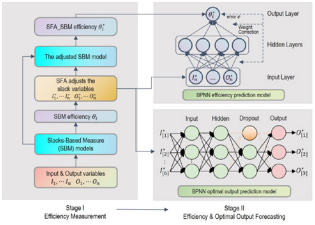
Improving the evaluation and prediction of prevention and treatment efficiency during public health emergencies by using the SBM-BPNN algorithm



Mejora de la evaluación y predicción de la eficacia de la prevención y el tratamiento durante emergencias de salud pública mediante el algoritmo SBM-BPNN

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RESUMEN

- La respuesta a las crisis es la clave para reducir el impacto y los daños de las emergencias de salud pública. Los estudios anteriores sólo se centraban en medidas específicas de respuesta a emergencias, pero rara vez se ha hablado de la eficacia de estas medidas. ¿Qué ocurre con la eficacia de la respuesta a las crisis en las emergencias de salud pública? ¿Qué ocurrirá con la eficacia de la respuesta a las crisis tras la transformación de las medidas de emergencia de salud pública? Para responder a estas preguntas, se construyó un novedoso marco de investigación combinando los algoritmos slacks-based measure (SBM) y back propagation neural network (BPNN). En la Etapa I, se realizó una evaluación de la eficiencia de la SBM con resultados no deseados para evaluar la eficiencia de la prevención y el tratamiento durante las emergencias de salud pública, y se llevó a cabo un análisis de frontera estocástica para mitigar la influencia de los factores ambientales y el ruido estadístico. En la fase II, se predijo la eficacia ajustada con el modelo BPNN. Las unidades de decisión se mejoraron eficazmente incorporando variables de holgura, lo que permitió predecir y optimizar los casos óptimos dados los recursos epidemiológicos. Un análisis empírico de la respuesta de 43 países miembros del G20 a la pandemia de COVID-19 demostró que el novedoso marco podía evaluar la eficacia de la prevención y el tratamiento en todas las regiones y predecir la eficacia y la salida óptima de casos tras los cambios en las medidas preventivas de la epidemia. Tras la evaluación, el error cuadrático medio del modelo BPNN de predicción de la eficacia fue de sólo 0,0014, mientras que el del modelo BPNN de predicción de los resultados óptimos fue de 0,126. Por lo tanto, este nuevo marco es adecuado para evaluar la eficacia de la prevención y el tratamiento en todas las regiones. Por lo tanto, este novedoso marco resulta adecuado para evaluar y predecir la eficacia de la respuesta a las crisis en emergencias de salud pública, lo que proporciona la ayuda necesaria para la toma de decisiones en casos de crisis por parte del gobierno y las organizaciones de gestión de emergencias,
- **Palabras clave:** Emergencias de salud pública, Pandemia COVID-19, Eficacia de la respuesta a las crisis, Evaluación, Predicción.

ABSTRACT

Crisis response is the key to reducing the impact and damage of public health emergencies. Previous studies only focused on specific measures for emergency response, but the effectiveness of these measures has seldom been discussed. How about the effective of the crisis response on public health emergencies? What will happen to the effectiveness of crisis response after the transformation of public health emergency measures? To address these questions, a novel research framework was constructed by combining slacks-based measure (SBM) and back propagation neural network (BPNN) algorithms. At Stage I, an efficiency evaluation was conducted on SBM with undesirable outputs to evaluate the prevention and treatment efficiency during public health emergencies, and stochastic frontier analysis was performed to mitigate the influence of environmental factors and statistical noise. At Stage II, the adjusted efficiency was predicted with the BPNN model. The decision-making units were effectively improved by incorporating slack variables, thus enabling the prediction and optimization of optimal cases given the epidemic resources. An empirical analysis of the response of 43 G20 member countries to the COVID-19 pandemic showed that the novel framework could evaluate prevention and treatment efficiency across regions and predict the efficiency and optimal case outputs following shifts in epidemic preventive measures. After evaluation, the mean squared error of the BPNN efficiency prediction model was only 0.0014, whereas that of the BPNN optimal output prediction model was 0.126. Therefore, this novel framework is suitable for evaluating and predicting the effectiveness of crisis response on public health emergencies, which provides necessary assistance for crisis decision-making by the government and emergency management organizations.

Keywords: Public health emergencies, COVID-19 pandemic, Crisis response efficiency, Evaluation, Prediction.

1. INTRODUCTION

Globalization has revolutionized the mode and speed of public health emergency (PHE) transmission, necessitating a swift international response, as in the case of the Corona Virus Disease 2019 (COVID-19) [1]. The COVID-19, due to its evolving virus strains and high transmission rates, resulted in an unparalleled shock to the global economy and public health [2]. Appropriate preventive measures and diagnostic strategies have been developed by countries and international organizations [3-4]. Different governments responded to the epidemic with a variety of different measures. The differences during their responses aroused widespread concern. Although strict prevention and treatment strategies could undoubtedly slow down the outbreak [5], which lead to increased economic costs and exacerbate the global economic uncertainty [6]. However, excessive input reduction jeopardizes public safety and fuels social panic too. The trade-off between saving the economy and protecting public health during PHEs is a critical challenge faced by all countries [7]. If public health and economic development are considered as different decision-making goals, the practical problem of "balancing public health and the economy" is transformed into a theoretical problem of "analyzing the effectiveness of prevention and treatment strategies". The more efficient a country is in crisis response, the better the health-economy trade-off is. If a country is the most efficient in crisis response, it would have the optimal output and the optimal balance between public health and the economy.

At the theoretical level, the effectiveness study of prevention and treatment strategies in PHEs attracted widespread academic interests. Early theoretical studies considered the impact of emotions on the efficiency of decision-making based on subjective initiative [8-9]. Additionally, there are studies focused on measuring and evaluating the instantaneous effectiveness of prevention and treatment strategies from an objective perspective [6-7]. Scholars focused on measuring efficiency from a single perspective, such as treatment cases number [10]. And they often considered undesirable outputs, such as confirmed and death cases number solely, which leading to one-sided selectivity in assessment results [12]. Subsequently, considering that PHEs often last for a long period of time, scholars expanded their studies on the effectiveness of prevention and treatment from evaluation to prediction [14-15]. Due to the excellent performance in non-linear prediction field, machine learning methods were introduced and were proven to predict the future efficiency of prevention and treatment more accurately [19-20]. However, most of the existing studies conducted evaluation and prediction work respectively, which are helpful to identify the most efficient countries, but could not answer the question of "What is the optimal output (optimal balance between public health and the economy) for the PHEs prevention and treatment and how it can be achieved." Efficiency improvements in the PHEs prevention and treatment are constrained by the healthcare resource allocation [16-17]. Sometimes, the optimal efficiency scenarios evaluated by efficiency may be too difficult to achieve, which require resource inputs beyond the capacity of decision-making units (DMUs). This phenomenon is known as the "Best Practice Trap" [18]. In order to overcome the "Best Practice Trap", it is necessary to further expand the above question to "What is the optimal output for the PHEs prevention and treatment with the limitation of inputs, and how it can be achieved."

This study provides several contributions. (1) A comprehensive indicator system is introduced to measure efficiency. Resource inputs from prevention, diagnosis, and treatment are considered together with desirable and undesirable outputs to provide a global view of measuring PHEs' prevention and treatment efficiency. (2) A highly effective efficiency measurement model is constructed. The slacks-based measure and stochastic frontier approach (SBM_SFA) model was divided into two parts, slacks-based measure (SBM) model and stochastic frontier approach (SFA) model. The SBM model incorporated the resource slack value into the efficiency measurement process. Meanwhile, the SFA model was integrated into the measurement process to mitigate the effects of environmental factors and statistical noise. The SBM_SFA model can yield objective results on the effectiveness of prevention and treatment strategies in each country. (3) The prediction of prevention and treatment efficiency and the optimal case outputs are expanded. A back propagation neural network (BPNN) efficiency prediction model and a BPNN optimal output prediction model are constructed to provide powerful support tools for emergency management organizations (EMOs) to predict future development trends and optimize epidemic strategies.

The rest of this study is organized as follows. Section 2 presents state of the art. Section 3 delineates the research design. The empirical research results and discussion are given in Section 4. Section 5 concludes the research and presents future research directions.

2. STATE OF THE ART

In response to the widespread question of "what is the optimal output (optimal balance between health and economy) and how to achieve it" in the practice of PHEs' prevention and treatment, studies were conducted to analyze the optimal output from the perspective of the effectiveness of prevention and treatment strategies, and relevant studies were carried out by using evaluation and prediction methods respectively. (1) Evaluation methods were used to analyze the instantaneous efficiency of current prevention and treatment strategies and to judge whether the status quo has achieved the optimal output. Since the prevention and treatment in PHEs should balance multiple objectives such as public health and economic development, it is a multi-objective optimization and decision-making problem. The analytic hierarchy process (AHP) and the technique for order preference by similarity to an ideal Solution (TOPSIS) are widely used when the attribute indicators of decisions are observable [26]. Conversely, data envelopment analysis (DEA) is more suitable when outputs can be readily observed [13,29]. Therefore, scholars used DEA model widely, a linear programming technique for assessing the efficiency of DMUs in a multi objective environment, to evaluate the prevention and treatment efficiency in different countries and regions [11]. A multistage DEA model that considers confirmed and death cases as undesirable outputs was constructed [12]. Scholars identified that population, territory, economic, and ideology substantially affect the prevention and treatment efficiency, while considerable geographic differences were highlighted in previous studies, with European and American countries generally exhibiting lower efficiency than Asian and African countries [12]. However, the traditional radial model widely used in previous studies was unable to adequately reflect the slack improvement in the efficiency evaluation, and the influence of external factors on the efficiency of prevention and treatment was clearly present [14-15]. These studies confirmed that DEA could be used to measure the efficiency of PHEs prevention and treatment and identify optimal output DMUs. However, previous studies overlooked the effects of environmental factors and statistical noises on the efficiency evaluation, and have also neglected the role of desirable outputs. (2) Prediction methods are used to analyze the effectiveness of future prevention and treatment measures and to determine whether optimal outputs are achievable in the future. To understand the efficiency in future time window, machine learning (e.g., artificial neural network (ANN)) was introduced into efficiency prediction [21-22], and such nonlinear methods have been widely adopted in various areas, such as aquaculture [23], power generation [24], environment [25], banking [18], and supply chain operations [26-28]. High uncertainty in PHEs is a complex system suitable for machine learning [19-20]. The DEA-ANN approach is applied in the assessment, classification, and prediction of treatment progression for COVID-19 [30]. Meanwhile, the BPNN possesses properties such as feedback correction data and high interpretability, enabling it to avert local convergence problems [39]. Its ease of implementation makes it popular among scholars in the field of ANN [40]. These studies showed that efficiency could be evaluation and prediction both. However, previous studies lacked consideration of the slack improvement of the input and output indicators [13].

In all, to solve the "optimal output balance between health and economy" problem, DEA for multi-objective decision-making is proven to be used to determine which DMU is instantaneous effective, and machine learning methods for non-linear and complex relationships are proven to be used to predict which DMU will be effective in the future. However, few studies pay attention to analyze the possible optimal output scenarios and improvement paths for inefficient DMUs. In fact, the slack improvement of input and output indicators could be used as a clue to closely link the evaluation and prediction of prevention and treatment efficiency by different ranges of slack value of indicators. Then, machine learning algorithms can uncover nonlinear relationships between variables in large-scale, high-dimensional datasets to perform predictive tasks, thereby compensating for the shortcomings of DEA [31]. In view of this, this study develops a new analytical framework. A combined modeling approach that leverages the DEA-ANN complementarity was employed to facilitate the assessment, prediction, and optimization of prevention and treatment efficiency during PHEs. For the inefficient DMUs identified by the evaluation process, the optimal outputs are predicted after improvement by different ranges of slack value of indicators, aiming to answer the question "What are the optimal outputs (optimal balance between health and economy) for the prevention and treatment?". Here, the different ranges of slack value of indicators are the candidate answers of "How to achieve?".

3. METHODOLOGY

3.1. RESEARCH FRAMEWORK

A novel framework is developed for evaluation and prediction in this study (Fig. 1). The SFA_SBM model is introduced to evaluate the countries' performance under the exclusive influence of the governance effectiveness of epidemic prevention and treatment.

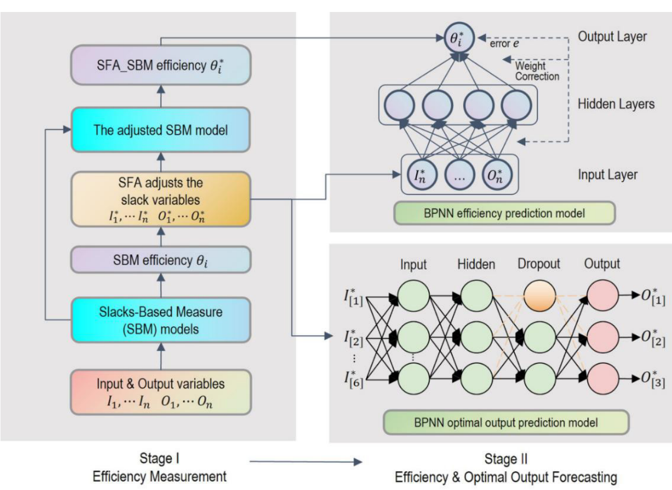

Fig. 1. Evaluation and prediction framework for PHE prevention and treatment efficiency.

Specifically, the slack value of input variables measured by the SBM model is combined with the environmental variables for SFA regression to obtain the adjusted input variables. Then, each country's adjusted efficiency for outbreak prevention and treatment is re-measured. Beyond identifying the DMUs that accomplish optimal outputs, this study focuses on the methods which allow inefficient DMUs to attain such outputs. Prediction techniques offer remarkable contribution to this effort. Therefore, the BPNN based on the SFA_SBM model is utilized to enhance the adaptive prediction ability of the efficiency model and provide further decision support for EMOs. The BPNN efficiency prediction model is trained to predict and evaluate epidemic prevention and treatment efficiency under hypothetical scenarios by adopting the SFA_SBM model's input and output indicators as the input layer and its efficiency as the output layer. On this basis, inefficient DMUs are projected onto the efficient frontier by using the slack value of the SFA_SBM model's input and output variables. The optimal input variables are used as the input layer, and the optimal output variables are employed as the output layer. Afterward, the BPNN optimal output prediction model is trained to evaluate the gap between the optimal and actual case outputs under given epidemic resources. The approach provides EMOs a measurement tool to evaluate PHE prevention and treatment work, and it serves as a helpful supplement for optimizing epidemic prevention measures.

3.2. INDICATOR SELECTION AND DATA DESCRIPTION

COVID-19, a global pandemic, required the concerted efforts of all countries to contain its proliferation. Since the outbreak, most countries have been persistently reporting information about infection rates, resource utilization, and other pertinent developments. The Group of Twenty (G20) is highly representative because it considers a balanced interest from developing countries, developed countries, and various regions. Therefore, this study evaluated the G20 countries' prevention and treatment performance during the COVID-19 pandemic to examine the applicability of the research model in PHEs.

Identifying the global anti-epidemic performance can guide countries toward targeted adjustments in their prevention and treatment strategies and facilitate progress toward a human health community. The SARS-CoV-2 Outbreak Handling Systems incorporate prevention, diagnosis, and treatment levels [3]. Although scholars have implemented this system, they generally ignore undesirable outputs [10]. Incorporating these outputs, however, can enhance evaluation accuracy [11]. On the basis of existing literature, this study designated each level's input and output variables and developed an indicator system that encompasses undesirable outputs to assess the outbreak prevention and treatment efficiency of different countries. Relative indicators (per 1,000 people) were used in the selection of variables to minimize the differences caused by demographic and economic disparities among countries. In addition, missing data were filled in using linear interpolation.

As shown in Table 1 (see section: supplementary material), the input indicators included prevention, diagnostic, and treatment components. The prevention indicators included the stringency index and the number of vaccinations. The stringency index refers to non-medical government interventions for COVID-19, as reported through the COVID-19 Government Response Tracker developed by the University of Oxford [32]. Meanwhile, the number of vaccinations refers to the population per thousand who have received at least one dose of the COVID-19 vaccine. The diagnostic indicators include the number of tests, namely, the number of COVID-19 nucleic acid tests per 1,000 people. The two indicators were obtained through the Our World in Data (OWID) COVID-19 Vaccination Tracker [33-34]. The treatment indicators consider the primary care level in each country, including human resources for healthcare (i.e., number of doctors and nurses per 1,000 people), funds for healthcare (i.e., expenditure of public funds on healthcare per 1,000 people), and infrastructure for healthcare (i.e., number of general and ICU beds per 1,000 people). The data on infrastructure were obtained through the OWID database, the data on funds were derived from the World Development Indicators (WDI) database published by the World Bank [35], and the data on human resources were from the International Statistical Yearbook 2021 [36].

For the output indicators, the COVID-19 recovered, confirmed, and death cases per 1,000 people were considered. The recovered cases were adopted as a desirable output, and the confirmed and death cases were undesirable outputs. The data from various countries were retrieved from the Center for Systems Science and Engineering at Johns Hopkins University [37].

In SFA regression, population density, urbanization level, and economic development level are critical environmental factors that affect the effectiveness of prevention and treatment strategies [38]. The data on these environmental variables were from the WDI database [35].

Overall, 516 COVID-19 performance samples (from January 2021 to December 2021) exemplified by 43 G20 member countries were analyzed in this study. The EU was subdivided into 27 countries, including France and Germany. China does not include data from Hong Kong, Macao, and Taiwan. Table 2 (see section: supplementary material) summarizes the statistics for the input and output variables and their application in models.

The sample countries were further divided into three categories, namely, the EU, developing countries, and developed countries, to observe the differences in the variables. This study provided a nuanced understanding of the differing prevention and treatment strategies across various areas, as shown in Fig. 2 (see section: supplementary material).

In terms of the stringency index, an overall downward trajectory was observed among the EU, developing, developed, and G20 countries from January to September, suggesting the loosening of epidemic prevention policies in many countries, except China. With regard to vaccinations, the disparity among countries was insignificant in the year's first half. However, a substantial increase occurred in China in the latter half of the year, followed by developed countries, and developing countries recorded the lowest vaccination rates. With regard to diagnostic inputs, the number of tests in China was consistently greater than that in the other countries across all months; specifically, in December, nearly 70 tests were conducted per 10 people. Meanwhile, the developing countries exhibited a low test growth rate, with the value gradually falling to below the average level of G20 countries. In addition, a notable surge in recovered, confirmed, and death cases was observed, indicating that the prevailing COVID-19 pandemic was still ongoing in 2021. Notably, the death cases in the developing countries exceeded those in the developed countries in the second half of 2021. Meanwhile, China exhibited remarkably low annual outputs, demonstrating its achievements in epidemic prevention and treatment efforts.

3.3. METHODS

3.3.1. Stage I: SFA_SBM efficiency evaluation model

(1) Construction of an undesirable output SBM model to analyze initial efficiency

Assuming that there are n decision units DMU_j, m input variables X, s_1 desirable output variables Y^g, and s_2 undesirable output variables Y^b, the set of production possibilities $\widetilde{P}$ containing undesirable outputs is defined as follows:

$$P=\{(x,y^g,y^b)\,|\,x\geq X\lambda, y^g\leq Y^g\lambda, y^b\leq Y^b\lambda, \lambda\geq 0\} \tag{1}$$

where $\lambda\in R^n$ is the vector of weight coefficients with the following linear programming equation for efficiency assessment:

$$\begin{aligned}\theta=\min&\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i_0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r_0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r_0}^b}\right)}\\ s.t.\ & x_0=X\lambda+s^-\\ & y_0^g=Y^g\lambda-s^g\\ & y_0^b=Y^b\lambda+s^b\\ & s^-\geq 0, s^g\geq 0, s^b\geq 0, \lambda\geq 0\end{aligned}, \tag{2}$$

where $s^-\in R^m$ refers to the excess inputs, $s^b\in R^{s_2}$ is the excess production of undesirable outputs, and $s^g\in R^{s_1}$ is the production shortfall of desirable outputs. θ is within the [0, 1] range and denotes the DMUs' efficiency.

If the convexity constraint $\sum_{j=1}^{n}\lambda_j=1$ is added to Eq. (2), the model shifts from constant returns to scale (CRS) to variable returns to scale (VRS). The selection of CRS or VRS can be determined by two semiparametric tests referred to as Banker's tests.

(2) Introduction of SFA regressions to separate managerial inefficiency

To evaluate the DMUs' performance under the sole effect of managerial inefficiency, this study utilizes SFA regressions, which separate the three effects through the following formula:

$$S_{ni}=f(Z_i;\beta_n)+v_{ni}+\mu_{ni}; i=1,2,\cdots,l; n=1,2,\cdots,N, \tag{3}$$

where S_{ni} is the slack value of the input variable X_n in DMU_i. $Z_i=[1\,q_{1i}\,q_{2i}\cdots q_{pi}]$ and β_n are the matrix and coefficients of the environmental factors, respectively, and $f(Z_i;\beta_n)$ denotes the effect of environmental factors on the slack variables. $v_{ni}+\mu_{ni}$ is the mixed error term, and v_{ni} and μ_{ni} are the random error term and managerial inefficiency, respectively, indicating the effects of random disturbances and managerial factors on the input slack variables that obey $v\sim N(0,\sigma_v{}^2)$ and $\mu\sim N^+(0,\sigma_\mu{}^2)$.

First, managerial inefficiency μ_{ni} is separated. The conditional expectation formula of μ_{ni} is as follows:

$$E(\mu|\varepsilon)=\sigma^*\left[\frac{\varphi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})}+\frac{\lambda\varepsilon}{\sigma}\right], \tag{4}$$

where $\sigma^*=\sigma_\mu\sigma_v/\sigma$, $\sigma=\sqrt{\sigma_\mu{}^2+\sigma_v{}^2}$, and $\lambda=\sigma_\mu/\sigma_v$.

Second, on the basis of the estimated value β_n of parameter β_n in the SFA regression, the random error term v_{ni} is calculated as

$$E[v_{ni}|v_{ni}+\mu_{ni}]=s_{ni}-f(z_i;\beta_n)-E[u_{ni}|v_{ni}+\mu_{ni}], \tag{5}$$

Last, in consideration of the calculated values above, the input variables are adjusted as

$$X_{ni}^A=X_{ni}+[\max(f(Z_i;\beta_n))-f(Z_i;\beta_n)]+[\max(v_{ni})-v_{ni}]\quad i=1,2,\cdots,l; n=1,2,\cdots,N, \tag{6}$$

The adjusted and pre-adjusted input variables, X_{ni}^{A} and X_{ni}, are subject to adjustment through $[\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)]$ and $[\max(v_{ni}) - v_{ni}]$ to ensure that equalization of the external environment and luck factors is performed for each DMU.

The adjusted input variables X_{ni}^{A}, desirable output variables Y^{g}, and undesirable output variables Y^{b} are applied to the SBM model to reevaluate the efficiency and obtain the adjusted epidemic prevention and treatment efficiency θ^{*} for each DMU.

3.3.2. Stage II: BPNN prediction model

BPNN is a multilayer mapping network that employs the error backpropagation algorithm, where the errors are minimized and propagated backward, and the information is transmitted forward. A typical BPNN contains input, hidden, and output layers. Neighboring layers are connected by weights in the [−1, 1] range. The optimal weights are determined by training the neural network to obtain the training pairs' basic features.

The error backpropagation algorithm utilizes the gradient descent method for network training, which minimizes the errors between all training pairs' target and actual values. The error can be expressed by Euclidean distance E as follows:

$$E = \frac{1}{2}\sum_{k}[T_k - Y_k]^2 , \tag{7}$$

where T is the target output and Y is the activated output of neurons k. The network outputs' feed-forward process computation serves as the starting point for backpropagation learning, as illustrated in Eq. (8). The network is presented with pairs of input and output patterns in this process.

$$Y_k = f(y_{netK}) = f(\sum_{j} H_j w_{jk}) , \tag{8}$$

A nonlinear activation function, f, is applied to the net outputs y_{netK} of the neurons k. The inputs from the hidden neurons j to the output neurons k and their corresponding weights are denoted as H_j and w_{jk}, respectively.

The next process involves feed-forward input representation and error computation. Error propagation is a reverse process from the output layer–hidden layer–input layer, and weight adjustments between neighboring neurons are made by minimizing E. The weight changes between the input neurons i and the hidden neurons j and between the hidden neurons j and the output neurons k are denoted by $\Delta v_{i,j}(t)$ and $\Delta w_{j,k}(t)$, respectively, as shown in Eqs. (9) and (10).

$$\Delta v_{i,j}(t) = -\frac{\partial E}{\partial v_{i,j}} , \tag{9}$$

$$\Delta w_{j,k}(t) = -\frac{\partial E}{\partial w_{j,k}} . \tag{10}$$

Then, the new weights between the relevant neurons are calculated with the following equations in consideration of the learning rate η and epoch t.

$$v_{i,j}(t+1) = v_{i,j}(t) + \eta\Delta v_{i,j}(t) , \tag{11}$$

$$w_{j,k}(t+1) = w_{j,k}(t) + \eta\Delta w_{j,k}(t) . \tag{12}$$

In summary, errors are minimized by the backpropagation algorithm by adjusting preset weights using training data until convergence conditions are fulfilled.

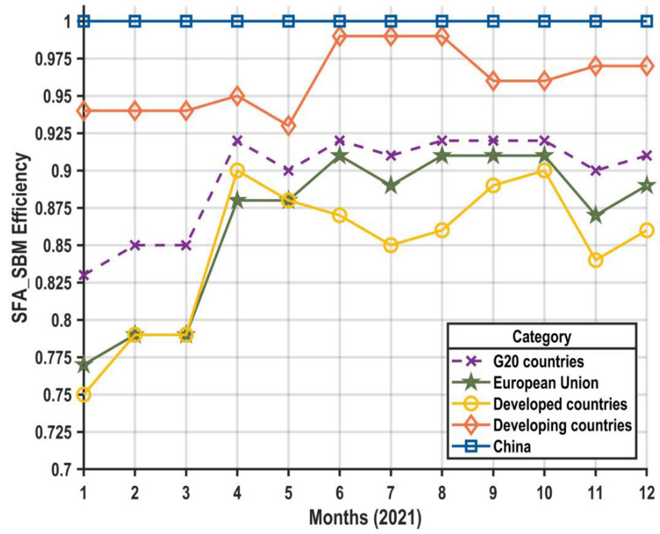

Fig. 3. Comparison of the prevention and treatment efficiency of countries in different categories.

Furthermore, the dropout layer was introduced in this study to mitigate the overfitting phenomenon during the training of small datasets. It is set up to randomly deactivate neurons with a probability of p in each iteration and assign their outputs as 0.

4. RESULTS

4.1. SFA_SBM EFFICIENCY ANALYSIS AND IMPROVEMENT

After performing Banker's test, a VRS SBM model with undesirable outputs was constructed. The adjusted input variables were derived through SFA regression. The adjusted epidemic prevention and treatment efficiency for each country was assessed using MATLAB R2020b software. Only the inefficient countries in January 2021 are presented in Table 3 (see section: supplementary material) due to the limited space.

The SFA_SBM model results show that 23 countries in the G20, including China and Finland, performed efficiently (with an efficiency of 1), that is, 53.5% of the countries efficiently handled the COVID-19 pandemic in January 2021. Meanwhile, the ineffective countries' efficiency ranged from 0.16 to 0.87, with France having the lowest efficiency and Portugal having the highest (difference of 0.71). In terms of country categorization, 27.8% and 60% of the developing and developed countries had ineffective prevention and treatment strategies, respectively. This discrepancy can be attributed to the premature relaxation or removal of comprehensive prevention policies that led to a rapid increase in confirmed cases and inefficiency in combating the pandemic.

Fig. 3 shows the comparative epidemic prevention and treatment efficiency trends of the G20 countries, the EU, developed countries, developing countries, and China from January to December 2021. An overall general improvement in efficiency was observed across the various categories, indicating that noteworthy progress had been achieved in implementing epidemic prevention and treatment strategies in each country. In all months, the efficiency of the developing countries surpassed that of the developed countries, and its values approached 1 from June to August. By contrast, the EU and developed countries' efficiency was below the average level. Moreover, China's epidemic prevention and treatment efficiency consistently remained effective, signifying the full available resource utilization and optimal output achievement under the given inputs.

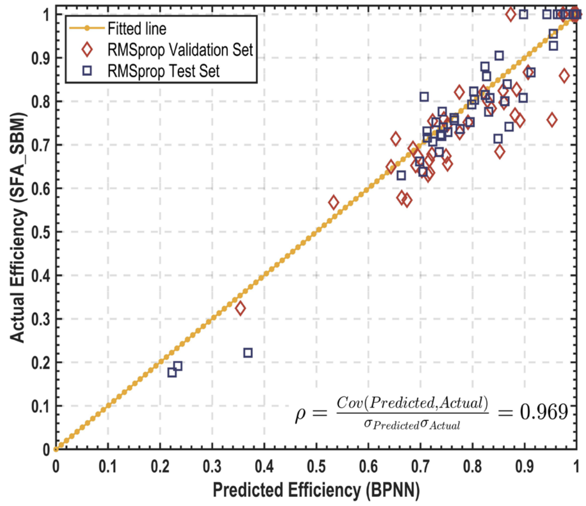

Fig. 4. BPNN (RMSProp) efficiency prediction model fitting effect.

4.2. BPNN EFFICIENCY PREDICTION MODEL

Random allocation was performed to divide the 516 samples from 43 countries into training, validation, and test sets, and a 6:2:2 ratio was maintained. Then, the adjusted input and output variables $I_1^*, \cdots, I_6^*, O_1^*, \cdots, O_3^*$ were normalized to correspond to the nine nodes in the input layer. The output layer was the efficiency calculated by the SFA_SBM model θ_i^*. After the evaluation, the middle layer optimal structure consisted of two hidden layers and one dropout layer, with each layer activated by the ReLU nonlinear function.

Table 4 summarizes the performance of the BPNN efficiency prediction models trained with different optimizers. Without sacrificing test set accuracy, all models showed superior predictive performance in the validation set. Efficiency prediction model optimal fitting was achieved using the RMSProp optimizer during neural network training, resulting in a remarkable reduction in the mean square error (MSE) of only 0.14% on the test set.

Fig. 4 shows a two-dimensional comparison of the actual and predicted efficiency in the validation and test sets for the BPNN efficiency prediction model. The correlation coefficient ρ was

Optimizer	Data	MSE	MAE	RMSE	R²
Momentum	Validation	0.0019	0.0226	0.0435	0.9168
	Test	0.0027	0.0286	0.0522	0.9002
Adam	Validation	0.0022	0.0240	0.0464	0.9050
	Test	0.0027	0.0277	0.0521	0.9006
SGD	Validation	0.0022	0.0239	0.0468	0.9036
	Test	0.0026	0.0273	0.0511	0.9045
AdaGrad	Validation	0.0027	0.0308	0.0524	0.8790
	Test	0.0025	0.0295	0.0496	0.9102
RMSProp	Validation	0.0021	0.0236	0.0460	0.9067
	Test	0.0014	0.0191	0.0375	0.9487

Table 4. Performance of BPNN efficiency prediction models with different optimizers.

0.969. The substantial correlation between the values provided compelling support for the model's superior generalized learning characteristics, underscoring BPNN's impressive predictive prowess in regression problems. Overall, DMUs that are deemed efficient (efficiency score of 1) demonstrate superior predictive results, while the predictions of inefficient DMUs show a slight overestimation.

4.3. BPNN OPTIMAL OUTPUT PREDICTION MODEL

Fig. 3 presents various countries grappling with inefficient epidemic control practices. By predicting each country's optimal case outputs, we can identify the gap between the optimal and actual cases under the given epidemic resources in an inefficient country, thus providing data support for the practical improvement of each country's prevention and treatment efficiency. Therefore, this study analyzed each DMU's redundancy of slack variables and calculated the corresponding target improvement value. Table 5 shows the slack variable values of inefficient countries in January 2021.

In table 5, $s^{x_n^-}, n = 1, 2, \cdots 6$ is the slack variable for the SFA_SBM model inputs, and s^{y^+}, $s^{b_1^-}$, and $s^{b_2^-}$ are the slack variables for the desirable and undesirable outputs. As shown in Table 5, France exhibited the lowest efficiency of 0.16 in January 2021. An increase of 41.25 recovered cases per 1,000 population and a reduction of 0.23 death cases were required to reach the efficient state. A re-

DMU	$s^{x_1^-}$	$s^{x_2^-}$	$s^{x_3^-}$	$s^{x_4^-}$	$s^{x_5^-}$	$s^{x_6^-}$	s^{y^+}	$s^{b_1^-}$	$s^{b_2^-}$
Portugal	1.31	0.00	8.32	171678.83	2.21	0.00	0.00	12.83	0.15
Latvia	5.75	0.00	0.00	337105.13	0.59	1.72	0.00	4.59	0.09
Romania	5.47	0.00	10.68	565076.33	0.47	2.27	0.00	1.62	0.20
Lithuania	0.30	0.00	0.00	161620.58	4.01	0.76	0.00	17.21	0.15
Austria	0.00	0.00	10.42	2135497.70	2.22	2.02	0.00	0.00	0.17
Spain	3.27	0.00	2.20	1202744.19	1.20	0.00	0.00	10.07	0.37
Poland	3.76	0.00	9.17	553710.77	0.49	1.99	0.00	5.33	0.26
UnitedStates	27.78	0.00	1.17	2838308.38	2.73	0.00	0.00	24.18	0.22
Slovakia	0.00	143.60	1.82	0.00	1.07	1.19	0.00	37.32	0.27
Italy	1.82	0.00	3.72	1513973.94	5.54	0.00	0.00	5.20	0.81
Canada	0.00	0.00	4.56	2949909.35	6.04	0.22	0.00	1.05	0.28
Greece	5.41	69.36	6.64	962624.62	4.39	1.66	0.00	0.70	0.37
Hungary	5.72	37.75	11.13	835704.04	2.90	2.87	0.00	10.10	0.72
Sweden	1.82	0.00	3.94	3886387.68	7.80	0.00	0.00	24.53	0.53
Germany	0.00	0.00	7.57	4014772.02	9.31	3.84	0.00	1.36	0.31
UnitedKingdom	44.66	0.00	14.61	2487773.71	5.80	0.13	0.00	29.61	1.56
Ireland	0.00	0.00	11.75	2918871.29	8.00	0.64	15.87	16.60	0.30
Cyprus	2.77	363.10	7.13	1263168.58	1.92	1.01	11.26	12.34	0.00
Belgium	0.00	0.00	0.00	2409705.44	7.83	0.86	40.16	13.64	0.95
France	0.00	0.00	0.73	2242979.71	7.32	0.87	41.25	0.00	0.23

Table 5. Slack variables of inefficient countries (January 2021).

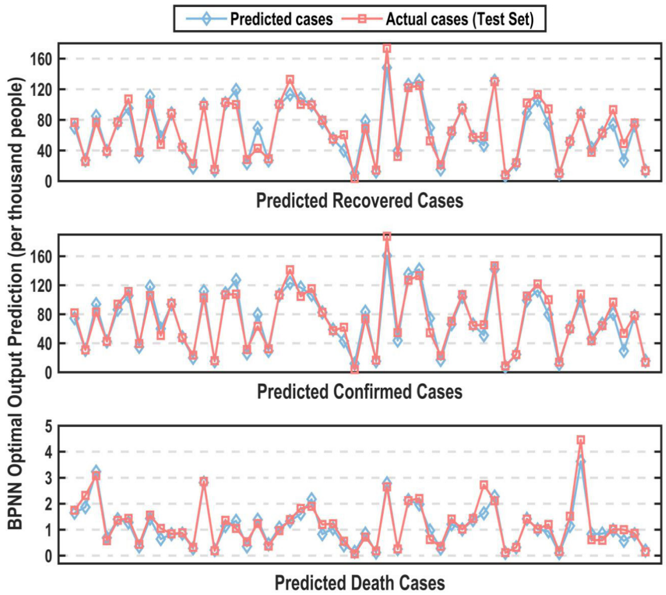

Fig. 5. BPNN (RMSProp) model efficiency prediction.

duction in each input would also be effective. If only the outputs' change was controlled, the calculated efficiency could increase by 60%, reaching 0.76. Similarly, the rest of the inefficient DMUs could be optimally improved in accordance with the slack variables.

After adjusting all DMUs to their efficient state, the input variables $I_1^*,\cdots,I_6^*$ were employed for the BPNN optimal output prediction model. Meanwhile, the predicted values of the output layer encompassed three output variables $O_1^*,\cdots,O_3^*$, namely, recovered, confirmed, and death cases.

Experiments were conducted to validate the improved dataset's potential to boost model prediction accuracy. The experiments involved the following steps: (a) constructing Origin_set with an original efficiency of 1, (b) crafting Improve_set with an improved efficiency of 1, and (c) formulating All_set by combining the original and improved efficiency of 1. The training process was conducted separately. The dataset was randomly divided into training, validation, and test sets at a 6:2:2 ratio. Then, two hidden layers and one dropout layer were built using the RMSProp optimizer. The prediction errors of the model trained on different sets are shown in Table 6.

The results revealed that Origin_set exhibited superior predictive performance during model training and had the lowest MSE of 0.0532. However, its predictive capability was low, and the generalization errors were large in the test set. Improve_set lagged behind the other sets in all the assessment indicators, indicating that relying solely on the dataset with an improved efficiency of 1 resulted in poor fitting of the prediction model. By contrast, All_set (i.e., using Origin_set and Improve_set) demonstrated stable and superior performance in the validation and test sets. Consequently, this study used All_set to construct the BPNN optimal output prediction model.

Dataset	Data	MSE	MAE	RMSE	R²
Origin_set	Validation	0.0532	0.8924	0.2308	0.9560
	Test	0.1418	0.6845	0.3766	0.8324
Improve_set	Validation	0.2872	0.9329	0.5359	0.7295
	Test	0.2969	0.9518	0.5449	0.6892
All_set	Validation	0.0795	0.7576	0.2820	0.9023
	Test	0.1263	0.8150	0.3554	0.8853

Table 6. Performance of the BPNN optimal output prediction model on different datasets.

The plots in Fig. 5 depict the discrepancy between the predicted and actual values of recovered, confirmed, and death cases in each country in the validation set. The predictive model showed excellent accuracy and strong generalization capability.

4.4. ROBUSTNESS

In this section, model validation and out-of-sample prediction were conducted to ensure the findings' robustness. First, the BPNN model's prediction performance was compared with that of various machine learning regression algorithms. Second, the sample time interval was expanded, and a new small-scale dataset was used for prediction. The results revealed the consistently superior performance of all the BPNN prediction models.

4.4.1. Multimodel performance comparison

In the field of ML, support vector regression, ridge regression, polynomial regression, gradient boosting decision tree (GBDT), and random forest are popular algorithms for regression prediction. They were constructed to compare their prediction performance with that of the BPNN algorithm. Table 7 shows each model's performance difference in efficiency and optimal output predictions on the test set. The BPNN algorithm had the smallest MSE and the highest R^2 in the efficiency and optimal output predictions. Despite the GBDT algorithm's superior efficiency prediction performance, it still exhibited a considerable disparity with BPNN in optimal output prediction.

4.4.2. Out-of-sample prediction

To assess the BPNN models' out-of-sample prediction performance, we analyzed the data of G20 countries in January 2022. The results showed that the MSE of the BPNN efficiency prediction model was 0.0078, and the MSE of the BPNN optimal output prediction model was 0.1526. Fig. 6 (see section: supplementary material) presents a two-dimensional comparison of the predicted and actual values after standardization. The correlation coefficient ρ was 0.943.

The prediction performance of the BPNN models constructed in this study surpassed that of other machine learning algorithms. The constructed BPNN models showed a robust generalization ability even with small-scale datasets. Consequently, they offer enhanced adaptability to diverse input and output variations encountered during the implementation of epidemic prevention and treatment strategies across countries.

5. CONCLUSIONS

A new framework is proposed in this study to evaluate and predict the efficiency during PHEs on the basis of SBM and BPNN models. The effectiveness of the framework is confirmed by an empirical analysis that focused on the crisis responses of 43 G20 member countries to the COVID-19 pandemic public health emergencies. Similar findings were found compared to previous studies.

Model	Efficiency forecasts		Optimal output forecasts	
	MSE	R²	MSE	R²
Support vector regression	0.0019	0.8169	0.3132	0.6745
Ridge regression	0.0061	0.4229	0.2410	0.7535
Polynomial regression	0.0113	0.6268	0.2307	0.7571
GBDT	0.0036	0.8827	0.1869	0.8029
Random forest	0.0059	0.8067	0.1803	0.8148
BPNN	0.0014	0.9487	0.1263	0.8853

Table 7. Comparison of the predictive performance of different models (test set).

(1) According to the empirical analysis results of SFA_SBM model with undesirable outputs, real epidemic prevention and treatment strategies could be observed after considering the resource slack value and mitigating the effects of environmental factors and statistical noise. An overall upward trend in anti-epidemic performance efficiency is observed across all country categories.

(2) The epidemic prevention and treatment efficiency under a hypothetical scenario could be predicted by constructing BPNN model. The BPNN efficiency prediction model has a minimal MSE of merely 0.0014. On this basis, a BPNN optimal output prediction model might be further constructed, and its MSE on the test set was only 0.126. The robustness test of the above mentioned prediction models are passed both.

With the continuous acceleration of globalization, the impact of public health emergencies on citizens' health and life is becoming increasingly significant. A system that can quickly evaluate and predict the effectiveness of emergency response is necessary and important. The proposed research framework effectively facilitates the evaluation and prediction of PHEs' efficiency, providing a solution to the question of "what is the optimal output and how to achieve it". It is a valuable multistage tool for guiding the development of prevention and treatment strategies and long-term planning.

It should be noted that there are some limitations in this study. The crisis response efficiency of some countries might be evaluated to be 1 by the above framework, which indicates that their crisis responses are efficient. However, in fact, there are also differences in the effectiveness of crisis response among these countries. Therefore, in the future, the crisis response efficiency of these countries will be explored using super-efficiency model to further separate the efficiency differences among efficient countries (i.e., countries with an efficiency of 1). Moreover, the efficiency determinants in PHEs and the effects of adjustments made in prevention and treatment strategies on regional economies and industries might be further investigated in the future.

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SUPPLEMENTARY MATERIAL

http://www.revistadyna.com/documentos/pdfs/_adic/11109-1_en.pdf

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