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Research paper

Implementation of Stochastic Processing Parameters in a General Finite Element Analysis of a Laser Welding Process

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Abstract

The deterministic nature of finite element method for computational analysis is limited in describing the behaviour of actual processes which normally have certain degrees of uncertainties and deviations. Nevertheless, uncertainty factors can be incorporated into an FEM analysis using statistical approach to closely simulate real-life operating conditions. However, integrating stochastic parameters into commercial finite element solvers can be problematic, requiring the need for suitable interfacing using customized subroutine codes and implementation strategies. In this paper, a Monte Carlo approach was proposed for the incorporation of stochastic input parameter in a finite element analysis simulation of a laser welding process. A linear congruential generator together with a Box-Muller algorithm were used to generate normally distributed random numbers. The algorithms, written in Fortran77, was verified to be able to generate a gaussian distribution for 100, 1000, and 10,000 random numbers. The algorithms were then integrated into a user subroutine in MSC MARC/Mentat for the generation of variable laser power input values. A butt-welding simulation was executed using stochastic laser power input of, P having a mean, μ = 300 W, and standard deviation, σ = 10 W. A simulation with constant power input P= 300 W was also conducted for comparison. The results show that the stochastic input values resulted in a minor increase in the calculated surface temperature of the welded plates, which was probably due to the increased laser power at several time steps in the simulation. The findings and methods in this work can serve as a guideline for the incorporation of stochastic parameter inputs into finite element analysis simulation.

Keywords: *Finite Element Analysis; Laser Welding; Monte Carlo; Stochastic Analysis; Welding Simulation*

1. Introduction

The finite element method (FEM) is a widely accepted numerical method for solving problems in science and engineering. Among its application is in structural analysis, heat transfer, fluid mechanics and electromagnetic fields. However, FEM is deterministic and is thus limited to describe the general characteristics of a system. It cannot directly study a system reliably where there exists some degree of uncertainty. The classic FEM has been combined with other methods to create a new type of analysis to study systems with random variation and/or uncertainty in parameters. Statistical methods allow the effect of uncertainty and variability to be incorporated into finite element models.

Stochastic approach has been used in FEM for structure reliability analysis [1], fatigue crack growth analysis [2], microstructure evolution [3] and vibrational analysis [4], among others. A summary of the practical applications of the stochastic finite element method has been reviewed by Mena et al. (2016) [5].

However, stochastic methods must be able to be interfaced with widely used commercial finite element solvers for it to be widely accepted. Thus, this paper presents a strategy in implementing a Monte Carlo approach into the FEA simulation of a laser welding process.

2. Monte Carlo simulation

Stochastic Finite Element Methods (SFEM) merges the Monte Carlo simulation technique with the deterministic FEM. Monte Carlo simulation (MCS) is the most general and direct approach for SFEM. MCS uses probability distributions such as normal, lognormal, uniform, and triangular to model a stochastic or random input variable. Since MCS rely mostly on randomized number inputs, it is necessary to have a source of good random numbers. These numbers can be obtained from a table of random numbers, true-random number generators (TRNG) or pseudo-random number generators (PRNG). In computing, PRNG are generally the preferred choice, as a software implementation is more reliable, easier to integrate to other programs, and because they can be programmed, they can generate sequences of random numbers in a predictable manner, and the statistical properties of these pseudo-random numbers are also predictable. The algorithm is usually initialized with a number as the seed, and the resulting sequence of numbers depends on this seed. The main disadvantage of PRNG algorithm is that the random number sequence is periodic.

However, most algorithms have very long period of repeatability, which is sufficient for most applications.

2.1. Generation of random numbers using PRNG

2.1.1 Linear Congruential Generators (LCG)

For Monte Carlo analyses, the most widely used PRNG are linear congruential generators (LCGs). These are simple random number generators with a general form shown in (1) [6].

$$r_{n+1} = a \times r_n + c \ (\text{mod } m), \quad n=0,1,2,\ldots \tag{1}$$

where:

r_0 is a seed.

r_1, r_2, r_3 are the random numbers.

a, c, m are positive constants.

The selection of the values for a, c, m and r_0 drastically affects the statistical properties and the periodic length of the sequence. The random integers, r_n, produced would be uniformly distributed in (0, m-1). To return a value between 0 to 1, the integer r_n can be converted using equation (2)

$$R_n = \frac{r_n}{m}, \quad n= 1,2,\ldots \tag{2}$$

where:

R_n is the random number between 0 and 1

r_n is the random number generated in eq. 1

m is the positive constant from eq. 1

It is noted that the number generated is uniformly distributed. However, for many measured real-life values, the normal (or gaussian) distribution is more applicable.

2.1.2 Box-Muller algorithm

Normal random variable, *N* (0,1) can be obtained from the sequence of uniform random variables on (0,1). There are several different methods suggested in the literature to achieve this. One such method is by using the Box-Muller algorithm, introduced by Box-Muller in 1958. It is among the easiest to implement, although it can be numerically taxing and may not be the most efficient [7].
The algorithm is based on the transformation (u, v) to (x, y) given by equations (3) and (4), where u and v standard uniformly distributed random variables between 0 and 1.

$$x = \sqrt{-2\ln(u)}\,\sin(2\pi v) \tag{3}$$
$$y = \sqrt{-2\ln(u)}\,\cos(2\pi v)$$

This algorithm requires two uniform variables to generate a single standard normal variable.
Thus, the strategy for generating a normally distributed random numbers is to first use the LCG to generate uniformly distributed random numbers and then to feed these numbers as input data into the Box-Muller algorithm.

3. Methodology

In this study, a butt welding of C15 carbon steel using laser welding was modelled and simulated in FEM. The simulation was conducted in MSC MARC/Mentat, a general-purpose, nonlinear FEA commercial software. The software has a subroutine feature which enables the user to embed customized codes, written in Fortran77, to expand the capability of the program.

3.1. FEM model geometry

The geometry and boundary conditions of the weld configuration is modelled directly in MSC MARC/Mentat. Figure 1 shows the meshed geometries of the arranged C15 steel plates on the work table and the laser welding direction.

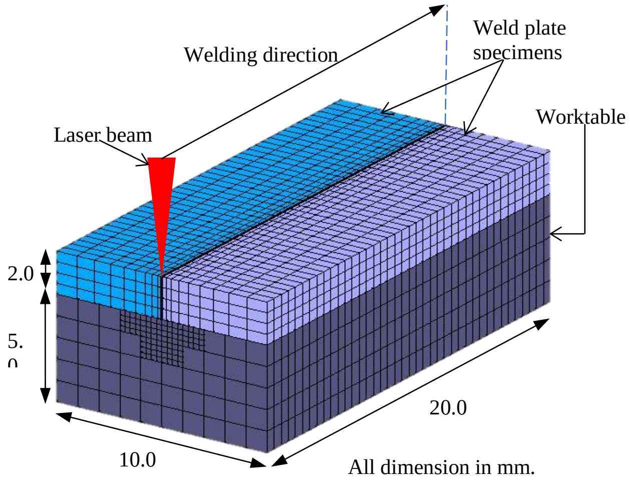

Fig. 1: Meshed geometries of C15 steel plate specimens arranged in buttweld configuration, shown with dimensional values and welding direction.

3.2. User subroutine

As MSC MARC/Mentat uses Fortran77 in its subroutine, it does not have its own built-in random number generator. Suitable PRNG algorithm is therefore required to be incorporated in the user subroutine. Having the ability to code the PRNG algorithm gives the flexibility in determining the desired distribution characteristics of the random number generated.

To review this Monte Carlo approach, the PRNG algorithm is first implemented in a general Fortran77 program to generate the variability in the power output parameter that follows a normal distribution. The program was tested to generate a sequence of random numbers that fulfil the required stochastic processing parameter (laser power). Figures 2, 3 and 4 shows the output of the program for 100, 1000, and 10,000 random numbers.

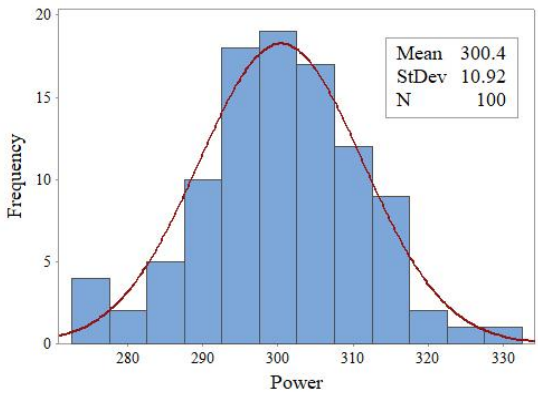

Fig. 2: Distribution of random numbers generated for N=100, μ (laser power) = 300 and σ = 10.

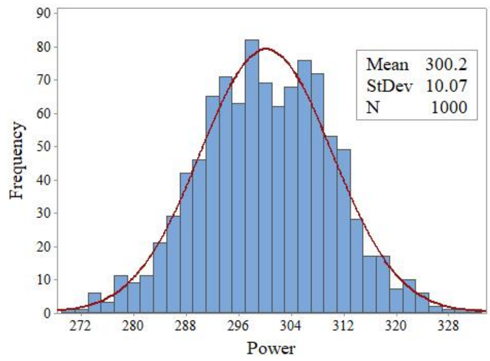

Fig. 3: Distribution of random numbers generated for N=1,000, μ (laser power) = 300 and σ = 10.

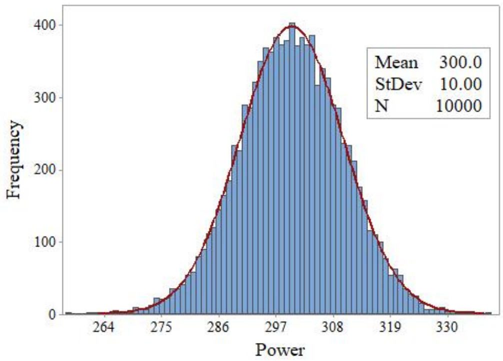

Fig. 4: Distribution of random numbers generated for N=10,000, μ (laser power) = 300 and σ = 10.

Once the algorithm was verified, it was incorporated into the MARC user subroutine. Figure 5 shows a flow chart of the stochastic algorithm implemented in the subroutine.

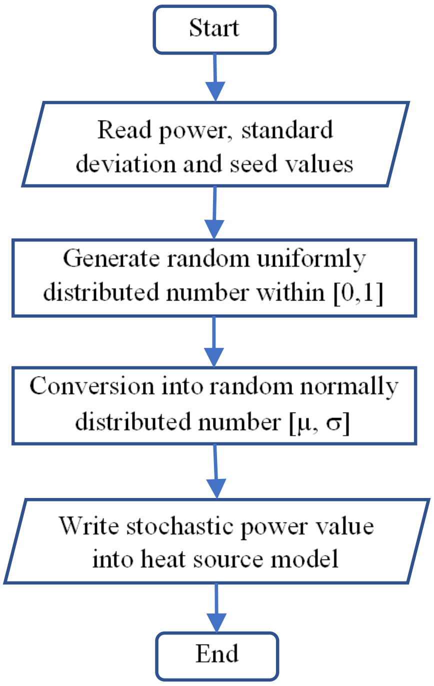

Fig. 5: Flow chart of the implementation of the PRNG algorithm into MSC.MARC/Mentat user subroutine.

The laser weld simulation was carried out using MSC.MARC. The simulation parameters are shown in Table 1.

Table 1: Parameters for laser weld simulations

Parameters	Model	
	Normal (Deterministic)	Monte Carlo (Stochastic)
Welding speed	5 mm/s	5 mm/s
Heat source model	Conical	Conical
Laser Power	300 W	μ= 300W, σ =10
Plate thickness	2 mm	2 mm
Plate material	C15 steel	C15 Steel
Time step	0.1 s	0.1 s
Total simulation time	10 s	10 s

4. Results and discussions

Figure 6 shows the Monte Carlo output of the laser welding power during the simulation run of 10 s. It shows that the power values of the laser were varied from 275W to 320W at each time steps (0.1 s) of the simulation. This range is within the required distribution for μ (laser power) = 300 and σ = 10.

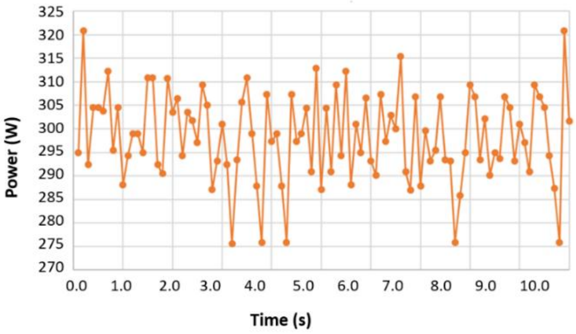

Fig. 6: Monte Carlo output of the laser welding power for laser welding simulation run (timestep = 0.1 s)

Figure 7 shows a comparison of the temperature distribution between the normal (deterministic) and the Monte Carlo finite element simulation results at time, t=2.3 seconds. Small observable differences in the results of the Monte Carlo model can be seen, where the temperature was higher towards the tail end of the weld path. This can be attributed to the increased power input over 300 W in the Monte Carlo implementation.

Due to the heavy computational load of the simulation, the meshed and model has been kept to a minimal to demonstrate the feasibility of the stochastic implementation. As shown in Figures 2 – 4, as the number of random number generated increases, the better is the fit of the data to the desired distribution. This can be implemented for finely meshed and full or life-sized models.

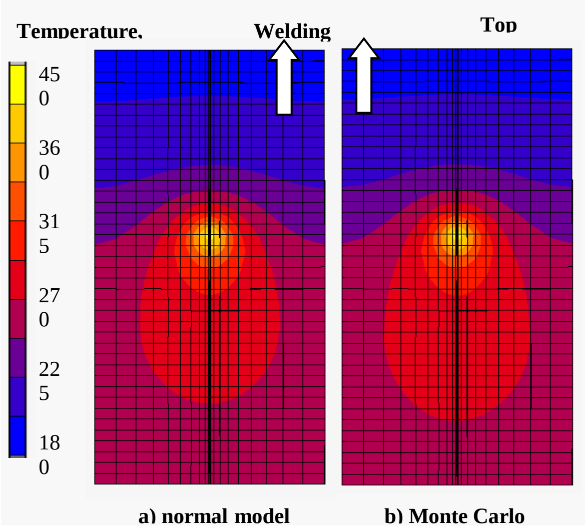

Fig 7: Comparison of temperature distribution on the welded plates at t=2.3 s for a) the normal and b) the Monte Carlo models.

It is noted that the random numbers generated follows a known sequence, based on the selected algorithm, and a truly random number generation is not obtained. This can be overcome by incorporating dynamic coefficients into the algorithm, such as those based on the time and date of the simulation execution. For example, the code shown in (4), can be incorporated into the Fortran77 subroutine to modify the seed values each time the simulation is executed.

```
call date_and_time(b(1),b(2),b(3),date_time)
seed =date_time(7)*0.001*seed                    (4)
power_random = normal ( mu, sigma, seed )
return
```

However truly random conditions are not always ideal for computational analysis. In general, a controllable and repeatable randomness is more desirable, especially in computational simulation, where iterative runs are the norm.

5. Conclusion

It has been demonstrated that stochastic processing parameters can be implemented in an FEA simulation run. In this simulation of an autogenous butt weld of two C15 carbon steel plates using low power laser, a Monte Carlo approach was used to randomize the input processing parameter of the laser power. A small difference was observed in the temperature distribution on the plate during welding, with the stochastic model exhibiting a slightly higher plate temperature towards the tail end of the weld path.

Although the observable difference between the results for the stochastic and the normal simulation run is minor, it should be noted that the model geometry is small, and the simulation time step is limited to 100 steps. It is anticipated that a noticeable difference would be more observable for large or life-sized specimens. Nevertheless, this study has demonstrated the applicability of incorporating stochastic variables into an FEA simulation, which can be extended to almost any input parameters, to closely resemble real-world conditions.

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