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A MATLAB/SIMULINK BASED ENVIRONMENT FOR INTELLIGENT MODELLING AND SIMULATION OF FLEXIBLE MANIPULATOR SYSTEMS

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1. Introduction

Flexible manipulator systems are receiving increasing attention due to their advantages over conventional robot manipulators. The advantages include faster response, lower energy consumption, relatively smaller actuators, higher payload to weight ratio and, in general, less overall cost [1]. Some of the current applications of such manipulators include spacecraft, remote manipulation and radioactive material handling in nuclear power plants. Due to their flexible nature, induced vibrations appear in the system during and after a positioning motion [2,3]. This restricts their wide spread use in industry. A considerable amount of research work has already been carried out on the vibration control of flexible manipulators. However, a generic solution to the problem is yet to be obtained [4,5].

To formulate and implement an effective control strategy for efficient vibration suppression of the system, it is important to recognise the flexible nature of the manipulator and construct a mathematical model for the system that accounts for the interactions with actuators and payload [6]. Such a model can be constructed using partial differential equations (PDEs). The finite element (FE) and finite difference (FD) methods have also been utilised to describe the flexible behaviour of manipulators [7]. The computational complexity and consequent software coding involved in the FE method is a major disadvantage of this technique [8]. An alternative solution is to utilise intelligent techniques, such as genetic algorithms (GAs) and neural networks (NNs) for modelling of flexible manipulator systems [9].

The approaches indicated above have proved to be effective in modelling and simulation of such systems for test and verification of controller designs. However, to allow interactive and user friendly features, that are desired especially in computer aided teaching and research, be incorporated a modelling, simulation and control environment is developed in this work for flexible manipulators using Matlab and Simulink. To this end the authors have developed an interactive and user-friendly environment referred to as SCEFMAS (**S**imulation and **C**ontrol **E**nvironment of **F**lexible **Ma**nipulator **S**ystems) [10]. As an on-going development process, the SCEFMAS environment is enhanced by the addition of intelligent modelling, a new menu driven user interface with GUI based facility, and the display of results within the GUI facility. Moreover, the environment is upgraded from Matlab 4.2 to Matlab 6.5. This paper describes these recent developments in SCEFMAS. The rest of the paper is structured as follows: Section 2 briefly describes the flexible manipulator system considered and the corresponding FD simulation process. Section 3 illustrates the GA and NN modelling strategies. Section 4 describes the implementation of the FD simulation algorithm, GA and NN modelling strategies within the SCEFMAS framework. The developed GUIs are also described in this section. The paper is concluded in Section 5.

2. The Flexible Manipulator System

The flexible manipulator system under consideration is modelled as a pinned-free flexible beam, with a mass at the hub, which can bend freely in the horizontal plane but is stiff in vertical bending and torsion. The model development utilises the Lagrange equation and modal expansion method [11,12]. To avoid the difficulties arising due to time varying length, the length of the manipulator is assumed to be constant.

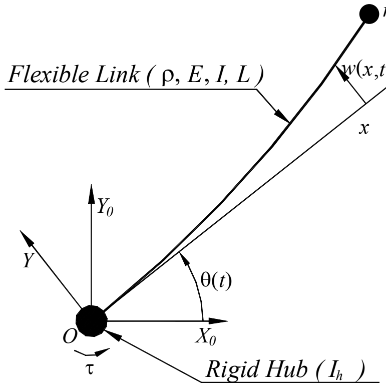


Figure 1: Schematic representation of the flexible manipulator system.

A schematic representation of the manipulator is shown in Figure 1, where X_oOY_o and XOY represent the stationary and moving co-ordinate frames respectively. The axis OX coincides with the neutral line of the link in its undeformed configuration, and is tangent to it at the clamped end in a deformed configuration. The τ represents the applied torque at the hub. E, I, ρ, S, I_h and m_p represent the Young modulus, area moment of inertia, mass density per unit volume, cross sectional area, hub inertia and payload of the manipulator respectively. $\theta(t)$ denotes an angular displacement (hub-angle) of the manipulator and $w(x,t)$ denotes an elastic deflection (deformation) of a point along the manipulator at a distance x from the hub of the manipulator. In this work, the motion of the manipulator is confined to the X_oOY_o plane. The width of the arm is assumed to be much greater than its thickness, thus, allowing the manipulator to vibrate (be flexible) dominantly in the horizontal direction. The shear deformation and rotary inertia effects are also ignored.

To obtain equations of motion of the manipulator, the associated energies have to be obtained. These include the kinetic, potential and dissipated energies. Thus, using the Hamilton's extended method, a partial differential equation (PDE) describing the dynamic equation of the flexible manipulator with associated boundary and initial conditions can be obtained [2]. The PDE thus obtained is of a hyperbolic type and can be classified as a boundary value problem. This can be solved using an FD method [7]. This involves dividing the arm into a finite number of equal-length sections and developing a linear difference equation describing the deflection of end of each section (grid-point). Thus, using the FD method, a solution of the PDE can be obtained and implemented on a digital processor [2].

3 Intelligent Modelling

In many cases, when it is difficult to obtain a model structure for a system with traditional system identification techniques, intelligent techniques are desired that can describe the system in the best possible way [9]. GAs and NNs are two intelligent techniques used commonly for system identification and modelling. The major advantage of utilising GAs for system identification is that GAs simultaneously evaluates many points in the parameter space and converge towards the global solution [13]. The superiority of a GA over recursive least squares (RLS) algorithm in modelling a fixed-free flexible beam is addressed by [14]. In contrast, NN approaches for system identification offer many advantages over traditional ones especially in terms of flexibility and hardware realisation [15]. This technique is quite efficient in modelling non-linear systems or if the system possesses nonlinearities to any degree.

Once a model of the system is obtained, it is required to validate whether the model is good enough to represent the system. A number of such validation tests are available in the literature [15]. These are one-step ahead (OSA) prediction; model predicted output (MPO), and correlation tests. Such techniques are incorporated within SCEFMAS for validating developed models. Moreover, with NN modelling, the input-output data set is divided into two halves. The first half is used to train the NN and the output computed. The NN usually tracks the system output well and converges to a suitable error minimum. New inputs are presented to the trained neural network and the predicted output is observed. If the fitted model is correct, i.e., correct assignment of lagged inputs and outputs, then the network will predict well for the prediction set. In this case the model will have captured the underlying dynamics of the system. If both the OSA and the MPO of a fitted model are good over the estimation and prediction data sets then most likely the model is unbiased.

3.1 GA Modelling

With GA modelling an initial population of potential solutions is created in the first step. Each element of the population is mapped onto a set of strings (the chromosome) to be manipulated by the genetic operators. In the second step, the performance of each member of the population is assessed through an objective function imposed by the problem. This establishes the basis for selection of pairs of individuals that will be mated together during reproduction. For reproduction, each individual is assigned a fitness value derived from its raw performance measure, given by the objective function. This value is used in the selection to bias towards more fit individuals. Highly fit individuals, relative to the whole population, have a high probability of being selected for mating, whereas less fit individuals have a correspondingly low probability of being selected [16].

In the manipulation phase, genetic operators such as crossover and mutation are used to produce a new population of individuals (offspring) by manipulating the *genetic information* usually called genes, possessed by the members (parents) of the current population. The crossover operator is used to exchange genetic information between pairs, on larger groups, of individuals. Mutation is generally considered to be a background operator, which ensures that the search process is not trapped at local minimum, by introducing new genetic structures in the population. After manipulation by the crossover and mutation operators, the individual strings are then, if necessary, decoded, the objective function evaluated, a fitness value assigned to each individual and individuals selected for mating according to their fitness, and so the process continues through subsequent generations. In this way, the average performance of individuals in a population is expected to increase, as good individuals are preserved and breed with one another and the less fit individuals die out. The GA is terminated when some criteria are satisfied, e.g., a certain number of generations completed or when a particular point in the search space is reached.

For parametric identification of the manipulator with GA, randomly selected parameters are optimised for different, arbitrarily chosen order to fit to the system by applying the working mechanism of GA as described above. The fitness function utilised is the sum-squared error between the actual output, $y(n)$, of the system and the predicted output, $\hat{y}(n)$, produced from the input to the system and the optimised parameters:

$$f(e) = \sum_{i=1}^{n} \left(\left| y(n) - \hat{y}(n) \right| \right)^2$$

Where, n is the number of input/output samples. With the fitness function given above, the global search technique of the GA is utilised to obtain the best set of parameters among all the attempted orders for the system. The output of the system is thus simulated using the best sets of parameters and the system input.

3.2 NN Modelling

Various modelling techniques can be used with neural networks to identify a non-linear dynamical system. These include state-output model, recurrent state model and non-linear autoregressive moving average process with exogeneous (NARMAX) input model. However, from the literature it has been established that if the plant’s input and output data are available, the NARMAX model is a suitable choice, for modelling systems with nonlinearities. Mathematically, the model is given as [17]:

$$\begin{aligned} \hat{y}(t) = f[(&y(t-1), y(t-2), \cdots, y(t-n_y), \\ &u(t-1), u(t-2), \cdots, u(t-n_u), \\ &e(t-1), \mathrm{e}(t-2), \cdots, e(t-n_e)] + e(t) \end{aligned}$$

Where, $\hat{y}(t)$ is the output vector determined by the past values of the system input vector, output vector and noise with maximum lags n_y, n_u and n_e respectively, $f(\cdot)$ is the system mapping constructed through multilayer perceptron (MLP) or radial basis function (RBF) neural networks with an appropriate learning algorithm. The model is also known as NARMAX equation error model. However, if the model is good enough to identify the system without incorporating the noise term or considering the noise as additive at the output the model can be represented in a NARX form [17,18] as:

$$\hat{y}(t) = f[(y(t-1), y(t-2), \cdots, y(t-n_y), \\ u(t-1), u(t-2), \cdots, u(t-n_u)] + e(t)$$

With both GA and NN modelling the manipulator is modelled from the input torque to hub-angle, hub-velocity and end-point acceleration. These are referred to as the hub-angle model, hub-velocity model and end-point acceleration model respectively.

4. SCEFMAS Environment

A major portion of the initial version of the SCEFMAS was developed using Simulink [10]. Moreover, SCEFMAS utilizes the Matlab Guide (GUI development tool) for the development of GUIs [19,20]. The working principle of the SCEFMAS is shown by a flow-chart in Figure 2.

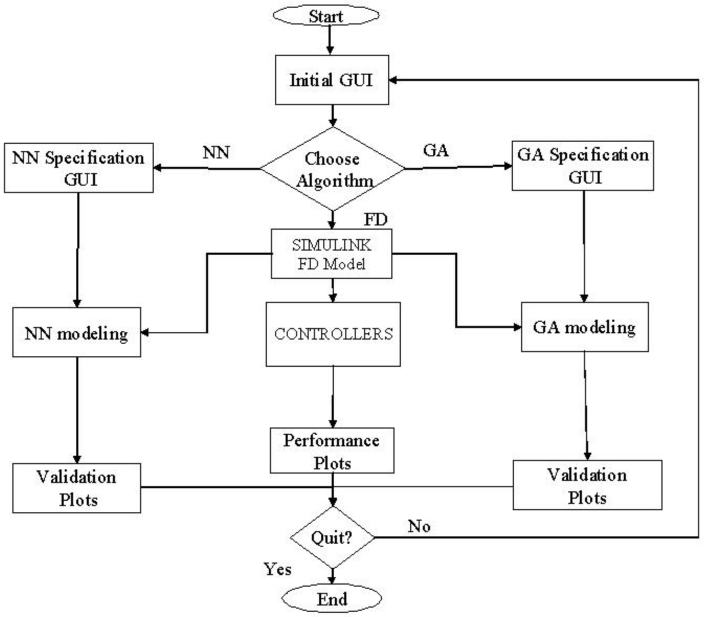
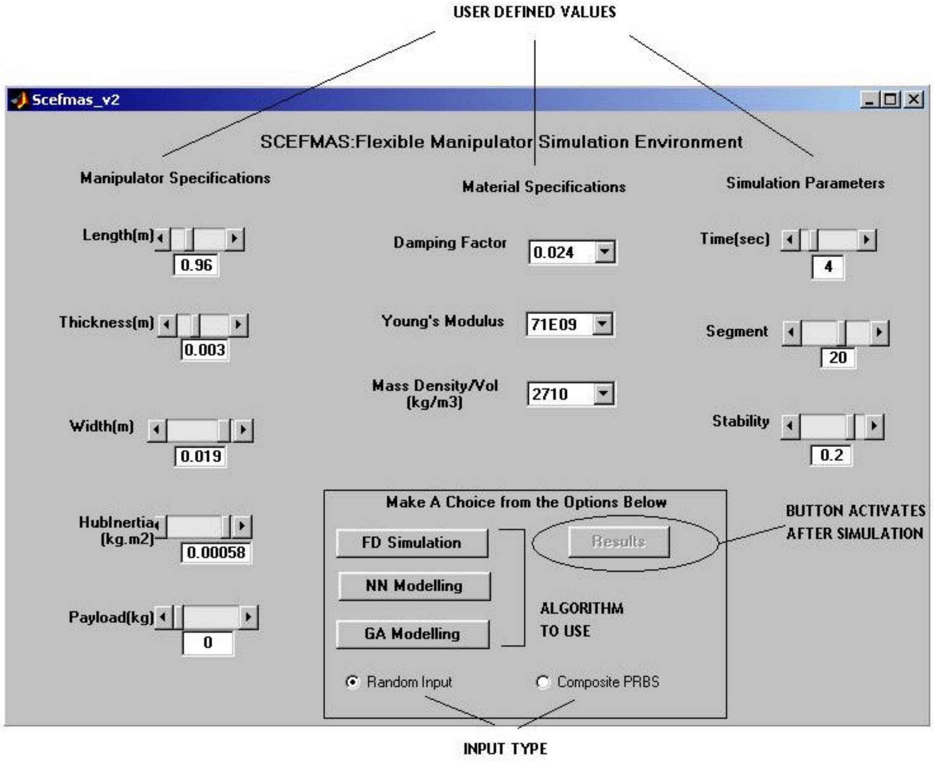


Figure 2: Flow-chart of the SCEFMAS environment.

The *Initial GUI* allows the user to provide the flexible manipulator specifications, material properties and simulation parameters. Following this the user will have the option to choose algorithm type for simulation and model type. The choices are: FD simulation, GA modelling, NN modelling.

4.1 Initial GUI

The initial GUI is named as Scefmas_V2 and is used as gateway to the SCEFMAS environment (Figure 3). Through this GUI the user will have the choice to provide three sets of parameters. These are *Manipulator Specifications*, *Material Properties*, and *Simulation Parameters*. Manipulator parameters involve the length, thickness and width of the manipulator along with the hub inertia and payload. While the material properties constitute damping factor, young's modulus and mass density per volume. Finally, the total simulation time, number of segments, and stability factor for the FD algorithm constitute the simulation parameters. The user then needs to choose the type of algorithm options from the bottom right side box of the GUI window. The options are: FD Simulation, NN Modelling or GA Modelling.


USER DEFINED VALUES
Scefmas_v2
SCEFMAS:Flexible Manipulator Simulation Environment
Manipulator Specifications
Material Specifications
Simulation Parameters
Make A Choice from the Options Below
FD Simulation
NN Modelling
GA Modelling
Results
ALGORITHM TO USE
BUTTON ACTIVATES AFTER SIMULATION
INPUT TYPE

Length(m) 0.96

Thickness(m) 0.003

Width(m) 0.019

HubInertia (kg.m2) 0.00058

Payload(kg) 0

Damping Factor 0.024

Young's Modulus 71E09

Mass Density/Vol (kg/m3) 2710

Time(sec) 4

Segment 20

Stability 0.2

● Random Input ○ Composite PRBS

Figure 3: Startup GUI for the SCEFMAS environment.

At the bottom of the option selection box there are two radio buttons, which can be used to select excitation input of the flexible manipulator. The inputs are *Random input* and *Composite PRBS* input. Both of these inputs provide sufficient excitation for all the modes associated with a flexible manipulator system within the frequency range of excitation.

5.2 FD Simulation and display of results

Once the user clicks on the FD Simulation button within the Scefmas_V2 GUI, the user has the option of either opening a pre-developed model or one of their own models. Figure 4 shows such a pre-developed model with a flexible manipulator connected to a random input in an open-loop manner. The *Auxiliary block* within the model produces data set for 3D plot within the Result GUI. After a simulation run the input and outputs are passed to the Matlab environment through the yin and yout blocks.

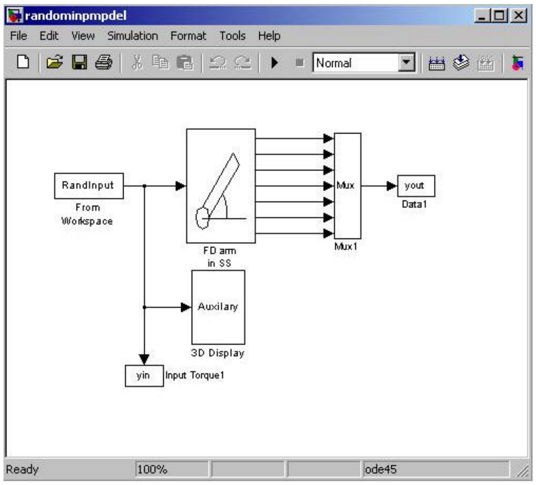
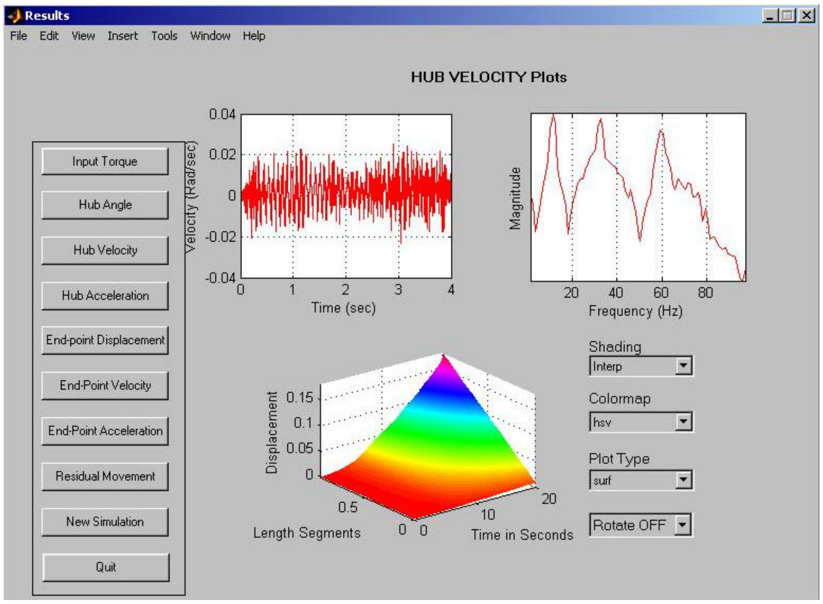


Figure 4: Excitation of a flexible manipulator using a random input.



Shading
Interp

Colormap
hsv

Plot Type
surf

Figure 5: Displaying the results obtained from FD Simulation

At the end of the simulation, a button called Results will be displayed within the Initial GUI (Figure 3). A click on this button will open a new GUI called Results, which can be used to display all the input and outputs produced through this simulation process (Figure 5).

The left hand side of the GUI includes option buttons, top right side contains time domain and frequency domain result windows for the selected input or output parameter, bottom middle window is for displaying 3D plot of the complete motion of the manipulator for a given simulation. The drop down menus at the bottom right side can be used to choose properties of the 3D plot. After viewing the result, the user can choose to return to the Initial GUI by clicking on the New Simulation button or may exit SCEFMAS by clicking on the Quit button within the Results GUI. The complete FD simulation and display process can be presented through the flowchart shown in Figure 6. Within the flowchart *Simulink Controller* is shown as a part of SCEFMAS and has been reported earlier [10].

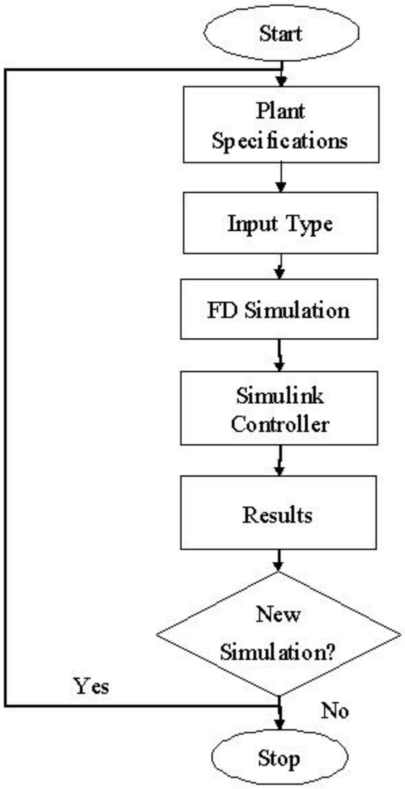


Figure 6: FD simulation flowchart.

4.3 Neural network modelling

The NN_template GUI, shown in Figure 7 is used for NN modelling of the flexible manipulator systems. The process starts by clicking on the NN Modelling button within the Scefmas_V2 GUI. The upper part of this window allows the user to choose the number of layers of neurons within the NN structure along with the property of neurons in each layer. At this point the user needs to generate the training data for NN modelling. The process starts by clicking on the Generate Data Set button. The user can choose from a set of FD Models available within the SCEFMAS environment. At the end of FD simulation the user can view the generated data for quality assurance. To start the NN training one has to click on the Train Network button at the bottom middle part of the GUI. This will start the training process and the *sum-squared error* will be displayed in a graphical window at the bottom left corner of the GUI. At the end of the training *Simulation Done* message will pop up at bottom right corner of the GUI. A new button called Validation Plots will also appear just below the Train Network button.

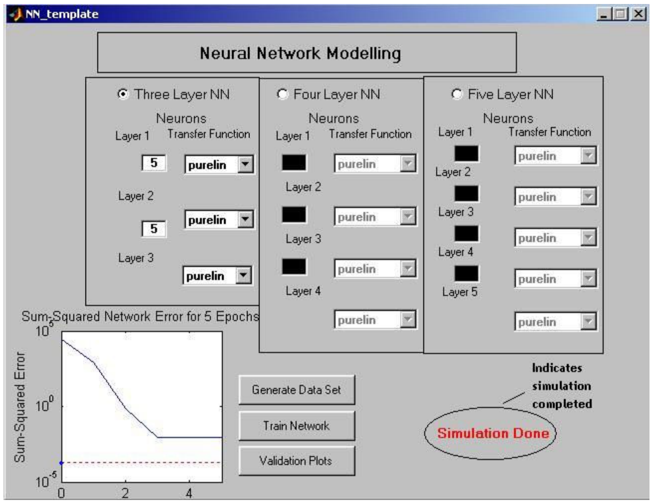


Figure 7: Neural network modeling GUI.

A click on the Validation Plots button will open the Validation Plots GUI as shown in Figure 8. This GUI is to display the time domain and frequency domain model validation properties. The left hand side of the GUI provides all the model option buttons. For each input output model there are two types of validation. One is comparison between the actual and model outputs in time and frequency domains and the other is a correlation test. The figure within the GUI shows the comparison between the actual and model outputs for input to hub angle model. The top left corner graphical window shows the normalized actual and predicted outputs while the top right corner graphical window shows the error between the actual (from FD simulation) and NN model output. Bottom graph window compares the actual and predicted outputs in the frequency domain. The performance of models from the input to each output can be displayed by clicking on the appropriate button.

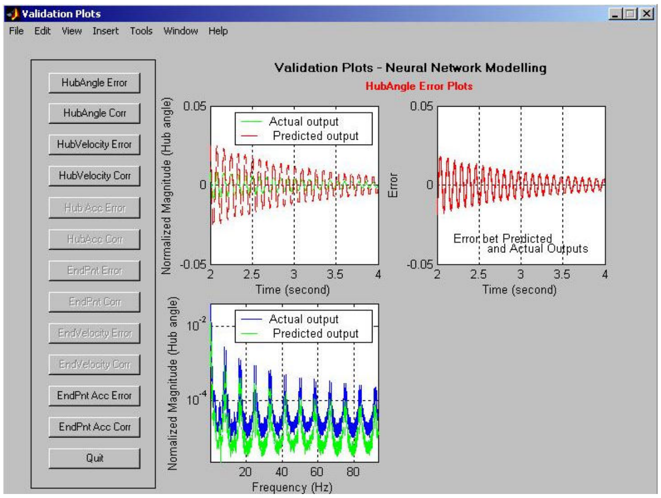


Figure 8: Validation plots for NN modeling.

There are couple of inactive model option buttons incorporated within the GUI. These can be used to validate further models developed within SCEFMAS. At the end of the validation process the user can click on the Quit button to return to the Scefmas_v2 GUI and start another simulation run. The flowchart shown in Figure 9 explains the NN modelling process.

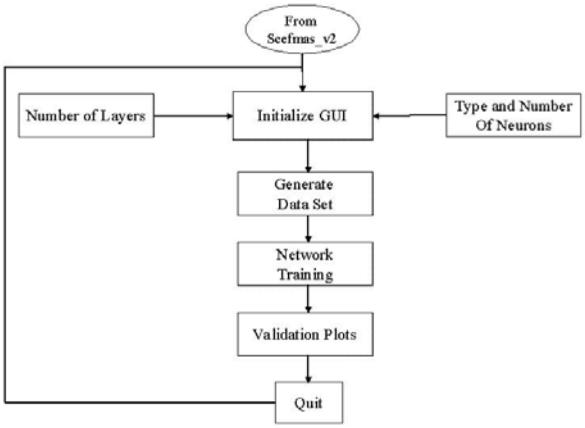
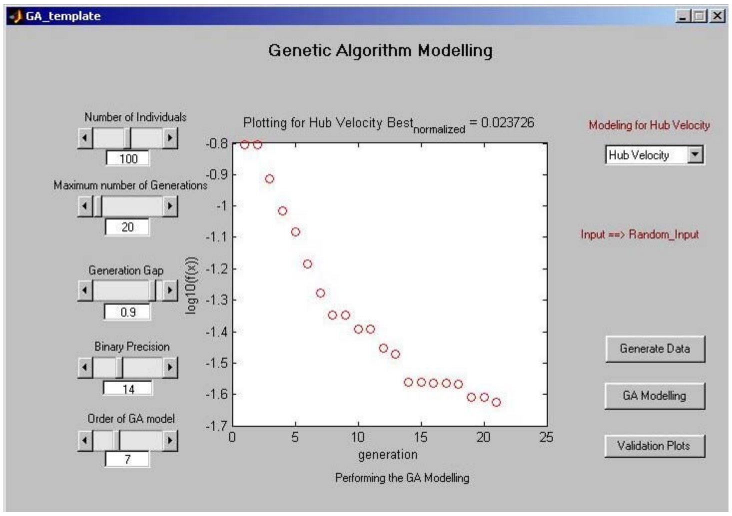


Figure 9: Neural network modeling flowchart.

4.4 Genetic algorithm modelling

Clicking on the GA modelling button within the Scefmas_V2 GUI will open the GA modelling GUI as shown in Figure 10. The left hand side of the GUI are provided with sliders, where a user can set the GA modelling parameters. These are *Number of individuals*, *Maximum number of generations*, *Generation gap*, *Binary precision* and *Order of GA model*. The top right corner of the GUI provides a drop down menu to choose a model type, such as, *Hub Angle*, *Hub Velocity* and *End Acceleration*. After entering all the model parameters and model type, the user can generate training data by clicking on the Generate Data button (one of the right bottom buttons). After the generation of FD simulation data, the user can proceed with the GA modelling by clicking on the GA Modelling button within the GUI. The progression through the GA modelling along with the fitness performance will be displayed in the figure window at the middle of the GUI.



Number of Individuals: 100

Maximum number of Generations: 20

Generation Gap: 0.9

Binary Precision: 14

Order of GA model: 7

Plotting for Hub Velocity Best$_{normalized}$ = 0.023726

Modeling for Hub Velocity

Hub Velocity

Input ==> Random_Input

Performing the GA Modelling

Figure 10 The GUI used for GA modelling process.

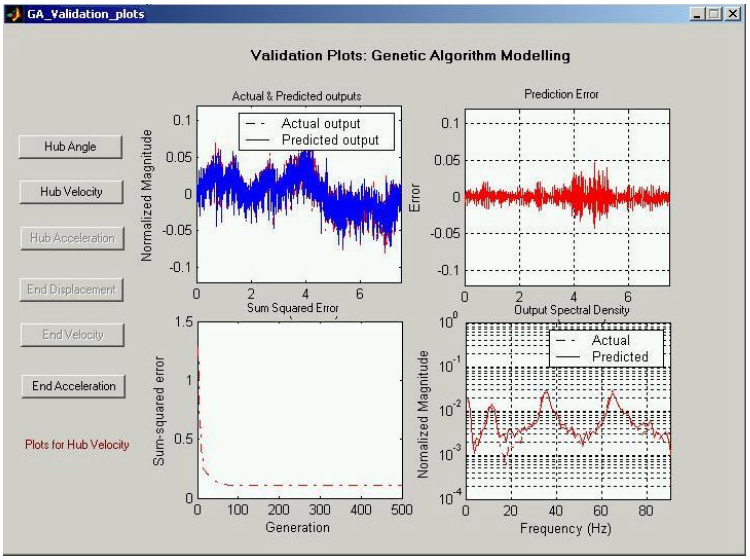


Figure 11: GA modeling validation GUI.

After the completion of the modelling process the Validation Plots button will be activated (bottom right corner of the GUI). The user can click on this button to observe the performance of the developed GA model through **GA_Validation_plots** GUI (Figure 11). The left hand side of the GUI is provided with buttons for choosing model types. The model validation outputs are displayed through four figure windows. Top two figure windows are for comparing the magnitudes of actual and predicted outputs. The bottom right window shows the comparison between actual and predicted outputs in the frequency domain. The bottom left window shows the sum-squared error for each generation. At the end of the GA model validation process the user can return to the Scefmas_V2 GUI for further modelling exercises. The GA modelling process is illustrated by the flowchart in Figure 12.

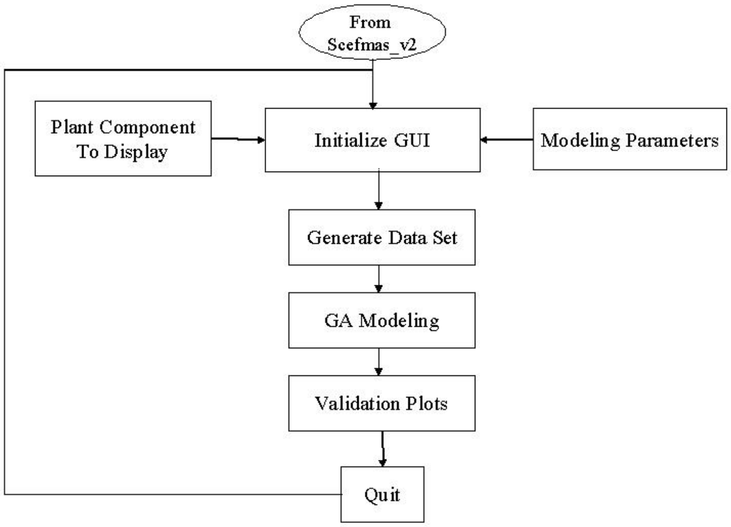


Figure 12: Genetic algorithm modeling flowchart.

5. Student response

The first version of the SCEFMAS is in use with the Automatic Control and Systems Engineering Department of University of Sheffield (UK). This package is used as a supporting tool to deliver a module of a M.Sc. program with the department. Although, there is no formal assessment for the effectiveness of this environment as a leaning tool, but students has expressed their opinion during the module end questioners. These opinions reflect that the software environment enables the students to understand the behaviour of a flexible manipulator system and also the effect of parameter variations. The learning process could be much difficult without this package. In addition to this, student can test the effectiveness of their controller designs without spending much time on system simulation. However, the introduction of new version of SCEFMAS would be followed by a detailed student evaluation.

6. Conclusions

As an on-going process of enhancing SCEFMAS, the development of intelligent modelling techniques through user friendly GUIs has been presented. The finite-difference simulation of a single-link flexible manipulator is the backbone of the SCEFMAS system. As a part of intelligent modelling techniques GA and NN models have been developed and realised using the Matlab and Guide environments. The interactive GUI allows the user to choose a model structure and monitor the developed model performance without going into the programming details. Moreover, a data analysis provision has been made within the package, to enable users to analyse their data obtained from a test run. This makes the environment more user friendly and saves the time and effort to transfer the data to another environment for analysis.

SCEFMAS has already proven to be a valuable education tool for understanding the behaviour of flexible manipulator systems and development of various controller designs. The addition of these new features will enhance the learning outcome of this environment. The GA and NN modelling features of SCEFMAS can easily be extended to the development of intelligent controllers within SCEFMAS. With the advent of Internet technology, the package can be further used as a distance teaching learning facility

The Simulink blocks can be utilised to investigate various other aspects of active vibration control in flexible manipulator systems. Users can design their own Simulink blocks and couple them to specific requirements.

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BIOGRAPHICAL INFORMATION

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