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Research Article

A Procurement Method in Oil Marketing Company Based on Forecast Model and Expectation Criterion

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Within the oil marketing operation, various entities compete and attempt to maximize their profits by providing sufficient supply to meet needs of market. It is an optimal method for oil marketing company operation with a dynamically reasonable inventory to maximize profit under oil price fluctuation and inventory sales lag. In this paper, we study the optimal procurement method of oil marketing company which confirms the reasonable inventory. We build a data fusion model for the GMDH- (group method of data handling-) type neural network and normal distribution forecast results, what is trying to confirm the safety stock (SS). On the basis of the expectation criterion of risk decision and safety stock limit, oil marketing companies can make scientific purchase decision for inventory income. Numerical results reveal that this method has a good effect for inventory income.

1. Introduction

The economics of an oil marketing company mainly depends on the two the interaction between key elements: the inventory operation and oil price. Traditionally, oil price can be predicted in a short period of time. As two important elements of inventory management, oil sales are affected by market demand, but oil purchase is controlled by oil marketing company. Therefore, the inventory operation of purchase according to the forecast oil price influences the oil asset management of oil marketing company directly. Studies on the oil products purchase management with uncertain prices were scarce as oil prices were relatively stable. However, the oil price has become fluctuate extremely. A procurement method is useful for oil asset appreciation of oil marketing company.

Purchase management needs to be based on a purchase model; EOQ (economic order quantity) is a more general classical model for procurement [1–3]. The limit operation condition of oil marketing company's inventory needs to be determined. The maximum inventory value should not exceed the controllable inventory, and the minimum inventory value should ensure normal sales of company. So, building a practical purchase model of oil marketing company is based on determining the limit inventory and confirming purchases dynamically under the oil price.

However, the limit operation inventory is named safety stock (SS) which to secure inventory performance against operation exception, sales forecast inaccuracy, lead-time change, etc. Forecast models of SS therefore directly results in service level improvements and reduced supply chain costs [4]. In this matter, an accurate and practical forecast model for SS will beneficial to improve the profitability of enterprises.

A lot of approaches are proposed for purchase of oil marketing company, such as simplex method [5], fuzzy set theory [6, 7], MCDA model [8, 9], MCDM model [10], and MRP [11]. But, data-driven decision supports the purchasing operation effectively, and the expectation criterion is one of the common methods. Using expectation criterion will provide a reliable and effective purchase decision for oil sales company.

SS is an important inventory factor, which is a limiting condition in oil marketing company inventory operations [12]. The statistical forecast model method is a classic forecast method [13]. The normal distribution forecast model can provide good forecast output value with a large amount of unary input value. The safety stock value is related to sale and purchase. Thus, sale and purchase can be used as input, and the oil inventory operation capacity (including safety stock value) can be predicted through this model. A GMDH-type neural network algorithm is a self-organizing data mine method commonly used to output value forecast, which does not depend on complex modeling [14–19]. Data preprocessing, model generation, and screening of GMDH are all self-adaptive processes, which rely on the interaction within the system to "discover knowledge" and hardly need the user's intervention in the mining process as the organizer. Given the numerous irrelevant variables found in input, the GMDH-type neural network performs self-learning and forecast through screening criteria [20]. Dempster–Shafer (D–S) data fusion function is used to fuse the forecast data from GMDH-type neural network algorithm and normal distribution, which is an effective method for SS determination [21, 22]. Company profitability is directly related to oil price and inventory. However, the oil price fluctuation is extremely difficult to forecast. The maximum company profitability can be acquired through risk decision under the safety stock limitation from this model.

GMDH algorithm and risk decision make the purchase model have the inherent advantages of convenience. Through the previous operation classification data, the result can be calculated without establishing a complex model. This quantitative model has data guiding significance for inventory management, what can avoid the empirical operation.

The contribution of the paper is threefold. First, we presented a method for SS determining of oil inventory operation based on data fusion of GMDH-type neural network algorithm result and normal distribution forecast result. Second, combined with the fluctuating oil price period and using data expectation criterion, an oil purchase decision model for improve inventory income is proposed. Third, numerical results suggest that the oil marketing company can make an economical purchase decision by using this procurement method.

The rest of this paper is structured as follows. Section 2 briefly reviews the related literature. Section 3 introduces the purchase model framework including safety stock determination of oil marketing company based on data fusion, forecast model method of normal distribution, GMDH-type neural network, and the expectation criterion of risk decision. The experimental setup, detailed results, estimate of one oil marketing company, and discussion are described in Section 4. Finally, some concluding remarks and ideas for future work are in Section 5.

2. Literature Review

Cachon and Fisher [1], Giannoccaro and Pontrandolfo [2], Netessine and Zhang [3], and Hosoda and Disney [4] proposed the purchase method based on EOQ. Dewi et al. [23] argued that it is an effective method to purchase decisions with safety stock as the constraint and the inventory profitability as the reference.

SS determination is the first step for purchase decision-making. Many researchers have been done in developing approaches for SS determination. Fotopoulos et al. [24] present a SS determination method, which is derived by using inequalities on the basis of probability arguments. Yücesan et al. [25] proposed an analytical expression for calculating safety stock. With the growth of computer technology, artificial neural networks to forecast model were widely introduced to SS determination (Zhang et al. [26], Zhang et al. [26], Zhong and Zhang [27], and Zhao and Liu [28]). Artificial intelligence (AI) approaches, such as artificial neural networks (ANN), have good effect for forecast data. According to Yi [29]), Yu [30], and Chen [31], the advantage of BP neural network is that it has strong nonlinear mapping ability to forecast object. Luo [32] proposed an inventory management model based on BP neural network. Adaptive neuro-fuzzy inference systems (ANFIS) has advantages in forecast to fuzzy uncertain systems (Kazemi et al. [33]; Abghari and Sadi [34]; Bakyani et al. [35]). Torkabadi and Mayorga [36] present an inventory management approach based on ANFIS for storage control. Paul et al. [37] developed a method based on ANFIS for inventory level forecasting. In addition, with the help of a large number of operations, SVM can achieve good forecast results (Cui and Curry [38] and Wang et al. [39]). The application of GMDH network algorithm in various scientific fields has achieved good results (Najafzadeh [40]; Najafzadeh, Movahed, and Sarkamaryan et al. [41]; Nkurlu et al. [42]). The GMDH network has the advantages of self-adaptive representation of the forecast object and implementation of training quickly by using the least square method (Najafzadeh and Saberi-Movahed [43]). Furthermore, the researchers argued that GMDH has good performance in accuracy with simply operation. Ongkicyntia and Rahardjo [22] considered that SS is between forecast data and historical data. In this paper, we tried to fuse forecast value based on neural networks (GMDH) and normal distribution (forecast value of historical data) to approximate the SS truth value.

Researchers have developed many different approaches for data fusion to improve data accuracy, include ordered weighted averaging (OWA) (Rezamand et al. [44]), maximum likelihood estimation (Monte-Morenoet al. [45]), Bayes Estimation (Gai and Wang [46]), Kalman filtering (Lanckriet Gert et al. [47]; Caron et al. [48]), robust information fusion (Wang et al. [49]) and Dempster–Shafer (D–S) evidence theory (Varshney [50]; Kam et al. [51]; Radman et al. [52]; Guo and Xu [53]), etc. Moreover, Kordestani et al. [54] proposed a mixed data fusion method based on OWA and Kalman filtering. In contrast, the advantage of D–S evidence theory is that it can separate the strict conditions from the possible ones, so that any lack of information related to a priori probability can be displayed.

As in the previous papers, expected value criteria were introduced, Popovic et al. [55] introduced lots of risk decision method. Ye [56] introduced a weighted method for expected values criteria. Charnetski and Soland [57] presented an expected values criteria model based on numerical integration and Monte Carlo simulation.

In conclusion, using neural network forecast data and historical data to determine SS makes the data approximate the true value. At the same time, D–S evidence theory is helpful to fuse SS forecast. The expected value criteria are used to simulate the purchase process and then made an economic purchase decision.

3. Methodology and Modeling Process

3.1. Framework for Safety Stock Determination Model. Safety stock determination is the first step in the operating model. The operating model is based on two forecast models. The safety stock value (SS) can be obtained through these models. SS can be calculated by using data fusion. The model process is shown in Figure 1.

Data fusion integrates data from different nodes by using various some methods and tools to improve the data accuracy. Weighted coefficient, cluster analysis, and Dempster–Shafer (D–S) reasoning data fusion methods are commonly used in previous studies [21].

The forecast result is calculated by GMDH-type neural network algorithm, so the forecast output value is inclined to theoretical value. By contrast, the normal distribution results use the operated values directly, so the forecast output value from the normal distribution forecast model is inclined to empirical value. Thus, the GMDH-type neural network and normal distribution forecast model output values through data fusion are used to obtain accurate and reasonable safety stock value [13, 19, 20, 58].

According to belief (Bel_i) and plausibility (Pls_i) functions of the data, D-S data fusion function is calculated as [58]

$$S = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}\overline{S}_1 + \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\overline{S}_2, \tag{1}$$

where $\overline{S}_1$ is the mean value of the S_1 set, $\overline{S}_2$ is the mean value of the S_2 set, σ_1^2 is variance of the S_1 set, σ_2^2 is variance of the S_2 set, and S is the fusion value.

The weighted coefficient data fusion method function is calculated as

$$S = K_1 S_1 + K_2 S_2, \tag{2}$$

where S_1 is SS calculated by GMDH, S_2 is SS calculated by normal distribution forecast model, K_n is the weighted coefficient of S_n ($K_1 = (\sigma_{\mathrm{GMDH}}^2/(\sigma_{\mathrm{GMDH}}^2 + \sigma_N^2))$, K_2 in the same analogy), and S is the fusion value (SS).

3.1.1. Safety Stock Based on Forecast Model Method of Normal Distribution. As shown in Figure 2, the inventory operation is based on EOQ and JIT in theoretical condition [25]. The actual operation is affected when the arrival of the oil is delayed. Thus, a buffer inventory must be considered to ensure the normal storage operation. SS of oil storage based on EOQ is regarded as the buffer inventory.

Purchase and sale are the two main factors, which directly affect SS. Theoretically, the minimum safety stock value ($SS_{\min}$) appears at the front of the purchase point, as shown in Figure 2. Mapping exists between sale and $SS_{\min}$. As shown in Figure 3, $SS_{\min}$ has changed with sale change because of mapping. Thus, $SS_{\min}$ obeys the same distribution. $SS_{\min}$ function is calculated as

$$\begin{aligned} SS &= \mathcal{F}(S, P), \\ SS &= K * \sigma_S, \\ SS_{\min} &= K_{\min} * \sigma_S, \end{aligned} \tag{3}$$

where $K_{\min}$ is the safety factor and σ_S is the standard deviation of sale.

The maximum safety stock value ($SS_{\max}$) is similar to $SS_{\min}$. Mapping exists between purchase and $SS_{\max}$. As shown in Figure 4, $SS_{\max}$ obeys the same distribution of purchases. The $SS_{\max}$ is calculated as

$$\begin{aligned} SS &= \mathcal{F}(S, P), \\ SS &= K * \sigma_S, \\ SS_{\max} &= S_{\max} - K_{\max} * \sigma_P, \end{aligned} \tag{4}$$

where $S_{\max}$ is the maximum oil inventory capacity, $K_{\max}$ is the safety factor, and σ_p is the standard deviation of purchase.

According to the historical data of the same period, $K_{\min}$ and $K_{\max}$ are confirmed by standardisation.

3.1.2. Safety Stock Based on GMDH-Type Neural Network. According to the actual work of inventory management, there is no accurate calculation value of safety stock, which is usually determined by empirical value. The factors that affect the reasonable inventory mainly include two categories: one is the oil depot factor, and the other is the demand factor.

So, the empirical value of SS is used as the output value of GMDH. The GMDH self-organization model needs to embrace all kinds of operated variables as much as possible to find the relationship between variables that is not easy to find. According to the actual operation of inventory management and control, the factors of oil depot (available stock, bottom oil, ratio of gas and diesel, and transportation time) and demand factor (daily demand) have an important impact on the determination of safety stock. Those values are used as the input value of GMDH. And, GMDH is trained with the minimum mean square error of global neurons as the stopping criterion.

The preparation of the data classification is significant. The classification of the actual data based on SS is shown in Table 1:

The GMDH software, Knowledge Miner, GMDH Shell, and self-made programme of MATLAB are the most common software used to calculate SS.

3.2. Risk Decision. Oil prices are adjusted according to a certain period of time. This period is called the oil price window period. Given the classic inventory operation model (i.e., EOQ) [25], the oil inventory operating model is shown in Figure 5.

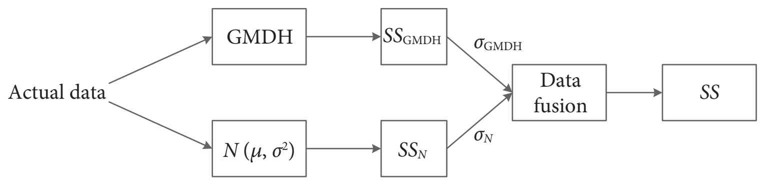


Figure 1: Framework for the SS determination model.

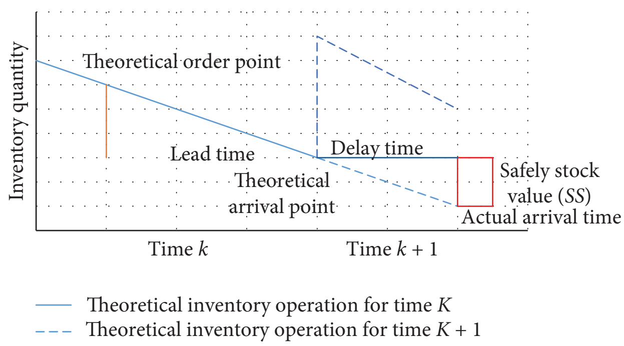


Figure 2: SS based on EOQ.

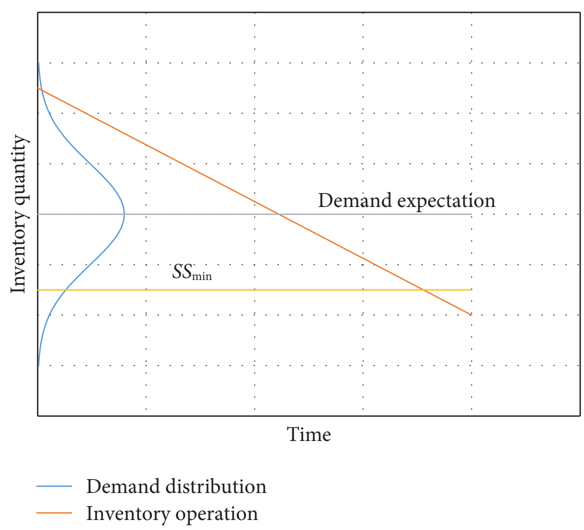


Figure 3: Relationship between SS_{min} and sale.

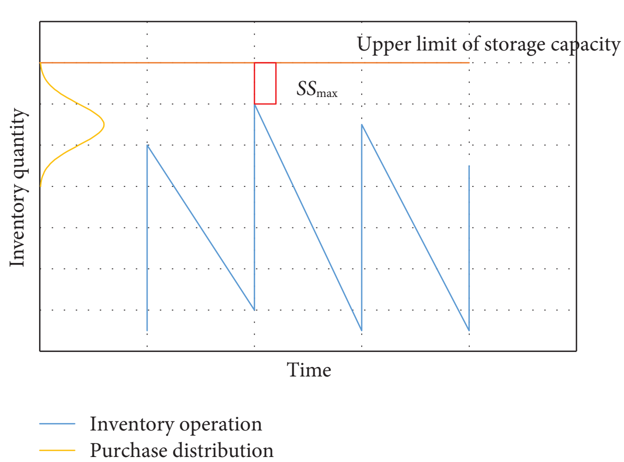


Figure 4: Relationship between SS_{max} and purchase.

Table 1: Classification of input data.

$X1$	Available stock value
$X2$	Daily demand
$X3$	Bottom oil
$X4$	Ratio of gas and diesel
$X5$	Transportation time (max)
$X6$	Transportation time (min)
$X7$	On-order inventory

Bottom oil is the oil in the bottom of the tank and the pipe.

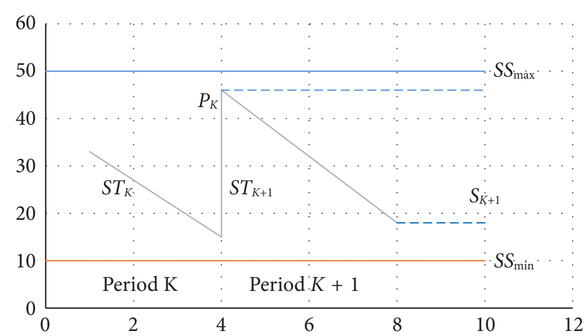


Figure 5: Oil inventory operating model.

For the maximum profitability under the safety stock limit, the function is calculated as follows:

$$Z = \max\left(ST_{K+1} + S_{K+1}\right) * PR_{K+1},$$
$$\begin{cases} ST_{K+1} = ST_k + P_K - S_{K+1}, \\ ST_k + P_K \leq SS_{\max}, \\ ST_{K+1} \geq SS_{\min}, \end{cases} \tag{5}$$

where ST_{K+1} is the inventory value in the end of period $K+1$, PR_{K+1} is the oil price of period $K+1$, P_K is the purchase value in period K, and S_{K+1} is the sale value in period $K+1$.

The income of inventory in a period is calculated is calculated as follows:

$$\begin{aligned} SV_K &= VE_K - VB_K, \\ VE_K &= \left(ST_{K-1\_e} + P_K - S_K\right) \times PR_K + S_K \times \left(PR_K + PR_{K-\text{Add}}\right), \\ VB_K &= \left(ST_{K-1\_e} + P_K\right) \times PR_{K-1}, \end{aligned} \tag{6}$$

where SV_K is the income of inventory in a period K, VE_K is the inventory value in the end of period K, VB_K is the inventory value at the beginning of period K, ST_{K-1_e} is the inventory in the end of period $K-1$, and $PR_{K-\text{Add}}$ is the transport price.

The income of inventory function is rewritten as follows:

$$SV_K = \left(S_{K-1\_e} + P_K\right) \times \Delta PR + S_K \times PR_{K-\mathrm{Add}}, \quad (7)$$

where ΔPR is the change of oil price between window period $K-1$ and window period K.

In Function (5), S_K is beyond the oil marketing company control. P_K is an independent variable, under the oil marketing company control. S_{K-1_e} is the dependent variable from purchase and sale. Thus, the definition of the purchase is the key for maximum profitability.

Purchase and oil price are the key to inventory operation. In actual operation, oil marketing companies can accurately forecast next oil price window period. Moreover, oil marketing companies can forecast the subsequent oil price window period after the first forecast. However, the probability of accuracy forecast is not more than 0.5. Determining the purchasing strategy can be considered the expectation criterion [13]. The expectation criterion for purchase with oil price is listed in Table 2:

The lag effect, which is the effect of the inventory of period K on the inventory income of period $K+1$, greatly influences the inventory income. The expectation criterion has a good effect on eliminating the lag effect. Thus, the expectation criterion of the inventory operation management model supports the purchase decision in each period for oil marketing companies.

4. Simulation and Results

In this section, an operation analysis on one oil marketing company is presented on the basis of the purchase model.

4.1. SS by Forecast Model of Normal Distribution. Firstly, the trend of the sale market in the past year is characterised by calculating the standard deviation of sale in the same year. The sale data in 2018 of an oil marketing company are shown in Table 3:

Thus, the standard deviation of 2018 is $\sigma_Y = 47{,}517.08$.

Secondly, the calculation of the standard deviation of sale in the last quarter includes gas and diesel. The standard deviation defines the demand of gas and diesel. The oil marketing company sale data within approximately three months are shown in Table 4:

Thus, the standard deviation of gas and diesel is $\sigma_{Q-\mathrm{gas}} = 389,96.25$ and $\sigma_{Q-\mathrm{diesel}} = 181,66.56$, respectively. Combined with the past year trends and recent demands, the standard deviation of sale is calculated using equation (2): $\sigma_{gas} = (\sigma_Y^2/(\sigma_Y^2 + \sigma_{Q-\mathrm{gas}}^2))\sigma_Y + (\sigma_{\mathrm{gas}}^2/(\sigma_Y^2 + \sigma_{Q-\mathrm{gas}}^2))\sigma_{Q-\mathrm{gas}} = 44{,}087.83$; $\sigma_{\mathrm{diesel}} = (\sigma_Y^2/(\sigma_Y^2 + \sigma_{Q-\mathrm{diesel}}^2))\sigma_Y + (\sigma_{\mathrm{gas}}^2/(\sigma_Y^2 + \sigma_{Q-\mathrm{diesel}}^2))\sigma_{Q-}$ diesel $= 43{,}774.13$.

Using the equation (3), the following is calculated: $SS_{\mathrm{min-gas}} = K_{\mathrm{gas}} \times \sigma_{\mathrm{gas}}$; $SS_{\mathrm{min-diesel}} = K_{\mathrm{diesel}} \times \sigma_{\mathrm{diesel}}$.

Table 2: Expectation criterion for oil marketing company purchase.

Schemes S_i	Probability of oil price: Period K: Rise	Keep	Fall	Period $K+1$: Rise P_{2R}	Keep P_{2K}	Fall P_{2F}	Expected value
	Incomes						
S_1 (bulk)	$a11$			$b11$	$b12$	$b13$	Z_1
S_2 (appropriate)		$a22$		$b21$	$b22$	$b23$	Z_2
S_3 (bit)			$a33$	$b31$	$b32$	$b33$	Z_3

The calculation method of the safety factor is $K = ((4 \times \sum_{1\le i\le 3} S_i)/\sum_{1\le i\le 12} S_i)$. This formula integrates the standardised proportion of the annual sale volume within approximately three months. Thus, $K_{\mathrm{gas}} = 0.9448$ and $K_{\mathrm{diesel}} = 1.0910$.

In the actual operation of the oil inventory, the bottom oil is needed. Thus, the safety stock value (SS_{min}) is rewritten as follows: $SS_{\mathrm{min}} = (SS_{\mathrm{min-gas}} + SR_{\mathrm{gas}}) + (SS_{\mathrm{min-diesel}} + SR_{\mathrm{diesel}})$, where SR_{gas} is the bottom oil of gas and SR_{diesel} is the bottom oil of diesel.

Thus, $SS_{\mathrm{min}} = (41{,}652.7 + 33{,}603) + (47{,}755.8 + 25{,}304) = 148{,}315.4$ (tons).

Similar with SS_{max}, the standard deviation of purchase in the past year is calculated by characterising the trend of purchase in the past year. The purchased data in 2018 of an oil marketing company are shown in Table 5:

Thus, the standard deviation of 2018 is $\sigma_Y = 40{,}703.96$. The purchase data within approximately three months of the same company are shown in Table 6.

Thus, the standard deviations of gas and diesel are $\sigma_{Q-\mathrm{gas}} = 6{,}262.00$ and$\sigma_{Q-\mathrm{diesel}} = 26{,}569.58$, respectively. Combined with the past year trends and recent demands, the standard deviation of purchase is calculated using equation (2): $\sigma_{\mathrm{gas}} = 39{,}907.65$; $\sigma_{\mathrm{diesel}} = 36{,}480.89$.

Similar to the sale safety factor, the following are obtained: $K = ((4 \times \sum_{1\le i\le 3} P_i)/\sum_{1\le i\le 12} P_i)$, $K_{\mathrm{gas}} = 0.9412$, and $K_{\mathrm{diesel}} = 0.9984$.

Using equation (4), the following is obtained: $SS_{\mathrm{max}} = S_{\mathrm{max}} - (K_{\mathrm{gas}} \times \sigma_{\mathrm{gas}} + K_{\mathrm{diesel}} \times \sigma_{\mathrm{diesel}}) = 601000-(37{,}559.94 + 36{,}423.91) = 527{,}016.1$ (tons).

4.2. SS by GMDH. No. 92 gasoline oil depot data of one day in January 2018 are provided in Table 7. By using the GMDH software, the K–G functions and plot can be obtained. The K–G functions can be calculated as follows [8]:

$$\begin{aligned} Y_{92-\mathrm{min}} &= 2.705X_7^2 - 0.9046e^{-1}X_1X_7 - 1.797e^{-3}X_1^2 - 9.21e^{-2}X_7 + 1.675e^{-1}X_1 + 0.738e^{-1}X_3 + 0.9708e^{-1}X_2, \\ Y_{92-\mathrm{max}} &= 1.513e^{-1}X_1 + 12.1X_2 + 2.198X_3. \end{aligned} \quad (8)$$

Table 3: 2018 sale data of the oil marketing company.

Month	January	February	March	April	May	June
Amount (tons)	822,200	710,888	831,425	794,995	768,670	788,468
Month	July	August	September	October	November	December
Amount (tons)	783,105	774,119	693,660	861,895	722,430	782,089

Table 4: Sale data within approximately three months of the oil marketing company.

(tons)	October	November	December
Gas	435,656	340,316	382,897
Diesel	426,239	382,114	399,192

Table 5: 2018 purchase data of the oil marketing company.

Month	January	February	March	April	May	June
Amount (tons)	769,606	714,151	833,799	822,721	801,155	829,424
Month	July	August	September	October	November	December
Amount (tons)	808,090	720,351	797,552	725,203	769,182	772,630

Table 6: Purchase data within approximately three months of the oil marketing company.

(t)	October	November	December
Gas	392,037	376,862	386,385
Diesel	333,166	392,320	386,245

The forecast SS of No. 92 gasoline oil provided by the GMDH software is indicated in Figure 6.

Moreover, $\sigma_{92-\min} = 3{,}585$; $\sigma_{92-\max} = 6{,}215$; $SS_{92-\min} = 98{,}998$ (tons); and $SS_{92-\max} = 179{,}318$ (tons).

Similar to No. 92 gasoline oil, $\sigma_{95-\min} = 943$; $\sigma_{95-\max} = 1{,}998$; $SS_{95-\max} = 42{,}029$ (tons); $SS_{95-\min} = 15{,}292$ (tons); $\sigma_{0-\min} = 2{,}111$; $\sigma_{0-\max} = 8{,}663$; $SS_{0-\max} = 284{,}796$ (tons); and $SS_{0-\min} = 84{,}943$ (tons). The forecast SS of No. 95 gasoline oil and No. 0 diesel oil is indicated in Figure 7.

According to the GMDH software, the fitting coefficients (R-squared) are $R^2_{\text{92-min}} = 0.803$; $R^2_{\text{92-max}} = 0.785$; $R^2_{\text{95-min}} = 0.925$; $R^2_{\text{95-max}} = 0.967$; $R^2_{\text{0-min}} = 0.752$; and $R^2_{\text{0-max}} = 0.876$. in the result of those R-squared, since the sales of No. 95 gasoline is less, the influence of randomness is not much, so the curve fitting degree is better.

4.3. SS Data Fusion. The data of $SS_{(\min)}$ of January 2018 based on forecast model of normal distribution are calculated as follows: $\sigma_{N-\text{gas}} = 44{,}087.83$; $\sigma_{N-\text{diesel}} = 43{,}774.13$; $SS_{N-\min-\text{gas}} = 75{,}255.7$; $SS_{N-\min-\text{diesel}} = 73{,}059.8$. $SS_{\min}$ includes the bottom oil.

The data of $SS_{\min}$ based on GMDH are calculated as follows: $\sigma_{\text{GMDH}-\text{gas}} = 3{,}261$; $\sigma_{\text{GMDH}-\text{diesel}} = 2{,}111$; $SS_{\text{GMDH}-}$ min − gas = 114,290; $SS_{\text{GMDH}-\min-\text{diesel}} = 84{,}943$.

Using equation (1), the following is calculated:

$$SS_{\min-\text{gas}} = \frac{\sigma^2_{N-\text{gas}}}{\sigma^2_{N-\text{gas}} + \sigma^2_{\text{GMDH}-\text{gas}}} SS_{N-\min-\text{gas}} + \frac{\sigma^2_{\text{GMDH}-\text{gas}}}{\sigma^2_{N-\text{gas}} + \sigma^2_{\text{GMDH}-\text{gas}}} SS_{\text{GMDH}-\min-\text{gas}} = 75,468 \text{ (tons)}. \tag{9}$$

Similar to $SS_{\min-\text{gas}}$, $SS_{\min-\text{diesel}} = 73{,}087$ (tons). Thus, $SS_{\min} = 148{,}555$ (tons).

The data of $SS_{\max}$ of January 2018 based on normal distribution are calculated as follows: $\sigma_N = 38347.68$; $SS_{N-\max} = 527{,}016.1$. The data of $SS_{\max}$ based on GMDH are calculated as follows: $\sigma_{\text{GMDH}} = 7{,}720$; $SS_{\text{GMDH}-\max} = 506{,}144$.

Using equation (1), $SS_{\max} = 526{,}203$ (tons).

4.4. Purchase Decision Using Expectation Criterion. In the actual situation, an oil company can accurately forecast the next oil price period. The probability of forecast accuracy of the subsequent periods after the first forecast is not more than 0.5. The gas operation actual data (windows periods 0, 1, and 2 of 2018) of the same company are listed in Table 9:

4.4.1. Inventory Income of Period 1 from Purchases in Period 0. At the end of the period 0, $SS_{\max-\text{gas}} = 254{,}950$ (tons) and $SS_{\min-\text{gas}} = 75{,}468$ (tons). The purchase is ordered in period 0 by the given oil price (i.e., 3149), and purchase arrival is in period 1.

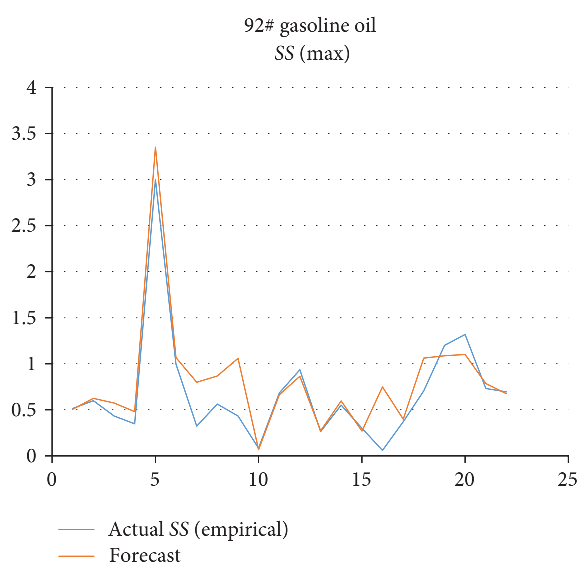
The purchase schemes in period 0 are calculated as follows (suppose that $S_{0\_e} = 150{,}000$ [tons]):

$P_{\text{bulk}} + S_{0\_e} = SS_{\max-\text{gas}} + S_k$, so $P_{\text{bulk}} = 344{,}950$ (tons)

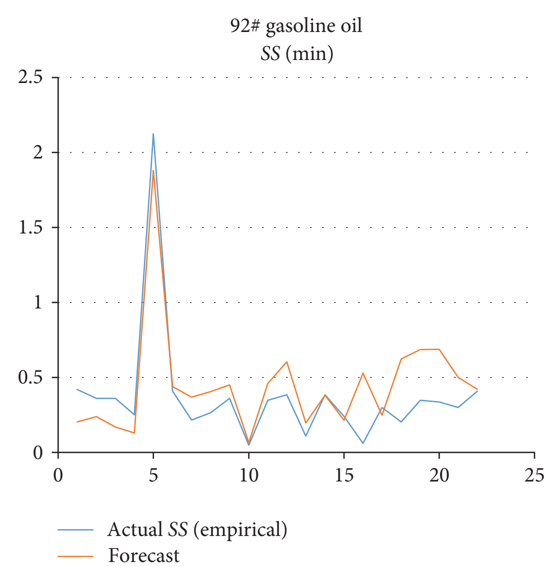
$P_{\text{appropriate}} = P_{\text{actual}} = 207{,}708$ (tons)

Table 7: No. 92 gasoline oil depot data (10,000 tons).

Oil depot	SS (empirical)		Available stock value	Daily demand	Bottom oil	Ratio of gas and diesel	Transportation time (day)		On-order inventory
	Min	Max					Max	Min	
			X1	X2	X3	X4	X5	X6	X7
A	0.35	0.43	0.63	0.0442	0.03	1.3446	8	6	0.19564
B	0.3	0.5	0.69	0.0437	0.05	1.1012	8	6	0.19564
C	0.3	0.36	0.55	0.0522	0.06	1.1018	8	6	0.19564
D	0.21	0.29	0.43	0.0453	0.06	1.1807	8	6	0.146
E	1.77	2.5	3.53	0.1211	0.28	0.7928	8	6	1.02711
F	0.34	0.83	1.12	0.0125	0.12	1.6648	11	6	0.292
G	0.18	0.27	0.99	0.0192	0.05	1.2887	11	6	0.219
H	0.22	0.47	1.09	0.0206	0.05	1.0626	8	6	0.219
I	0.3	0.36	1.09	0.0488	0.11	1.4261	8	6	0.365
J	0.04	0.07	0.1	0.006	0	2.5754	11	11	0.003
K	0.29	0.57	0.81	0.0333	0.04	1.3946	8	5	0.03
L	0.32	0.78	1.11	0.0313	0.04	1.783	8	5	0.03
M	0.09	0.22	0.31	0.0274	0.02	1.068	8	5	0.009
N	0.32	0.46	0.66	0.037	0.05	1.2689	8	5	0.03
O	0.2	0.25	0.36	0.0149	0.01	1.6912	8	5	0.02
P	0.05	0.05	0.85	0.053	0.05	0.9807	6	5	0
Q	0.25	0.31	0.44	0.0092	0.04	1.4914	6	5	0.04
R	0.17	0.59	1.05	0.0636	0.11	0.4816	6	5	0.01
S	0.29	1	1.21	0.0287	0.1	1.3365	7	5	0.02
T	0.28	1.1	1.2	0.0254	0.11	2.021	7	5	0.02
U	0.25	0.61	0.87	0.0345	0.07	0.9576	7	5	0.03
V	0.34	0.58	0.75	0.0297	0.06	1.4601	8	5	0.04



(a)



(b)

Figure 6: Forecast SS of No. 92 gasoline oil based on GMDH software.

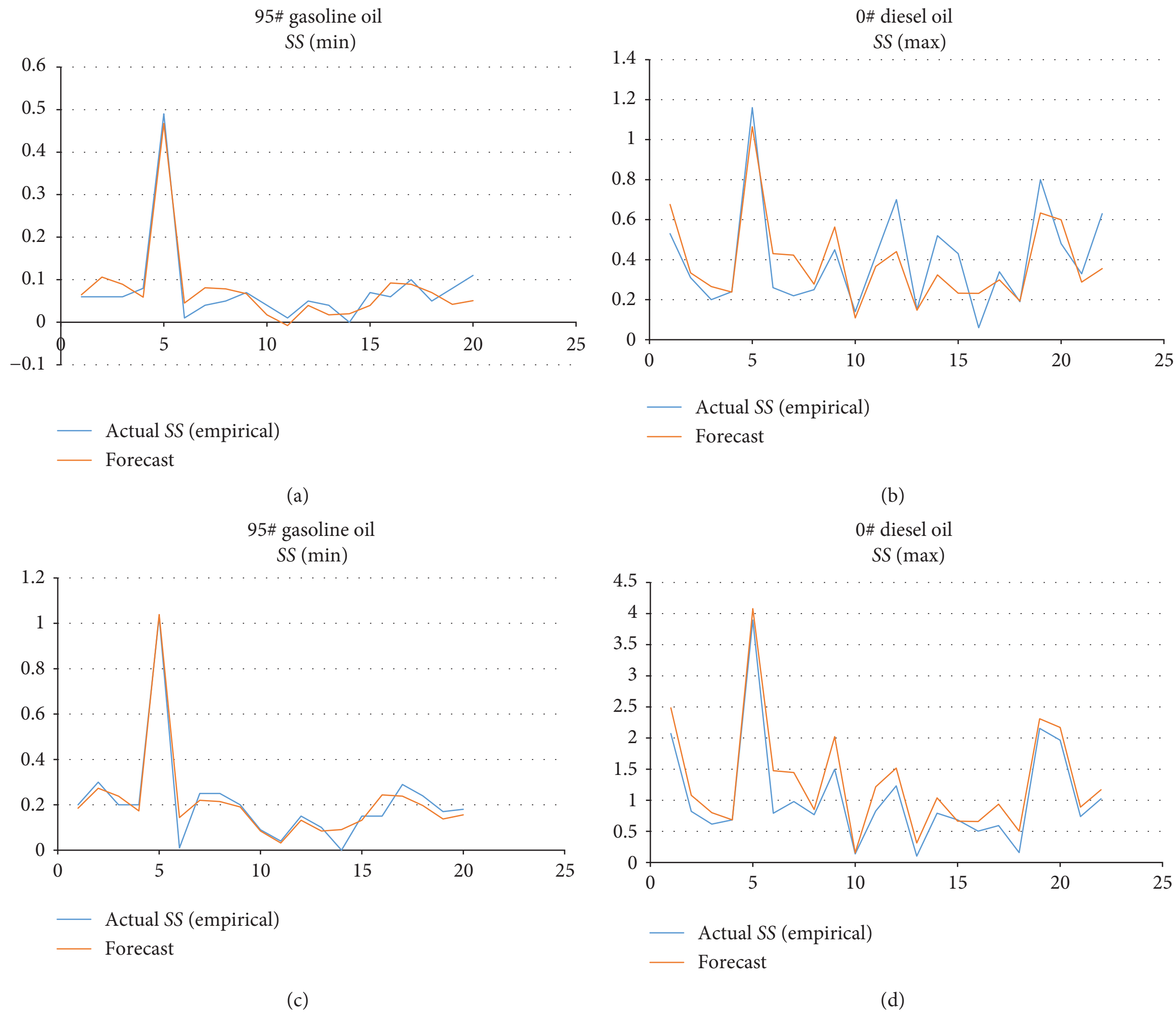


Figure 7: Forecast SS of No. 95 gasoline oil and no. 0 diesel oil based on GMDH software.

$P_{\text{bit}} + S_{0\_e} = SS_{\text{min-gas}} + S_k$; thus, $P_{\text{bit}} = 165{,}468$ (tons)

According to equation (7), $PR_{1-\text{Add}} = 100$ (Yuan). Thus, $SV_1 = P_0 \times \Delta PR + S_1 \times PR_{1-\text{Add}}$. The inventory income of period 1 from purchases is calculated as follows:

$$a1 = (150{,}000 + 344{,}950) * 50 + 23{,}500{,}000 \approx 48{,}200{,}000$$

$$a2 = (150{,}000 + 207{,}708) * 50 + 23{,}500{,}000 \approx 41{,}385{,}400$$

$$a3 = (150{,}000 + 165{,}468) * 50 + 23{,}500{,}000 \approx 39{,}000{,}000$$

4.4.2. Inventory Income of Period 2 from Purchases in Period 0. Virtual purchases for period 2 based on the oil price probability in the same period are used to obtain the correct purchase decision in period 0. The purchase decision in period 1 is based on the oil price in period 2 and oil price probability in period 3. The purchase decision in each window period is repeated in turn.

The purchase decision is based on the following rules: (1) when the oil price is decreasing, the inventory closes the minimum safety stock; (2) when the oil price is increasing, the inventory closes the maximum safety stock; and (3) when the oil price is uncertain, the purchase is based on the forecasted sale.

The inventory at the end of period 1 is calculated as follows:

S_{1_e} (bulk in period 0) $= (150{,}000 + 344{,}950) - 235{,}000 = 259{,}950$ (tons)

S_{1_e} (appropriate in period 0) $= (150{,}000 + 207{,}708) - 235{,}000 = 122{,}708$ (tons)

S_{1_e} (bit in period 0) $= (150{,}000 + 165{,}468) - 235{,}000 = 80{,}468$ (tons)

The purchases made in period 2 according to the purchase decision rules are shown in Table 10:

The oil price probability is as follows: rise = 0.05; keep = 0.15; down = 0.5; unknown = 0.3. Thus, Table 10 is based on the expectation criterion rewritten in Table 11.

Thus, according to equation (7), $SV_2 = P_2 \times \Delta PR + S_2 \times PR_{2-\text{Add}}$. The inventory income of period 2 from purchases is calculated as follows:

$$S_{K2} \times PR_{2-\text{Add}} = 200{,}000 * 100 = 20{,}000{,}000$$

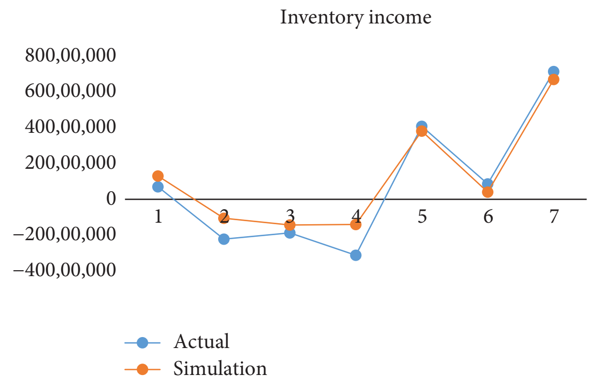


Figure 8: Oil inventory income.

Table 8: *SS* from different data sources.

SS	Min		Max	
	Value	Relative error (%)	Value	Relative error (%)
Actual (empirical)	155700		481845	
From normal distribution	148315	4.74	527016	9.37
From GMDH	199233	27.96	506143	5.04
Data fusion	148555	4.59	526203	9.21

SS from different data sources are shown in Table 8. We can find that the each forecast value is generally consistent with the actual (empirical) value. We can also find that, through data fusion, we can better correct the impact of data randomness on the forecast data.

Table 9: Gas operation actual data of the oil marketing company.

	Period 0	Period 1	Period 2
Actual oil Price (Yuan/ton)	3,149	(3,149) + 50	(3,149 + 50) − 140
Purchase (ton)	207,708	224,064	
Forecast Sale (ton)		240,000	200,000
Actual Sale (ton)		235,000	

Table 10: Virtual purchase for period 2.

Schemes S_i	Oil price status Period 2 Probability				
	Rise (close the SS_{max})	Keep (median value)	Down (close the SS_{min})	Unknown	
	Purchase				Expected value
	P_{1R}	P_{1K}	P_{1D}	P_{1Un}	
S_1	195,000	105,259	15,518	200,000	Z_1
S_2	332,242	242,501	152,760	200,000	Z_2
S_3	374,482	284,741	195,000	200,000	Z_3

$$b1 = (259{,}950 + 93{,}298) * (-140) + 20{,}000{,}000 \approx -29{,}454{,}699$$

$$b2 = (122{,}708 + 189{,}367) * (-140) + 20{,}000{,}000 \approx -23{,}690{,}535$$

$$b3 = (80{,}468 + 218{,}935) * (-140) + 20{,}000{,}000 \approx -21{,}916{,}455$$

The inventory expectation income is shown in Table 12:

According to Table 12, the bulk purchase is the optimization scheme in period 1.

Using the above method, the oil marketing company purchase is simulated. The simulation results are compared with the actual operation as shown in Table 13.

The oil inventory income is as indicated in Figure 8. The total income 82,940,610 of the model is greater than 55,547,840 of the actual total income. From the oil

Table 11: Expectation purchase for period 2.

Schemes S_i	Oil price status Period 2 Probability Rise (close the SS_{max})	Keep (median value)	Down (close the SS_{min})	Unknown	Expected value
	Purchase				
	0.05	0.15	0.5	0.3	
S_1	195,000	105,259	15,518	200,000	93,298
S_2	332,242	242,501	152,760	200,000	189,367
S_3	374,482	284,741	195,000	200,000	218,935

Table 12: Inventory expectation income.

Schemes S_i	Incomes Period 1	Period 2	$\sum$
S_1 (bulk)	48,200,000	−29,454,699	(max) 18,745,301
S_2 (appropriate)	41,385,400	−23,690,535	17,694,865
S_3 (bit)	39,000,000	−21,916,455	17,083,545

Table 13: Purchase simulation and inventory income.

		Period1	Period2	Period3	Period4	Period5	Period6	Period7
Oil price		3,149 + 50	3199 − 140	3059–190	2869 + 0	2869 + 170	3039 + 50	3089 + 255
Sales		235,000	240,500	240,000	258,000	251,800	259,800	262,080
Purchase	Actual	224,064	175,000	199,000	282,000	210,000	221,000	321,000
	Simulation	344,950	56,018	240,000	256,402	401,580	125,820	444,680
Inventory of end period	Actual	139,064	158,564	134,000	223,000	240,200	171,200	279,920
	Simulation	259,950	75,468	75,468	73,870	223,650	79,670	262,270
Income in period	Actual	6,953,200	−22,198,960	−18,760,000	−31,220,000	40,834,000	8,560,000	71,379,600
	Simulation	12,997,500	−10,565,520	−14,338,920	−14,035,300	38,020,500	3,983,500	66,878,850

inventory income, this method has a good effect for inventory income.

4.5. Results and Discussion. This paper proposed model is that the data are all from the actual operation data without any transformation. The model not only ensures the inventory in a reasonable operation scope by forecast model of GMDH-type neural network, normal distribution, and data fusion but also gets good profitability by risk decision. Meanwhile, the calculation results from this model provide guidance for oil asset management.

However, the dissatisfied consistency of curves is shown in Figures 6 and 7. Generally, consistency is an important criterion for forecast models. Especially, in this model, the fitting coefficient of fitting curve based on GMDH algorithm can well represent this standard. The input value of the GMDH comes from empirical factors. So, the accuracy of the model will be improved by adding empirical correction coefficient.

Moreover, a gap exists in the magnitude of the standard deviation between the GMDH method and the forecast model of normal distribution. The gap influences the effectiveness of data fusion. The utilisation of the forecast model of the normal distribution in each oil depot results in a rigorous forecast model. The operation granularity depends on the proposed model based on EOQ.

5. Conclusion and Future Works

In this study, a purchase model of oil marketing companies is presented. This model is based on GMDH-type neural network, forecast model of normal distribution, data fusion, and risk decision. A GMDH-type neural network has an advantage in researching uncertainty in complex systems. The purchase and sale of oil marketing companies follow normal distribution. The normal distribution forecast model for safety stock determination is created according to the mapping relationship of the normal distribution. Two kinds of forecast results with data fusion are explored to determine accurate and reliable forecast results. The safety stock and expectation criterion of risk decision provide a scientific operating model for the inventory operation management of oil marketing companies.

However, the model needs to forecast the safety stock firstly. Fuzzy set theory has a good response to uncertainty. Meanwhile, Choquet integral and OWA operator are good data fusion methods for *SS*. Therefore, in the future, we will use a large number of inventory income data to explore the optimal fusion approach by experimental method. In addition, the purchase decision-making comes from a set of discrete values of expectation criterion results. If we can use a better algorithm to simulate the purchasing profitability curve and get the extreme value, we will make a better purchasing decision.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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