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Fuzzy Logic Modeling and Control for Drilling of Composite Laminates : Simulation

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ABSTRACT

In drilling of composite laminates, it is important to minimize or reduce occurrences of delaminations. In particular, a peel-up delamination at entrance and push-out delamination at exit are common. Delaminations may be avoided by regulating the drill thrust force can be controlled by adjusting the feedrate of the drill. Dynamics involved in drilling of composite laminates is time varying and nonlinear. In this paper, a fuzzy logic model and control strategy are proposed. Simulation results show that the fuzzy model can describe the nonlinear time-varying process well. The fuzzy controller realizes a fast rise time and a little overshoot of drilling force.

Key Words : Drilling model, Drilling control, Fuzzy model, Fuzzy control, Delamination

1. Introduction

Drilling is one of the most common machining operations, and accounts for up to 50% of all machining. In spite of such dramatic statistics, drilling is yet to receive adequate attention of researches with respect to the numerous potential benefits of process control. These benefits include cycle time, tool breakage, and cost reduction, in addition to part quality improvements[1].

Composite materials provide distinctive advantages in manufacture of advanced products because of attractive features such as high strength and light weight. However, they are easily damaged unless machining is performed properly. A typical damage is delamination during drilling when the drilling force exceeds a threshold value at critical stages, e.g. at the entry and the exit of a drill bit. A quantitative model based on delamination fracture mechanics was suggested by Hocheng and Dharan[2]. Their model relates delamination damage of the laminate to drilling parameters and composite material properties: i.e. at the exit, the critical thrust force at the onset of crack propagation is

$$F_a = \pi\sqrt{\frac{8G_{IC}EH^3}{3(1-\nu^2)}}\left(\frac{h}{H}\right)^{\frac{3}{2}} \tag{1}$$

and at the entrance, the critical cutting force at the onset of delamination is

$$F_c = k_{slope}\pi\sqrt{\frac{8G_{IC}EH^3}{3(1-\nu^2)}}\left(1-\frac{h}{H}\right)^{\frac{3}{2}} \tag{2}$$

where H is the thickness of the laminate, h is the uncut depth under the tool, G_{IC} is the critical crack energy release rate, E is the modulus of elasticity and ν is the Poisson's ratio. k_{slope} is a constant defined by λ (the helix angle at the drill tip) and μ (the coefficient of friction between tool and work). Equation (1) shows that the thrust force must be small at the exit to preclude drilling damage.

Several approaches have been examined for controlling the drilling process[1, 3]. Their objective is to keep the thrust force or torque almost constant in the drilling process. The major difficulty encountered in designing a control system for drilling is that the dynamics of the drilling process are not fully understood and therefore cannot be accurately modeled mathematically. Empirical models exist which relate feed rate to thrust force and torque for various materials and tool geometry. These models of the drilling process offer a convenient form, but have coefficients that themselves are variables of the work piece material, cutting conditions and tool wear. In addition, most of work done in the modeling of drilling process presents only static relationships and is valid only at middle stage in which the drill head is completely embedded in the specimen.

Depending on the mode of operation, an appropriate control strategy may be selected by an upper layer, often called the supervisory control layer, of the control system[4]. Ozaki, et al., proposed a supervisory PID controller with gain scheduling for drilling force control[5]. Their supervisory controller selected an appropriate strategy, based upon drill position (depth-of-hole), for use at the process control level as well as the appropriate reference signal, which resulted in superior hole quality, short operation time and small delamination. One problem is that it is not easy to solve the gain varying problem due to factors such as drill wear, etc. This gain varying will cause performance deterioration of PID controller. The PID controller may be replaced by more sophisticated controllers to improve performance.

Sheng, et al., studied the dynamic modeling of thrust force in the drilling process of carbon fiber-reinforced composite laminates[6]. A fixed gain PI controller and an adaptive predictive control strategy were proposed. The adaptive predictive controller utilized least square identification of the process gain and the multi-step-ahead prediction model. A short rising time and no overshoot were desired in their force control. Two modifications of the adaptive predictive controller were introduced to further reduce overshoots with some success. It is not obvious to choose a suitable incremental step of the process gain in order to achieve small overshoot and rapid response at the same time when the process gain is subjected to rapid large variations.

Neural networks (NN) based controllers have received much attention in recent years. Stone, et al., proposed a NN control strategy in which a NN forward model was used to model the drilling process and a NN inverse model is used to act as the controller to control the drilling of composite material respectively[7]. They do not take into consideration of the gain variation caused by drill wear or different drilling stages, i.e., entrance, middle and exit stages. Even though diamond tipped drill is used in their study, and triangular profile signals are used to train the NN forward model, the overshoot is too large, about 25%. Therefore, the objective of this paper is to introduce a fuzzy modeling and control method that control the drilling force for both high productivity and small delamination in the drilling of composite materials.

2. Experimental Set-up

High-strength woven carbon fiber prepreg was used to make the specimens for the tests, and each prepreg ply consisted of a balanced weave of 210 GPa modulus fiber (Toray 300). The prepreg resin matrix was Fiberite 934 which is a 177 °C curing epoxy system. 63 plys were used in the compression molding of each flat plate laminate, giving a thickness of 8.0 mm and a fiber volume fraction of 0.63. A quasi-isotropic symmetric layup was used throughout with the layup of $[0/45]_{31S//0}$, where 0 is a single layer of the fabric (which consists of equal number of 0° and 90° fibers) and 45 refers to a layer of fabric oriented at 45° to the 0° direction. The drills used in the experiments were 3/8”-dia. High-speed-steel (HSS) and carbide-tipped (CT) twist drills. All tests were run without coolant, at a spindle speed of 2000 rpm. A Matsuura MC510-VSS machining center equipped with a PC-based controller was used in the experiments. The machining center is a 3-axis system, and the positioning resolution is 1 micrometer. A L-adapter was attached to convert the rotation of spindle to the Y-axis direction in order to get a simpler driving dynamics compared to the Z-axis direction. The composite laminate specimens were held in a rigid fixture attached to a force-torque Kistler 9271A dynamometer during drilling, as shown in Fig. 1.

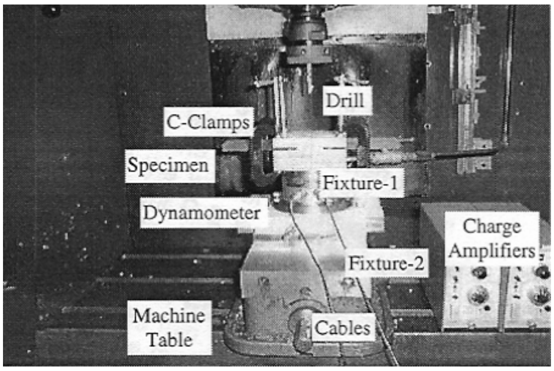

Fig. 1 Experimental setup of Drilling control

3. Dynamic Fuzzy Model for Drilling

Experimental results indicate that the thrust force varies as a function of the drilling depth as shown in Fig. 2[5, 8]. At the beginning of drilling, the thrust force rises sharply(segment A-B of Fig. 2) due to the large thrust acting on the chisel edge when it begins to engage by extrusion and secondary cutting. Segment B-C represents the gradual rise due to the thrust force acting on the chisel edge and cutting edge when they begin to engage in extrusion, primary and secondary cutting. There is a mild drop in segment C-D during the full engagement of the drill, which is attributed to the lifting up of the specimen by the contact force between the flutes of the drill and the wall of the hole drilled. The sudden drop in segment D-E is attributed to the disappearance of the large thrust resistance acting on the chisel edge due to change of the cutting condition from plane strain to plane stress when the uncut plate below drill bit becomes very thin. As the drill begins to exit from the workpiece, the thrust force decreases gradually in segment E-F due to the thrust force acting on the chisel edge and cutting edges.

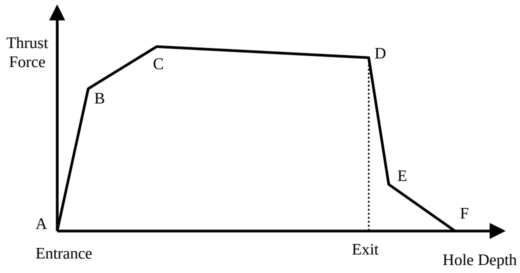

Fig. 2 Typical shape of thrust force vs. hole depth curves

Experimental results show two distinctive features of drilling. The first is the strong dependence of the drilling force on the drill depth, and the second is the nonlinear relationship between the drilling force and feed rate. In the construction of a drilling model, therefore, the fuzzy model divides the entire process into three different sub-models according to the stages(entrance, middle, and exit stage) as shown in Fig. 3. Next, each sub-model consists of three linear equations to consider the non-linearity between the drilling force and feed rate, where, B, M and S mean big, medium, and small, respectively. Each linear equation is proposed as a linear ARMA(Auto-Regressive Moving-Average) model, and a generalized equation is like this:

$$y_m(k+p) = a_1 y(k-1) + \ldots + a_r y(k-r) + b_1 u(k-d) + \ldots + b_q u(k-d-q+1) + c \quad (3)$$

where, y_m (.) : model output, p : prediction step of output, d : delay step of input. All the parameters are simply trained by a gradient descent algorithm. To obtain the parameters of the modeling equation, when the cost function is defined by

$$J = \frac{1}{2}e^2 = \frac{1}{2}(y(k) - y_m(k))^2 , \quad (4)$$

each parameter is updated as follows:

$$a_{i,new} = a_{i,old} + \Delta a_i \quad (5)$$

$$b_{j,new} = b_{j,old} + \Delta b_j \quad (6)$$

$$c_{new} = c_{old} + \Delta c \quad (7)$$

where, $\Delta a_i = \eta_a \frac{\partial J}{\partial a_i}$, $\Delta b_j = \eta_b \frac{\partial J}{\partial b_j}$, $\Delta c = \eta_c \frac{\partial J}{\partial c}$.

η_a, η_b and η_c are learning rates.

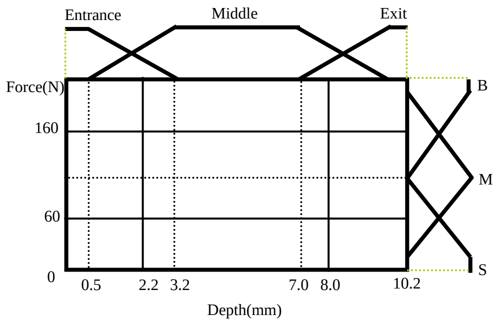

Fig. 3 Fuzzy partition for drilling model

4. Fuzzy Learning Control for Drilling

In learning control, it is very important to propose a target output that control is available. If we think of a model providing a desired future output based on the present input, it seems reasonable to ask what control action at the present instant would bring the future output to the desired value. If a plant with input-output pair, {*u(k-d)*, $y_p(k)$} is given, and a reference model with {*r(k-d)*, $y_r(k)$} is introduced, the objective is to determine the control input, *u(k-d)* so that the actual output, $y_p(k)$ is equal to the desired output, $y_r(k)$ as shown in Fig. 4[9]. In the drilling system, even the maximum input contributes only less than 10% to the variation of output, and it has relatively heavy inertia because the sampling time(5ms) is too short. We cannot but consider the possibility of drill breakage if a rapid step response is enforced for high productivity. To avoid a sudden increase of the thrust force, we propose a second-order system with a critical damping ratio(ζ=1) as a reference model. When a sampling time is *T*, the reference target is as follows:

$$y_r(k) = r(k-d)(1-(1+\omega_n kT)\exp(-\omega_n kT)) \quad (8)$$

In view of the conventional tracking control, the fuzzy implication *R* using the truth-value is[9]

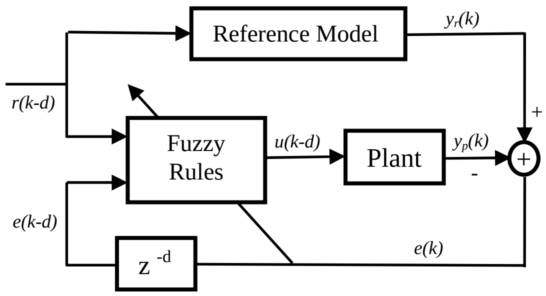

Fig. 4 Block Diagram of Fuzzy Learning Controller

$$R : O(y) \wedge E(e) \wedge C(c) \Rightarrow v \quad (9)$$

The *k*-th control rule R_k is presented by

$$R_k : O_k(y) \wedge E_k(e) \wedge C_k(c) \Rightarrow v_k \quad (10)$$

After training, the control input is implemented by a fuzzy relation and is defined as follows:

$$\Delta u = \sum_{k=1}^{N} \Phi_k \times v_k \quad (11)$$

When the product-sum inference method is used,

$$\Phi_k = \frac{\mu_{O_k(y)} \wedge \mu_{E_k(e)} \wedge \mu_{C_k(c)}}{\sum_{i=1}^{N} \mu_{O_i(y)} \wedge \mu_{E_i(e)} \wedge \mu_{C_i(c)}} \quad (12)$$

where, $\mu_{O_k(y)} \wedge \mu_{E_k(e)} \wedge \mu_{C_k(c)}$ is a weighting factor of the *k*-th rule in the control input.

Finally, the plant input is obtained by the integration of PD control rules.

$$u = \sum \Delta u \quad (13)$$

The learning algorithm is to adjust each control input so that the actual output is equal to the desired output. When a cost function *J* is defined as the summation of output error

$$J = \sum_{h=0}^{\infty} J(k+h) \quad (14)$$

where, $J(h) = \frac{1}{2}[\eta_e \varepsilon(h)^2 + \eta_c c(h)^2]$, $\varepsilon(h) = y_p(h) - y_r(h)$,

and $c(h) = \varepsilon(h) - \varepsilon(h-1) = y_p(h) - y_p(h-1) = \Delta y_p(h)$.

To minimize the cost function *J*, it is necessary to change the control input in the direction of the negative gradient of *J*.

$$\Delta v_k \propto -\frac{\partial J}{\partial v_k} \qquad (15)$$

If a control input *u* has a dominant effect on the *d*-step ahead output, *y(k+d)*, we can determine the control input, *u(k)* to minimize the *d*-step ahead output error. The future step, *d* is then determined to make the derivative of the output with respect to the input positive.

$$\Delta v_k \propto -\frac{\partial J(k+d)}{\partial v_k} = \eta_e \varepsilon(k+d)\Phi_k \frac{\partial y(k+d)}{\partial u(k)} + \eta_c c(k+d)\Phi_k \frac{\partial \Delta y(k+d)}{\partial u(k)} \qquad (16)$$

Thus, the learning algorithm is expressed by

$$v_{k,new} = v_{k,old} + \Delta v_k \qquad (17)$$

$$\Delta v_k = \Phi_k \{\eta_e \varepsilon(k+d) + \eta_c c(k+d)\} \qquad (18)$$

where, η_e and η_c are learning rates with arbitrary positive constant if $\frac{\partial y(k+d)}{\partial u(k)}$ is a monotone increasing function. The learning delay *d* introduces a certain amount of phase advance into the plant and is dependent on the lag amount of the process. In a non-minimum phase plant, a sufficiently large learning delay must be considered to make the derivative positive[9].

5. Results of Simulation

5-1 Drilling Model

From the real drilling data sets, we have trained linear ARMA models for the entire system. All the parameters start from nearly zero initial conditions(-0.001~+0.001) but are not zero for the training of the parameters. If we want to get one linear ARMA model for the case that *p*=0, *r*=2, *d*=0, and *q*=3, the modeling equation is as follows:

$$y_m(k) = 1.35y(k-1) - 0.36y(k-2) + 0.31u(k) + 0.01u(k-1) - 0.31u(k-2) \qquad (19)$$

If we want to get a model with 3-step prediction output and 1-step delayed input(*p*=3 and *d*=1), the modeling equation was

$$y_m(k+3) = 1.41y(k-1) - 0.50y(k-2) + 0.86u(k-1) + 0.04u(k-2) - 0.83u(k-3) \qquad (20)$$

Likewise, we trained 9 force models and 9 depth models by the fuzzy partition of Fig. 2 using the following equation:

$$y_m(k) = a_1 y(k-1) + b_1 u(k-1) + b_2 u(k-2) + c \qquad (21)$$

5-2 Fuzzy Controller

All the state variables are divided into 3 fuzzy sub-sets. In the case of the output variable, they are Small, Middle and Large, and they are Negative, Zero and Positive in the error or error-rate variable. Therefore the total number of rules is 27(3x3x3) in each stage. At first, the initial control rules are completely zero, and the initial fuzzy sub-sets are equally divided.

Using this nonlinear fuzzy model, we trained the fuzzy control rules. Since the thickness of a material is 8.0mm, and the length of entrance and exit is 2.2mm each, the total drilling depth is 10.2mm. The training target is as follows: First, in the entrance stage, the thrust force is increased to 120N after maintaining 30N for 0.3mm from the surface. Next, it is maintained 120N in the middle stage. Finally, in the exit stage, it is decreased to 30N to reduce the delamination. In Fig. 5(a), the target trajectory was a dotted line, and the thrust force after training was controlled such as a solid line. The control result was basically excellent even though there was a little overshoot of about 2%. Fig. 5(b) was the result according to the drilling depth. We can see that there was no increase of the drilling depth until the thrust force reached to 30N. It is necessary to remember that the entrance stage ends at the drilling depth of 2.2mm and the exit stage starts from the drilling depth of 8.0mm. The total drilling time is 2.3sec because the sampling time is 5ms. Fig. 5(a) shows that the entrance stage took 0.4sec, the middle 1.3sec, and the exit 0.6sec. To reduce delimination, the drilling time of the exit stage took longer than the entrance stage although the length is equal to each other. There was also little variance of the drilling depth when the force was suddenly decreasing.

In the simulation, we have to remember that this fuzzy model is definitely not perfect. The drill wear is also very important problem during the drilling process. Therefore, it is necessary to investigate the sensitivity of the fuzzy controller for the modeling error. Even though we have got a drilling model with the error less than 1%, we tried to apply this controller for a model with the error of ±30%. The results were shown in Fig. 6 and 7. When we considered 30% larger output model, it was possible to control the same thrust force using about 70% input as shown in the simulation of Fig. 6. On the other hand, when we considered 30% smaller output model, about 1.3 times of input was necessitated to maintain the given thrust force as shown in Fig. 7. From these simulations, we can conclude that the fuzzy controller is very robust for the modeling error or the drill wear. Next, it is also important to examine the generality of the controller whether the controller trained for a particular thrust force can be applied or not to the other targets. Fig. 8 and 9 show the control results when the thrust force is changed to 140N and 100N, respectively. From the simulation results, there are no problems to use this fuzzy controller even when other thrust forces are given.

6. Conclusions

In drilling of composite laminates, the control of the thrust force to reduce delimination is very important but difficult. The reason is that the conventional control techniques are for a linear and time-invariant system whereas dynamics involved in drilling of composite laminates is time varying and nonlinear. This paper proposed a fuzzy logic model and control strategy to deal with such a dynamic system. When the drilling model was divided into three different stages such as entrance, middle, and exit, the fuzzy logic model could describe the nonlinear time-varying process well, and the fuzzy controller realized a fast rise time and a little overshoot of drilling force. This fuzzy controller was so robust that we could apply to the untrained trajectories as well as a little different system with some modeling error. Now, we are preparing real experimental results using this control strategy.

Acknowledgement

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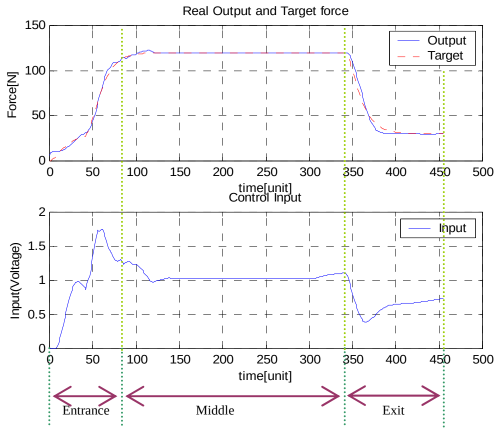

Fig. 5(a) Original training target and control result after training

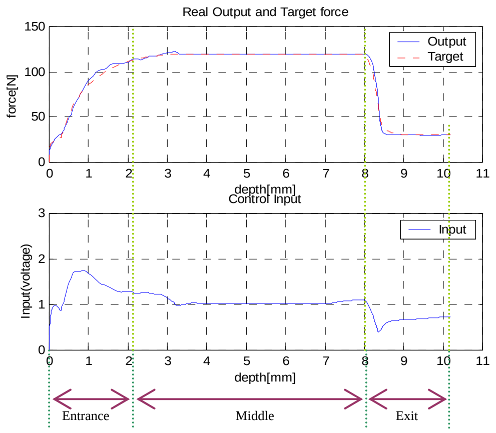

Fig. 5(b) Control input and output according to drilling depth

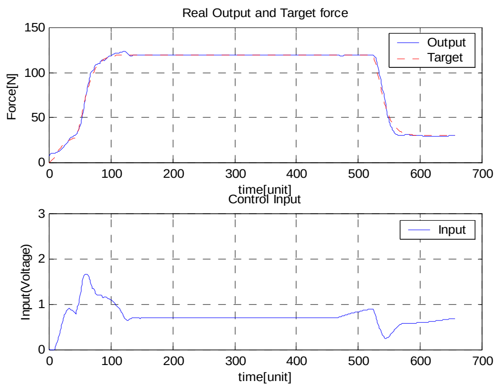

Fig. 6 Control result with the modeling error of +30% (when the output of model is increased by 30%)

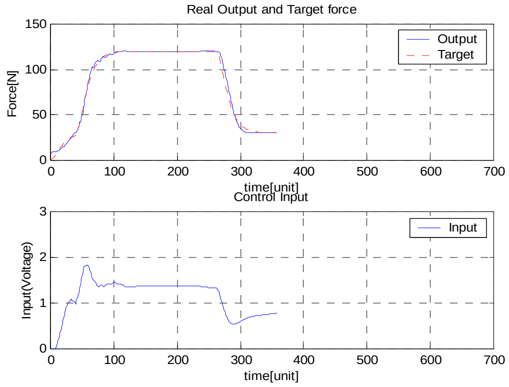

Fig. 7 Control result with the modeling error of -30% (when the output of model is decreased by 30%)

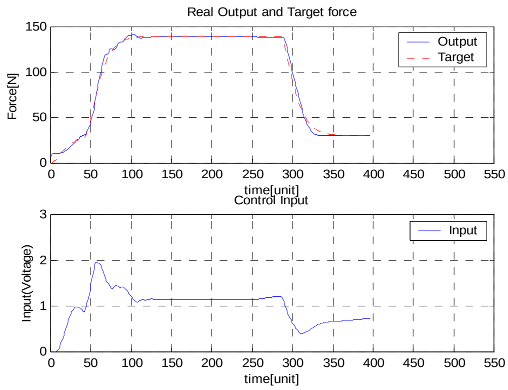

Fig. 8 Application result for higher target without additional training

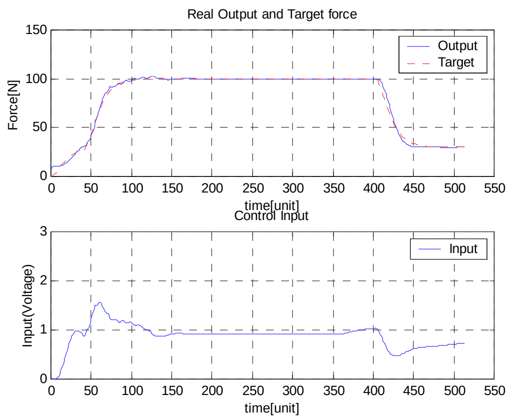

Fig. 9 Application result for lower target without additional training