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A Hybrid Model Based on Grey Wolf Optimizer and Lagrangian Support Vector Regression for European Natural Gas Consumption Forecasting

Kai Tang [a*], Jiahui Li [a], MengTing Yang [a], Xinyi Yang [a], Junxiong Feng [a] and Suhang Liu [a]

[a] *School of Science, Southwest University of Science and Technology, Mianyang 621010, China.*

Authors' contributions

This work was carried out in collaboration among all authors. Author KT contributed to conceptualization, methodology, data curation and wrote original draft. Authors JF and XY wrote, reviewed and edited the manuscript. Author MY wrote, reviewed the manuscript. Authors JF and SL managed the data analysis. All authors read and approved the final manuscript.

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ABSTRACT

Natural gas plays an important role in industry as a clean energy, with the intensification of the Russia-Ukraine war, there is a large-scale energy shortage in Europe, and the natural gas supply in Europe has a natural gas crisis due to the cut-off of the Nord Stream No.1 pipeline. Therefore, it is necessary to accurately predict the consumption of natural gas. In order to fulfill this requirement, this paper uses the Lagrangian Support Vector Regression model with $Sorensen$ kernel based on the Nonlinear Auto-Regressive model and Grey Wolf Optimizer for 5-step forecasting of monthly natural gas consumption in all European countries. Under three time lags, comparing the 5-step predict results of GWO-$LSVR$ with SVR, RF, $LightGBM$, $XGBoost$, and MLP, those five models'

**Corresponding author: E-mail: KTang2322@163.com;*

hyperparameters also optimized by GWO, it found that GWO-$LSVR$ has smallest $MAPE$ in almost all cases, and the numerical results of $MAPE$ generated by GWO-$LSVR$ is from 5.844% to 11.622%, the smaller the forecasting step size, the better the effect. Moreover, compares the difference of GWO and WOA, it is found that GWO can obtained better model hyperparameters and smaller $MAPE$ results. To sum up, the proposed GWO-$LSVR$ model has strong generalization performance and robustness, and is a reliable natural gas consumption prediction model.

Keywords: Lagrangian support vector regression; grey wolf optimizer; nonlinear auto-regressive; kernel learning; natural gas consumption in Europe.

1. INTRODUCTION

As a clean and efficient low-carbon energy, natural gas is a very important part of the global energy structure, accounting for about 25% of European energy consumption. Coupled with the intensification of the situation in Russia and Ukraine, there is a serious shortage of natural gas supply in Europe. Therefore, it is necessary to accurately predict the consumption of natural gas [1].

Natural gas consumption forecasting has always been a hot issue. Scholars at home and abroad mostly use the following five types of models for the prediction of NGC, time series models [2,3], grey system models [4,5,6], machine learning models [7,8,9], neural networks models [8,10] and other models.

Due to its superior performance, support vector regression models are also used in the prediction of natural gas consumption. But the performance of SVR-based models are mostly based on the choice of kernel function. Mangasarian et al. [11] proposed the Lagrangian support vector machines based on the Support vector machine used for classification problem, Balasundaram et al. [12] modified the classification model into a regression model in 2010 for regression prediction tasks, and give its iterative solution algorithm. The kernel learning method developed by SVR is also widely used in energy forecasting, and different kernels can be applied in different forecasting fields. This paper uses the $LSVR$ model and selects a $Sorensen$ kernel [13] that has never been used on the model.

In order to transform univariate time series data sets into machine learning supervised learning data sets, the nonlinear auto-regressive (NAR) [14] model are used to achieve this goal. The reconstructed data set is used to train the $LSVR$ model and for multi-step forecasting. The initial parameters of the model often cannot achieve good results, so this paper uses Grey Wolf Optimizer (GWO) to optimize the model hyperparameters. Deng et al. [15] applied $NAR + LSSVR + WOA$ in the natural gas load forecast in Chengdu, China. Zhang et al. [16] applied $NAR+XGBoost+SSA$ in the natural gas consumption in Netherlands and UK. Their research demonstrates that such hybrid models achieve good predictive performance. In this paper, a new combined model NAR+$LSVR$+GWO is proposed and applied to energy consumption forecast for the first time.

2. DESIGN OF THE FORECASTING MODEL

In this section, the detailed mathematical model of the $LSVR$ (Lagrangian Support Vector Regression) with $Sorensen$ kernel and the GWO (Grey Wolf Optimizer) used in this paper will be presented in **Section 2.1** and **Section 2.2,** respectively. And the complete multi-step forecasting model based on NAR (Nonlinear Auto-Regressive) model as out-of-sample holdout validation will be shown in **Section 2.3**.

2.1 Lagrangian Support Vector Regression with $Sorensen$ kernel

The standard SVR formulation is a constrained, quadratic optimization problem, written in matrix form is as follows:

$$\min \frac{1}{2} w^t w + v(e^t \xi + e^t \xi^*)$$
$$s.t. \begin{cases} y - Aw - be \le \varepsilon e + \xi \\ Aw + be - y \le \varepsilon e + \xi^* \end{cases} \quad (1)$$

where $\xi_i, \xi_i^* \geq 0 \; for \; i = 1, 2, \ldots, m$, ξ and ξ^* are the slack variables, t represents the transpose of the matrix, matrix $A \in R^{m \times n}$, $LSVR$ has made two changes on the basis of SVR:

(1) Change ξ and ξ^* in 1-norm to be the square of 2-norm, which makes make it unnecessary for the slack variable to be greater than 0.
(2) Add b^2 to $w^t w$ in **Eq(1)**.

Thus the $LSVR$ can be formulated as the following form:

$$\min \frac{1}{2}(w^t w + b^2) + \frac{v}{2}\sum_{i=1}^{m}(\xi_i^2 + \xi_i^{*2}) \quad (2)$$
$$s.t. \begin{cases} y_i - A_i w - b \leq \varepsilon + \xi_i \\ A_i w + b - y_i \leq \varepsilon + \xi_i^* \end{cases}$$

where ε and v are the input parameters.

To solve the convex quadratic problem above, introducing two Lagrange multipliers $u_1 = (u_{11},\ u_{12}, \dots, u_{1m})^t$ and $u_2 = (u_{21},\ u_{22}, \dots, u_{2m})^t$, the Lagrangian Function L can be obtained as follows:

$$L = \frac{1}{2}(w^t w + b^2) + \frac{v}{2}\sum_{i=1}^{m}(\xi_i^2 + \xi_i^{*2}) + \sum_{i=1}^{m} u_{1i}(y_i - A_i w - b - \varepsilon - \xi_i) + \sum_{i=1}^{m} u_{2i}(A_i w + b - y_i - \varepsilon - \xi_i^*) \quad (3)$$

###

The optimality condition is that the partial derivative of L with respect to the original variable is 0, we can obtained the solution of **Eq(3)**:

$$w = A^t(u_1 - u_2) and\ b = e^t(u_1 - u_2) \quad (4)$$

and the dual problem can be written as the minimization problem:

$$\min \frac{1}{2}[(u_1 - u_2)^t(A^t A + ee^t)(u_1 - u_2)] + \frac{1}{2v}(u_1^t u_1 + u_2^t u_2) - y^t(u_1 - u_2) + \varepsilon e^t(u_1 + u_2) \quad (5)$$

The linear $LSVR$ is the method to output a approximate function $f(\cdot)$, based on the **Eq(4),** the linear regression estimation function is given as:

$$f(x) = [x \quad 1]\begin{bmatrix} A^t \\ e^t \end{bmatrix}(u_1 - u_2) \quad (6)$$

Define an augmented matrix $D = [A \quad e]$, the **Eq(5)** can be equally expressed as:

$$\min \frac{1}{2}[u_1^t \quad u_2^t] M \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} - p^t \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (7)$$

Where

$$M = \begin{bmatrix} \frac{1}{v} + DD^t & -DD^t \\ -DD^t & \frac{1}{v} + DD^t \end{bmatrix} \quad (8)$$

and

$$p = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} y - \varepsilon e \\ -y - \varepsilon e \end{bmatrix} \quad (9)$$

The linear $LSVR$ in **Eq(7)** can be extend to nonlinear model with kernel matrix K. In this paper, we used the Sorensen kernel which expressed as the following form:

$$K(u, v) = \frac{2u \cdot v}{\|u\|_2^2 + \|v\|_2^2} \quad (10)$$

where $u \cdot v$ is a inner product of the two vectors.

Replacing DD^t by $K = K(D, D^t)$ in **Eq(7)**, for any $x \in R^n$, the kernel regression estimation function $f(\cdot)$ is obtained to be of the following form:

$$f(x) = K([x^t \quad 1], D^t)(u_1 - u_2) \quad (11)$$

2.2 Grey Wolf Optimizer

The GWO algorithm is inspired the unique hunting and hierarchy behavior of the grey wolves. Grey wolves have a very strict social dominant hierarchy, in order to mathematically model the hierarchy in GWO, the best solution is α, the second and the third best solutions are β and δ, and the rest of the candidate solutions called ω. The hunting behavior is divided into two stages: Encircling and hunting for prey. The specific mathematical modeling steps for the two stages are described below.

Encircling: The Grey wolves encircle the prey first when they hunt. The encircle behavior modeled as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(l) - \vec{X}(l)\right| \quad (12)$$

$$\vec{X}(l+1) = \vec{X}_p(l) - \vec{A} \cdot \vec{D} \quad (13)$$

where l represents the current iteration, $\vec{X}_p$ is the position of the prey, $\vec{X}$ is the position of a grey wolf, and $\vec{A}$ and $\vec{C}$ are coefficient vectors, which calculated as follows:

$$\vec{A} = 2\vec{a}\cdot\vec{r}_1 - \vec{a} \quad (14)$$

$$\vec{C} = 2\cdot\vec{r}_2 \quad (15)$$

where $\vec{r}_1, \vec{r}_2$ are random vectors in $[0, 1]$, the components of $\vec{a}$ are linearly decreased from 2 to 0 during the course of iterations.

Hunting: The hunt of the prey always guided by the α wolf, sometimes, the β and δ wolf participate in the hunt. Assume that the α, β and δ have better knowledge of the prey in the abstract space. Therefore, save the best three solutions obtained so far, and update other search agents' position (including ω) according to the position of the best search agents. This progress is modeled as follows:

$$\vec{X}_{1,2,3} = \vec{X}_{\alpha,\beta,\delta} - \vec{A}_{1,2,3}\cdot\vec{D}_{\alpha,\beta,\delta} \quad (16)$$

$$\vec{X}(l+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (17)$$

where $\vec{X}_{1,2,3}$ represents $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$, $\vec{X}_{\alpha,\beta,\delta}$ represents $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$.

2.3 Complete Multi-step Forecasting Strategy Based on NAR Model

In this section, the NAR model which can transform the original time series to supervised learning dataset will be given in **Section 2.3.1**, the out-of-sample holdout validation scheme presented in **Section 2.3.2**, and the complete algorithm flow will be shown in **Section 2.3.3**.

2.3.1 Nonlinear Auto-Regressive model for multi-step forecasting

A machine learning model is a class of models with high-dimensional inputs, Preferably without using raw time series data as input. The Nonlinear Auto-Regressive (NAR) model is a type of model that reconstructs the original data set based on phase space reconstruction and lag methods. Given a Univariate times series data $U = \{u_1, u_2, u_3, \ldots, u_n\}$, phase space reconstruction of U yields a new dataset Φ in **Eq(18)** for supervised learning, the new dataset (matrix: Φ) can be expressed as follows:

$$\Phi = \begin{pmatrix} u_1 & u_2 & \cdots & u_\tau & u_{\tau+1} \\ u_2 & u_3 & \cdots & u_{\tau+1} & u_{\tau+2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ u_{n-\tau} & u_{n-\tau+1} & \cdots & u_{n-1} & u_n \end{pmatrix} \quad (18)$$

Where τ is the time lag.

2.3.2 out-of-sample holdout validation

In this paper, we use the out-of-sample holdout validation to validate the best hyperparameters of the model. Different with conventional *k-fold* cross-validation in machine learning models, the out-of-sample holdout validation requires only one validation on the validation set, *k-fold* cross-validation will disrupt the order of the data set when performing multiple cross-validation, but there is a certain irrationality in the validation of the time series model. Because it is unreasonable to validate past data with future data.

Split the reconstructed data set according to the ratio of about *8:1:1* according to the sequence, the split datasets are training, validation, and test sets, respectively. First, the default hyperparameters of $LSVR$ are used to train the model on the training set, then GWO will optimize the model hyperparameters on the validation set, and the final multi-step forecasting process will be performed on the test set.

$$MAPE = min\frac{1}{n}\sum\left|\frac{u_j - \hat{u}_j}{u_j}\right| \times 100\% \quad (19)$$

Throughout the process, we use $MAPE$ which presents in **Eq(19)** as an indicator to evaluate model performance. The smaller the $MAPE$, the better the model performance.

2.3.3 Complete multi-step forecasting model

The completed multi-step forecasting model will be shown in this part. The detailed model flow chart is shown in Fig. 1, and the specific model prediction process is divided into the following five steps:

(1) Phase space reconstruction of the original time series U into a supervised learning dataset using NAR model.
(2) Split the dataset in a ratio of about *8:1:1.*
(3) Train the $LSVR$ model on the training set with default hyperparameters.
(4) With the minimum $MAPE$ as the goal, use GWO for optimization on the validation set.
(5) Multi-step prediction on test set.

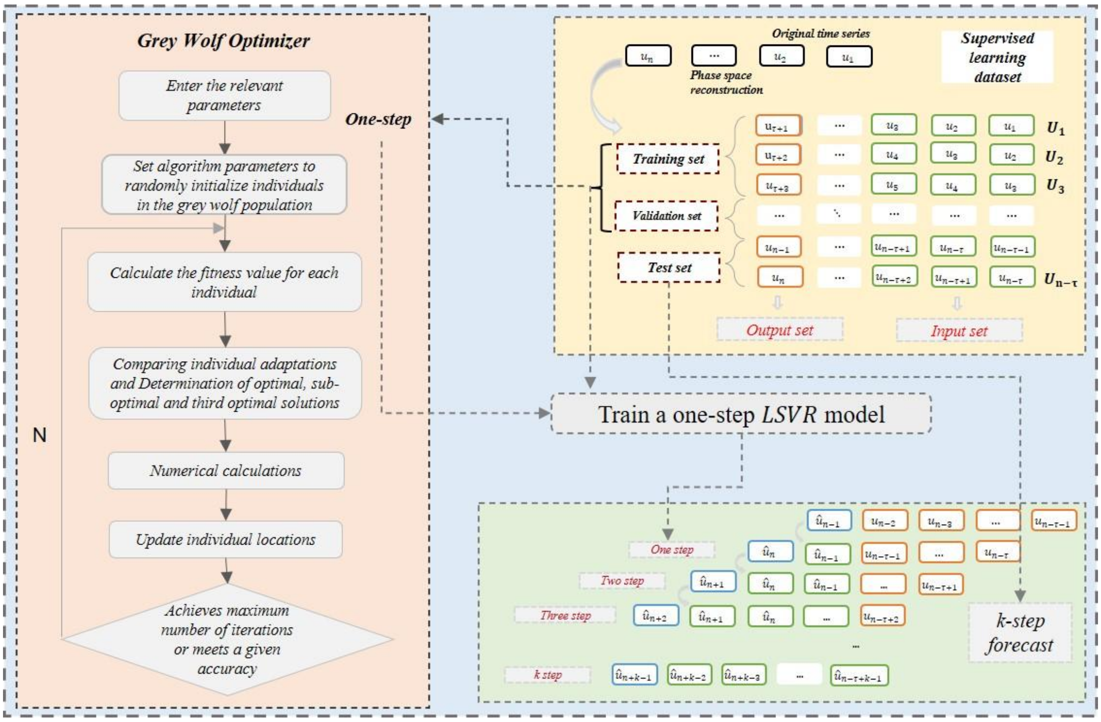

Fig. 1. Complete algorithm flow

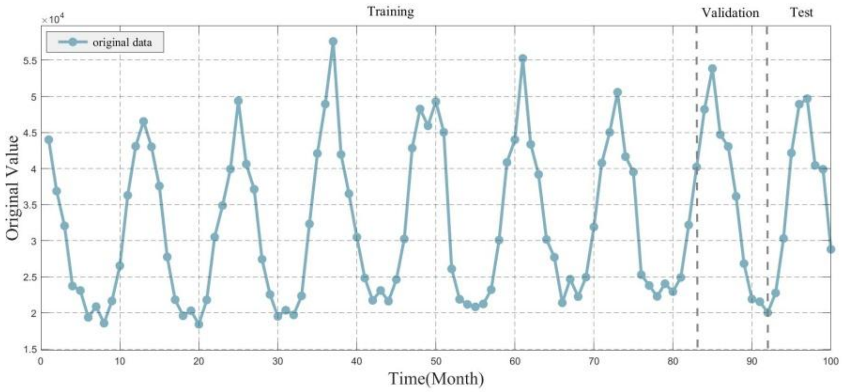

Fig. 2. Original dataset

3. DATASET DESCRIPTION

In this paper, the dataset we used is from the publicly available European natural gas consumption (NGC) dataset in the Eurostat (https://ec.europa.eu/eurostat), which collects monthly NGC data from Jan 2014 to May 2022 for a total of 100 months. Total monthly natural gas consumption for a total of 27 countries within Europe. Use the first eighty points to train the LSVR model, use the next ten points to find the optimal hyperparameters of the model, and use the last ten points for multi-step forecasting. The original dataset is shown in Fig. 2.

4. MULTI-STEP FORECASTING RESULTS AND DISCUSSION

In this section, we compared GWO-$LSVR$ with five machine learning models with high generalization performance at three different time lags. These five models include SVR similar to $LSVR$, tree models Random Forest (RF), Light Gradient Boosting Machine ($LightGBM$), and Extreme Gradient Boosting ($XGBoost$), neural network model Multilayer Perceptron (MLP). The modeling and optimization process of these five models is the same as GWO-$LSVR$. The detailed comparison results are shown in **Section 4.1**.

The impact of different optimization algorithms on the results is discussed in **Section 4.2**.

4.1 Analysis of the Multi-step Forecasting Results

In order to quantitatively analyze the performance of the model, the $MAPE$ of multi-step forecasting is used as the evaluation standard. In all experiments, for a more comprehensive comparison of these models, three different lags (that is, τ=3, τ=4, τ=5) were chosen. In the multi-step forecasting process, we predict 5 steps forward under the three time lags, and calculated the MAPE of each step.

Applying the proposed model to the forecast of monthly NGC for all countries on a European scale. The detailed $MAPE$ results shown in Table 1. It can be plainly seen that from the table, the proposed GWO-$LSVR$ model yields the minimal $MAPE$ almost all cases. The numerical result of its $MAPE$ is from 5.844% to 11.622%. Only when τ=4, GWO-$XGBoost$ has better $MAPE$ than GWO-$LSVR$ at the fourth step. But in this case, the results of the proposed model are better than the other four models. Detailed $MAPE$ results also shown in Fig. 3.

In order to judge the performance of the model more impartially, we also use $RMSE$ as the evaluation metric. Detailed numerical $RMSE$ results shown in . When the forecasting step is 3, the proposed $GWO-LSVR$ slightly worse than other models, but the one-step model in the optimization progress is the best of all models. Out of a total of 15 cases, 11 results are the best, which shows that in general GWO-$LSVR$ can produce good results. Different choices of lag will also lead to different prediction performance of the model. From the results of RMSE, GWO-$LSVR$ may have the possibility of a large lag.

Fig. 4 is when τ=5, the output value of the machine learning model after data reconstruction, a total of 95 points, the comparison between the predicted value of the 6 models and the original value. It can be seen that the effect of SVR is a bit worse, and there is a phenomenon of underfitting in the training set, lead to poor prediction results in the test set. MLP has a certain overfitting phenomenon, over-learning the information of the data set, resulting in very complicated results in the training set. The best performance on the training set is GWO-$XGBoost$, but his prediction results are slightly worse than GWO-$LSVR$.

To sum up, the proposed GWO-$LSVR$ hybrid model can get very good forecasting results whether it is the training set or the test set, and the obtained $MAPE$ is also the best among all comparison models, with strong generalization performance and robust.

Table 1. **$MAPE$(%) of the forecasting models**

	Steps	$LSVR$	SVR	RF	$LightGBM$	$XGBoost$	MLP
	step1	***5.844***	6.966	7.728	7.444	8.913	15.372
	step2	***9.504***	10.193	12.301	10.167	10.637	25.778
$\tau = 3$	***step3***	***9.138***	14.148	11.190	13.419	12.804	45.638
	step4	***11.199***	15.376	11.424	17.868	12.938	56.474
	step5	***11.418***	14.914	15.193	17.450	14.291	64.856
	step1	***6.368***	7.264	7.548	8.286	6.628	10.296
	step2	***8.069***	9.955	9.414	12.249	8.892	14.273
$\tau = 4$	***step3***	***9.632***	12.218	10.142	16.000	10.217	24.397
	step4	11.622	15.345	11.927	19.467	***10.870***	31.967
	step5	***10.932***	14.487	13.120	21.004	11.538	41.182
	step1	***6.114***	28.309	6.823	6.799	7.746	7.746
	step2	***7.874***	28.077	9.863	9.729	9.403	9.403
$\tau = 5$	***step3***	***10.058***	26.557	10.972	11.534	12.287	12.287
	step4	***11.532***	27.004	12.557	12.585	14.067	14.067
	step5	***11.118***	30.294	13.497	11.588	15.163	15.163

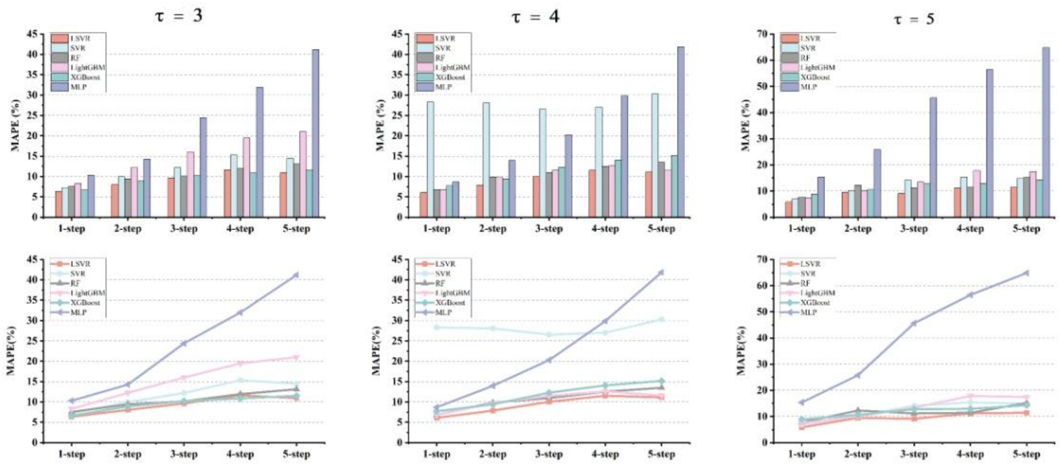

Fig. 3. $MAPE$ **results for a 5-step forecast with 3 time lags**

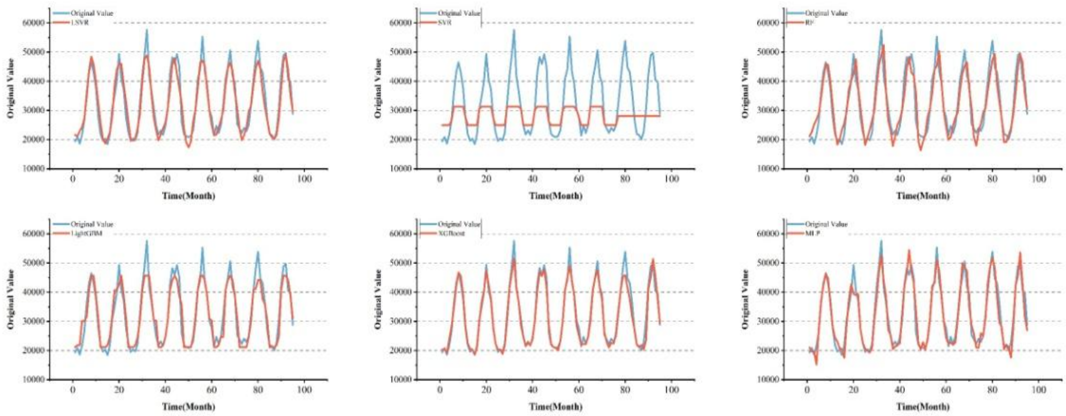

Fig. 4. **Predict data when** τ**=5**

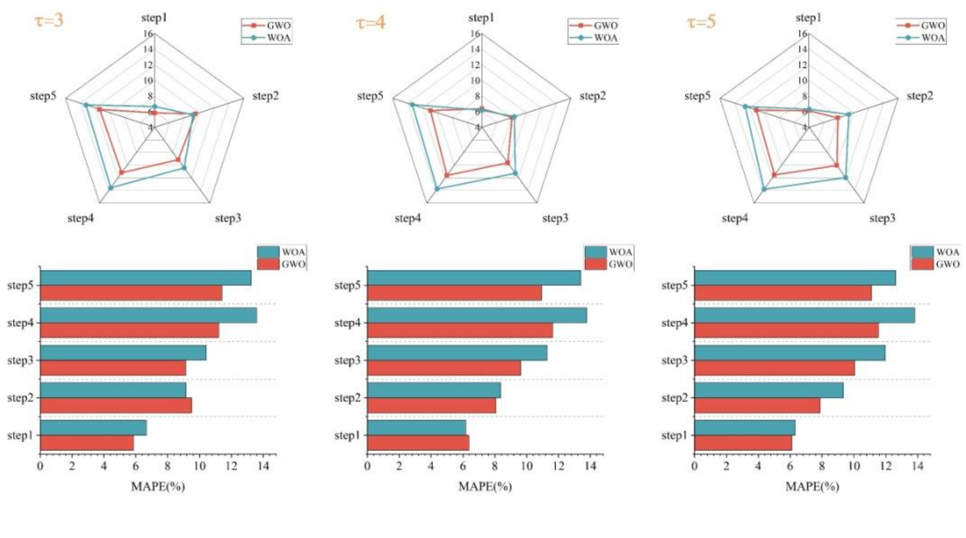

Fig. 5. $MAPE$ **results yield by** $GWO\text{-}LSVR$ **and** $WOA\text{-}LSVR$

Table 2. $RMSE$ of the forecasting models

		$LSVR$	SVR	RF	$LightGBM$	$XGBoost$	MLP
	step1	**2483.907**	12654.75	3372.684	3183.683	3633.375	5543.267
	step2	**4108.882**	13188.42	4469.207	5218.579	5520.993	11130.08
$\tau = 3$	***step3***	5390.395	13733.93	**5034.078**	5533.764	7218.339	18335.6
	step4	5592.956	14570.42	**5167.301**	6024.135	6505.426	24694.7
	step5	5435.476	15697.61	6015.199	6492.311	**3655.083**	29648.08
	step1	**2943.45**	3616.895	3217.157	4108.357	3049.498	4745.642
	step2	**3859.341**	5203.121	4910.678	5119.283	4749.084	7616.78
$\tau = 4$	***step3***	**4688.764**	6606.234	5829.993	6214.313	5324.508	14028.67
	step4	**5254.986**	7330.213	5826.283	6643.063	5503.314	19858.24
	step5	**6064.432**	7300.149	7853.442	7323.668	6185.733	25858.34
	step1	**2751.89**	12357.61	2924.35	2863.813	3589.565	3581.575
	step2	**3740.463**	12841.06	4565.178	4580.491	4263.338	4820.321
$\tau = 5$	***step3***	**4801.581**	13317.49	5488.381	5537.557	5890.575	10466.57
	step4	**5550.836**	14092.92	5715.439	5911.509	6338.934	16892.69
	step5	5988.395	15195.73	**5967.692**	5982.283	7027.027	23313.46

Table 3. $MAPE$ results of GWO-$LSVR$ and WOA-$LSVR$

optimizer	Lag	step1	step2	step3	step4	step5
	$\tau = 3$	***5.844***	9.504	***9.138***	***11.199***	***11.418***
GWO	$\tau = 4$	6.368	***8.069***	***9.631***	***11.622***	***10.932***
	$\tau = 5$	***6.114***	***7.874***	***10.058***	***11.532***	***11.118***
	$\tau = 3$	6.661	***9.157***	10.433	13.576	13.261
WOA	$\tau = 4$	***6.181***	8.366	11.279	13.776	13.383
	$\tau = 5$	6.317	9.350	11.970	13.816	12.614

4.2 Discussion

In this section, we discuss the impact of different swarm intelligence optimization algorithms on the performance of $LSVR$ models. Similar to GWO, WOA is also widely used to solve the problems of complex nonlinear systems. The following are the specific discussion results.

Under three time lags, the 5-step forecasting is performed respectively, and the detailed $MAPE$ results generated by GWO-$LSVR$ and WOA-$LSVR$ are listed in Table 3. Under the combination of three time lags and five forecasting steps (15 cases in total), WOA produces only two results that are slightly better than GWO.

Both WOA and GWO can produce relatively small $MAPE$ results in the first and second steps, but from the third step onwards, the results produced by WOA are larger than those of GWO, and the gap gradually increases. The smallest difference is τ=4 at the first step, which is only 0.187%, and the largest difference is τ=4 at the fifth step, with a difference of 2.451%. The detailed results presented in Fig. 5.

5. CONCLUSION

Under the influence of the Russia-Ukraine war, there are energy tensions in Europe, especially the shortage of natural gas. Accurate forecasting of natural gas consumption is necessary.

This paper uses the Lagrangian Support Vector Regression model with the $Sorensen$ kernel, combined with the Grey Wolf Optimizer and Nonlinear Auto-Regressive model, for multi-step forecasting of monthly natural gas consumption, based on the out-of-sample holdout validation. The proposed model was applied to forecast the total monthly natural gas consumption of 27 countries within Europe. Comparing the model with SVR, RF, $LightGBM$, $XGBoost$, and MLP's five combined models based on GWO. It's find that the GWO-$LSVR$ has the best generalization performance and most robust of all hybrid models. The $MAPE$ yield by GWO-$LSVR$ of each step at three time lags are from 5.844% to 11.622%. It also discussed the difference of the GWO and WOA, and find that GWO can better optimize the model hyperparameters in most cases. It can be concluded that the proposed GWO-$LSVR$ model can be used to accurately predict natural gas consumption, and has strong generalization performance and robustness.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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