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PRAM: A Novel Approach for Predicting Riskless State of Commodity Future Arbitrages With Machine Learning Techniques

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ABSTRACT Arbitrage risk management is a very hot and challengeable topic in the commodity future market. To resist the possible risk of an arbitrage, exchanges have to withdraw margin from clients referring to the case of maximum risk. However, if this arbitrage is in the riskless state actually, the capital of clients will be inefficient. Therefore, by investigating the applications of machine learning techniques, we here propose a novel algorithm named PRAM to predict the riskless state of arbitrage, by integrating multi-scale data ranging from contract quotation to contract parameters. Unlike the traditional models, PRAM explores the arbitrage risk management from the view of minimum risk, which can form a powerful supplement with the available risk management systems. Benchmark results based on DCE database implicate that PRAM outperforms existing methods. Then, we discover that features of different arbitrage types depended by PRAM are odds with being identical. In addition, we identify some trade situations, such as delivery and near-delivery months, which seriously impact the effectiveness of PRAM. Furthermore, considering different varieties involved in intra-commodity arbitrages, we create personalized PRAMs, which can deeply improve the accuracy of prediction.

INDEX TERMS Arbitrage risk management, riskless state, machine learning, trade situations, personalized models.

I. INTRODUCTION

In the commodity future market, it is such a difficult thing to conduct an effective arbitrage risk management [1]–[4]. From the perspective of an administrator, there mainly exists two reasons. First, the price of contract is influenced by so many elements that it is impossible to make an accurate prediction. Second, because of the complicated correlations among contracts inside an arbitrage, which cannot be exactly quantified, it is hard to make an adequate offset. Given these, for the defense of the probable risk of each arbitrage on the next trade date, a lot of exchanges have to choose margin considering the maximum risk case. While, if the margin is in high level, the financial liquidity of clients will be seriously blocked, whose investments are practically in the riskless state [5]–[7].

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In general, the current risk management systems of exchanges could be classified into three clusters. Firstly, the strategic risk models using linear algorithms, are adopted by several Chinese exchanges, such as DCE (Dalian Commodity Exchange) and SHFE (Shanghai Future Exchange). Based on VaR (Value at Risk) theory, this kind of methods respectively produces margins of positions with different directions and then makes a comparison [8]. Finally, the higher one is picked out as the final margin. The aim of such models is to prevent the potential maximum risk exposure substantially, when the original arbitrage is split due to offset of the position with lower margin. Secondly, the models depend on multiple scenarios analysis, such as TIMS (Theoretical Intermarket Margin System) presented by OCC (Option clearing Company) [9], SPAN (Standard Portfolio Analysis of Risk) framework created by CME Group (Chicago Mercantile Exchange Group) [10] and so on. TIMS, born in 1986, could make a sampling of twenty different price scenarios of an arbitrage, which mainly takes advantage of univariate risk management. At last, the maximum loss scene is selected for the purpose of ultimate margin deducing. As for SPAN system, initialized by CME group in 1988, possesses a significant share of the global market. There are over fifty agents including exchanges, clearing houses and supervision organizations, etc. regarding SPAN as their official standard of margin performance [11]. SPAN computes the risk level of sixteen scenarios of a portfolio, derived from different PSR (Price Scan Rate) along with VSR (Volatility Scan Rate). After the fundamental risk resulted from the worst scene is settled down, the supplement of intra-commodity, the discount of inter-commodity, the addition of delivery month and SOM (Short Option Minimum) parameters will be all deployed step by step to make a precise correction. Then, the SPAN total margin is finally achieved. Thirdly, this kind of models are inferred from statistical methods, like Prisma pattern designed by Eurex [12] and STANS (System for Theoretical Analysis and Numerical Simulations) framework proposed by OCC in 2006 [13], etc. Prisma, on the basis of HVaR (Historical VaR), constructs many extreme price scan situations, which can accurately evaluate the potential risk of an arbitrage. Additionally, in comparison with TIMS, Prisma proceeds cross-validation and elimination to the extreme historical records, in order for a precise and robust risk assessment. However, Prisma can be only applied in the area of derivatives currently, owing to the huge computation. As a multi-variant risk evaluation model, STAN manipulates sufficient offset, considering relationships not only within the same product but also among different products. Nevertheless, due to large scale Monte-Carlo simulations creating over 10000 theoretical profit and loss scenarios, it is difficult to support such high complexity and recur a certain scenario. Consequently, STAN cannot be generally applied. Totally speaking, the orientation of maximum risk situation is the foundation for both models based on linear algorithm and multiple scenario analysis. Although the risk is fully covered, the riskless state of the arbitrage is ignored all the time. Moreover, there also exists some underlying issues, such as over-investment of risk management of exchanges, as well as the restriction of cash flow of clients resulted from the excessive margin. As to the models derived from statistical methods, though an efficient offset can be provided, the tremendous computation and non-recurrence make it unfit for generation.

Recently, machine learning models, especially deep learning algorithms, perform remarkably well on dynamic curve fitting [14]–[16]. Therefore, many approaches have been used to explore the risk management of derivatives. In particular, some studies assess the underlying risk by anticipating the financial index. For instance, with the purpose of potential risk estimation of currency future market, DTW-WT (Hybrid Dynamic Time Warping -Wavelet Transform) model was proposed by Bagheri et al. This approach was used to capture the changing motif of FX time series, which was efficient in future price forecasting [17]. Later, based on ADSS (Auto-Adaptive Decision Support System) algorithm, Chiang et al performed a simulation on the yield return in stock index future market, which can effectively lock the risk at the client level [18]. In 2017, in order to control the price risk of stock market, Zhong et al tried to predict daily stock price. They developed an algorithm with the combination of PCA (Principle Component Analysis) and ANN (Artificial Neural Networks) [19]. More recently, Kim et al presented a hybrid algorithm named GEW-LSTM. It adopted LSTM (Long Short-Term Memory) with inputs generated from three kinds of volatility predictive model. The benchmark results on KOSPI 200 index proved that this model well outperformed other approaches in stock price volatility anticipation [20].

While, the other researches have paid attention to the construction of EWS (Early Warning System), which is used for financial crisis forecasting. For example, Sevim et al presented three different EWS based on decision trees, LR (Logistic Regression) and ANN, respectively. Moreover, they also made a comparison on the Turkey economy, where ANN yielded the best in the early warning of monetary crisis [21]. Then, Dabrowski et al proposed the EWS constituted with dynamic Bayesian network. It can make a significantly precise perdiction of bank's system risk with respect to LR [22]. Later, Frische et al implemented the EWS to forecast the national economic recession. This system used BRT (Boosted Regression Trees) algorithm, along with datasets such as short-term interest rate and stock price [23]. Recently, an ensemble model was presented by Chaizis et al, as a means of predicting the stock market crisis episode. The approach was based on multi-scale data involving stock price, bond price, currency rate and interbank offered rate, etc. It employed LR as the final model, which absorbed results from a series of machine learning methods [24]. As we mentioned before, machine learning algorithms have been widely used in the financial risk management. However, these researches merely concentrates on the maximum risk forecasting, the riskless state has always been disregarded.

In this paper, we present a novel algorithm named PRAM to accurately predict the riskless state of inter- and intra-commodity future arbitrage. PRAM is based on machine learning techniques, as well as multi-scale data. These datasets can make a supplement with each other and effectively improve the prediction accuracy. Unlike the traditional algorithms, PRAM means that for the first time the arbitrage risk management is investigated from the view of minimum risk. Hence, a mutual supplement can be made to the current risk management system, leading to a more reasonable discount of margin. The benchmark results on sixth database of DCE demonstrate that our model remarkably outperforms the other popular algorithms. Besides, we discover that the features of different arbitrage types used by PRAM are widely different. In addition, some trade situations are found, including delivery and near-delivery months, which can significantly impact the accuracy of PRAM. Moreover, we further propose personalized models, referring to the varieties involved in intra-commodity arbitrage, which can improve the prediction accuracy in depth.

II. METHODS

A. THE DEFINITION OF RISKLESS STATE

According to the arbitrage orders from DCE, the two-contract arbitrage here was constructed with longing one contract with low price and shorting another with high price. Therefore, this two-contract arbitrage equals to shorting a contract with the core of spread. Besides, contracts with low and high price are also named as low and high leg, respectively. Then, based on whether they belong to the same product or not, we placed them into intra- or inter-commodity type.

With respect to contract in short, if the maximum price on date $T+1$ is less than the clear price on date T, there will not exist credit risk from clients. On the other side, there is no need of margin for exchanges [3]. This theory is projected on the two-contract arbitrage we established above, inferring these following definitions. First, the possible maximum spread of arbitrage i on date $T+1$ was specified as TMS (Theoretical Maximum Spread) as follows

$$\delta_i^{T+1} = \max(\beta_{i,h}^{T+1}) - \min(\beta_{i,l}^{T+1}), \tag{1}$$

where $\max(\beta_{i,h}^{T+1})$ is the highest price of high leg and $\min(\beta_{i,l}^{T+1})$ is the lowest price of low leg. TMS means the upper limitation of spread of arbitrage i on date $T+1$. Second, the clear spread of arbitrage i on date T was described as follows,

$$\varepsilon_i^T = \alpha_{i,h}^T - \alpha_{i,l}^T \tag{2}$$

where $\alpha_{i,h}^T$, $\alpha_{i,l}^T$ represent the clear price of high leg and low leg on date T, respectively. Third, we defined the judging criteria of RTD (Riskless Trade Date) as follows,

$$\varepsilon_i^T \geq \delta_i^{T+1}. \tag{3}$$

If the inequality is true, date $T+1$ of arbitrage i will be regarded as RTD, which means this arbitrage on date T is in riskless state. Here, δ_i^{T+1} responses to the maximum price on date $T+1$ of the single short contract, and the same with ε_i^T to clear price on date T.

B. DATASET AND MODLE

1) SAMPLE COLLECTION

At first, we extracted arbitrage quotation, including both inter- and intra-commodity arbitrage type, from DCE sixth database, ranging from 2007.6.19 to 2017.5.10. Then, we took each trade date of each arbitrage as a sample and calculated its clear spread and TMS. Finally, with the judging criteria of RTD, we labeled the sample as positive if it is in riskless state, and on the opposite side we labeled it as negative. In total, we obtained 120015 and 34751 samples for intra- and inter-commodity arbitrage, where there exists 10552 and 4894 positive samples, respectively.

2) FEATURE SELECTION

Taking samples we collected above into account, we absorbed features from four different classes within DCE sixth database in TABLE 1, including contract quotations, contract parameters, arbitrage quotations and generated features. Because of two-contract arbitrage, the features of high leg and low leg were both extracted in terms of contract quotations and parameters. As for the three generated features, TMS of sample here comes from date T but not date $T+1$, the same with CLEAR_SPREAD. And DIFF_DIFF is the difference between clear spread and TMS on date *T-1* and date *T*, respectively. At last, every feature above was normalized in z-score method as follows

$$\tilde{f}_i = \frac{f_i - \bar{\chi}_i}{\sigma_i}, \tag{4}$$

where $\bar{\chi}_i$ and σ_i represents the average and standard deviation of ith feature, separately. Totally, we obtained 141 different features of each sample.

On the basis of greedy algorithm, we here proposed a new feature selection model. Firstly, considering SNR (Signal to Noise Ratio) approach [25], we initialized the feature set as follows

$$SNR_i = \frac{\left|\bar{\chi}_p^i - \bar{\chi}_n^i\right|}{\sigma_p^i + \sigma_n^i}, \tag{5}$$

where $\bar{\chi}_p^i$ and $\bar{\chi}_n^i$ are the mean value of positive and negative samples of the ith feature, respectively. σ_p^i and σ_n^i are the corresponding standard deviations. Given this, we chose feature with the maximum SNR for initialization. Secondly, we put the other features in turn into the set. Hence, the mean F1 of each feature combination was computed. The process engaged equation (6) and 10-fold cross-validation with random forest algorithm [26]. Then, the one with maximum mean F1, namely $\overline{F1}_{\max}^2$, was selected as the second feature. Thirdly, we repeated the second step to update the set by adding one feature each time. Meanwhile, the maximum mean F1 vector $\left[\overline{F1}_{\max}^2, \overline{F1}_{\max}^3, \cdots, \overline{F1}_{\max}^i, \cdots, \overline{F1}_{\max}^{141}\right]$ was also obtained. Finally, if the value in the maximum mean F1 vector reached the top, we picked up the corresponding features set as the ultimate result.

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FN}, \\ F1 &= \frac{2 \times precision \times recall}{precision + recall} \end{aligned} \tag{6}$$

Here, TP, FP and FN is the amount of true positive, false positive and false negative samples, respectively.

3) PRAM CONSTRUCTION

Integrated with the feature selection above, we proposed PRAM model, used to predict whether arbitrage is in the riskless state or not. The flow chart of PRAM was displayed

TABLE 1. Feature list.

Contract Quotations	Contract Parameters		Arbitrage Quotations	Generated Features
OPEN_PRICE	LAST_CLEAR_PRICE	RISE_LIMIT_RATE	RISE_LIMIT	DIFF_DIFF
CLOSE_PRICE	SPEC_NEW_BUY_RATE	FALL_LIMIT_RATE	FALL_LIMIT	TMS
LOW_PRICE	SPEC_NEW_SELL_RATE	RISE_RANGE	BID_QTY	CLEAR_SPREAD
HIGH_PRICE	HEDGE_NEW_BUY_RATE	FALL_RANGE	ASK_QTY	
TURNOVER	HEDGE_NEW_SELL_RATE	RISE_DIFF		
MATCH_TOT_QTY	SPEC_BUY_RATE	FALL_DIFF		
OPEN_INTEREST	SPEC_SELL_RATE	ALL_SELF_SELL_POSI_QUOTA		
CLEAR_PRICE	HEDGE_BUY_RATE	ALL_AGENT_SELL_POSI_QUOTA		
LIFE_LOW	HEDGE_SELL_RATE	ALL_TOT_SELL_POSI_QUOTA		
LIFE_HIGH	SPEC_NEW_BUY	SELF_TOT_SELL_POSI_QUOTA		
LAST_MATCH_QTY	SPEC_NEW_SELL	AGENT_TOT_SELL_POSI_QUOTA		
LAST_CLEAR	HEDGE_NEW_BUY	CLIENT_SELL_POSI_QUOTA		
LAST_CLOSE	HEDGE_NEW_SELL	ALL_SELF_BUY_POSI_QUOTA		
INIT_OPEN_INTEREST	SPEC_BUY	ALL_AGENT_BUY_POSI_QUOTA		
BID_PRICE	SPEC_SELL	ALL_TOT_BUY_POSI_QUOTA		
BID_QTY	HEDGE_BUY	SELF_TOT_BUY_POSI_QUOTA		
BID_IMPLY_QTY	HEDGE_SELL	AGENT_TOT_BUY_POSI_QUOTA		
ASK_PRICE	OPEN_FEE	CLIENT_BUY_POSI_QUOTA		
ASK_QTY	OFFSET_FEE	BEFORE_DELIVERY_POS		
ASK_IMPLY_QTY	SHORT_OPEN_FEE	MONTH_DAY_NO		
AVG_PRICE	SHORT_OFFSET_FEE	SELF_TOT_BUY_POSI_QUOTA		
	EXEC_FEE	AGENT_TOT_BUY_POSI_QUOTA		
	PERFORM_FEE	CLIENT_BUY_POSI_QUOTA		
	DELIVERY_FEE	BEFORE_DELIVERY_POS		
	RISE_LIMIT	MONTH_DAY_NO		
	FALL_LIMIT			

TABLE 2. The DNN classifier of PRAM.

Layer	Nodes	Dropout	Activation
Input	Intra/Inter	NULL	NULL
1	512	0.5	Tanh
2	128	0.3	ReLU
3	256	0.4	Sigmoid
4	128	0.3	ReLU
5	256	0.4	Tanh
6	128	0.3	ReLU
7	256	0.4	Sigmoid
8	128	0.3	ReLU
Output	1	NULL	Sigmoid

in FIGURE 1. From FIGURE 1, we can see that a classifier was developed with DNN (Deep Neural Network) algorithm [27] and its details were described in TABLE 2. Here, Layer in TABLE 2 represents the index of each layer in the DNN classifier. Nodes means the amount of units in each layer. We here employed Inter and Intra to represent the different unit number of input layer, considering features from inter- and intra-commodity arbitrage samples, respectively. To prevent PRAM from overfitting in the training process, we hired dropout approach [28] and recorded the coefficients in the Dropout column. Activation column preserves the activation function we used for each layer. As to the practical programming, we adopted Keras, based on TensorFlow with v1.13.0, as well as the gradient descent depending on Adam approach. As to the problem of imbalanced sample set, we solved it by taking advantage of over sampling algorithm realized by R package of ROSE (Random Over Sampling Examples) [29], [30].

III. RESULT

A. BENCHMARK RESULTS

To validate the performance of PRAM, we applied it to the intra- and inter-commodity arbitrage samples. Alternatively, we also created two simple methods derived from PRAM, named as PRAM-ORI and PRAM-ALL-ORI. In PRAM-ORI, a sample is predicted to be riskless

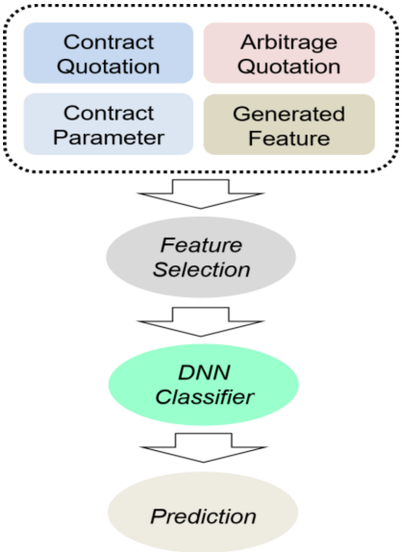

FIGURE 1. The flow chart of PRAM.

without using the DNN classifier, but only relying on the random forest algorithm. As for PRAM-ALL-ORI, it is even more primitive that we just made the prediction by random forest model with the original 141 features. Furthermore, our PRAM approach was compared with two popular methods, GEW-LSTM and an ensemble model proposed by Chazis et al. GEW-LSTM takes advantage of LSTM algorithm for financial crisis prediction, which regards results produced from three volatility estimation models as inputs, involving GARCH (Generalized Auto-Regressive Conditional Heteroscedasticity), EGARCH (Exponential GARCH) and EWMA (Exponential Weighted Moving Average) [20]. As a EWS, Chazis's ensemble model adopts multi-scale data including stock price, bond price, currency rate and interbank offered rate, etc. Furthermore, it implements LR as the final classifier, gathering outputs generated from six algorithms, including CART (Classification And Regression Tree), random forest, SVM (Support Vector Machine), extreme gradient tree, NN (Neural Network) and DNN [24]. TABLES 3 and 4 kept the performance of different models depicted above, where all the metrics were computed as the average with 10-fold cross-validation.

From results shown in TABLES 3 and 4, we could firstly see that our PRAM approach performed best in terms of all metrics for both inter- and intra-commodity arbitrage, which fully demonstrates the efficiency of PRAM.

Secondly, the phenomenon, where PRAM outperformed PRAM-ORI, implied that the DNN classifier we designed is significantly effective. Similarly, we noticed that the feature selection method is also remarkably valid, considering the comparison between PRAM-ORI and PRAM-ALL-ORI.

Thirdly, PRAM achieved better performance than both Chazis's ensemble model and GEW-LSTM. And we here analyzed the possible reasons. Although Chazis's ensemble model digested six sub models with LR, it conducted no feature selection at all. This hence gave rise to the defect that a large amount of noise and features, unconcerned with prediction, were imported. Besides, except for several dominant two-contract arbitrages, others in general were pushed to the market for trade less than 20 days. Therefore, they were hard to support GEW-LSTM, requiring at least 22 trade days for each arbitrage.

TABLE 3. Benchmark results of different algorithms for intra-commodity arbitrage.

Algorithm	Precision	Recall	F1
PRAM	0.6987	0.737	0.7158
PRAM-ORI	0.5029	0.6011	0.5331
PRAM-ALL-ORI	0.2774	0.3399	0.3101
Chazis	0.6102	0.6447	0.635
GEW-LSTM	0.5297	0.5861	0.5643

TABLE 4. Benchmark results of different algorithms for intra-commodity arbitrage.

Algorithm	Precision	Recall	F1
PRAM	0.6506	0.6562	0.6534
PRAM-ORI	0.4873	0.5152	0.5062
PRAM-ALL-ORI	0.198	0.3014	0.263
Chazis	0.5951	0.6228	0.609
GEW-LSTM	0.5001	0.529	0.5277

B. FEATURE SETS ANALYSIS

To validate whether features of different arbitrage types tend to be in common, a permutation test here was given with hypergeometric distribution (P-value = 0.2132). Hence, it is obvious that feature sets belonging to different arbitrage categories are mutually independent.

In addition, features of different arbitrage types were kept in TABLE 5, where the ones initialized with "L" and "H" were subject to the low and high leg contracts, respectively. From TABLE 5, we can see that all three generated features exist in both intra- and inter-commodity arbitrage sets. It implies that they are useful for the riskless state prediction with no limitation of arbitrage type.

C. THE IMPACT ON PRAM FROM DIFFERENT TRADE SITUATIONS

In the commodity future market, if the contract is in different periods, such as OM (Ordinary Months) and DNDM (Delivery and Near Delivery Months), the trade situations will be diverse [31], [32]. We here characterize three primary causes. Firstly, as long as the contract steps into near-delivery month, speculators will generally close their position rather than delivering the real commodity. Therefore, compared with OM, the number of participant gradually decreases, as well as the shrinkage of open interest and turnover. Secondly, although the vitality of market goes down in DNDM, fluctuations of quotation tend to become more complicated and unpredictable, owing to several uncertain and short-lived

TABLE 5. Feature sets for different arbitrage types.

Intra-Commodity Arbitrage		Inter-Commodity Arbitrage	
H_ASK_PRICE	L_SPEC_SELL_RATE	L_OPEN_INTEREST	H_ALL_SELF_SELL_POSI_QUOTA
L_CLIENT_SELL_POSI_QUOTA	L_ALL_TOT_SELL_POSI_QUOTA	H_SELF_TOT_BUY_POSI_QUOTA	CLEAR_SPREAD
L_BID_PRICE	L_OPEN_FEE	H_SPEC_NEW_SELL_RATE	H_HEDGE_BUY_RATE
L_AVG_PRICE	H_LOW_PRICE	L_HEDGE_BUY_RATE	L_HIGH_PRICE
L_MATCH_TOT_QTY	L_CLIENT_BUY_POSI_QUOTA	L_RISE_DIFF	H_SPEC_SELL_RATE
L_FALL_LIMIT	L_ALL_SELF_BUY_POSI_QUOTA	LOW_SPEC_BUY	L_SPEC_NEW_SELL
H_AVG_PRICE	L_FALL_DIFF	L_SPEC_BUY_RATE	L_AVG_PRICE
L_INIT_OPEN_INTEREST	H_BID_IMPLY_QTY	DIFF_DIFF	L_ALL_SELF_SELL_POSI_QUOTA
CLEAR_SPREAD	H_ALL_SELF_BUY_POSI_QUOTA	H_ASK_IMPLY_QTY	L_ALL_AGENT_SELL_POSI_QUOTA
L_FALL_LIMIT_RATE	H_HEDGE_BUY	L_ASK_PRICE	L_FALL_DIFF
L_MONTH_DAY_NO	L_ASK_QTY	H_RISE_LIMIT	RISE_LIMIT
L_EXEC_FEE	FALL_LIMIT	L_MATCH_TOT_QTY	L_LAST_CLEAR_PRICE
DIFF_DIFF	L_DELIVERY_FEE	H_FALL_DIFF	H_HEDGE_NEW_SELL
L_HEDGE_NEW_BUY_RATE	H_BID_PRICE	L_BID_QTY	H_LIFE_LOW
H_ALL_SELF_SELL_POSI_QUOTA	L_SPEC_NEW_SELL	FALL_LIMIT	H_CLEAR_PRICE
H_SPEC_SELL	L_BEFORE_DELIVERY_POS	H_LAST_MATCH_QTY	L_SPEC_NEW_BUY
H_FALL_DIFF	L_AGENT_TOT_BUY_POSI_QUOTA	H_MONTH_DAY_NO	H_ALL_AGENT_SELL_POSI_QUOTA
H_HEDGE_NEW_SELL_RATE	L_ALL_TOT_BUY_POSI_QUOTA	L_CLIENT_SELL_POSI_QUOTA	L_FALL_LIMIT
L_HEDGE_BUY_RATE	TMS	H_SELF_TOT_SELL_POSI_QUOTA	H_SPEC_NEW_SELL
L_LIFE_HIGH	L_LAST_MATCH_QTY	H_SHORT_OFFSET_FEE	L_ASK_QTY
L_LAST_CLOSE	L_LAST_CLEAR	H_HEDGE_SELL	BID_QTY
RISE_LIMIT	L_BID_IMPLY_QTY	H_SPEC_NEW_BUY_RATE	L_ALL_TOT_SELL_POSI_QUOTA
L_RISE_DIFF	L_CLOSE_PRICE	L_BID_PRICE	L_EXEC_FEE
H_SPEC_BUY_RATE	L_LOW_PRICE	H_OPEN_FEE	H_RISE_RANGE
H_RISE_LIMIT_RATE	H_BEFORE_DELIVERY_POS	L_SPEC_NEW_BUY_RATE	H_ALL_SELF_BUY_POSI_QUOTA
L_SHORT_OFFSET_FEE	H_ALL_TOT_SELL_POSI_QUOTA	L_INIT_OPEN_INTEREST	TMS
L_ALL_SELF_SELL_POSI_QUOTA	L_HEDGE_SELL_RATE	H_ASK_QTY	H_ASK_PRICE
L_SPEC_SELL	L_TURNOVER	L_FALL_LIMIT_RATE	L_AGENT_TOT_SELL_POSI_QUOTA

arbitrage chances. Thirdly, if the contract enters into its DNDM, the exchange will bit by bit enhance the margin ratio. This policy slows down the cash flow of clients, in case the event of market corner occurs. For this reason, the normal order of market can be well maintained.

Taking these factors into consideration, we here explored the impact on PRAM from different trade situations. At first, samples were broken down into two parts according to whether the trade date of sample belongs to DNDM or OM. Finally, there are 92130 and 27885 samples in OM and DNDM for intra-commodity arbitrage, respectively. In terms of inter-commodity arbitrage, there exists 30600 and 4145 samples in OM and DNDM, separately. Then, referring to 10-fold cross-validation, we trained different PRAMs, namely OM-PRAM and DNDM-PRAM with samples in OM and DNDM, correspondingly. Finally, results of different arbitrage types were kept in TABLES 6 and 7, respectively.

From TABLES 6 and 7, we noticed that due to the complexity of trade environment of DNDM, it is hard to capture the pattern of spread fluctuation. So it results in the insufficiency of DNDM-PRAM compared with OM. Moreover, we also discovered that OM-PRAM outperformed PRAM, because samples of DNDM were involved with respect to PRAM rather than OM-PRAM. Accordingly, we can deduce that the more DNDM samples are drawn, the more serious impact exists for PRAM.

D. PERSONALIZED PRAMS

For the further promotion of PRAM, we developed personalized models for each sixteen varieties from intra-commodity arbitrage. At first, we partitioned samples into sixteen groups, as $S_i, i \in \{1, 2, 3, \cdots, 16\}$, where the sample ratio of each variety was displayed in FIGURE 2. Then, based on leave one out method, we initialized the basic model of each variety with the complementary set of S_i. Finally, the fine tuning process [33] was applied with S_i so that the personalized model $PRAM_i$ was achieved. The average results of $PRAM_i$ based on 10-fold cross-validation were kept in TABLE 8.

From TABLE 8, we can see that eight $PRAM_i$ in front performed better than PRAM while the others didn't. In so far as this phenomenon, it is possible that the sample ratio for the last eight $PRAM_i$ cannot satisfy the requirement of fine

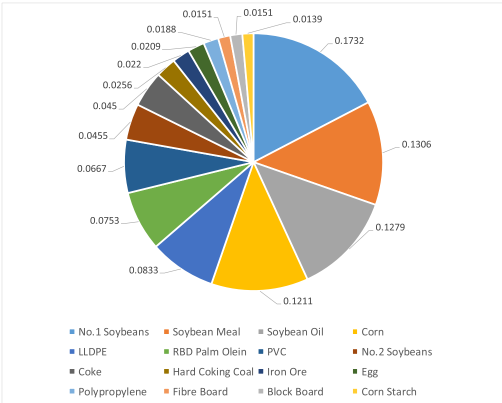

FIGURE 2. The sample ratio of each variety.

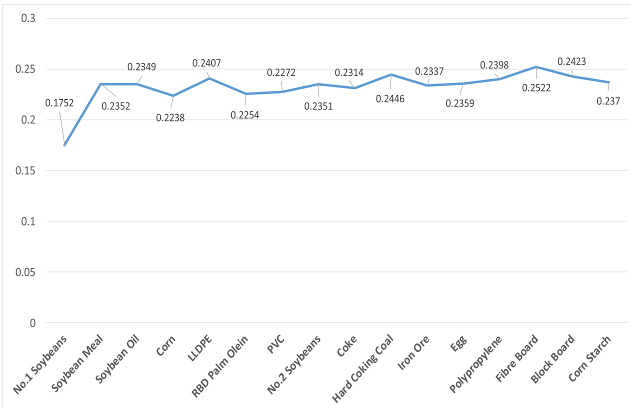

FIGURE 3. The sample ratio of DNDM in each variety.

TABLE 6. Results of PRAM in different trade situations of inter-commodity arbitrage.

Algorithm	Precision	Recall	F1
OM-PRAM	0.6569	0.681	0.675
DNDM-PRAM	0.5531	0.5975	0.588
PRAM	0.6506	0.6562	0.6534

TABLE 7. Results of PRAM in different trade situations of inter-commodity arbitrage.

Algorithm	Precision	Recall	F1
OM-PRAM	0.7139	0.7416	0.7321
DNDM-PRAM	0.5829	0.6262	0.6087
PRAM	0.6987	0.737	0.7158

tuning process. The models thus tend to be impersonal for these varieties [34], [35].

Besides, From TABLE 8, we can also observe that although some varieties possessed a high sample ratio, their personalized models didn't perform as well as we expected, including LLDPE, hard coking coal, fibre board and block board. To uncover it, we counted the DNDM samples in every S_i,

TABLE 8. The results of $PRAM_i$.

Variety	Precision	Recall	F1
No.1 Soybeans	0.8109	0.8461	0.8231
Soybean Meal	0.7945	0.812	0.805
Soybean Oil	0.8009	0.8107	0.8026
Corn	0.7914	0.8133	0.7951
LLDPE	0.7491	0.7511	0.75
RBD Palm Olein	0.7577	0.7742	0.7645
PVC	0.7552	0.7587	0.7564
No.2 Soybeans	0.7079	0.7319	0.7238
Coke	0.7012	0.7128	0.7046
Hard Coking Coal	0.582	0.6254	0.606
Iron Ore	0.6086	0.6311	0.6249
Egg	0.602	0.6234	0.6188
Polypropylene	0.5333	0.5529	0.5394
Fibre Board	0.4827	0.502	0.4961
Block Board	0.4878	0.5295	0.5037
Corn Starch	0.4916	0.5386	0.514

and the results were showed in FIGURE 3. From FIGURE 3, we can clearly see that the DNDM sample ratio in each variety we listed above is obviously higher than the others. This therefore can be sufficiently responsible for the unexpected performance.

IV. DISCUSSION AND CONCLUSION

In this paper, a novel computational model, namely PRAM, was created for the riskless state prediction of commodity future arbitrages. Compared with the existing risk management mechanisms and researches, PRAM starts from the view of minimum risk. It can make a powerful supplement for the available risk assessment models in some exchanges. Hence, a further discount will be offered for clients, which can deeply improve their market competitiveness. Furthermore, as we designed the PRAM, it is the first time to describe the riskless state quantitatively and systematically with the innovation of TMS and RTD.

The benchmark results on real data from DCE have well confirmed the effectiveness of PRAM. Additionally, it has been fully proved that the DNN classifier can significantly improve the accuracy of prediction. As to the feature selection approach, we have also demonstrated its effectiveness in extracting useful information from multi-scale data. In terms of the features from different arbitrage types, we conclude that features of each arbitrage tend to be independent. While, the generated features are perfectly fit for PRAM without the limitation of arbitrage type. With respect to the impact of trade situations, we can see that DNDM impacts PRAM seriously. For the purpose of further improvement of prediction accuracy, personalized PRAMs were built. And the results of experiments indicate that the method takes obvious effect merely on some specific varieties, which possessed both adequate sample size and low DNDM disturbance.

In spite of the good performance of PRAM, we noticed that there still exists room to improve this approach. Firstly, before we conducted the feature selection, the weights of these multi-view data were regarded as equal for default. In future work, we will present more effective methods to make this integration. Secondly, our PRAM merely focused on two-contract arbitrages with shorting the spread, while there are a lot of portfolios with more than two contracts in practice. Hence, if such factor is taken into consideration, the generalization of our PRAM is trusted to be improved. Last but not least, although PRAM can make an accurate prediction, it still retains a bias. Therefore, in the actual settlement, we need to formulate a more strict constitution, referring to both PRAM and the current risk management models. It thus can not only guarantee the risk to be fully covered, but also provide clients a more plausible discount of margin.

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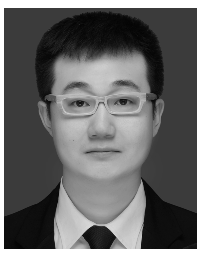

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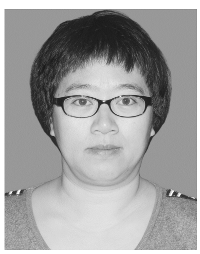

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