Research Article

Application of Artificial Intelligence for the Estimation of Concrete and Reinforcement Consumption in the Construction of Integral Bridges

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Estimation of basic material consumption in civil engineering is very important in the initial phases of project implementation. Its importance is reflected in the impact of material quantities on forming the prices of individual positions, hence on forming the total cost of construction. The construction companies use the estimate of material quantity, among other things, as a base to make a bid on the market. The precision of the offer, taking into account the overall conditions of the business realization, directly influences the profit that the company can make on a specific project. In the early stages of project implementation, there are not enough available data, especially when it comes to the data needed to estimate material consumption, and therefore, the accuracy of material consumption estimation in the early stages of project realization is smaller. The paper presents the research on the use of artificial intelligence for the estimation of concrete and reinforcement consumption and the selection of optimal models for estimation. The estimation model was developed by using artificial neural networks. The best artificial neural network model showed high accuracy in material consumption estimation expressed as the mean absolute percentage error, 8.56% for concrete consumption estimate and 17.31% for reinforcement consumption estimate.

1. Introduction

Cost estimation in construction represents a quantitative estimate of the probable resource expenses required for completing the activity [1]. A lot of factors affect the cost price. Each of these factors must be analysed, quantified, and estimated.

Estimating the final price requires a large number of elements to be synchronized. The process of defining the elements determining total costs includes the calculation of work quantities and then transferring them into expected costs. The basic elements or resources used and involved in the project during construction can be divided into several groups as follows:

(i) Work

(ii) Material

(iii) Equipment

(iv) Profit

(v) Time [2]

In order to carry out a project, it is necessary to organize teams with a large number of people. The initiative for entering the process of project implementation is started by the investor. The other participants in the project are a consultant, designer, expert supervision, contractor, and stakeholders.

In addition to the investor, the contractor has an important role on the project, since he represents a direct executor of the construction. An investor chooses a contractor based on certain criteria. Most commonly, these criteria require the construction of the highest quality structure with the minimum amount of money expended and in the shortest time possible. Clearly, these are the criteria that strive to idealize the entire course of the project and are therefore difficult to achieve.

The investor and contractor estimate costs for themselves, separately. Depending on the cost estimation results, the decisions are made about the further steps in the project. It is often the case that certain project implementation is withdrawn after the estimation, or the design is significantly modified.

A large number of factors, such as availability, quality, and the level of details in technical documentation, estimation method as well as the expertise of people performing the estimate, determine its quality and reliability from the aspect of satisfactory accuracy. The initial phases of project implementation are characterized by the insufficient data quantity. Each subsequent phase brings new data. The availability of the necessary data helps to increase the accuracy of the estimate. In 1974, Barnes presented the dependence of cost estimate accuracy and the phase of the project (see Figure 1).

The price offered by a contractor for project implementation is usually the main and quite often the only criteria based on which the investor chooses a contractor. Thus, the procedure for choosing a contractor according to this criterion is extremely simple, since the bidder with the lowest price will be chosen as the contractor. The problem with this method of contractor selection is the inability to see whether the project will be successfully completed, i.e., whether the contractor who offered the lowest price will be able to complete the project in the expected or at least satisfactory way (taking into account expenses, quality, and time).

A preliminary project cost estimate is the first serious estimate to be made on a project. During the initial phases of project implementation, it is not necessary to have a sufficiently accurate cost estimate. Since the material is one of the elements that affects the overall cost of the project, in order to reach its estimate, it is necessary, among other things, to determine the quantities of construction material required in the project. After determining the quantities, they are multiplied by the corresponding unit prices of these materials, and thus, we arrive at an estimate of the material costs which is one of the items in the sum of total expenses. The advantage of the cost estimation algorithm, in which there is a cost breakdown of items, is that it updates the cost separately, position by position, when new data become available. Also, the positive side of this approach is that positions can be monitored separately, allowing decision makers to make better decisions about the project during its initial phase.

In this study, the estimate of material consumption is performed for the materials which are most present in bridge construction, reinforcement, and concrete. The estimate is based on the values taken from the bills of quantities and cost estimates from the design documentation based on which the works were contracted.

2. Application of Artificial Neural Networks in Construction

Application of neural networks, one of the artificial intelligence techniques, in construction engineering, is quite widespread. They can be used in all the project implementation phases. The journal Microcomputers in Civil Engineering published a paper in 1989 which refers to the use of neural networks in this area. The authors of this paper are Adeli and Yeh [4]. The application of neural networks in construction is becoming more and more common because, in addition to the wide range of abilities they have, the rapid development of software packages has contributed to this.

Neural networks can be used for different types of estimates. One of them is the cost estimation of different types of construction and it has been processed by a large number of authors in their works [5–11]. In addition to cost estimation, neural networks can be used to estimate the duration of construction projects, which was also a topic dealt with by certain authors [8, 12]. Estimation of material consumption for the facility construction is another one of the estimates that is possible to be performed by applying neural networks. Despite this, there are only few papers in the literature that present the results of neural network applications for the purpose of estimating material consumption.

Fragkakis et al. represented the conceptual model for cost estimation of bridge foundations, which also gives the estimation of material consumption. Independent variables, which are relevant to the model, were identified by experts in the interviews. For defining this model, the authors used the stepwise regression methodology in order to determine whether the results were consistent with the expert opinion. The main assumptions underlying the correct application of the regression method were examined, and the necessary adjustments were made. The proposed method of conceptual cost estimation and material consumption estimation provides quick and reliable results that can be very useful in the early phases of a project [13].

An estimation of required material quantities, concrete, and reinforcement in multistorey buildings was performed by Mučenski et al. The forecasting model was defined using neural networks. Model analysis and definition data were taken from 115 major multistorey projects. The input variables of the model for forecasting the required amount of concrete and reinforcement are as follows: total gross area, average gross floor area, number of stiffening walls, longitudinal raster, transverse raster, and type of landing structure. The best results were shown by a network trained with the BFGS (Broyden–Fletcher–Goldfarb–Shanno) algorithm with an average error of 12.49% [14].

Garcia de Sotto et al. made an estimate of the materials and presented the methodology which was used to achieve estimate of satisfactory accuracy in the early phases of project implementation. They used neural networks, among other things, for modelling. Obtained results showed a significant improvement compared to the situation in practice [15].

The same authors, Garcia de Sotto et al., aimed to devise a process for developing a model which would be used for the preparation of preliminary estimates of construction material quantities taking into consideration data which are available during the early phases of the project and to assess the model by using the Akaike information criterion. The
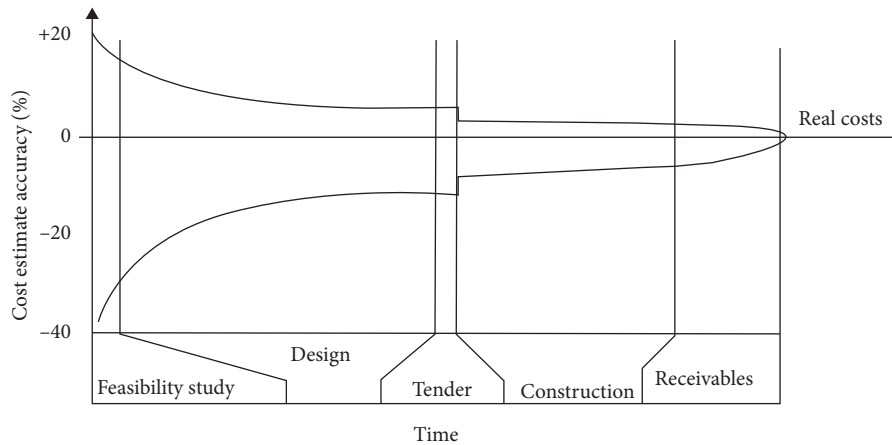
FIGURE 1: Cost estimate reliability [3].

proposed procedure is illustrated by an example in which data from 58 designs were used to define the model. These data were used for estimating used up concrete and reinforcement by using the neural network technique. For choosing the model with the highest accuracy, Akaike information criteria were used [16].

3. Materials and Methods

The first step undertaken for the purposes of this research is data collection and analysis. The data collected, after analysis, had to be prepared for model formation. In the end, two final models for the estimation of construction material consumption were defined, one for the concrete consumption and the other for reinforcement consumption.

The data were collected from the Main Designs of Integral Road Bridges, which were built on highways in the territories of Montenegro, Bosnia and Herzegovina, and Serbia. The term integral bridges is a modern term for concrete and composite frame structures of bridges without expansion joints and bearings [17]. There are several definitions of integral bridges. According to some, integral bridges are single-span frames with no expansion joints and bearings. In addition to this, we can find other definitions in the literature. They define this type of bridges as continuous frames without expansion joints and bearings just above the piers.

The research included 101 structures. Among them, there are 48 bridges from Montenegro, 29 bridges from Bosnia and Herzegovina, and 24 bridges from Serbia. The design documentation was prepared in three countries, so its form differs from one another. Therefore, the analysis and data preparation processes were complex. Only the same types of work were taken from all the bills of quantities and cost estimates in order to achieve data uniformity. In bills of quantities and cost estimates, the types of works are divided into preliminary, earthworks, concrete, reinforcement, tensioning works and prestressing, insulating, asphalt, and finishing works. Data on quantities of concrete and reinforcement were taken from concrete and reinforcement types of work.

An integral part of the technical documentation for the main design of bridges is the bill of quantities and cost estimate, and all the necessary data are obtained from them. The spans of these bridges range from 11.5 to 28 meters, the number of spans is from 1 to 18, the length of bridges without wing walls ranges from 11.5 to 784.4 meters, and the pier height is from 2.8 up to 65 meters. These projects were carried out in the period from 2010 until 2016.

After collecting the material quantity data, model input data were determined. Model inputs will represent certain design characteristics of bridges. The criteria for choosing such characteristics were their direct impact on material consumption. Based on this, the following characteristics were chosen: bridge length, bridge width, pier height, and bridge span. The data about bridge characteristics were taken from the main designs of these structures. Some of the data, such as pier height and bridge span, had to be corrected in such a way that a single value could be used as an input size. This is the reason why, when pier height is mentioned, as input data, it implies the mean height of middle piers. In case of a single-span structure, as a mean pier height, it is implied that the mean abutment height was used. Regarding the span of the bridge, this parameter had to be corrected for the fact that it is not the same if you have a larger number of smaller spans or a smaller number of larger spans in the identical length of the bridge. Due to this fact, the bridge span, as an input parameter, implies the mean of the span. The input data, prepared in the aforementioned manner, are presented with their limit and mean values in the table (see Table 1).

In order to improve the model for the material consumption estimate, as the input parameters, the data on construction technology and structure foundation are introduced.

For the span structure of analysed bridges, two types of formworks were used: formworks on a fixed scaffolding and formworks on mobile scaffolding. For that reason, the new input variable, named construction technology, has a value of 0 for formworks on a fixed scaffolding and the value is 1 when the formworks are on a mobile scaffolding.

The method of founding determines the amount of material used for founding. The bridges whose data were

TABLE 1: Input data.

Input data number	Input data description	Data type	Meas. unit	Min	Max	Mean value
Input 1	Bridge length	Numeric	m	11.5	784.4	153.25
Input 2	Bridge width	Numeric	m	6.5	30.55	11.52
Input 3	Pier height	Numeric	m	2.8	35.9	13.65
Input 4	Bridge span	Numeric	m	11.3	44.5	24.07
Input 5	Construction technology	Discrete	—	0	1	—
Input 6	Founding method	Discrete	—	0	2	—

used in this research were founded shallow, deep, or combined. The new input variable, named the founding method, depending on the method of founding, has the following values: 0 in case of shallow founding, 1 in case of deep founding, and 2 in case of combined founding.

The next step is defining the model output data. Based on the considered parts of the research, one output from each model was determined, which is the total amount of concrete and the total amount of reinforcement for the construction of integral road bridges (see Tables 2 and 3).

In the process of model formation using artificial neural networks, the available data should be divided into two sets. These two sets represent the training and test sets. The data of the training set are used for training and from the test set for checking the network.

Various recommendations can be found in the literature regarding the percentage ratio of these sets. A large number of authors select data in the ratio 90% to 10%, 80% to 20%, 85% to 15%, or 70% to 30% [18]. Of course, these are just recommendations, and the specificity of each of the problems being solved makes us decide on the appropriate ratio between the two sets. In this research, the training and test set will be divided in the ratio 80% to 20%. In 6 models, a direct division will be made into training and test sets, and in 2 models, a random selection of data will be done. The cross-validation procedure (k-fold cross-validation and leave-one-out cross-validation) shall be used to randomly select data.

Network training is preceded by a transformation, i.e., scaling data to fit everyone within a certain size range. The choice of ranges for scaling inputs and outputs depends on the activation function of the output quantities. Data can be scaled using standardization and normalization [19, 20]. The result of these methods is to reduce certain data to the same order of magnitude. Moreover, they enable the analysis of data of the same importance when forming the model, which means that it will also provide data analysis with a smaller size range. The data scaling methods used in the study are StandardScaler (Z-score normalization) and min-max normalization.

Network formation begins with determining the network architecture. This involves defining the number of layers and the number of neurons in each of the layers. Some authors recommend that it is not necessary to take more than two hidden layers when defining an artificial neural network [18, 21, 22]. The confirmation that the networks with two hidden layers gave reliable results is found in many theoretical results and numerous simulations in various engineering fields. In addition, there are theoretical results that indicate that a single hidden layer is sufficient for the

network to approximate any complex nonlinear function with sufficient accuracy [23].

The number of neurons in the hidden layers is not uniquely determined. There are recommendations in the literature but not a precise and reliable way of determining them. A large number of neurons lead to the problem of overfitting, while the insufficient number of neurons leads to the problem of underfitting, i.e., poor approximation of the dependence between input and output quantities. The number of neurons should be such that it does not lead to any of these issues, but to enable data to exhibit its most useful characteristics. The recommendations made by some authors refer to the upper limit of the number of neurons in the hidden layer. Lippmann (1987), Nielsen (1987), and Hecht-Nielsen (1990) recommend determining the number of neurons following inequality (1), whereas Rogers and Dowla (1994) give recommendations for the maximum number of neurons, N_H, following inequality (2). It is advisable to accept a smaller number from the ones stated in the inequality, where N_i is the number of input parameters and N_S is the number of training samples:

$$N_H \leq 2 \times N_i + 1, \tag{1}$$

$$N_H \leq \frac{N_S}{N_i + 1}. \tag{2}$$

In the process of defining a model, one must strive to find a model with the best possible opportunity for generalization. Generalization is a process in which knowledge that is valid for a certain set of cases is transferred to some of its supersets [24], i.e., based on data which are not presented to the model during the training (the validation set), the model has the ability to result in satisfactory sizes even though based on data which are not presented during training. The validation set is introduced to avoid the problem of overfitting or determine stopping points of the training process [25]. Generalization in forecasting is further enhanced by the cross-validation process. This procedure is performed on the data from the test set.

Constant performance measurement is done during the model definition. Performance measurement, in fact, is an accuracy forecast. The difference between the actual (desired) and the forecast value is the forecasting error, and a measure of accuracy is defined. There are a number of accuracy measures for forecasting in the literature. The accuracy of the model in this study was determined using the mean absolute percentage error (MAPE). A satisfactory generalization probability in models is achieved if the

TABLE 2: Output data of the first model.

Output data number	Output data description	Data type	Meas. unit	Min	Max	Mean value
Output 1	Total quantity of concrete	Numeric	m³/m²	1.05	3.11	1.54

TABLE 3: Output data of the second model.

Output data number	Output data description	Data type	Meas. unit	Min	Max	Mean value
Output 1	Total quantity of reinforcement	Numeric	kg/m²	117.26	415.58	250.8

TABLE 4: Activation functions of a multilayer perceptron model of the artificial neural network.

Function	Mark	Explanation	Range
Identity	x	Only in the output layer	$(-\infty, +\infty)$
Rectified linear unit function	$\text{Max}(0, x)$	Neuron activation is forwarded directly as an output if positive, and if negative, it is forwarded to 0. It has been shown to have 6 times better convergence than a hyperbolic tangent function	$(0, +\infty)$
A hyperbolic tangent	$[2/(1 + e^{-2x})] - 1$	Neuron activation is forwarded directly as an output if positive, and if negative, it is forwarded to 0. It has been shown to have 6 times better convergence than a hyperbolic tangent function	$(-1, +1)$

deviation between the forecasted and expected results at the training and test set is small.

The forecasting model was formed in Python 3.7 software package. In order to solve the problem that is the subject of the research, models about estimating material consumption, a multilayer perceptron MLP is formed, which is one of the artificial neural network types.

The most commonly used neuron activation functions in the hidden layers are logistic sigmoid (logistic), a hyperbolic tangent (tanh), and the function of rectified linear unit (ReLu). The activation function of output neurons is mostly linear. Bearing in mind, the number and other data characteristics, following the aforementioned recommendations, during the model formation, for hidden neurons, the function of rectified linear unit (ReLu), and a hyperbolic tangent (tanh) were used, whereas for the output neurons, the identity function was used (see Table 4).

4. Results

Artificial neural network models, multilayer perceptron (MLP), are formed based on defined input and output sizes and other required parameters. The number of layers as well as the number of neurons in hidden layers is determined based on recommendations, and the number of neurons in the input and output layer is determined based on the number of input and output sizes. The largest number of hidden neurons which was taken in the models is 13 based on expressions (1) and (2). 8 artificial neural network models were formed. In one half of these models, the data were used which were scaled by using the StandardScaler procedure, whereas for the other the min-max procedure was used.

All neural networks in both models, NMB1, NMB2, NMB3, NMB4, NMB5, NMB6, NMB7, and NMB8 for the model forecasting concrete consumption and NMA1, NMA2, NMA3, NMA4, NMA5, NMA6, NMA7, and NMA8

for the model forecasting reinforcement consumption, have 6 input and 1 output size. Neural network models with StandardScaler standardization for forecasting concrete consumption and reinforcement consumption are presented in tables (see Tables 5 and 6). They also list the characteristics of each model with a measure of accuracy given by the mean absolute percentage error (MAPE).

The following three neural network models are formed using the data which were scaled by applying the principle of min-max normalization. Data about model characteristics as well as the estimation accuracy which is determined by the mean absolute percentage error (MAPE) are presented in tables (see Tables 7 and 8).

Random data selection was done with two models using k-fold cross-validation for $k = 10$ and leave-one-out cross-validation (LOOCV). Estimation accuracy in these models is determined through mean absolute percentage error (MAPE) (see Tables 9–12). In those models where data division was done in accordance with k-fold cross-validation, the data were scaled by using a Standard Scaler, and in those models where the division was done with LOOCV, the data were scaled with min-max function. Two of each model that gave the best results are presented here.

By comparing presented models, it can clearly be seen that models NMB1 and NMA8 have the highest estimation accuracy. For model NMB1, StandardScaler was used for scaling the data. It defines 3 layers of neurons, one of which is input and one output layer. In the hidden layer, there are 12 neurons. The activation function of a hidden layer is the function of rectified linear unit (ReLu). The measure of the accuracy assessment model is expressed through mean absolute percentage error and is 8.56%.

Model NMA8 processed data which were scaled by using min-max normalization. The network architecture of this model is represented by 3 layers of neurons. There are 6 neurons in the input layer, 1 in the output, and 9 neurons in a hidden layer. The activation function of a hidden layer is

TABLE 5: Artificial neural network models for estimating concrete consumption (StandardScaler).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB1	MLP 6-12-1	ReLu	Identity	7.68	8.56
NMB2	MLP 6-4-1	Tanh	Identity	10.7	11.51
NMB5	MLP 6-7-1	ReLu	Identity	8.01	9.95

TABLE 6: Artificial neural network models for estimating reinforcement consumption (StandardScaler).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA1	MLP 6-7-1	Tanh	Identity	18.85	20.74
NMA2	MLP 6-13-1	ReLu	Identity	10.83	18.51
NMA5	MLP 6-8-1	ReLu	Identity	16.74	19.33

TABLE 7: Artificial neural network models for estimating concrete consumption (min-max normalization).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB3	MLP 6-11-1	ReLu	Identity	9.97	10.5
NMB4	MLP 6-12-1	Tanh	Identity	10.78	10.81
NMB6	MLP 6-7-1	ReLu	Identity	8.78	10.73

TABLE 8: Artificial neural network models for estimating reinforcement consumption (min-max normalization).

Model name	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA3	MLP 6-7-1	ReLu	Identity	18.28	19.03
NMA4	MLP 6-3-1	Tanh	Identity	19.15	19.41
NMA6	MLP 6-9-1	ReLu	Identity	18.26	18.78

TABLE 9: Artificial neural network models with random data choice for estimating concrete consumption (k-fold cross-validation, $k = 10$).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE (%)	σ (%)
NMB7	StandardScaler	MLP 6-4-1	ReLu	Identity	12.69	3.64

TABLE 10: Artificial neural network models with random data choice for estimating concrete consumption (LOOCV).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMB8	Min-max	MLP 6-11-1	ReLu	Identity	10.69	11.06

TABLE 11: Artificial neural network models with random data choice for estimating reinforcement consumption (k-fold cross-validation, $k = 10$).

Model name	Data-scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE (%)	σ (%)
NMA7	StandardScaler	MLP 6-4-1	ReLu	Identity	22.91	2.5

TABLE 12: Artificial neural network models with random data choice for estimating reinforcement consumption (LOOCV).

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of an output layer	MAPE training set (%)	MAPE test set (%)
NMA8	Min-max	MLP 6-9-1	ReLu	Identity	14.12	17.31

the function of a rectified linear unit (ReLu). Mean absolute percentage error is 17.31%.

The two models with the highest accuracy were selected as the final models for the estimation of concrete and reinforcement consumption, and based on them, the forecasting models were defined.

5. Conclusion

Based on the results presented in the study, it is concluded that the models with the highest accuracy of concrete consumption and reinforcement for the construction of integral road bridges are artificial neural network models whose architecture is represented by three layers of neurons, six of which are in the first layer, and one in the last output layer. In the hidden layer, there are 12 neurons in the concrete consumption estimation model, while 9 neurons are in the reinforcement consumption estimation model. The activation function of the hidden layers of neurons is the function of a rectified linear unit (ReLu), while the activation function of the output layers is linear (Identity). The accuracy measure is represented in both models by mean absolute percentage error (MAPE). In the model for concrete consumption, MAPE = 8.56%, whereas MAPE for the estimate of reinforcement consumption is 17.31%.

It is possible to improve the accuracy of a forecasting model by increasing the number of data in the data base. Additionally, the forecasting model would have the potential to be more widely applied if the database was expanded with certain features of the structures such as the type of cross section, height of the cross section, number of spans, number of piers, and structural system. The database could be improved by entering data on the category of the road (type and significance of the road) on which the bridges are located. The justification for the existence of this type of data in the database lies in the fact that the category of the road directly affects the load of bridges, which affects main characteristics of bridges and thus the amount of concrete and reinforcement. The potential parameters by which the database could be expanded would, in fact, be the input parameters of the forecasting model.

The use of a forecasting model would be particularly beneficial to the contractor when he is also the designer (for the contract-type design-build). With the help of a forecast model, without having to develop the preliminary design and only on the basis of sketches, the contractor could estimate the amount of material. The estimated amount of material is significant to him in the competitive bidding phase in order to submit as precise a bid as possible.

In the early phases, the amount of data available on future structures is insufficient for forming the accurate estimate. This means that the error in estimating material consumption is also greater than the estimates made in the subsequent phases of implementation. Quantity, type, and quality of data, which are available at the time of evaluation, condition the application of a model. This is the reason why it is necessary to adjust the input parameters to the data we have. The estimation importance in the early phases lies in the fact that the results of this early estimate directly affect assessing a total cost which in the further process determines/recommends us, or not for entering into the project implementation.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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