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# IDENTIFICATION OF A COMPLEX DRIVE CHAIN BASED ON LOCAL LINEAR MODEL TREE

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**Abstract.** This paper uses the local linear model tree (LOLIMOT) method for modeling the angular velocity of a complex nonlinear system called Gamma-log. The drive chain of the Gamma-log contains nonlinear parts such as an AC servo drive or a worm gear drive. The drive chain is modeled with LOLIMOT algorithm. An experiment was conducted to collect data from the original system and to simulate the kinematics of the track. The best model was selected from ARX and FIR models using a correlation coefficient based performance index.

*Keywords*: LOLIMOT, AC servo, electromechanical drive chain

## 1. Introduction

State-of-the-art industrial applications frequently use different kinds of actuators with electromechanical kinematic chains (EKC). A wide range of these cannot be controled only with a single motor but different kinds of gears and gearboxes are applied. The drive chains thus developed include a great number of different nonlinear components, such as motors, gears and bearings. The nonlinearities of the components of the chain make it hard to control the system precisely. It is a common requirement to supervise or monitor such systems, therefore modeling and simulation are important.

There can be found several references where complex drive chains are modeled with different methods. One common method is when the system components are separately modelled with differential equations. An example [1] introduces this method where a PMSM AC servo with its drive is included. Erdogan models an electric drive system with differential equations combined with object-oriented technics and verifies also the simulation model with an experiment [2]. The disadvantage of these methods is the need for a deep knowledge of the system components, which is regularly not available. After the simulation process a validation procedure follows when the real parameters are identified.

Systems can also be modeled with the ‘black box’ method. Inputs of the analysed process are matched to the inputs of the black box and the process should be carried out with the outputs as well. The black box can be e.g. a neural network structure or a locally linear neuro-fuzzy structure (LLNF). During the training process, these kinds of mathematical structures can find any nonlinear relation between the inputs and outputs if any level of correlation exists. So this method can powerfully assist as a general function approximator [3].

Neuro-fuzzy modeling is used in a wide range of applications. E.g. modeling and identification of a vehicle suspension was carried out with the neuro-fuzzy method [4]. A black box model for a temperature control pilot plant called RT542, which is equipment for engineering education [5], is another example. The structure can be used to model high nonlinearities such as the dynamics of centrifugal compressors [6]. There can also be found examples of its use for solving the identification and control problem of a combustion engine’s exhaust [7]. Besides the modeling, this method can also be used for predictive control [8].

The literature does not detail the process of model selection or a comparison of the different local linear neuro-fuzzy (LLNF) based models which are connected to drive chains. This paper presents a nonlinear black box model for a drive chain of the mobile Gamma-log equipment. The aim is to develop a LLNF model using LOLIMOT algorithm that captures the dynamic properties of the system over a wide operating range.

The paper covers the identification process, starting with a detailed description of the investigated equipment. After that Section 3 deals with measurements on the real system. Section 4 is about preprocessing the measured data. Section 5 shows the basics of the Neuro-Fuzzy LOLIMOT and its dynamical extension, followed by a comparison of the different utilized external dynamics and results.

## 2. Introduction of the investigated system

The section introduces the investigated Mobile Gamma-log equipment from many aspects. First the aim of the Mobile Gamma-log will be clarified, then the main construction of the device will be detailed. Following this, the investigated drive chain will be discussed.

### 2.1. Mobile Gamma-log equipment

During onshore exploratory oil drilling, in order to determine the exact depth of the core which contains oil, the natural gamma-ray spectral of the core is logged. To refine the local measurements, experiments are conducted on the raised bore cores in a laboratory. The result of the site experiments can be refined with the correlation of the two measurements. One of the most important details in the measurements is that the measured gamma spectrum of the bore core section should not slip from the exact depth value. Therefore accurate moving of the gamma-ray detector is needed during the experiments.

The main components of the investigated mobile equipment can be seen in Fig. 1. The bore core lies on a lead case in the centre line of the modular, one meter long, railway part. The detector-carrier-track carries the gamma-ray detector. The necessary power, the control signal of the controller PC and the resulting measurement signals go through the energy chain.

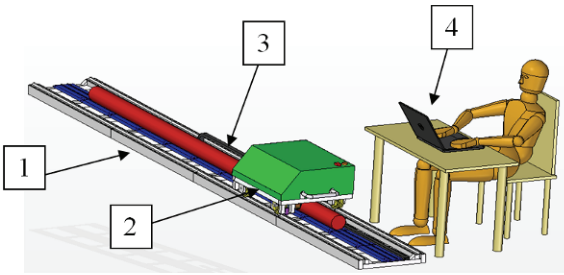


**Figure 1.** Main components of MGL-01F gamma-log equipment
1: modular railway; 2: detector-carrier-track; 3: energy chain; 4: controller PC

### 2.2. Drive chain of the track

The main drive in the actuator chain of Gamma-log is a 200W AC servo motor manufactured by Omron. The shaft of the motor is connected to a worm gearbox, which is a product of Bonfiglioli (Fig. 2). The reducing gear ratio of the worm gear is 70. The rear left wheel of the track is the drive wheel which is connected to the worm gear. An incremental encoder is assembled to the front left wheel of the track. The encoder senses the movement of the track in the railway. The resolution of the encoder is 1000 pulses per rotation. Every wheel of the track has bearings on both sides [9].

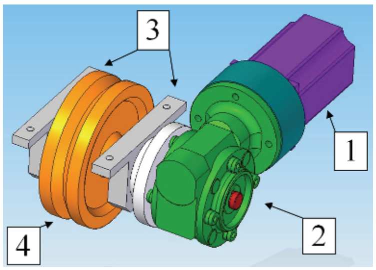


**Figure 2.** Drive chain of Gamma-log
1: Omron AC servo motor; 2: Bonfiglioli worm gear; 3: Bearings; 4: Wheel with V-profile

### 3. Measurements

Measurements were performed to model the kinematic and dynamic behaviour of the Gamma-log track. The measurement set-up can be seen in Fig. 3. The main difficulty was that the track was moving while the data acquisition was in progress. During the measurements the track was controlled with different accelerations and different velocities. During the different measurements the moving distance of the track was set to a constant length of 100 millimetres. For the measurement NI CompactDAQ modular equipment was used. The sampling frequency was set to 5 kHz per channel.

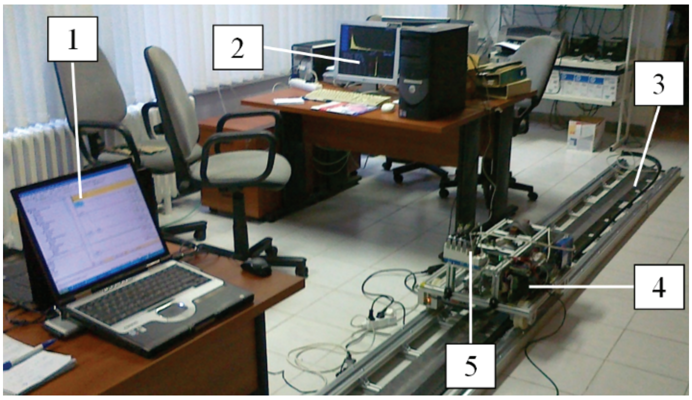


**Figure 3.** Measurement rig of the drive chain of Gamma-log
1: Control PC during the measurements; 2: PC for data acquisition;
3: Railway of the track; 4: Detector-carrier-track; 5: NI Compact DAQ modular unit

Not all of the parameters of the system could be measured because of the construction of the drive chain. The electrical parameters such as exciting currents ($I_1$, $I_2$, $I_3$) on all 3 phases and line voltages ($V_{12}$, $V_{23}$, $V_{31}$) were measured in addition to the rotation of the wheel with an incremental encoder.

The velocity profile of the track can be calculated from the signal of the encoder (v). The intervals of the measured parameters can be found in Table 1.

**Table 1.** Intervals of measured parameters

| Parameter | Unit | Lower limit | Upper limit |
|---|---|---|---|
| Current ($I_1$, $I_2$, $I_3$) | A | -0.5 | 0.5 |
| Phase-to-Phase Voltage ($V_{12}$, $V_{23}$, $V_{31}$) | V | -25 | 25 |
| Velocity of the Track (v) | mm/s | 0 | 30 |

## 4. Data pre-processing for modeling

The measured data required pre-processing before modeling. The velocity profile of the track was calculated from the signal of the encoder. It was used later as output of the neural network.

The signals of voltages and currents were filtered with a low pass filter. The well-known Park or coordinate-frame transformation for three-phase machinery can provide a useful framework for the investigation. The rotating transformations are commonly used for machine design and control, but the simplifications that result from applying the transformation can also be useful for modeling [10,11].

The three-phase values were calculated in the reference frame of stator using the following formula (1) [12]:

$$\begin{bmatrix} T_\alpha \\ T_\beta \\ T_0 \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & -\sqrt{3}/2 \\ 1/2 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} T_1 \\ T_2 \\ T_3 \end{bmatrix} \tag{1}$$

Here $T_1 \ldots T_3$ are the three-phase parameters, currents or voltages. $T_\alpha$ and $T_\beta$ are the same components in the reference frame of the stator.

The measured signals show mainly sinusoidal characteristics with some noise added. Using this transformation, the shapes of the new signals are also sinusoidal but the frequency decreases.

Other transformations were also applied to the signals to get their amplitudes. The angle of the rotating vector can be calculated from the $T_\alpha$ and $T_\beta$ components. The changes of the values in the time domain were applied as inputs during the modeling. Between the transformations the signals are filtered and resampled to speed up the modeling process.

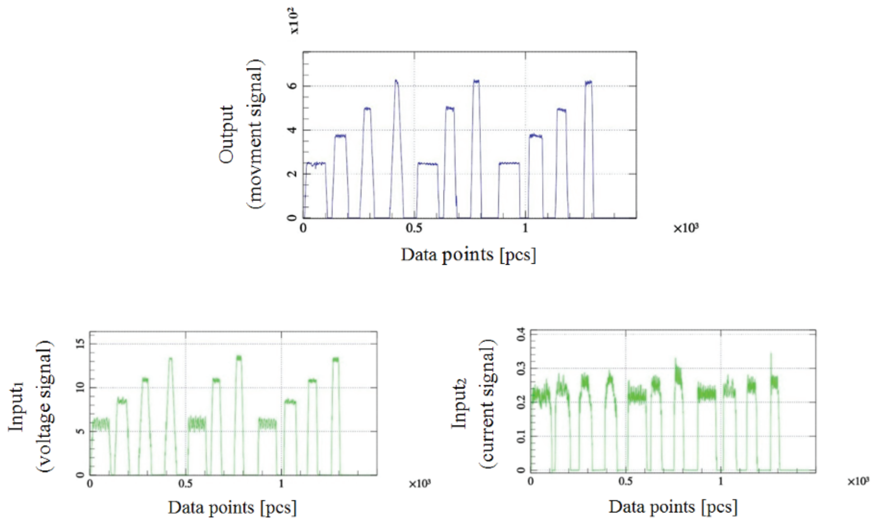


**Figure 4.** Resampled and transformed training datasets

From the measurements two datasets were created. One of them was the training dataset which was used during the training process (Fig. 4). The other dataset was the validating dataset which was applied during testing the network. The validating set was different from the training set in order to test the extrapolating performance of the model.

### 5. LOLIMOT model and algorithm

To model the system the Local Linear Model Network, LLMN, which is an extension of the radial basis function network (RBFN) by Nelles is used. This structure also deals with local linear neuro-fuzzy models referred to as the Takagi-Sugeno fuzzy model [13, 14].

In this structure the weights of the output layer are replaced with a linear function of the network's input. Furthermore, the RBFN is normalized [13]. The structure of the network can be seen in Fig. 5.

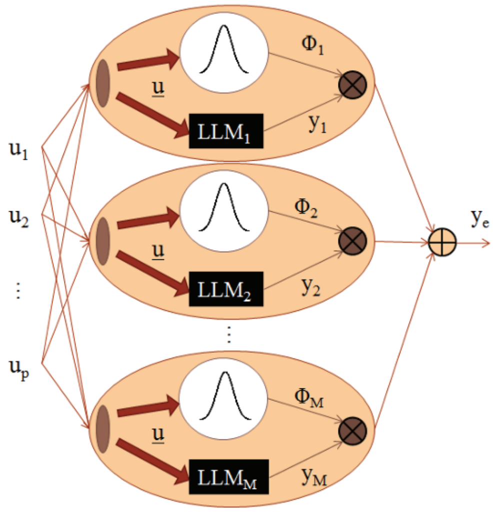


**Figure 5.** Structure of LOLIMOT neural network

The output of the network ( $y_e$ ) can be calculated with the following formula (2) [13]:

$$y_e = \sum_{i=1}^{M} \phi_i(\underline{u}, c_i, \sigma_i)(w_{i0} + w_{i1}u_i + \ldots + w_{ip}u_p), \tag{2}$$

where: $M$ is the number of sub-models; $\underline{u}$ is the input vector; $p$ is the number of inputs; $w_{xy}$ is the y$^{th}$ parameter in the x$^{th}$ neuron. $\phi_i$ is the normalized Gaussian validity function which determines the regions of the input space where each neuron (Local Linear Model) is active. Furthermore, the nonlinear parameters are $c_i$ (center) and $\sigma_i$ (standard deviation).

The local linear model can be taught using the local linear model tree algorithm. This training method is stable, very fast and robust and also has a good convergence feature. The training process has two stages: a) in the first part of the training the input space is decomposed by determining the parameters of the validity function, b) in the second step the LLM is optimised to the region by the least square method.

The training process begins with a globally identified linear model. In the first iteration the global region is divided into two local linear models. The generated local models are valid in their own regions. The models are identified separately and the global model comes from the summation of the local models. In the next iteration the worst model is selected and further divided into two new models. Some steps of the iteration can be seen in Fig. 6.

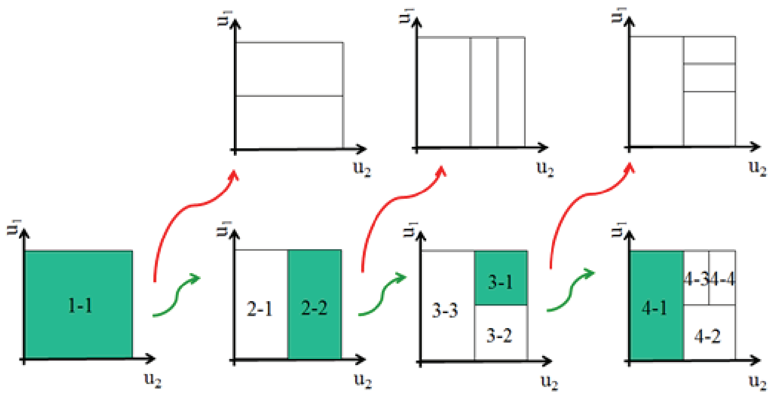


**Figure 6.** The first four iterations of LOLIMOT algorithm

## 6. Modeling the system with LOLIMOT

A drive chain is a dynamic system by nature. During the modeling the relationship should be discovered between the inputs and the output. The investigated system can be described by a Multi Input Single Output (MISO) model. The transformed excitation current ($u_1$) and voltages ($u_2$) were the inputs and the movement of the track was the output ($y$) of the mathematical model.

The previously described network structure is able to model static systems but some external dynamics has to be added to the inputs to characterise the dynamic feature of the system.

External dynamics means that virtual inputs are generated by adding new inputs to the network. The new inputs can be transformed from the real inputs using one time delay transformation.

Two different model structures were investigated during the simulations.

The first model uses only the input parameters of the system with some virtual inputs added. This model structure is called FIR model and it is basically a feedforward model (Fig. 7a). This model approximates the function $f$ in the following form:

$$y_e = f(u_1(t-1), u_1(t-2), u_2(t-1), u_2(t-2)) \tag{3}$$

The other model structure was the ARX model, where beside the inputs ($u_1$ and $u_2$) the time delay real output ($y$) was also applied as input to the network (Fig. 7b). The approximation of the model structure can be described by Eq. 4:

$$y_e = f\big(u_1(t-1), u_1(t-2), u_2(t-1), u_2(t-2), y(t-1), y(t-2)\big). \tag{4}$$

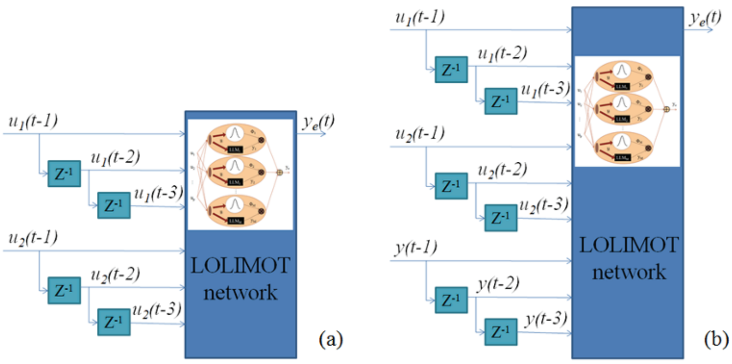


**Figure 7.** MISO system with FIR input configuration (a) and with ARX external dynamics (b)

To achieve the best result, the structure of the networks was changed by changing the number of virtual inputs. The following six different structures were analysed:

- FIR input configuration with one time delay per input. It is called 2i0o.
- FIR input configuration with two time delays per input. It is called 4i0o (Eq. 3).
- FIR input configuration with three time delays per input. It is called 6i0o.
- ARX input configuration with one time delay per input, the one time delayed transform required output use as input. It is called 2i1o.
- ARX input configuration with two time delays per input, the two time delayed transforms required output use as input. It is called 4i2o. (Eq. 4)
- ARX input configuration with three time delays per input, the three time delayed transforms required output use as input. It is called 6i3o.

On every structure 35 iterations were applied using the training algorithm. In every iteration step the correlation coefficients [15] of both the validating and the training datasets were calculated from the estimated output of the system and the required datasets. The best mode was selected using a performance index which was calculated from correlation coefficients:

$$I_{perf} = \sqrt{CORR_{train}^2 + CORR_{valid}^2} \; . \tag{5}$$

## 7. Results

Using a performance index the best model can be found. The calculated performance indexes for the 210 models can be found in Fig. 8.

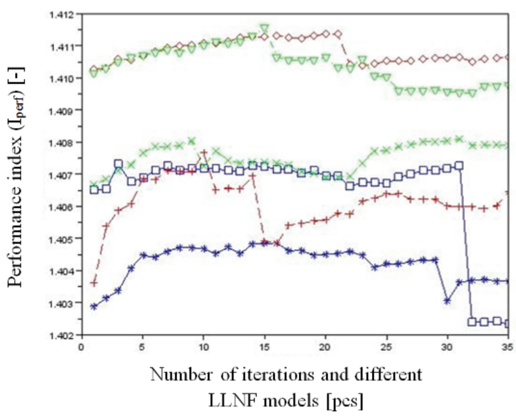


**Figure 8.** Performance indexes of investigated models
star: 2i0o; square: 2i1o; plus: 4i0o; diamond: 4i2o; cross: 6i0o; triangle: 6i3o

Generally the higher number submodels make better solutions but increase computation time and complexity of the global model. In some cases a new submodel can decrease the performance of the global model because the LOLIMOT training does not analyse whether a separation of a region is good for the global model or not. This is the explanation of the big performance losses of the models with a higher number of submodels comparing to less complicated models.

To find the best model with the best correlation feature, different structure types of the models were compared. The selection criterion of the best model was the previously defined performance index (5). To find the globally best model, the locally selected best model was chosen. The models were compared using performance index and MSE of the datasets. The results are summarised in Table 2. The higher performance index is better.

**Table 2.** Best model selection using performance index

| Structure type | Performance index | Index of best model | MSE of training dataset | MSE of validation dataset |
|---|---|---|---|---|
| 1. FIR structure (2i0o) | 1.4048 | 16 | 54.948 | 67.317 |
| 1. ARX structure (2i1o) | 1.4073 | 3 | 48.875 | 47.509 |
| 2. FIR structure (4i0o) | 1.4076 | 10 | 43.171 | 48.798 |
| 2. ARX structure (4i2o) | 1.4113 | 21 | 17.280 | 19.497 |
| 3. FIR structure (6i0o) | 1.4081 | 31 | 23.029 | 55.013 |
| 3. ARX structure (6i3o) | 1.4115 | 15 | 14.706 | 19.007 |

Increasing the number of the inputs makes the models better, but it also increases the computation time and the necessary resources. Both model structures provided good solutions but the best model came from the ARX structure called 6i3o.

## Conclusion

An electrical drive chain of real mobile equipment was modeled with an artificial intelligent method. The datasets were collected from the real system during the measurements. Two feedforward structure types were used and compared. The investigation shows that the LOLIMOT algorithm was able to learn the behaviour of the system. Both of the network structures were suitable for modeling the process but the ARX structure gave better results. To select the best model a performance index was established based on correlations of the datasets and estimations. The results can be used for fault detection and fault diagnosis of the system.

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