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GENETIC PROGRAMMING BASED IDENTIFICATION OF AN OVERHEAD CRANE

Zastosowanie programowania genetycznego w identyfikacji modelu dynamiki suwnicy pomostowej

Abstract: *Overhead cranes carry out an important function in the transportation of loads in industry. The ability to transport a payload quickly and accurately without excessive oscillations could reduce the chance of accidents as well as increase productivity. Accurate modelling of the crane system dynamics reduces the plant-model mismatch which could improve the performance of model-based controllers. In this work the simulation model to be identified is developed using the Euler-Lagrange method with friction. A 5-step ahead predictor, as well as a 10-step ahead predictor, are obtained using multi-gene genetic programming (MGGP) using input-output data. The weights of the genes are obtained by using least squares. The results of 15 different genetic programming runs are plotted on a complexity-mean square error graph with the Pareto optimal solutions shown.*
Keywords: genetic programming, crane, nonlinear model, identification

Streszczenie: Suwnice pomostowe pełnią istotną funkcję w transporcie technologicznym w różnych obszarach przemysłu. Podniesienie wydajności i zapewnienie bezpiecznej realizacji zadań transportowych przez suwnice wymaga zastosowania skutecznych układów sterowania. Opracowanie dokładnego modelu dynamiki suwnicy jest istotnym elementem projektowania systemu sterowania, w szczególności sterowania predykcyjnego. W niniejszej pracy wykorzystano programowanie genetyczne MGGP oraz metodę najmniejszych kwadratów do identyfikacji modeli predykcji pozycji i kąta wychylenia ładunku przemieszczanego przez suwnicę. W rezultacie przeprowadzonych badań uzyskano modele 5- i 10-krokowej predykcji dla modelu suwnicy wyprowadzonego z równań Eulera-Lagrange'a. Wyniki poddano analizie wielokryterialnej z uwzględnieniem złożoności modelu i błędu średniokwadratowego w celu wyznaczenia rozwiązania optymalnego w sensie Pareto.
Słowa kluczowe: programowanie genetyczne, suwnica, model nieliniowy, identyfikacja

1. Introduction

Overhead cranes, an example of material handling system, play an important role in several sectors, such as transportation and manufacturing. Cranes are a classic example of a nonlinear underactuated system which leads to difficulty in simultaneously controlling the positioning of the crane as well as suppressing the payload oscillations. Excessive oscillations can not only increase settling time and reduce positional accuracy but can also be dangerous to surroundings as well as to the payload itself, especially in the case of transportation of hazardous or heavy loads. In order to achieve effective control of both positioning and oscillation suppression it is important to have an understanding of the underlying dynamic model describing the system.

Many control methods require a dynamical model of the system to be able to determine its effectiveness in terms of stability and feedback performance characteristics and thus providing a better model can result in better performance. Several methods for modelling material handling systems have been used such Lagrangian method, bond-graph approach, Takagi-Sugeno fuzzy models [19] or Multibody dynamics simulation [7]. Inadequate dynamic models, due to initial assumptions or the result of system changes associated with ageing, result in plant-model mismatch. Model mismatch causes deterioration of performance in model-based controls such as model predictive control, generalized predictive control or feedback linearizing control. In some instances, improperly configured controller parameters can eventually lead to system failure [8]. In order to obtain a more accurate model, input-output identification methods can be used. Genetic programming, which was developed by Koza [11] and is related to genetic algorithms, has been used in input-output identification of nonlinear dynamical systems [4,9,15] without having selected a particular model structure a priori. There have been several works [1,2,3,10,17] that have utilized genetic algorithms for the control, identification and planning of cranes. In contrast to other machine learning methods such as artificial neural networks, which have been able to fit models to high accuracy, but as black box models lose their interpretability [5], genetic programming is capable of symbolic regression in which an analytical relationship of the model is obtained.

The rest of the article is organized as follows. Section 2 describes the dynamical model of the crane with friction, this model is used in the simulation of the system to obtain input-output data. Multi-gene genetic programming used to obtain the mathematical expression describing the predictors is described in section 3. The numerical simulation is carried out in MATLAB/Simulink and results are presented in section 4. The final remarks are made in section 5.

2. Dynamic model

A planar model of an overhead crane is shown in fig. 1, where the trolley of mass M moves on a rigid bridge only in the x-direction and the position denoted by x. The rope is assumed to be an inflexible cable with length l carrying a payload, modelled as a point mass m suspended below the trolley, the payload swing angle is denoted by θ. While friction between the trolley and the bridge are modelled, we neglect the effect of friction and air resistance acting on the payload.

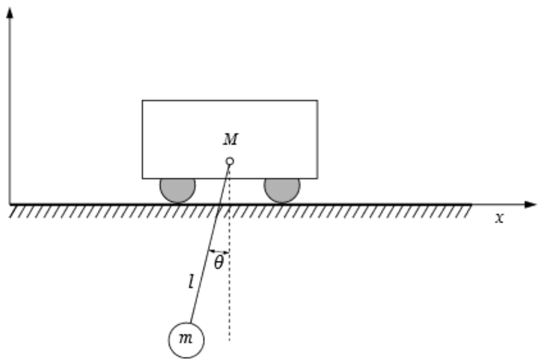

Fig. 1. Planar model of an overhead crane

The equations are obtained using the Euler-Lagrange (1) method [12] and are shown below:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}}\right) - \frac{\partial L}{\partial q} = F \tag{1}$$

For the generalized coordinates $q = [x, \theta]^T$, external force F and Lagrangian function as the difference between the kinetic and potential energy. The kinetic energy K and potential energy U as well as the Lagrangian L are given in (2)

$$\begin{aligned} K &= \frac{1}{2}M\dot{x}^2 + \frac{1}{2}m\left(\left(\dot{x} + l\dot{\theta}\cos\theta\right)^2 + \left(l\dot{\theta}\sin\theta\right)^2\right) \\ U &= mgl(1-\cos\theta) \\ L &= \frac{1}{2}M\dot{x}^2 + \frac{1}{2}m\left(\left(\dot{x} + l\dot{\theta}\cos\theta\right)^2 + \left(l\dot{\theta}\sin\theta\right)^2\right) - mgl(1-\cos\theta) \end{aligned} \tag{2}$$

The derivatives with respect to the generalized coordinates are given in (3)

$$
\begin{aligned}
&\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{x}}\right) = (M+m)\ddot{x} + ml\ddot{\theta}\cos\theta - ml\dot{\theta}^2\sin\theta \\
&\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}}\right) = ml^2\ddot{\theta} + ml\ddot{x}\cos\theta - ml\dot{x}\dot{\theta}\sin\theta \\
&\frac{\partial L}{\partial x} = 0 \\
&\frac{\partial L}{\partial \theta} = -ml\dot{x}\dot{\theta}\sin\theta - mgl\sin\theta
\end{aligned}
\tag{3}
$$

We then obtain the equations of motion of the overhead crane

$$
\begin{gathered}
(M+m)\ddot{x} + ml\ddot{\theta}\cos\theta - ml\dot{\theta}^2\sin\theta = F \\
ml^2\ddot{\theta} + ml\cos\theta\,\ddot{x} + mgl\sin\theta = 0
\end{gathered}
\tag{4}
$$

The total force F is composed of the actuating force on the trolley as well as the friction between the trolley and the bridge. The nonlinear friction model is composed of the sum of Coulomb friction, damping and a third term which approximates other nonlinear effects [20]. The friction model is given below:

$$
F_{fr} = f_{fr0}\tanh\left(\frac{\dot{x}}{\xi}\right) + k_p\dot{x} + k_r|\dot{x}|\dot{x} \tag{5}
$$

3. Multi-gene genetic programming

Genetic programming is an evolutionary algorithm that is similar to genetic algorithm. While other techniques require a model structure a priori, genetic programming searches for the model structure given a set of functions. The most common way to represent individual functions in genetic programming is by using syntax trees.

Similar to other evolutionary algorithms genetic programming creates an initial population randomly. There are several methods of initialization such as *full*, *grow*, and *ramped half-and-half* [18], and PTC2 [13]. In *full*, a maximum depth is specified, and a random tree is generated by choosing terminal nodes only once the maximum depth is reached. In *grow*, a maximum depth is specified but a terminal or nonterminal node can be chosen at any depth, although this leads to a wider variety of tree shapes and sizes compared to the *full* method there is no control on the expected tree size. In *ramped half-and-half*, half of the population is initialized with the *full* method while the other half is initialized with the *full* method. In PTC2 a maximum depth is specified as well as a probability distribution of tree sizes allowing more control over tree size. When the PTC2 algorithm chooses a tree size from the distribution. It should be noted that PTC2 does not guarantee the tree size as it can produce a tree that is slightly larger.

A new population is created in every subsequent generation by genetic operators such as subtree crossover, subtree mutation and direct reproduction. In direct reproduction the individuals that have the best fitness in the entire population are carried on directly into the next generation without any alteration. When crossover occurs, random individuals are chosen which undergo tournament selection. Once two parents are obtained then a random gene is chosen in each parent, then a random node is chosen at each tree and subtrees are swapped as shown in fig. 2. When mutation occurs, a random individual is selected from the population after which a random node is selected, and the subtree replaced by a newly created subtree as is shown in fig. 3.

In multi-gene genetic programming the individual is composed of one or more genes each represented by a tree. The overall function is then a weighted linear combination of genes [6] with respect to the parameters.

$$\hat{y} = w_0 + \sum_{i=1}^{i=n} w_i G_i(\boldsymbol{x}) \tag{6}$$

Where w_i is the ***i***-th gene weight, $G_i(\boldsymbol{x})$ is a function obtained by genetic operations and is represented by the tree structure. This linear in the parameter structure makes it possible to use least squares to obtain the parameter values w_i using (7)

$$w = (G^T G)^{-1} G^T y \tag{7}$$

Where the i-th columns of the matrix G are obtained by evaluating $G_i(\boldsymbol{x})$ using the input vector $\boldsymbol{x}$.

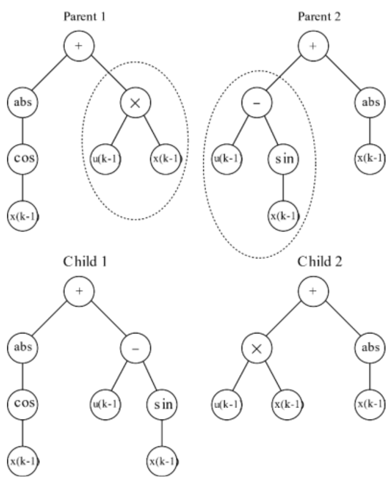

Fig. 2. Crossover operator

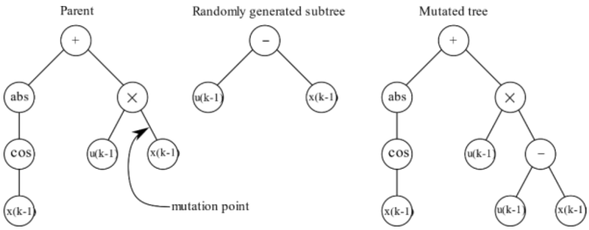

Fig. 3. Mutation operator

4. Simulation and Results

Simulation of the overhead crane with parameters given in table 1 to obtain the training and validation data for multi-gene genetic programming based identification for a 5-step ahead predictor as well as a 10-step ahead predictor for both the sway and the position of the trolley. The input signal was chosen to be white noise to persistently excite the system. The simulation was carried out for 25s with a sampling time of 0.05s. The PTC2 initialization method was chosen as it helps fight bloat caused by the subtree mutation by being able to specify a desired tree size [14].

The genetic programming parameters are given in table 2. The vector x is composed of past data while the vector u is composed of the white noise signal for the position predictor, and the position for the sway predictor. The objective is to minimize the mean square error of the n-step ahead predictor. The function set consists of addition, multiplication, tanh and analytic quotient [16]. Analytic quotient is given in (8)

$$\mathrm{adiv}(a,b) = \frac{a}{\sqrt{b^2+1}} \tag{8}$$

The genetic program is run 15 times for both the position and sway predictor model. The best solution from each run is taken together with its MSE as well as its complexity, where the complexity is calculated as the sum of all gene nodes. Then a Pareto optimal solution that minimizes both MSE and complexity from all runs.

Table 1

Model parameters

Trolley mass	500kg
Payload mass range	[1-50]kg
Rope length range	[1-10]m
Coulomb friction coefficient	4.4
Damping coefficient	0.05
Coefficient of approximation of other effects	0.01
Static friction coefficient	0.01

Table 2

MGGP parameters

Parameter	**Value**
Population size	64
Number of generations	100
Initialization method	PTC2
Max tree depth initialization	5
Max number of genes	6
Terminal Set	x(k-1), x(k-2), x(k-3), u(k-1), u(k-2), u(k-3), M, m, g, l
Non-terminal set	+,×,adiv, tanh
Crossover frequency	0.84
Mutation frequency	0.14
Direct reproduction	0.04

The 5-step ahead predictor, as well as the 10-step ahead predictor, are shown in figs. 4-5 and figs. 8-9 respectively. Figs. 6-7 and figs. 10-11 show the residuals of the predictors for the position and sway respectively. The maximum residuals for system parameters m = 24 kg and l = 5m of the sway angle are 0.0019 and 0.0069 for the 5-step ahead and 10-step ahead predictors respectively while the maximum residuals for the position of the trolley are 0.0074 and 0.0330 for the 5-step ahead predictor and 10-step ahead predictor respectively.

The plot of complexity and the MSE for the best solution of each run is shown in figs. 12-15 with the green circles indicating the Pareto frontier. The resulting 5-step ahead and 10-step ahead predictors describing the sway obtained from the Pareto frontier are given in (9) and (10) for position and sway respectively. The values for the weights of each predictor are given in table 3.

$$x(k+5) = w_1 x(k) + w_2\big(x(k) + u(k-1)\big) + w_3\big(3x(k-1) + x(k-2)\big) + w_4 u(k) + w_5\big(2x(k-1)\big) + w_6 u(k)$$

$$\begin{aligned} x(k+10) = {} & w_1 u(k) + w_2\Big(\mathrm{adiv}\Big(u(k-1), \mathrm{adiv}\big(x(k) + x(k-1), u(k-1)\big)\Big)\Big) \\ & + w_3\Big(\mathrm{adiv}\Big(\mathrm{adiv}\Big(u(k), \mathrm{adiv}\big(u(k), u(k-2)\big)\Big), \mathrm{adiv}\big(u(k), u(k-2)\big)\Big)\Big) + w_4\big(2x(k) + x(k-1)\big) \\ & + w_5\big(x(k-1) + x(k-2)\big) + w_6 x(k-1) \end{aligned} \tag{9}$$

$$\begin{aligned} \theta(k+5) = {} & w_1\Big(\tanh\Big(\tanh\big(Mx(k-2)\tanh(\theta(k))\big)\Big)\Big) + w_2\big(x(k) + \tanh(\theta(k-1))\big) \\ & + w_3\Big(\tanh\Big(\mathrm{adiv}\big(\tanh(\theta(k-2)), l\big)\Big)\Big) + w_4\big(\theta(k) + \tanh(\theta(k-2))\big) + w_5\theta(k-1) \\ & + w_6\Big(\mathrm{adiv}\big(\tanh(\theta(k-1)), l\big)\Big) \end{aligned}$$

$$\begin{aligned} \theta(k+10) = {} & w_1\big(\theta(k)\mathrm{adiv}(\tanh(M), 2l)\big) + w_2\Big(\mathrm{adiv}\big(\theta(k-2), \tanh(M + \theta(k))\big)\Big) + w_3\theta(k) \\ & + w_4\theta(k-1) + w_5\theta(k) \\ & + w_6\Big(\mathrm{adiv}(\tanh(M), 2l)\mathrm{adiv}\Big(\theta(k-1), \mathrm{adiv}\big(\theta(k-1), \theta(k-2)\big)\Big)\Big) \end{aligned} \tag{10}$$

Table 3

Gene weights

Predictor	w_1	w_2	w_3	w_4	w_5	w_6
$x(k+5)$	21.6148	-9.7671e-5	15.6090	-0.0104	-41.5254	0.0105
$x(k+10)$	3.5431e-4	-3.8221e-4	-1.7925e-4	-188.5501	59.4905	447.6691
$\theta(k+5)$	-1.6793e-4	5.9987	0.9877	11.9312	-43.8523	-1.0403
$\theta(k+10)$	-9.9848	45.6474	21.5550	-74.4195	21.5550	9.2207

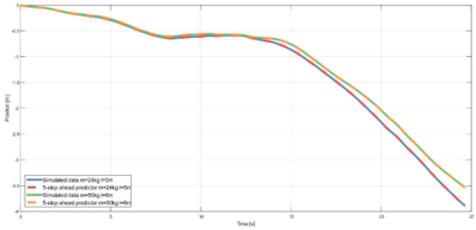

Fig. 4. Position 5-step ahead

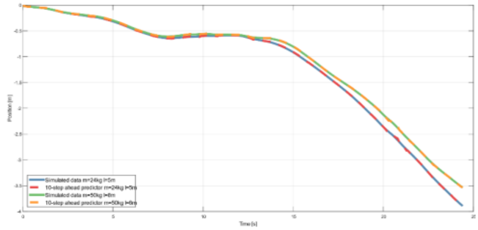

Fig. 5. Position 10-step ahead

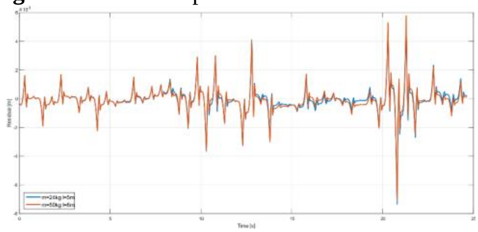

Fig. 6. Position residual 5-step ahead

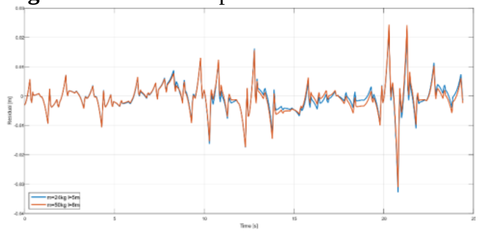

Fig. 7. Position residual 10-step ahead

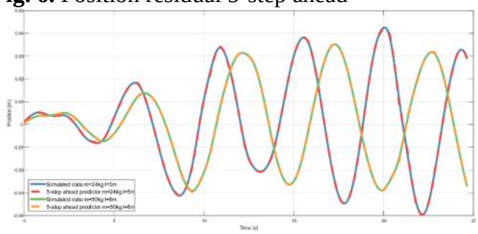

Fig. 8. Sway 5-step ahead predictor

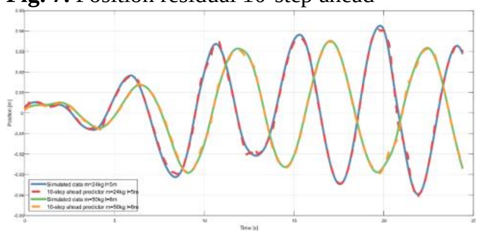

Fig. 9. Sway 10-step ahead predictor

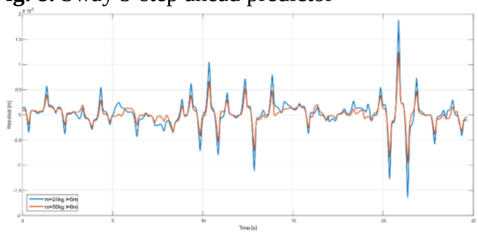

Fig. 10. Sway 5-step ahead residual

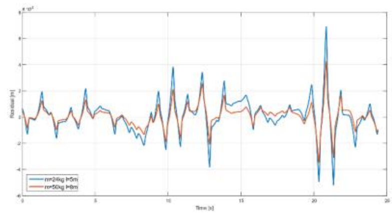

Fig. 11. Sway 10-step ahead residual

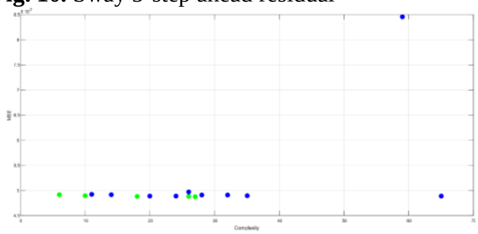

Fig. 12. Best 5-step ahead position solutions from all runs

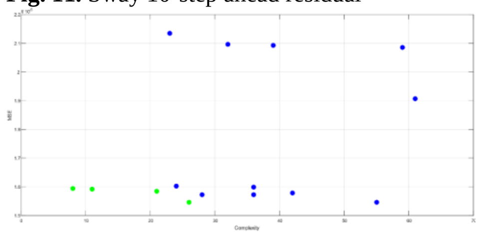

Fig. 13. Best 10-step ahead position solutions from all runs

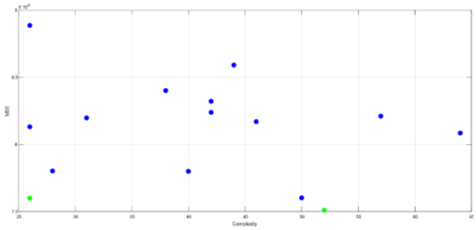

Fig. 14. Best 5-step ahead sway solutions from all runs

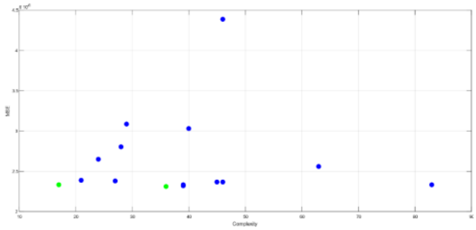

Fig. 15. Best 10-step ahead sway solutions from all runs

5. Conclusions

In this article we propose a MGGP approach for identification of an overhead crane using input-output data. The data used for training and validation were obtained from simulations in which the model was described by equations obtained from Euler-Lagrange method with added friction between the trolley and the bridge. MGGP was then used to obtain both the 5-step ahead predictor as well as the 10-step ahead predictor for both the trolley position and the payload sway. We show that MGGP provided satisfactory results in majority of the runs.

Future work would include identification of a model with fewer assumptions such as a flexible cable as well as air resistance acting on the payload, as well as identification based on input-output data from an experimental stand.

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