaughter and the sizes of the incoming creatures are not always the same. However, only certain products are obtained from each poultry in certain proportions. The density of orders from customers varies according to the day, and it can be a product that can be obtained at low rates from a poultry creature. To meet all incoming orders, the number of products that need to be stored in poultry meat and meat products production facilities will also increase. Due to the short shelf life of poultry products and the costly storage processes, poultry meat and meat products production facilities aim to meet the incoming orders in a way that the minimum level of products from the poultry that come to the slaughter is in stock.

Poultry meat and meat products production facilities have a certain daily production capacity. Due to the production capacity, restrictions are placed on the order days of the customers by the poultry meat and meat products production facilities. These restrictions may provide changes in cases such as the increase in the capacity of the poultry meat and meat products production facility, periodic changes, and increase in the number of customers. While meeting all the products ordered by the customer is an important factor, on the manufacturer's side, this means that the orders are balanced, and the product left over from the use of raw materials is the least. For this reason, an optimization process is applied by comparing the products ordered by the customer daily with the amount and kilograms of future poultry and making cuts to customer loyalty.

In the study, it is aimed to forecast customer orders daily with time series models with product breakdown, and to evaluate the orders coming to the poultry meat and meat products production facility earlier thanks to these estimations, and to meet more balanced and larger orders with the help of early actions. The customer and product information in the order for every day plays a major role in the cuts and measures to be made. In order optimization studies, future order quantity estimation for a product is provided. In the study, customer and product breakdown estimations were made. In these estimations, the order days of each customer were determined, and their habits were monitored; the increase in the production capacity of the poultry meat and meat products production facility and the restrictions that the facility will bring to the customer side were evaluated and historical data was organized. In the literature reviews, it has been determined that there are not many case studies related to product-based order estimation from poultry. In a study conducted by Kozaklı *et al.* [3], it was observed that the monthly production amounts for 2021 were modelled by the time series method by using the monthly broiler production numbers obtained from the Turkish Statistical Institute. As a result of the modelling, it was estimated that 1353245283 broiler chickens should be produced for 2021 [3]. Another study showed that Thailand Industry made predictions for cooked chicken products exported to Japan using a Recurrent Neural Network (RNN) model [4]. Studies on forecasts for different sectors using Facebook Prophet [5] and Long Short-Term Memory (LSTM) [6] models were checked, their similarities and differences were determined, and they were adapted for this study. In the literature review, it has been seen that the relevant models are discussed in different areas such as order estimation of companies [7], estimating the electricity requirement of a country [8], vehicle spare part requirement estimation [9].

When the literature is reviewed, it is observed that there are many different studies on customer order forecasting. However, these studies are inadequate for poultry meat and meat products production facilities. The most important contribution of this study is to enable the prediction of daily customer orders and the fulfillment of incoming orders using product-specific time series models such as LSTM and Prophet for poultry meat and meat products production facilities.

2. Production Planning

Product planning incorporates all the decisions, steps, and tasks oriented internally that are essential for creating a successful product. In other words, it encompasses all actions that directly impact the product itself. On the other hand, go-to-market planning involves all the external steps taken to promote and market your product to the public. Production planning can be defined as a model that shows the production capacity of the company, the workforce, the optimum use of tools and equipment, and the amount and method of producing the desired product according to the possibilities and when [1]. In other words, production planning can be defined as “deciding in advance which product will be produced, when, how, where and by whom”. The main purpose of production planning is to plan and control the inputs and outputs of the enterprise, together with the optimum profit return, in line with the objectives of the companies. At this point, a structure is created that keeps elements such as production planning, customer demands, financing situations, production capacity under control [1]. Planning gives the firm the ability to think systematically and to make and implement decisions. The main reason for many problems is due to an unplanned management approach. Planning is the basic measure to prevent such problems from occurring. Production planning provides high efficiency in production targets. The high efficiency obtained enables to produce the demanded products at the desired time and with the lowest cost.

Production planning is a guide for factors such as quantity, duration, value, according to the goals and objectives of the company's production activities. For this reason, since it draws the attention of production managers to these targets, it prevents waste of parameters such as labour and time and ensures that production is measured. The expected benefits from production planning can be listed as follows:

– to evaluate the factors of production according to appropriate criteria,
– to prevent production pauses and idle capacity,
– to reduce stock costs and prevent their increase by determining stock planning,
– to determine the balance between the production volume of the enterprise and customer demands,
– to determine production costs,
– to ensure that all the facilities of the company are used in line with the determined purposes.

3. Poultry Production System

An order-based mass production is applied in poultry production systems. The raw material obtained daily is provided from the animals grown. The height and size of these grown animals can vary. In production planning, it is not enough for poultry meat and meat products production facilities to have basic information about the poultry that will come to the daily slaughter, such as live maintenance and air temperature. Deaths experienced during the shipment of poultry to be slaughtered affect the number of raw materials to be included in the production planning and cause a decrease in the order fulfilment rate. Meeting the raw material needs in poultry production systems is provided from the poultry houses with which the poultry meat and meat products production facility is contracted. In the event that the chicks transferred to the relevant poultry houses reach certain maturity, the living creatures are sent to the poultry meat and meat products production facility and slaughtered for product production. After the transfer of poultry to the disinfected poultry houses of the producers, slaughter planning preparations begin. The slaughter planning process aims to meet the daily product need by transporting the chicks to the poultry meat and meat products production facility by vehicles after they reach a certain age.

The time for a normal poultry to reach sufficient maturity and size has been determined as 45 days [10]. In the feed policy supervised by the Ministry of Agriculture, the poultry that come to the slaughter must be fed the last three days before slaughter, which is called the finishing feed [11]. These poultry, which are sent to slaughter, are examined daily by veterinarians approved by the Ministry of Agriculture, and their Average Live Weight (ALW), ammonia burn [12], and hygiene information are collected. This collected information is then transmitted to the poultry meat and meat products production facility. ALW gives theoretical information about whether the poultry weighs enough for the product to be produced. Ammonia burn is the information that is caused by hygiene and affects the meat quality of the poultry. In case of high ammonia burn, the relevant poultry cannot be used in the production of some products and can be used for second-class products called B quality.

In production processes of poultry products, stocking time is limited due to shelf life [13]. Daily cuts are determined by live cut planning processes. Order needs are tried to be met according to the dimensions of the slaughtered poultry. Customer-based demands may differ on a daily or periodic basis. By giving different days to each customer, order restriction is ensured, and this need is tried to be met with planned cutting records. While raw material can be used as a product in poultry production, different products can be obtained by breaking the raw material. The products obtained from the crushed raw material were calculated proportionally from the poultry. Poultry shredding rates are given in Table 1.

Table 1. Poultry Shredding Rates

Type	Percentage
Chicken Breast	%48,36
Chicken Legs Hip	%39,97
Chicken Wings	%10,47
Other	%1,2

The stocking cost of the remaining products is high, and if they are not consumed from the stocks within two days, processed products (salami, sausage, doner, etc.) are obtained in the further processing factories. The main purpose in poultry meat and meat products production facilities is to use all poultry slaughtered during the day as product within the order and to leave the least product on the stock side. However, the products requested in the orders from the customers may cause an imbalance in different products. The case of an imbalance may cause excess products to remain in stocks. For this reason, incoming orders are evaluated, and cut-off processes are applied in a way that they can be met at the maximum level and that the least product is left in stock. In the optimization made to eliminate the imbalance and leave the least product in stock, the demanded products are brought to the balance by applying deduction processes according to customer loyalty. The graphics in Figure 1 and Figure 2 show the monthly incoming order quantities according to the product groups of the poultry meat and meat products production facility and the poultry kg information needed for these order quantities.

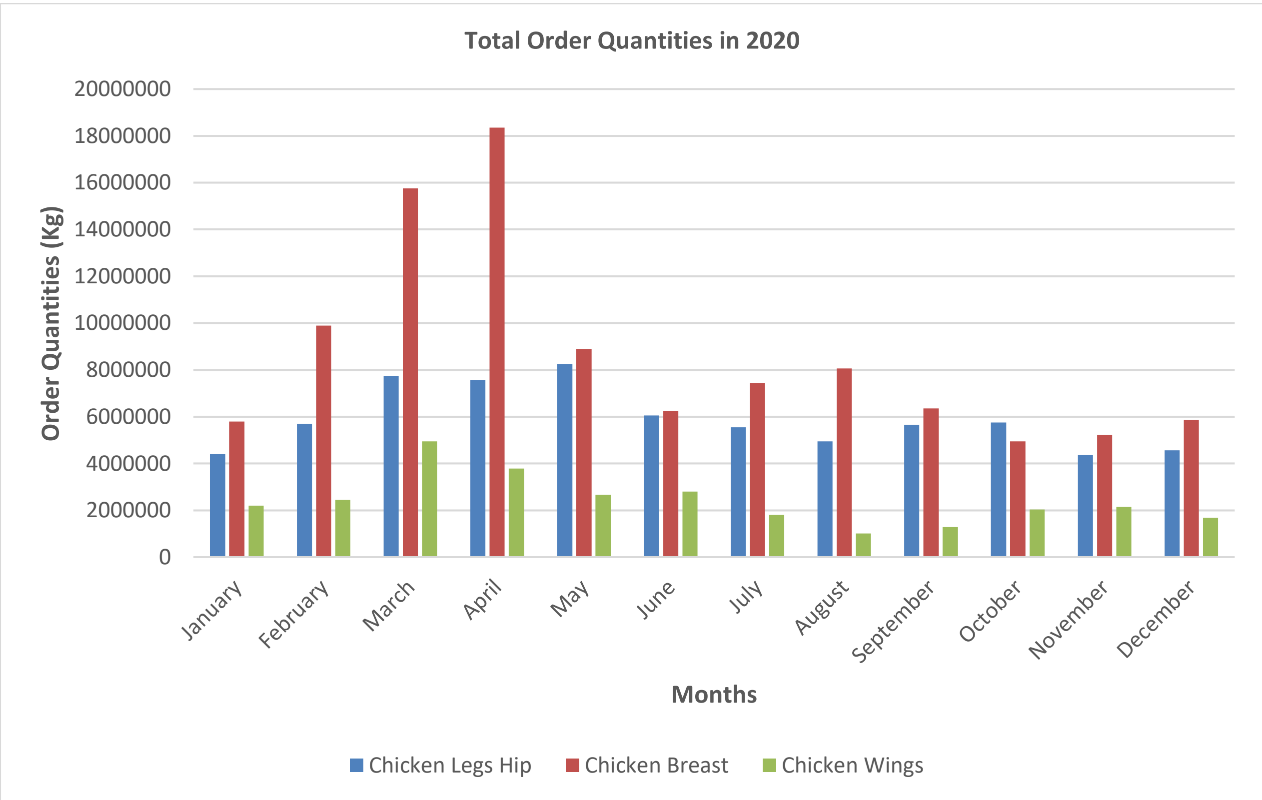

Figure 1. Total Order Quantities in 2020

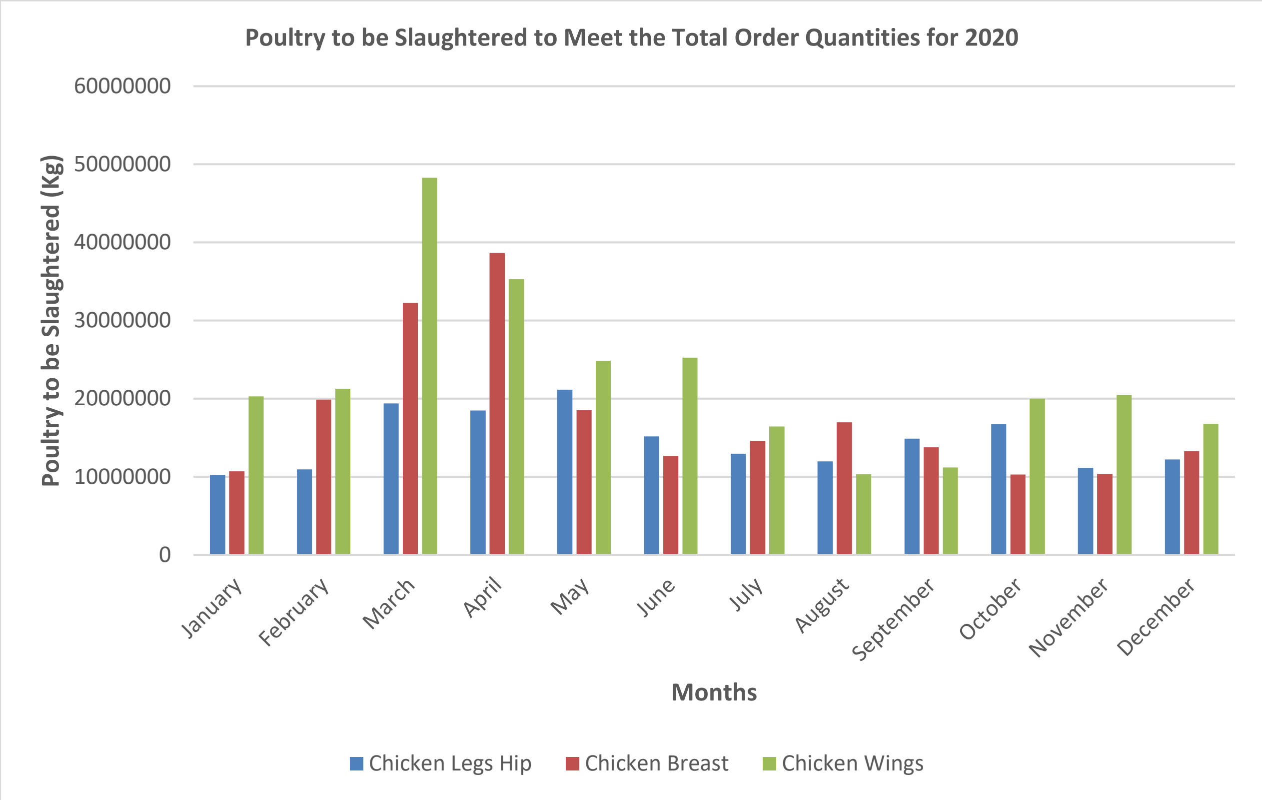

Figure 2. Poultry to be Slaughtered to Meet the Total Order Quantities for 2020 (Kg)

The ordered products change periodically, and if the products with the lowest shredding rate are ordered more, there are difficulties in meeting the orders.

3.1. Determination of Raw Material Requirement Quantity for an Order and Deduction Procedures

The raw material needed to produce an ordered product is obtained by dividing the ordered quantity by the ratio of the product type and completing it one hundred percent. In the event of fulfilling the order, the remaining raw materials can be used to fulfill orders in different product groups. However, if the density of the ordered products belongs to a single product group, it means that the products in the other product group cannot be used, and this is called an unbalanced order. The amount of raw material needed to meet the order is as much as the raw material of the product that will need the rawest material from the products in the order list. Calculation of raw material required quantity (RMRQ) is given in Equation (1).

$$RMRQ = \frac{Order\ Quantity\ (Kg)\ *\ 100}{Poultry\ Shredding\ Rate} \tag{1}$$

To give an example of this process, let the orders given by a customer be as in Table 2:

Table 2. Order Example

Product Group	Quantity
Chicken Legs Hip	100 Kg
Chicken Breast	50 Kg
Chicken Wings	50 Kg

According to the orders given in Table 2, in the preparation of the orders given by the customer:

- Chicken Legs Hip: $\frac{100*100}{39,97} = \sim 250\ kg$
- Chicken Breast: $\frac{50*100}{48,36} = \sim 103\ kg$
- Chicken Wings: $\frac{50*100}{10,97} = \sim 477\ kg$

Considering the maximum value among the obtained values, the amount of raw material required to meet the order will be determined. However, if this order is fulfilled, there will be a surplus for some product groups.

- $477 * \frac{48,36}{100} = \sim 230\ kg\ Chicken\ Breast$

  $Increased\ Chicken\ Breast$: $230\ kg - 50\ kg = 180\ kg$
- $477 * \frac{39,97}{100} = \sim 190\ kg\ Chicken\ Legs\ Hip$

  $Increased\ Chicken\ Legs\ Hip$: $190\ kg - 100\ kg = 90\ kg$

As a result, 180 kg of chicken breast and 90 kg of chicken legs hip will remain in excess. In case we make a 40% cut in the chicken wings order to optimize the order:

- Chicken Legs Hip: $\frac{100*100}{39,97} = \sim 250\ kg$
- Chicken Breast: $\frac{50*100}{48,36} = \sim 103\ kg$
- Chicken Wings (Amount of Deduction 40%): $\frac{\frac{50}{0,4}*100}{10,97} = \sim 273\ kg$

With the deduction for the chicken wing order:

- $273 * \frac{48,36}{100} = \sim 132\ kg\ Chicken\ Breast$

  $Increased\ Chicken\ Breast$: $132\ kg - 50\ kg = 82\ kg$
- $273 * \frac{39,97}{100} = \sim 109\ kg\ Chicken\ Legs\ Hip$

  $Increased\ Chicken\ Legs\ Hip$: $109\ kg - 100\ kg = 9\ kg$

As a result of the 40% cut for the chicken wing order, 82 kilograms of chicken breast and 9 kilograms of chicken legs hip increased. The less the amount of meat increased, the less the product remaining in the stock of the producer will be reduced, and the cost will also be reduced.

4. Methods and Tools

Daily order estimation was performed as a cumulative sum by querying separately for each customer and product information that has the right to order. Time series models are used for order forecasting processes. Time series forecasting stands as an extensively employed data science technique in sectors such as business, finance, supply chain management, production, and inventory planning [14]. Many estimation problems involve a temporal element, necessitating the estimation of time series data. Time series prediction is also a crucial domain in machine learning and can be approached as a supervised learning problem. Machine learning techniques like regression, neural networks, and support vector machines are applicable for time series predictions [15]. Time series forecasting aims to predict future value over a given period of time [16]. It is used to guide future strategic decisions by developing models based on previous data and making observations with these models [17]. LSTM and Facebook Prophet are the most preferred models for order forecasting processes.

4.1. Long Short-Term Memory Algorithms

Long Short-Term Memory (LSTM) Networks are an artificial Recurrent Neural Network (RNN) architecture used to predict time series data [18, 19]. LSTM has the ability to retain long-term time-dependent information and the optimal hyperparameters of the network [20]. In the RNN, LSTM utilizes the memory cell to resolve long-term dependencies between data blocks of time series provided in the dataset. LSTM endeavours to overcome the difficulties by acquiring an accurate forecasting model and giving consideration to the intrinsic properties of the time series model. Also, one of the main advantages of LSTM is its ability to capture nonlinear patterns in time series data. At the data cleaning point, the LSTM algorithm focuses on replacing the missing values using appropriate techniques to correct the data string that is noisy and contains missing values. LSTM's have feedback links. In addition to image data, they can process all data sequences such as speaking or video. A standard LSTM network comprises distinct memory blocks called cells [21]. Two states, namely the cell state and hidden state, are transmitted to the subsequent cell. These memory blocks are responsible for retaining information. There are three main mechanisms in the LSTM structure: input gate, output gate and forget gate [22]. Figure 3 shows the LSTM structure [23].

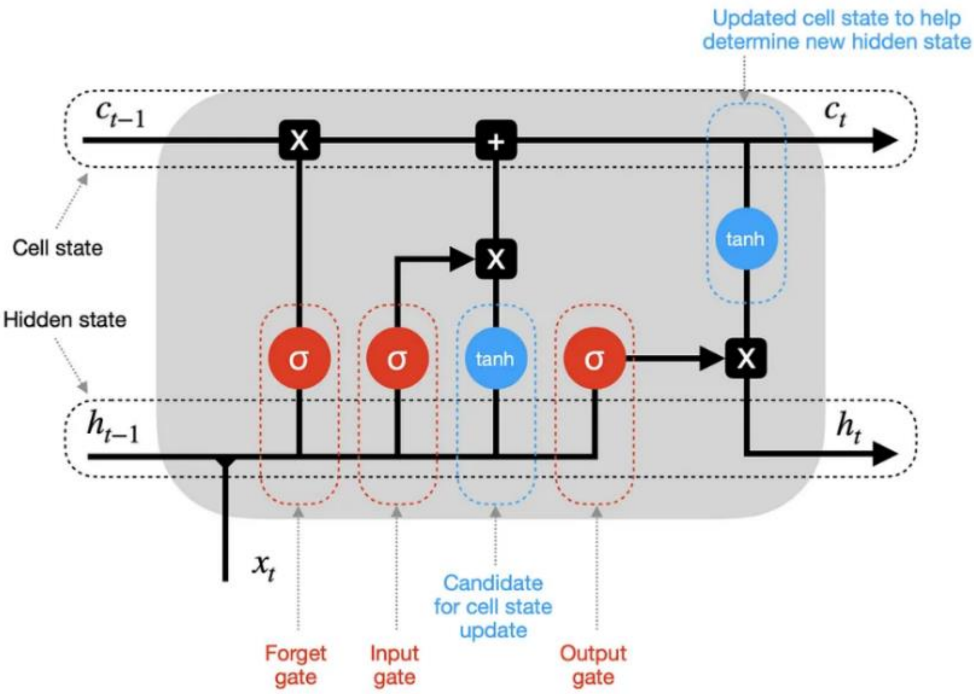

Figure 3. Structure of LSTM

In equations related to LSTM, these gates are i, o, and f; the operational memories of the network are denoted by the terms C and $\tilde{C}$. The cell remembers the values in the memory blocks, and these three gates regulate the flow of information entering and leaving the cell [24]. The LSTM estimation processes, which include the terms in Table 3, are explained in three steps.

Table 3. LSTM terms

Term	Definition
σ	Sigmoid function
h_{t-1}	Previous hidden state vector
c_{t-1}	Previous cell state vector
x_t	Input vector to the LSTM unit
c_t	Cell state vector
h_t	Hidden state vector

Step 1 – Forgetting doors that are not needed: Each input is associated with its respective weighted LSTM unit. In nonlinear transformations, the sigmoid activation function takes a value between 0 and 1. Information after processing, information in the storage memory unit is processed by c_{t-1}. The input operation regulates the transfer of information from the previous period in the storage memory unit. It outputs x_t of the current state and h_{t-1} of the previous state and analyses the historical output to decide which partitions to delete. For instance, in the case of an entry such as "Arya has a baby," the name "Zeynep" may be forgotten since the subject is Arya. The gate is referred to as the forget gate f_t and the gate output is determined as $f_t \times f_{t-1}$ [6].

Step 2 – Identifying and saving the newly entered x_t entry in the memory unit: By utilizing the sigmoid function, the decision to update or ignore new entries is made. Using the tanh function, new values are inputted, and the input updated to create vectors of all possible values. This new entry is added to the previous cell state vector (c_{t-1}) to obtain the cell state vector (c_t) [6].

Step 3 – Determining the output content: The memory unit computes all potential values through the tanh function, after which the matrix gets multiplied by the output of the *sigmoid* function. The hyperbolic tangent function is applied to non-linearly transform the updated value, and then the dot product determines whether the value will be smoothly output after the control calculation. For instance, when predicting blank words, the model leverages the names associated with "teacher" in memory, enabling it to promptly respond to the word "teach". It does not give a direct answer to the model but provides long-term learning outcomes [6].

LSTM alleviates the vanishing gradient problem stemming from the hindrance of backpropagation in RNNs [22, 29]. LSTM networks use gated mechanisms that enable continuous error flow to overcome the vanishing gradient problem encountered by RNNs. Thanks to its ability to learn long-term dependencies and maintain long-term memory in complex multivariate time series containing patterns of varying lengths, it eliminates the need for a predefined time window. The LSTM networks, formed as a result of stacking recurrent hidden layers sequentially, enable the processing of time series data at different time scales and the acquisition of a richer set of temporal features.

4.2. Facebook Prophet Algorithms

Prophet is an open-source algorithm introduced by Facebook in February 2017 for generating time series models [25]. Prophet was designed to tackle common challenges at Facebook, such as predicting user activity across different parts of their application or prioritizing feature development. This algorithm enables data analysts and data scientists to perform fast, powerful, and accessible time series modelling. It is well suited for scheduling forecasting challenges for extended events (longer events like school holidays) or special events (one-day events like Black Friday) [26].

When compared to certain traditional time series methods, Prophet is known for being simpler and more user-friendly. Because it covers the Python and R language interfaces, a Python predictive analysis environment can be easily created for time series analysis [25]. These benefits that Prophet has provided illustrate why it is popular with data scientists who actually work on demand forecasting. The time series model in Equation (2) basically consists of the sum of three-time functions (growth: *g(t)*, seasonality: *s(t)*, holidays: *h(t)*) and a noise term (ε_t).

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{2}$$

The growth function is used to model the overall trend of the data. The growth trend in the data can be present at all points or modified at change points. The seasonality function, weekly, monthly etc. is a simple Fourier Series used as a function of time to represent periodic changes. The holiday function allows to make time estimations for changes related to special reasons such as holidays and festivals. Finally, ε_t represents the noise term [25].

$$g(t) = \frac{c}{1 + e^{(-k(t-b))}} \tag{3}$$

In Equation 3, *g(t)* is a logical function; where *c* representing the capacity of the model, *k* representing the growth rate and *b* representing the offset [25].

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos \frac{2\pi\pi n}{T} + b_n \sin \frac{2\pi\pi n}{T} \right) \tag{4}$$

In Equation 4, *s(t)* denotes the periodic term that uses the Fourier series to estimate the periodic component. In this equation, T is the period and 2n is the expected number of cycles to be used in the model [25].

$$h(t) = \sum_{i=1}^{L} K_i 1(t \epsilon D_i) \tag{5}$$

$$Z(t) = [1(t \in D_1), \wedge, 1(t \in D_2)] \tag{6}$$

$$h(t) = Z(t)\kappa, \kappa \sim Normal(0, v) \tag{7}$$

h(t) allows a time estimation to be made, considering the probability that a holiday or an event will change in the future. In Equation 5, K_i denotes the effect of holidays in the period on the predicted value and D_i stands for the fourth dummy variable. If the time variable *t* belongs to the dummy variable, the dummy variable takes a value of 1; otherwise, it takes a value of 0. *i* represents the holiday, D_i represents the time *t* included in the window [25]. The working principle of the forecasting process used in Facebook Prophet is given in Figure 4.

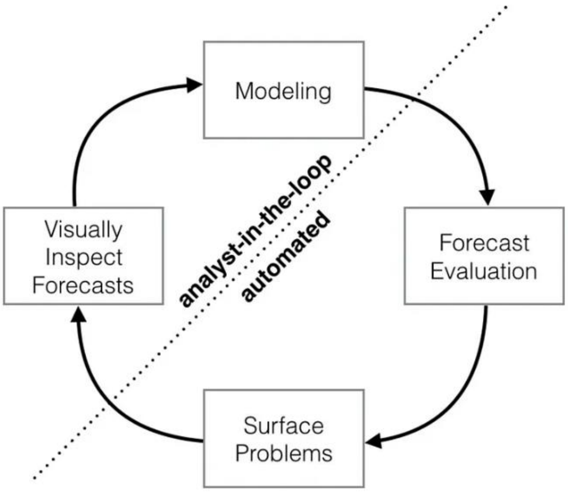

Figure 4. Forecasting Process in Facebook Prophet

4.3. Performance Evaluation Metrics

Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are the metrics that are commonly used to check the accuracy of the predictions made. The smaller the values obtained from the calculations for these three metrics, the smaller the estimation error [27].

Mean Absolute Error (MAE): It is a measure of the errors between the estimate and the actual value of each data. The MAE method sums the absolute values of each data error and then calculates the mean error with the formula in Equation (8) [27, 28].

$$MAE = \frac{1}{k}\sum_{t=1}^{k}(y_t - \bar{f_t})^2 \quad (8)$$

Mean Absolute Percentage Error (MAPE): It is a metric employed to assess the accuracy of a forecasting method, typically expressing forecast accuracy as a percentage. When the MAPE value is less than 10, it indicates the model's high accuracy. When the MAPE falls between 10 and 20, the model serves as a good estimator. A MAPE value between 20 and 50 suggests the model is a reasonable estimator. However, if the MAPE value is greater than 50, the model fails to produce correct results [27, 28]. The calculation of MAPE is demonstrated in Equation 9.

$$MAPE = \frac{1}{k}\sum_{t=1}^{k}\left|\frac{y_t - \bar{f_t}}{y_t}\right| * 100 \quad (9)$$

Root Mean Square Error (RMSE): It is a metric utilized to assess the mean difference between the predicted values and the true values of a statistical model [28]. RMSE is calculated with the help of the formula in Equation 10.

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}(y_t - \bar{f_t})^2} \quad (10)$$

5. Data Preparation

Historical order data from a poultry meat and meat products production facility were used for the estimations. This data includes order information from 2012 to 2021. The studies carried out to clean and organize the data are handled in the form of preparing customer-product-based data and arranging previous orders in case of an increase or decrease in customer demands.

5.1. Customer-Product Based Data Preparation

Customer order data includes different products from different product groups. Estimates made are based on customer product group. To carry out these transactions, existing orders are grouped according to order date, customer, and product categories. In addition, the order quantities for each product category were obtained. There are cancelled or repeated records in the data. For such records, elimination processes were carried out by looking at the order date-time, quantity, and product information. Elimination of cancelled or repetitive orders is also provided for each new order.

5.2. Arrangement of Past Orders According to Increase or Decrease in Customer Demands

A customer ordering a poultry meat and meat products production facility may increase or decrease in order quantities over time. In such cases, some adjustments are made to the previous order quantities for the estimations to be made. With these regulations, it is aimed to process the orders given in the past and today with the correct coefficient and to increase the accuracy of the estimations made. This process is achieved by obtaining a coefficient value by proportioning the orders made by the customer from the relevant product group and multiplying all orders with this coefficient value. Orders have been evaluated in 3-month seasonal periods for the arrangements to be made in order quantities. The maximum and minimum order quantities given by the customer from the relevant product group in each season were obtained, and these quantities were summed for each period and the weighted average was taken. By dividing the current season average with the previous season average, the ratio obtained with the order quantities entered in the previous season is ensured.

5.3. Arrangement of Days According to Past Order Information

Due to the fact that the daily capacity of the poultry meat and meat products production facility is certain and not all orders from all customers can be fulfilled with this capacity, the days that customers can place orders are limited. This restriction has been implemented for certain days of the week according to customer capacity. The days of the week that the customer will place an order on are determined annually and the customer is ensured to place an order only for the specified days. For example, a customer who is entitled to order on Mondays, Wednesdays and Fridays does not have the right to order on other days and the order quantity to be estimated due to this situation should be calculated as zero. In addition, giving the customer the right to order for a different day than the order days determined for the last year will cause problems in the estimation processes. For these cases, issues such as the number of days for which order right is granted in the current year is equal to previous years, the number of days for which order right is granted in the current year is less than previous years, and the number of days for which order right is granted in the current year is more than previous years.

6. Forecasting Customer Product Based Orders in Poultry Meat and Meat Products Production Facility

Forecasting processes, utilizing LSTM and Prophet models, were conducted on orders placed by a customer between the years 2013 and 2021. The training process for the estimation processes was carried out using three different processed data sets, and the results were evaluated on the root mean square error metric [5]. Forecasting processes are handled in three different ways: training and forecasting with the eliminated data of repeated and/or canceled orders, training, and forecasting by applying customer growth coefficient processes, arranging customer order day changes in historical data, and training and forecasting. Experimental studies on LSTM and Facebook Prophet models were carried out on Kaggle Notebooks. Examples from the dataset used in the training of the model are presented in Table 4.

Table 4. Dataset example

Order Date	Quantity	Month	Week	Weekday
12/20/2021	10	12	52	Monday
12/21/2021	0	12	52	Tuesday
12/22/2021	19	12	52	Wednesday
12/23/2021	0	12	52	Thursday
12/24/2021	23	12	52	Friday

6.1. Forecasting Made Using LSTM Algorithm

With the data preparation processes in the previous section, the customer's order data had repetitive orders cleared. The training phase utilized 80% of the data sets, while the remaining 20% was allocated for testing. For the training processes on the side of the LSTM model, estimations were made by looking back at the last 15 days before the relevant order date on each order day. The number of revolutions used in model training was determined as 35 through various experiments. The accuracy of the data obtained because of the training was provided with the root mean square error metric. The first data set to be trained with the LSTM model was provided over the data obtained by cleaning the repetitive orders. While performing this process, records that do not have an order entry in the data set are not included in the training and estimation. In the training and test processes, the root mean squared error values were obtained as 19.11 for the training data and 24.30 for the test data.

Another estimation process was carried out with the data obtained together with the cleaning of the repetitive orders in the data set, the periodic ratio and arrangement of the order data. While performing this process, records that do not have an order entry in the data set are not included in the training and estimation. In the training and test processes, the root mean squared error values were obtained as 9.02 for the training data and 8.39 for the test data. The final estimation process was carried out on the data obtained by cleaning the repetitive orders in the data set, arranging the order data periodically, and arranging the customer's order weekdays in the past years. While performing this process, the records that do not have an order entry in the data set are included in the training and estimation because they consist of fixed days. In the training and test processes, the root mean squared error values were obtained as 6.86 for the training data and 7.07 for the test data. The RMSE values obtained by using the LSTM algorithm on the data sets are shown in Table 5.

Table 5. RMSE values obtained by using LSTM algorithm on datasets

Data Sets	RMSE Values	
	Training	Test
1st Data Set	19.11	24.30
2nd Data Set	9.02	8.39
3rd Data Set	6.86	7.07

6.2. Forecasting Using Prophet Time Series Algorithm

To determine the holidays, the Facebook Prophet algorithm was not used in data sets where repetitive order data were deleted, and the data were periodically proportioned and arranged. It is ensured that this algorithm is used only in the data set in which customer order days are adapted to previous years.

The first data set to be trained with the Prophet model was carried out with the data obtained by cleaning the repetitive orders. While performing this process, records that do not have an order entry in the data set are not included in the training and estimation. In the training and test processes, the root mean squared error values were obtained as 13.11 for the training data and 13.98 for the test data.

Another estimation process was carried out with the data obtained together with the cleaning of the repetitive orders in the data set and the periodic ratio and arrangement of the order data. While performing this process, records that do not have an order entry in the data set are not included in the training and estimation. In the training and test processes, the root mean squared error values were obtained as 11.07 for the training data and 12.39 for the test data.

The final estimation process was carried out based on the data obtained by cleaning the repetitive orders in the data set, arranging the order data periodically and arranging the weekdays of the customer's orders in the past years. While performing this process, the records that do not have an order entry in the data set are included in the training and estimation because they consist of fixed days. In the Prophet model, the days when the customer cannot place an order are determined as holidays. In the training and test processes, the root mean squared error values were obtained as 9.08 for the training data and 10.96 for the test data. The RMSE values obtained by using the Prophet algorithm on the data sets are shown in Table 6.

Table 6. RMSE values obtained by using Prophet algorithm on datasets

Data Sets	RMSE Values	
	Training	Test
1st Data Set	13.11	13.98
2nd Data Set	11.07	12.39
3rd Data Set	9.08	10.96

7. Conclusions

In this study, the studies carried out to optimize the difficulties experienced in both meeting the raw material needs and meeting the order demands from the customers in the poultry meat and meat products production facilities are discussed. At this point, a study was carried out to meet customer order demands at the most optimum level by making daily order estimations considering the past order data of a poultry meat and meat products production facility. When the literature is reviewed, it is seen that there are many different studies for customer order forecasting, but these studies are insufficient for poultry meat and meat products production facilities. Detailed research was conducted on meeting the incoming order demands of poultry meat and meat products production facilities. With the research, 9 years (between 2013-2021) order data of a poultry meat and meat products production facility were collected in order to predict customer order demands, and data sets were created by grouping these data on customer and product basis. In the created data sets, pre-processes were applied to clear the repetitive orders, to rate the previous orders periodically, and to adjust the previous orders on a week-by-day basis based on the customer's weekly order days of the previous year.

Three different data sets obtained were trained and tested with LSTM and Facebook Prophet models. Root mean squared error values were calculated for each data set. In the results obtained, it has been observed that the pre-processing applied to the data set has a successful effect on the estimation. In the case of applying all pre-processes in the LSTM model training, the root mean squared error value was 7.07, while in the Facebook Prophet model, this value was calculated as 10.96. In line with the data set used, it was observed that the LSTM model was more successful than the Facebook Prophet model. With the help of these estimates, the poultry meat and meat products production facility will be able to make stock and production planning for the future. In addition, it will be able to meet customer order demands at the optimum level with the least amount of product remaining in stock. The study was carried out with the customer order requests of the poultry meat and meat products production facility. In addition, the study revealed that order demands change in product price transitions. In the future, studies can be carried out to obtain more accurate results based on the product price transitions of the poultry meat and meat products production facility.

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