# Artificial Neural Network Approach for Solving Forward Kinematics of Cable Robots

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***Abstract*—In contrast to serial robots, the forward kinematics of cable parallel robots is more difficult to solve because of their nonlinearity and complexity. For cable robots, the forward kinematics is more difficult to solve because it is also affected by the sagging of the cables and driven system. The solution for forward kinematics based on the dynamic model is quite complex, requiring many processing steps to solve the forward kinematics problem. In cable robot control, the forward kinematics problem is necessary to precisely control the position and velocity of its moving platform. The computational methods give suitable solutions for these cable robots, but these methods also have disadvantages like convergence. This paper describes using a neural network model in proposing a solution for the cable robot with cable sagging because of its weight in its workspace. The experiments conducted with the results show that the solution of the forward kinematics by the neural network model increases the convergence of the solutions with a very small evaluation error. A comparison of the calculation results shows that the used model has achieved prediction accuracy with an error of less than 0.1 mm corresponding to CDPR size 4200×3200×2900 mm.**

***Keywords*—cable robots, forward kinematics, inverse kinematics, cable sag, neural network, Multilayer Perceptron (MLP), backpropagation**

## I. INTRODUCTION

Cable Driven Parallel Robot (CDPR) is a type of parallel robot in which the end-effector is defined by cable instead of hard links [1, 2]. The challenges in research and implementation of CDPR are similar to those encountered in Stewart's parallel structure. Indeed, CDPR may be required not only for more flexible operations but also for accessible large workspaces and high loads. An important characteristic of CDPR is that the cables can only operate unilaterally through tension and without compression. The CDPRs have many different classification methods, they can be classified according to the following criteria, such as number of cables $-m$ and degrees of freedom $-n$. This kinematic classification was proposed by Ming and Higuchi [3] to distinguish between different type of CDPRs. An obvious criterion for classification is to consider the number of cables expressed in $m$ and the controllable degrees of freedom of the moving platform, denoted as $n$. Moreover, the redundant freedom $r = m - n$ is introduced too. We can distinguish between the following groups: $m < n \leqslant 6$ Under-constrained cable robot; $n = m$ Fully-constrained cable robot; $n + 1 = m$. The robot may be constrained via cables in certain positions; $n + 1 < m$. Over constrained and forces must be distributed between cables. Classification is important for many of the methods and algorithms described in model design options because different types of cable robots have different structures and control methods.

Calculating the Forward Kinematic (FK) problem of CDPR is difficult even when the ideal cable is assumed to be straight [5, 6], or more complicated with a more realistic model taking into account the pulley diameter [7], or assuming that the cable has a small diameter, average length and tension is always greater than a given value, allowing us to ignore elasticity in the calculation [8]. In this study, the cable model is calculated in general including cable sagging and pulley diameter based on the chain cable model presented in [9] allowing to take into account the influence of cable mass, model This has been applied and verified experimentally on CDPR [10, 11].

This paper introduces a new method to predict the FK problem of CDPR taking into account the influence of cable deflection and guide pulley size. The Inverse Kinematic Problem (IKP) is calculated and the Neuron network is used to find the value of the Forward Kinematic Problem (FKP), the model is applied on a four-cable fully constrained parallel robot with the effects of cable sag in its workspace that is only deflected by its own weight. In this study, a neural network is used with the following layers: an input layer, five hidden layers and an output layer. The training data is generated by the results of the robot's inverse kinematics. In the prediction and regression of neural networks, the data plays a very important role in the accuracy of the selection model. Therefore, generating data with noise is extremely important to ensure accurate training for the model. The first step in predicting process is to generate data based on the values of the robot's inverse kinematics with the cable's sagging at different locations of the moving

Manuscript received June 8, 2023; revised August 22, 2023; accepted October 25, 2023; published March 8, 2024.

doi: 10.18178/ijmerr.13.2.184-189

platform randomly in the robot's workspace. The generated data is divided into 2 parts: training and testing. In the next step, the Multilayer Perceptron (MLP) model is trained with the data with the input as the position of the moving platform and the output as the length of the cables generated in the previous step. The final step is to test and evaluate the model based on testing the data at different random points of the inverse kinematics in its workspace.

Besides, simulation has also been used to show that the proposed model has high convergence and small errors. Based on the results of analysis, simulation and experiment, this model increases the accuracy and the test error is small.

## II. Inverse Kinematic of the 4-Cable Robot

The kinematic model of a fully constrained suspended CDPR is shown in Fig. 1, $B_i$ and $M_i$ are attaching points to the moving platform and fixed frame of the robot ($i$ = 1, 2, 3, 4). $b_i$ is the position vector of $B_i$ in the fixed frame B. To better understand the CDPR kinematics, a pulley schematic associated with the movement of the moving platform and the CDPR is shown in Fig. 2. The $l_i$ is the vector of the variable cable's length, $r_i$ is the position vector of attaching points on a moving platform (moving frame E). $p$ is the position vector of the moving platform's center of mass in B frame. According to the vector diagram in Fig. 2, the $M_i$ can be obtained as:

$$\overrightarrow{O_0M_i} = \vec{r_i} + \vec{p} \tag{1}$$

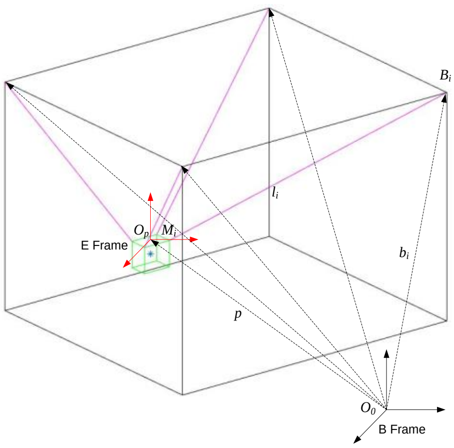


Fig. 1. Kinematic Modeling of a 4 cables robot in this study.

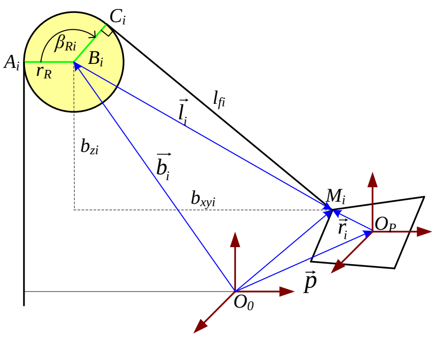


Fig. 2. Pulley kinematic modelling of fully constrained suspended CDPR.

The variable cable's length:

$$\vec{l_i} = \overrightarrow{O_0M_i} - \vec{b_i} = \vec{r_i} + \vec{p} - \vec{b_i} \tag{2}$$

Since the pulley has a radius of $r_R$, $L_t$ is the length of the ACM wire. The length of the cable is calculated from $A_i$, $C_i$, $B_i$ points:

$$L_{ti} = \beta_{Ri} r_R + l_{fi} \tag{3}$$

On the other hands:

$$b_{xyi} = \sqrt{(B_{xi} - M_{xi})^2 + (B_{yi} - M_{yi})^2} \tag{4}$$

$$b_{zi} = B_{zi} - M_{zi} \tag{5}$$

$$l_{fi} = \sqrt{b_{xyi}{}^2 + b_{zi}^2 - r_R^2} \tag{6}$$

where:

$$l_i = \sqrt{b_{xyi}{}^2 + b_{zi}^2}$$

From Fig. 2, we have:

$$\beta_{Ri} = \frac{\pi}{2} + \arccos(\frac{l_{fi}}{l_i}) + \arccos(\frac{b_{xyi}}{l_i}) \tag{7}$$

From Eqs. (3)–(7), we have like as.

$$L_{ti} = (\frac{\pi}{2} + \arccos(\frac{l_{fi}}{l_i}) + \arccos(\frac{b_{xyi}}{l_i}))\, r_R + \sqrt{b_{xyi}{}^2 + b_{zi}^2 - r_R^2} \tag{8}$$

In this study, Eq. (8) is used to solve the forward kinematics of cable robots. From there, velocity and acceleration can also be calculated. However, we only focus on the position of the cable robot with noise due to cable sagging.

Finding the end-effector position when knowing the joint variables is called the Forward Kinematic Problem (FKP). The FKP of CDPR is very complex and cannot be solved in a closed form. For the general case with 6 degrees of freedom, there can be up to 40 solutions for the forward kinematic problem [4], this would be very impractical to implement. In this paper, the NN network is used to find the response values of the forward kinematics problem of a fully constrained suspended CDPR. Along with building the CDPR kinematic model, a simulation method is also used to evaluate the computational model. The results show that the proposed method increases the convergence efficiency and achieves a very small error in the solution. On the other hand, the fast computation time is an advantage of the predictive method over the numerical method.

## III. Inverse Kinematic with Cable Sag Problem

The cable sagging model will assume that the cable is only deflected by its weight, neglecting wind and uneven distribution of weight. Consider a cable profile between two points B and M as in Fig. 3. Where B is the attachment point on the fixed frame, $M$ is attachment point on the moving platform, $L_S$ is the straight-line (Euclidean norm) distance between $A$ and $B$, $L$ is the catenary (actual) length between $B$ and $M$, $g$ is the acceleration due to gravity, $T$ is the cable tension with $X$ and Z components $T_x$ and $T_z$ at M, $T_{Bx}$ and $T_{Bz}$ are the X and Z components of the cable tension at $B$, and $(x_m, z_m)$ are the coordinates M. For this cable, the static catenary displacement equations for the inextensible case after simplification are [10–12]:

$$x_m = \frac{|T_x|}{\rho_L g}\left[\sinh^{-1}\left(\frac{T_z}{T_x}\right) - \sinh^{-1}\left(\frac{T_z - \rho_L g L}{T_x}\right)\right] \tag{9}$$

$$z_m = \frac{1}{\rho_L g}\left[\sqrt{T_x^2 + T_z^2} - \sqrt{T_x^2 + (T_z - \rho_L g L)^2}\right] \tag{10}$$

where $\rho_L$ is the linear density of the cable material.

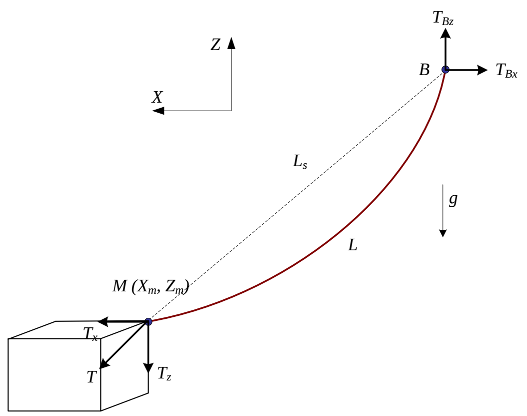


Fig. 3. The sag of cable between two points.

When considering the effect of cable sagging (i.e. the weight of the cable) in the modeling, cable tension must be taken into account to find cable length. Therefore, the kinetic and pseudo-random problems are combined and must be solved simultaneously, obviously from Eqs. (9) and (10). This is a system of implicit nonlinear equations, so there is no analytical solution, so it is imperative to use numerical methods. Li *et al.* [13] and Sridhar *et al.* [14] show that, for cases of minimal or under constraints, the catenary Eqs. (9) and (10) are solved with equilibrium equations:

$$\sum F_x = 0, \sum F_y = 0, \sum F_z = 0 \tag{11}$$

For cases of a 4-cable 3-dof (XYZ translation) fully constrained suspended CDPR in Fig. 1, a requirement arises that a solution of tension distribution must be selected because the equilibrium calculation does not have a unique solution. Since the number of variables is larger than the number of equations available, there can be an infinite number of valid solutions. Thus, solving static equilibrium equations (Fig. 4), for a given valid position, there can be an infinite number of valid combinations T = $[T_1\ T_2\ T_3\ T_4]^T$ for satisfying the equilibrium Eq. (11). In other words, at a given location there can be many valid cable tensioning solutions to maintain static equilibrium. To obtain a desired solution out of many possible solutions, mathematical optimization techniques are used.

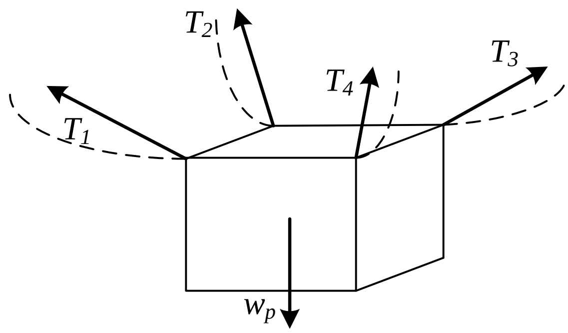


Fig. 4. The force acting on moving platform on static equilibrium.

There are various methods to optimize mathematics based on the nature of the problem. A common approach used in the field of robots is the Moore-Penrose pseudoinverse method of the Jacobian matrix, which helps minimize the Euclidean norm of cable tension. Another useful technique is Linear Programming, which helps to find solutions to the above problem, provided that the target function and constraints are linear.

When using the catenary Eqs. (9) and (10) to find the cable length of a fully-constrained cable robot, a viable approach is to solve it as a constrained optimization problem or specify the (m-n) number of forces before solving. The methodology adopted here to address the Inverse Position Kinematics and Statics problem is as described in [10, 12, 15]. The computational results of this method are shown in [12], and they are used to generate input data for a forward kinematic problem. Fig. 5 shows the results of straight-line and cable sag inverse kinematics. The sag of cables depends on the length of cables, the angle of cables with Z axis and the weight of the moving platform.

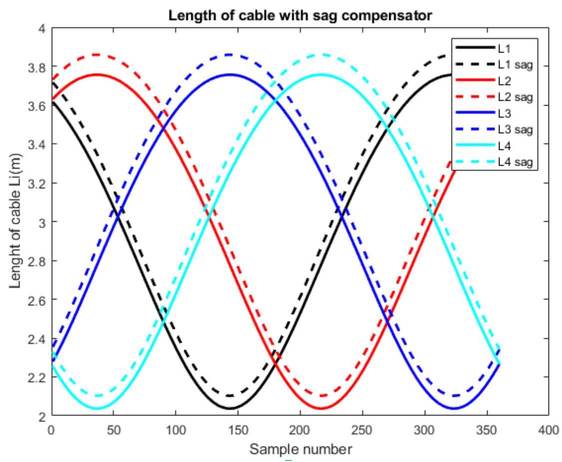


Fig. 5. Length of cables with sag compensator.

## IV. Neural Network for Forward Kinematics

An artificial or neural network (also known as an Artificial Neural Network-ANN or Neural Network) is a mathematical or computational model based on biological neural networks. It consists of a group of artificial neutrons (nodes) connected together and processes information by transmitting along the connections and calculating new values at the nodes (the connectionist approach to computation). In many cases, an artificial neural network is an adaptive system that changes its structure based on external or internal information flowing through the network during learning.

In actuality, many neural networks are nonlinear statistical data modeling tools. They can be used to model complex relationships between inputs and results or to look for patterns or samples in data [16]. From the equations that require input/output relationships, ANN is trained using sample data to construct input/output vector maps in a default way. Therefore, ANN can solve high nonlinear problems without determining the relationship between input and output [17].

The most common neural network used to solve FKP is the Multilayer Perceptron (MLP).

The graphical representation of MLP for the FKP solution is shown in Fig. 6. ANN's input is a vector of (1×4) L = [L1, L2, L3, L4]' corresponding to the length of the cables (variable joints). On the other hand, the coordinates of the working head are *X*, *Y*, and *Z* in the Cartesian coordinate system space. Because there is no theoretical method approach to determining the number of layers and neurons in each layer, so many neural networks (one hidden layer, two hidden layers,…) with different neurons were tested. The neurons in the hidden layer have the function of activating the sigmoid. The output layer has linear neurons. In this procedure, an end criterion is set to MSE and all initial weight coefficients are randomly assigned. Then the input vectors from the test data set are presented to the backpropagation network. The outputs of the network-the coordinates of the end effector P (*X*, *Y*, *Z*) are compared with the targets in the test data.

Based on the results of the testing process, we have designed and taught the five-layer ANN model with a sigmoid transfer function for the hidden layer and linear transmission function for the output layer to denote any functional relationship between inputs and outputs, if the sigmoid layer has enough neurons. Parallel robots with solid links usually have rather limited and complex workspaces, while cable robots with parallel kinematics have larger flexible workspaces.

Fig. 6 shows a model of generated data of the CDPR used in this study. The selection to generate data ensures uniform distribution in the workspace, which can be determined by geometric and linear algebra methods [13, 18]. With the robot's parameters used in this study, the workspace makes up the data in the range of 1,450, 1,950, and 2,030 (mm) in x, y, and z axes. The data from the inverse kinematic problem, Eqs. (8)–(10) are used as the input for ANN designed from 600 random coordinates. Table I shows a piece of the data from the inverse kinematic problem, that means, input variables in the forward problem ($L_1$, $L_2$, $L_3$, $L_4$) and the output variables (*X*, *Y*, *Z*) used to determine the structure of ANN) that was randomly determined. The general structure of the input/output of the model is shown in Fig. 7.

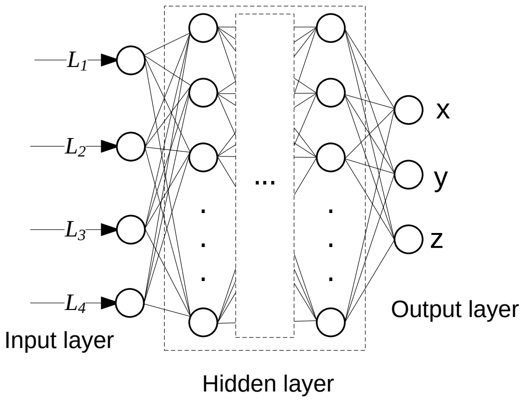


Fig. 6. Structure of an ANN model for the solution of Forward kinematics.

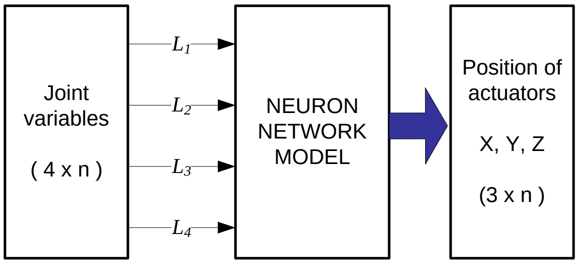


Fig. 7. Structure of proposed model.

TABLE I. DATA FOR TRAINING

| L1 | L2 | L3 | L4 | x | y | x |
|---|---|---|---|---|---|---|
| 4.455 | 3.615 | 1.731 | 3.125 | −1.168 | 1.292 | 0.725 |
| 2.305 | 2.641 | 2.815 | 2.503 | 0.286 | −0.122 | 1.514 |
| 2.516 | 1.52 | 2.977 | 3.589 | −0.693 | −0.84 | 1.589 |
| 1.155 | 3.049 | 3.989 | 2.819 | 1.373 | −0.848 | 1.964 |
| 3.329 | 4.223 | 2.749 | 0.898 | 1.164 | 1.317 | 1.73 |
| 4.288 | 3.786 | 0.855 | 2.187 | −0.699 | 1.744 | 1.948 |
| 3.296 | 4.077 | 2.861 | 1.559 | 0.993 | 1.081 | 1.09 |
| 4.284 | 4.926 | 3.348 | 2.302 | 1.018 | 1.674 | 0.056 |
| 2.193 | 2.943 | 3.112 | 2.415 | 0.664 | −0.131 | 1.36 |
| 3.304 | 4.366 | 2.917 | 0.601 | 1.405 | 1.353 | 2.246 |
| 4.455 | 3.615 | 1.731 | 3.125 | −1.168 | 1.292 | 0.725 |

## V. EXPERIMENTS AND DISCUSSIONS

Experiments are carried out with a fully constrained suspended CDPR. Specification of simulation CDPR is shown on Table II.

TABLE II. SPECIFICATION OF CDPR

| Dimension of base frame (L×W×H) | 4200×3200×2900mm |
|---|---|
| Tension limit | [40–800] N |
| Number of cables | 4 |
| Number of DOF | 3 |
| Maximum load | 80 kg |

The experimental coordinates are randomly taken in the feasible workspace, and 600 experimental coordinates are used to calculate the FK problem by ANN. The error results of the FK problem shown in Fig. 8 shows that the accuracy of the prediction model is stable, the error in 3 coordinates *X*, *Y* and *Z* are all less than 0.1 mm. The results show the appropriateness of CDPR's FK prediction model by ANN. This model initially gives high-precision results with the proposed CDPR configuration, which can be applied to solving linear kinematics. For CDPR, the advantage of the predictive model is the short computation time, which can be integrated with the cable sagging calculation models or the characteristic parameters of the cable actuators. However, the model is only simulated with a given CDPR configuration and corresponding tension distribution algorithm. The next research direction is to experiment with the algorithm on a concept CDPR to evaluate the calculation results and develop algorithms for other robot configurations and different tension distribution methods.

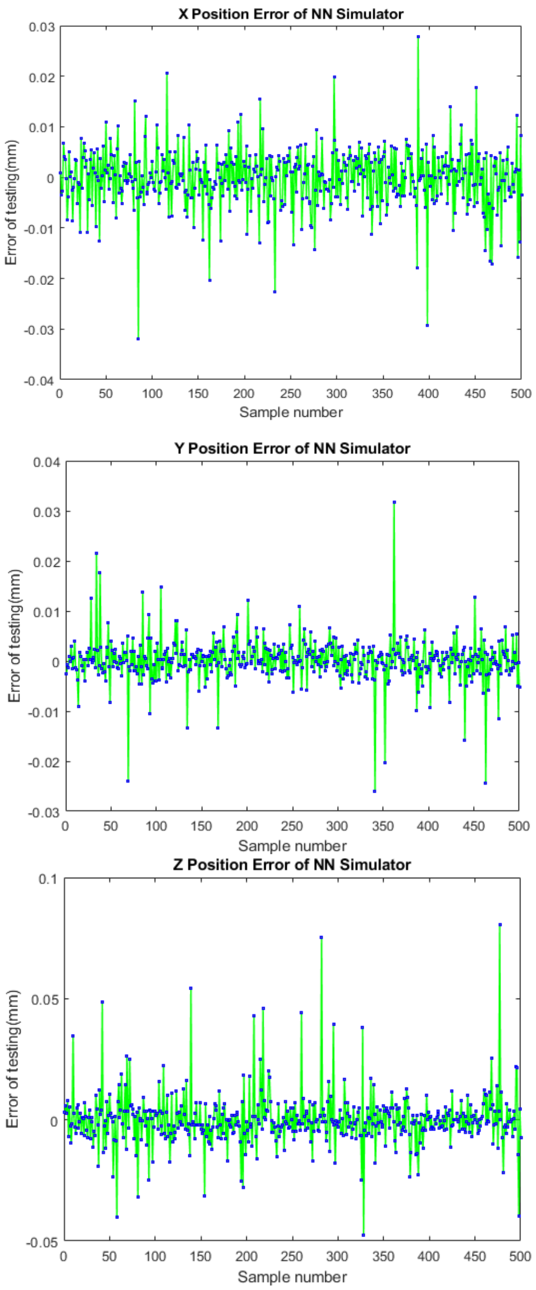


Fig. 8. The errors of the FKP of 4 cables robot modeling with ANN.

## VI. CONCLUSION

This study proposes the use of back-propagation MLP artificial neural networks for a cable robot's FKP solution, which can be constructed to generate the best estimate of the location of the moving platform. The results of this paper are interesting because they solve a problem in that no closed-form solution is known. Therefore, ANN can improve the accuracy of cable robots. In addition, a backpropagation network can explore high nonlinear functions and has been successfully applied to the approximate complex mapping between robot positions and cable lengths. The results of the simulation studies have demonstrated the advantages of this method in increasing the convergence with model accuracy which is superior to the corresponding methods for parallel robots.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Tuong Phuoc Tho, Nguyen Truong Thinh contributed to the analysis and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors discussed the results and contributed to the final manuscript. Besides, Nguyen Truong Thinh conceived the study and was in charge of overall direction and planning; all authors had approved the final version.

## FUNDING

This study was supported financially by HCMUTE Open Lab and Ho Chi Minh City University of Technology and Education, Vietnam.

## ACKNOWLEDGMENT

The authors wish to thank Ho Chi Minh City University of Technology and Education, Vietnam.

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