Hybrid WCMFO algorithm for the optimization of AWJ process parameters

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Abstract. Selecting optimal and proper cutting parameters for achieving desired results in the AWJ process is a demanding task. Therefore, the main contribution of this work is to apply a new reliable hybrid WCMFO algorithm for process optimization in the AWJ process. Based on the box-behnken design technique, 17 experimental runs were conducted and quadratic model for surface roughness was developed to fit with experimental data. Then, the WCMFO algorithm is implemented in the consideration of surface roughness as a fitness function. The key advantage of this algorithm is that it does not accumulate to any local optima, and the existence of a hybrid algorithm allows it to store the best solutions available so far. The predicted optimal settings were verified through confirmatory experiments, and the results validated.

1. Introduction

Composite materials are the most advanced engineering materials[1]. A composite is a heterogeneous material produced by the synthetic assembly of two or more components in order to obtain unique characteristics and properties[1]. Concern over preserving natural sources and recycling has led to renewed interest in biomaterials focused on sustainable raw materials. As a result, new forms of plant fibre composites have been produced in recent years. Natural-fibre reinforced composites offer a good mechanical performance and eco-friendliness. The use of composites based on natural fibres is growing rapidly[2]. Natural fibres, such as sisal, flax, banana, hemp, oil palm and jute, have range of techno-economic and ecological advantages over synthetic fibres (i.e. fibres of glass). The combination of fascinating mechanical and physical properties and their environmentally friendly character has given rise to interest in a number of industrial sectors, in particular the automotive industry[2]. However, there are some drawbacks in natural fibres composites that include inferior mechanical properties and high moisture absorption behaviour compared to their traditional synthetic counterparts. Mechanical properties also depend on processing stage, especially concerning the degree of fibre adhesion matrix, physical integrity and overall structural consistency[2].
Machining composite material causes significant problems due to the anisotropic and non-homogeneous nature of the material[2]. The process of machining composite material is distinct and complicated from that of metals. In traditional machining methods, such as turning, milling and drilling, the poor surface finish of the composite was poor and the removal of fibre, subsurface damage, delamination, and removal of bulk matrix are the major failures typically observed[2]. Technology advancement creates the use of non-conventional energy sources instead of the conventional process. Abrasive water-jet machining is such an non-traditional cutting process that uses a water-abrasive mixture as a high-speed water jet to extract material from the workpiece surface[3]. The high-speed water jet propels the abrasive mixing chamber to pass through a nozzle which enhances the jet's speed and leads it in a narrow zone to reach the work surface. The abrasive jet strikes at very high speed on the workpiece and extracts the substance through the erosive action of abrasives[3]. The brittle fracture is caused by the hammering action of the abrasives on the workpiece, and the residual wear fragments are separated from the machining region by the water jet[4]. One of the key benefits of the AWJM process over the AJM process is that no dust is created since a combination of water and abrasives is used to clean the material. The performance of an AWJM process depends on its various machining parameters, like stand-off distance, the diameter of the abrasive water-jet nozzle, abrasive concentration, nozzle pressure, abrasive grain size and feed rate of the nozzle, etc[4]. Kerf geometry is an important trait for abrasive water jet cutting. Kerf geometry is characterised by surface topography such as roughness and roughness along with kerf width and taper angle. It has wide access and, as the jet cuts through the material, its width decreases and the kerf is formed. Variation by millimetre of penetration as much as half of the kerf width can be described as kerf taper. Kerf tapers are formed as the jet loses its strength, piercing from the top to the bottom. In the present work, the AWJ cutting is proposed to assess the required input process parameters conditions for the improvement on the reduction of the surface roughness in cutting of natural fibre(pineapple) based composites. By conducting cutting experiments on the basis of the BBD design matrix. Further, a hybrid WCMFO algorithm is implemented to obtain the best AWJ optimal process parameters.

2. Experimental work

Pineapple Leaf Fiber (PALF) used as reinforcement fibre in most of matrices has shown its significant role in being inexpensive, having superior properties compared to other natural fibres, as well as encouraging agricultural economy[2]. PALF is described as multi-cellular and lignocelluloses materials, which is extracted from the leaves of the Ananas cosomus (belong to Bromeliaceae family) via retting process[2-3]. The high impact polystyrene mats were cut into rectangular pieces as per the dimension of mould cavity. Pineapple based fibre-reinforced polyester composite was fabricated, using the compression moulding method. In the compression moulding method starts by placing the mixture containing matrix and reinforcing materials on the bottom half of the preheated cavity mould. This method also allows the processing of short fibre laminates to be carried out. The mould is then closed and the top half is lower and the pressure is increased to the preset level. With increasing pressure, the materials begin to melt and flow into the cavity. Then the mould is cooled down and the product is removed from the mould. The schematic view of the AWJ cutting zone as shown in the Fig. 1. In this we mainly on three controllable parameters such as feed rate(4-10 m/min), stand-off distance (1-3mm) and water jet pressure (150-300MPa) and response variable (surface roughness), each factor has three levels designed by box-behnken design methodology and shown in Table 3. Surface quality is the intrinsic observation of every machined surface. In the same way, surface roughness is produced in the water jet machine due to the cutting mechanism involved. Mitutoyo make, surface roughness tester SJ 401 of measure collection/motion:80micron/0.001micron was used to calculate surface roughness values. The roughness significance was considered in three places at unlike locations chosen randomly and the standard value was directly measured for investigation.
Table 1. Experimental plan and collected responses

| Exp.No | Feed rate | Stand-off Distance | Water jet pressure | Surface Roughness(SR) |
|--------|-----------|--------------------|--------------------|-----------------------|
|        | m/min     | mm                 | Mpa                | Micron                |
| 1      | 4         | 1                  | 225                | 1.354                 |
| 2      | 10        | 1                  | 225                | 1.787                 |
| 3      | 4         | 3                  | 225                | 1.553                 |
| 4      | 10        | 3                  | 225                | 2.111                 |
| 5      | 4         | 2                  | 150                | 1.165                 |
| 6      | 10        | 2                  | 150                | 1.596                 |
| 7      | 4         | 2                  | 300                | 1.493                 |
| 8      | 10        | 2                  | 300                | 2.043                 |
| 9      | 7         | 1                  | 150                | 1.236                 |
| 10     | 7         | 3                  | 150                | 1.521                 |
| 11     | 7         | 1                  | 300                | 1.627                 |
| 12     | 7         | 3                  | 300                | 1.904                 |
| 13     | 7         | 2                  | 225                | 1.638                 |
| 14     | 7         | 2                  | 225                | 1.654                 |
| 15     | 7         | 2                  | 225                | 1.697                 |
| 16     | 7         | 2                  | 225                | 1.637                 |
| 17     | 7         | 2                  | 225                | 1.682                 |

3. Regression model representation

The DOE results were statistically analysed using the variance analysis (ANOVA) to assess the influence of the three variables tested for the response. Polynomial equations have been generated to create a relationship between significant factors and surface roughness. The proposed model in uncoded unit values was realised by the effect and interaction of each variable as shown in the following equation.
SR(Micron) = \(-0.35011 + 0.031583 \times \text{Feed Rate} + 0.062583 \times \text{Stand of distance} + 0.010156 \times \text{Water jet pressure} + 0.010417 \times \text{Feed Rate} \times \text{Stand of distance} + 1.32222 \times 10^{-4} \times \text{Feed Rate} \times \text{Water jet pressure}^2\) \(R^2 = 0.9939\) \hfill (1)

Predicted response values have been determined by the equations described above. The positive sign of the coefficients in the regression equation indicated a synergistic effect, while the negative sign indicated an antagonistic effect on the response. It has been observed from Eq. (1) that the all the process parameter variables are positive effects on the Ra. Further, the significance and adequacy of the developed model have been determined using ANOVA with 95% of CI. The value of the correlation coefficient \(R^2\) was 0.9538, which shows that 95.38% of total variations can be clarified by the model. In order to estimate the adequacy of the regression model, the diagnostic plots are given in Figures 2 and 3. The normal percentage probability plot is presented in Figure 6(b). The data points show that neither there is any apparent problem with normality nor the response transformation is required. The plot of the residuals versus the fits was used to examine the reliability of the model, as illustrated in Figure 6(c). As a result, no series of the increasing or decreasing points, of the patterns such as the increasing residuals with increasing fits and of a predominance of the positive or negative residuals should be found which is fortunately met in the work.

![Figure 2. Normal % probability plot of the residuals](image)

![Figure 3. Plot of residuals versus run number](image)
4. Hybrid WCMFO Algorithm and implementation

Hybrid WCMFO algorithm, which imitates the behavior of the nature flow of water cycle and moth navigation in the nature, has been introduced by the Khalilpourazari and Khalilpourazary in the year 2018[5]. Therefore, it constitutes a hybrid between the two techniques, comprising the water cycle and moth-flame optimization algorithms[6]. In order to avoid the trapping of the local Optima and the premature convergence of the population, the proposed algorithm incorporates the advantages of the water cycle algorithm(WCA) and the moth flame algorithm (MFA)[5]. The WCMFO that integrates the Levy operator with the MFO spiraling movement into the water cycle process, respectively, to increase the capacity of the WC for exploration and exploitation capability[6]. Ideally, WCA is able to explore the problem space with great capacity. The WCA maps streams and rivers towards the sea and allows search agents to change their role with regards to the best solution. But, the WCA tends to suffer from the lack of an efficient operator capable of performing exploitation. Instead, MFO makes very good use of its spiral movement capacity, but cannot effectively explore the solution area[6]. As every moth updates its location to its respective flame. The MFO therefore does not share information about the best solution obtained up to this point. This inspires the implementation of an efficient WCA and MFO hybridisation that can benefit from the advantaged effects of both algorithms[5]. The WCA is regarded as the fundamental algorithm in the proposed WCMFO algorithm[5-7]. In the WCA, the first step in changing the location of the streams and rivers is by using the spiral motions of the moths. The simple WCA update process only takes into account the space from the stream to the river when its location is changed. In short, in the space between the stream and the respective river is the next position of the stream[7]. Alternatively, the MFO algorithm updating procedure enables moths to change their location around their flames. The spiral system movement enables streams and rivers to improve their position, significantly improves the hybrid WCMFO's exploitability. The second change in the WCA is to improve the process of rainfall. In the metaheuristic algorithms, randomization plays an important role. There are two mechanisms are known in order to improve randomization in the WCMFO algorithm. As in fundamental WCA, the first is the raining cycle. During the cycle, WCMFO creates new solutions if the distance between a river or a stream and the sea is less than \(d_{\text{max}}\). The second is for a random walk (i.e.Levy Flight) to allow stream to flow alone in the solution area[5]. Take into account the WCA iteration, if the rivers are updated and no better solution is found, the n rivers and sea position should not be changed until next iteration. In hybridized algorithm, streams should change their location using the following equation in order to increase the randomness of the algorithm[5]

\[
x_{i+1} = x_i + \text{Levy(dim)} \otimes x_i
\]  
(2)

If \(x_{i+1}\) is the next position on the stream, \(x_i\) is the current position on the stream and dim is a decision variable. Then, the levy flight is determined with the following formula.

\[
\text{Levy}(x) = \frac{0.01 \times \sigma \times r_1}{|r_2|^\beta}
\]  
(3)

where \(r_1\) and \(r_2\) between zero and one, and are generated at random. The parameter \(\sigma\) is computed as follows by the below equation

\[
\sigma = \frac{\Gamma(1 + \beta) \times \sin \left(\frac{\pi \beta}{2}\right)}{\Gamma \left(\frac{1 + \beta}{2}\right) \times \beta \times 2^\left(\frac{\beta - 1}{2}\right)}
\]  
(4)
The WCMFO's pseudo - code is presented as follows[5]:

set the parameters of WCMFO such as $N_{pop}$, $N_{sr}$, $a$, and maximum number of iterations

for $i=1:N_{pop}$
   Create a random stream
   Calculate the objective function value of the stream
end for

sort the streams from best to worst based on their objective function value
Sea← the first stream
Rivers←$n_{sr}$
Stream←$n_{pop}$-$n_{sr}$

Determine the intensity of flow for rivers and sea
$i=0$;
While $i < $ maximum number of iterations
$i=i+1$;
   for streams
      Update the position of stream using spiral movement
      Stream_objective=objective function value of the new stream
      if Stream_objective < river_objective
         River_position= the new stream
      end if
      if Stream_objective < sea_objective
         Sea_position= the new stream
      end if
      if river_objective < sea_objective
         Sea_position =River_position
      end if
   end for
   for rivers
      Update the position of rivers using spiral movement
      river_objective =objective function value of the new river
      if river_objective < sea_objective
         Sea_position =River_position
      end if
   end for
   for streams
      Update the position of the streams using Levy flight
   end for
   for Rivers and streams
      $d$=calculate the distance between each river or stream and the sea
      if $d < d_{max}$
         raining process (for both rivers and streams)
      end if
   end for
   Linearly decrease the parameter $max d$
   Linearly decrease the parameter $a$
end while
The empirical equation (Eqn. 1) for surface roughness in the AWJ process formed using the RSM method was used as the objective or fitness function for optimizing using a hybrid WCMFO algorithm. A Matlab code has been compiled for executing the WCMFO. The corresponding code of WCMFO is subsequently run on MATLAB R2013a, 5 GB RAM and 2.30 GHz processor operating platform. The main goal of the process optimization on AWJ is to decide on the process parameters, namely the feed rate, stand-off distance and water jet pressure, in order to optimize the objective function which is surface roughness (SR). The problem was formulated as an unconstrained optimization problem where the objective was to minimize the surface roughness.

\[ \text{i.e. Minimize surface roughness, with the limits,} \]

\[ 4 \text{ m/min} \leq \text{ feed rate } \leq 10 \text{ m/min} \]
\[ 1 \text{ mm} \leq \text{ stand-off distance } \leq 3 \text{ mm} \]
\[ 150 \text{ Mpa} \leq \text{ water jet pressure } \leq 300 \text{ Mpa} \]

![Figure 4. Performance of the WCMFO algorithm across 100 generations](image)

The optimization process configuration is shown in Figure 4 illustrates the resulting values of the optimal SR values for the 100 iterations. There is a significant decrease in the best SR values until the global best solution was found in 77th iteration. The optimal values of the AWJ optimal conditions along with the respective surface roughness (SR) values are listed in Table 2.

| Table 2. Comparison between the initial and optimal conditions achieved by CS algorithm |
|----------------------------------------|----------------|----------------|----------------|
| Model Summary                         | Initial condition | Optimal condition | % of improvement |
| Process parameters                     |                 |                 |                 |
| Feed rate (m/min)                     | 4               | 5.245           |                 |
| Stand-off Distance (mm)               | 1               | 1.454           |                 |
| Water jet pressure (Mpa)              | 225             | 151.547         |                 |
| SR value                              | 1.354           | 1.09604         | 19.05           |
Table 3. Results of confirmation experiment

| Feed rate (m/min) | Stand-off Distance (mm) | Water jet pressure (Mpa) | Predicted | Confirmation Experiment | Relative Error(%) |
|-------------------|-------------------------|--------------------------|-----------|-------------------------|------------------|
| 5.245             | 1.454                   | 151.547                  | 1.09604   | 1.098                   | 0.1788           |

As seen from the Table 2, the percentage of improvement of surface roughness value to corresponding optimal condition is achieved by 19.05%. Further, the confirmation experiments were carried out to verify the corresponding surface roughness predicted by WCMFO algorithm. Table 5 shows that the percentage of error between the predicted and experimented values. From this analysis, it is observed that the calculated error (i.e. 0.1788) is very small and it proves the predictability and effectiveness of the proposed WCMFO algorithm.

5. Conclusion

The current work proposes an effective process parameter optimization approach that integrates RSM and a hybrid WCMFO algorithm on engineering optimization concepts. The proposed approach can effectively assist engineers in determining the optimal process parameter settings for AWJ under consideration of surface roughness. The following conclusions can be drawn.

1. Effective application of the Box–Behnken approach used for the experimentation.
2. The chosen response was modelled using the response surface methodology in terms of the AWJ process parameters.
3. A novel hybrid WCMFO algorithm is implemented to achieve the best optimal surface roughness value and the algorithm output showed that for achieving minimal surface roughness 1.09604 Microns.
4. The results of confirmation experiment performed and agree well with the predicted optimum values by WCMFO with minimum relative errors.
5. The results obtained would be useful and serve as a technical database for AWJ cutting industries for achieving better quality.

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