Experimental investigation and optimization of abrasive wear characteristics of polypropylene nanocomposites

Jafrey Daniel D and Panneerselvam K

1 Department of Mechanical Engineering, K. Ramakrishnan College of Engineering, Samayapuram, Tiruchirappalli-621112, Tamil Nadu, India
2 Department of Production Engineering, National Institute of Technology, Tiruchirappalli-620015, Tamil Nadu, India
3 Author to whom any correspondence should be addressed.

E-mail: jafrey.daniel@gmail.com and kps@nitt.edu

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Abstract
The applications of the polymer nanocomposites are increasing to a greater extent in several sectors. In this investigation, the matrix selected was Polypropylene (PP) and reinforcing filler was Cloisite 30B (C3B) with Elvaloy-AC-3427 (EAC) as a compatibilizer. Twin screw extruder was used for manufacturing of PP/C3B/EAC nanocomposites. C3B was added at the range of 1, 2, 3, 5 wt% to PP matrix. The manufactured composites was analysed for mechanical and thermal characterization. The tribological characteristics of manufactured nanocomposites were studied using abrasive wear tests. The input parameters considered for the abrasive wear tests were (i) load, (ii) C3B and (iii) sliding distance. The output parameters for the abrasive wear tests were weight loss, Coefficient of Friction (COF) and Specific Wear Rate (SWR). Grey relational analysis and grey fuzzy were done for the optimisation of abrasive wear characteristics. Analysis of Variance (ANOVA) was used for analysing the effect of input parameters over the output factors. Finally, the abraded wear samples of PP/C3B/EAC nanocomposites samples were examined microscopically.

1. Introduction
In the recent decades, researchers have started their research works on PP reinforced with fillers for producing polymer nanocomposites. Fillers are added to the polymer matrix to improve several properties like mechanical, thermal, flammability and optical transmittance [1]. The fillers added to the polymer matrix may be glass fibres, CNT, nanoclays etc. The conventional fillers are added up to 40 wt%, while nano-type fillers are added up to 5 wt%. The addition of fillers at minimum weight makes the production of polymer nanocomposites economical [2].

Polymer nanocomposites can be manufactured by sol-gel technology, solvent mixing and melt intercalation method [3, 4]. Though there are several techniques available, the melt intercalation method is the one which is often used for the manufacturing of polymer nanocomposites. Melt intercalation is done by extruders (single or twin) [5].

PP is the widely used material due to its advantages like cheaper rate, easy processability and its ease of availability in the market [6]. Kato et al. [7] concluded that PP is the commonly used material which is due to its improved physical and thermal properties. Though PP has many advantages in it, its poor strength and poor stiffness make PP not suitable for most of the applications. To overcome the drawbacks of PP certain fillers like mica and many other fillers have been infused initially. Although the addition of fillers increased the strength and stiffness, there was a need of more amount of fillers to be added to the matrix for achieving the required properties. The addition of more amount of fillers increases the weight of the composites produced. To reduce the weight and to improve the properties, nanofillers like nanoclays, nanotubes, glass fibres, etc are added to the PP matrix [1, 2].

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From previous studies, it can be concluded that reinforcing nanoclays to PP matrix is a beneficiary one. The challenge is to disperse the nanoclays in the PP matrix because PP is hydrophobic, while nanoclays are hydrophilic. This phenomenon resulted in an incomplete dispersal of nanoclays in the PP matrix \[8\]. To overcome this drawback, several authors have used various kind of compatibilizers \[9\--\[14\].

The investigation on tribological properties of manufactured polymer nanocomposites is of practical importance, for analysing the friction and wear characteristics. The material removal rate of materials might be slow, but it is a continuous process. Kumar \[15\] conducted experiments on two body abrasive wear of Low-Density Polyethylene / Ethylene Vinyl Acetate reinforced with smectite rich white montmorillonite with and without compatibiliser. The compatibiliser utilised in the study was poly (ethylene co-glycidyl methacrylate). The input parameters considered were grit size, load and abrating distance. The results indicated that there was an increase in abrasion resistance due to the presence of compatibiliser. The worn surface morphology studies showed that microploughing wear mechanisms during abrasive wear test.

Chang et al \[16\] carried out research works on wear performance of Ultra-High Molecular Weight Polyethylene reinforced with zinc oxide (micro & nano) as fillers. The experiments were carried out against 400 grit size paper. As a result, they concluded that the addition of zinc oxide in nano form to ultra-High Molecular Weight Polyethylene reduced wear rate when compared to the addition of zinc oxide in microform. The worn surface morphology revealed that the addition of nano zinc oxide has relatively uniform layers when compared to micro zinc oxide.

Grey Relational Analysis (GRA) is the one which describes the situation with black as absence of information and white as full information. The condition between the limits can be termed as fuzzy, grey or hazy. GRA is a combination of the systems which have some parts as recognised and the remaining portion of the system with no information. By the definition of GRA, the quality and the quantity of the information can be either complete or incomplete, i.e. from black to white through the grey. In GRA, the uncertainty always exists because the data can be somewhere in the extreme or middle or in a grey area. During the GRA process, the solution can be defined as no information at an absolute, and at the other extreme, there will be a unique solution. Though GRA cannot be applied for finding the best solution, it can be used for finding the appropriate solution \[17\].

The characteristics of abrasive wear input has particular influence during the abrasive wear process. The input parameters must be optimised to achieve better results. In recent years the most commonly used optimisation techniques are fuzzy logic, scatter search and many more techniques. Singh et al \[18\] used fuzzy based desirability optimisation technique to optimize the multiple bead geometry during the submerged arc welding process. Sibalija and Majstorovic \[19\] have applied an integrated process called Taguchi method and artificial intelligence for optimisation of multiple responses.

In recent years, GRA has been used for the optimisation of processes like electric discharge machining, welding and turning. The GRA was further improved when the fuzzy logic theory was implemented. Krishnamoorthy et al \[20\] studied the drilling characteristics of CFRP composite plates. The output of the drilling experiments was optimised using GRA and Grey fuzzy. They found that the grade values of grey fuzzy were improved when compared to GRA.

Although there are various works related to the PP matrix reinforced with different types of fillers, the use of EAC as a compatibiliser has not been reported anywhere. The abrasive wear properties of PP/C3B/EAC nanocomposites have not been published in the previous literature.

In the present study, the PP/C3B/EAC nanocomposites was manufactured using a twin screw extruder. The addition of C3B to PP matrix was varied at 1, 2, 3, 5 wt%. The test specimens were prepared by the injection moulding process. The experiments were done with C3B (wt%), sliding distance (m) and load (N) as input parameters and the output characteristics analysed were COF, SWR and weight loss. The results of abrasive wear characteristics were optimised by GRA and grey fuzzy analysis. SEM was used for analysing the worn surface morphology of abraded surfaces.

2. Experimental

2.1. Materials selected
The matrix material selected was PP (Repol H110MA) which has a melt flow index of 11 g 10 min\(^{-1}\) and density of 0.88 g cc\(^{-1}\). The nanoclay used in this study was Cloisite 30B (C3B). The compatibiliser utilised in the study was Elvaloy-AC-3427 (EAC) which has a density of 0.926 g cc\(^{-1}\), and melt flow rate of 4 g 10 min\(^{-1}\). It was added for enhancing the dispersal of C3B in the PP matrix.

2.2. Fabrication of PP/C3B/EAC nanocomposite
The PP/C3B/EAC nanocomposite was produced by melt intercalation method using a twin screw extruder. The parameters were selected from previous studies \[3\] for twin screw extrusion process for the manufacturing of
PP/C3B/EAC nanocomposites which are shown in table 1. Figure 1 depicts the temperature set at different zones of a twin screw extruder. The samples for testing were obtained using an injection moulding process, and the temperature set during the processing was maintained at 170 °C–190 °C (From inlet to die area). The processed samples were examined for analysing dispersion characteristics using transmission electron microscope. It showed a fine dispersion of C3B in the PP matrix when it was reinforced at 2 wt% and agglomerated structure at 5 wt% as shown in figures 2(a) and (b). The mechanical characteristics (tensile, flexural, impact & Shore D hardness), thermal characteristics (DSC, TGA analysis and dynamic analysis) and modelling of mechanical properties of processed composites were discussed in the previous studies [1, 2, 5].

2.3. Tribological studies

The tribological studies were carried out based on two-body-abrasive wear test as per ASTM G-99-05 using a pin-on-disc tribotesting machine. Theschematic sketch of the machine is presented in figure 3. The abrasive paper of 320 grit size was adhered to the top surface of D3 steel disc. The wear experiments were done with input parameters like (i) C3B wt%, (ii) load and (iii) sliding distance with a constant sliding velocity of 0.5 m s⁻¹. The PP/C3B/EAC nanocomposite sample perpendicular to 320 grit size paper parallel and antiparallel concerning the abrading direction is shown in figure 4. The following assumptions were made before the abrasive wear tests of PP/C3B/EAC nanocomposites (i) samples which had damages were discarded, (ii) surface roughness were uniform and (iii) load was applied directly at the point of contact.

The weight before and after the experiments were compared and the weight loss was evaluated. The SWR was calculated by equation (1).

\[
\text{Specific wear rate (K)} = \frac{m_1 - m_2}{\rho \times N \times S}
\]

In the above equation (1)

\(m_1\) and \(m_2\)—the mass of the pin before and after the experiment (g),

\(\rho\)—PP/C3B/EAC nanocomposite sample density (g mm⁻³),

\(N\)—number of revolutions of the disc, and

\(S\)—sliding distance (m)
Figure 2. (a) TEM of 2 wt% PP/C3B/EAC nanocomposites (b) TEM of 5 wt% PP/C3B/EAC nanocomposites.

Figure 3. Schematic diagram of a pin on disc setup.

Figure 4. Rotating disc with 320 grit size paper and PP/C3B/EAC nanocomposite sample.

N–Load (N),
S–sliding distance (m).
The COF was evaluated by the following equation (2).

\[
\text{Coefficient of friction (\(\mu\))} = \frac{\text{Frictional Force (F)}}{\text{Load (N)}}
\]  

(2)

The scanning electron microscope was used for studying the abraded samples.

2.4. Design of experiments
The optimisation of the parameters becomes more complicated when the input parameters are increased. When the input parameters get increased, simultaneously there was an increase in the number of experiments. To reduce this complexity, Taguchi methods used orthogonal arrays. The abrasive wear tests were carried out with parameters like C3B, load and sliding distance with a constant sliding velocity of 0.5 m s\(^{-1}\). Table 2 shows the levels and parameters considered. In the current research work, the two-body abrasive wear tests were designed and carried out according to the L\(^{16}\) orthogonal array. The output observed were weight loss, COF and SWR.

3. Grey relational analysis
Grey Relational Analysis (GRA) provided effective management of uncertainty and discrete data. During the GRA the black colour represents the absence of information while the white colour denotes the information. A grey system consists of data which is between white and black. The GRA can be applied for measuring the absolute value between the sequences, and it can also be implemented for measuring the relationship between the sequences. It is the practical way of studying the relationship between the sequences which have the least data, and it can also be applied for analysing the number of factors [21, 22].

The two-body abrasive wear tests were done according to the L’16 orthogonal array. During GRA sixteen wear experiments were considered as sixteen individual subsystems and each one called as a comparability sequence. The conditions with the higher values of GRG resulted in lower values of weight loss, SWR and COF. By this process, the multi-objective optimisation became a single objective optimisation using GRA.

3.1. S/N ratio for computing abrasive wear characteristics
During the abrasive wear of PP/C3B/EAC nanocomposites, the lower-the-better characteristics were considered for analysing weight loss, SWR and COF. The S/N ratio for lower-the-better characteristics are shown in equation (3)

\[
S/N_{\text{ratio}(\eta)} = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right)
\]  

(3)

3.2. Preprocessing of data
During GRA, the output, experimental data was initially normalised for the reduction of variability, which was termed as data preprocessing. It is essential to apply data preprocessing because the range and unit of each response will be different from others. Data preprocessing was carried out for transferring of original sequence to the comparable sequence. Due to this reason, they are normalized within the range of zero to one. The data preprocessing was done based on the data sequence characteristics [23–26].

When the original value was considered to be infinite, then it was termed as ‘higher-the-better’, and it was normalised by the following equation (4)

\[
x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)}
\]  

(4)

When lower the better characteristics was considered, then the normalisation of the original sequence can be carried out using the following equation (5).
\[ x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(1)}{\max x_i^0(k) - \min x_i^0(1)} \] (5)

However, if the desired value was to be achieved by the normalisation of the original sequence using the following equation (6)

\[ x_i^*(k) = 1 - \frac{\|x_i^0(k) - x_i^0\|}{\max x_i^0(k) - x_i^0} \] (6)

It can also be carried out by considering the original sequence value and dividing it by the first value in the particular order.

\[ x_i^*(k) = \frac{x_i^*(k)}{x_i^0(1)} \] (7)

In the above equation (7) \( x_i^0(k) \) represents the original sequence, \( x_i^*(k) \) represents the sequence of data after preprocessing, \( \max x_i^0(k) \) is the largest value of \( x_i^0(k) \), \( \min x_i^0(k) \) is the least value of \( x_i^0(k) \) and \( x^0 \) represents the desired value.

### 3.3. Calculation of grey relational coefficient and grey relational grade

GRA was applied for measuring the relevancy among the systems. The sequences which were used in the GRA could be termed as grey relational coefficient \( \xi(k) \), which was calculated by equations (8)–(11).

\[ \xi(k) = \frac{\Delta \min + \xi \Delta \max}{\Delta \min + \xi \Delta \max} \] (8)

where \( \Delta \min \) represents the absolute difference between \( x_i^0(k) \) and \( x_i^*(k) \) and it is termed as deviation sequence. \( \xi \) is the distinguishing coefficient. If the values of distinguishing coefficient are larger, then the values of distinguishing ability will also be larger. In most of the cases, the \( \xi \) value used was 0.5.

\[ \Delta \min = \min_{j=1}^{\mu} \min_{k=1}^{\nu} \|x_i^0(k) - x_i^*(k)\| \] (9)

\[ \Delta \max = \max_{j=1}^{\mu} \max_{k=1}^{\nu} \|x_i^0(k) - x_i^*(k)\| \] (10)

The Grey Relational Grade (GRG) was calculated by taking the average values of grey the relational coefficient, and it can be defined as follows [27–30]

\[ \gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \] (12)

The importance of several factors of the systems get varied concerning the real-time situations which depend upon several factors [30]. Equation (12) can be extended as

\[ \gamma_i = \frac{1}{n} \sum_{k=1}^{n} W_k \xi_i(k) \] (13)

In the above equation (13) \( W_k \) denotes the normalized weight of the factor \( k \). If the values of \( W_k \) is similar for all the factors, then equations (12) and (13) will be identical. The GRG will reveal the degree of influence by comparing the sequence of the reference sequence. If the value of a specific sequence is higher when compared to the reference sequence, then the values of the GRG for that particular sequence and reference sequence will be superior for that specific GRG.

### 3.4. Grey fuzzy logic

The GRG is calculated based on three conditions, namely (i) lower-the-better, (ii) higher-the-better and (iii) nominal-the-better characteristics. The grey fuzzy logic provides the way for representing the vagueness or absence of information related to the problem. Zadeh et al [31] concluded that the set of membership functions was a vital factor in making decisions when faced with uncertainty. The fuzzy set contains a large number of membership functions which map a universe of objects within the range of 0 to 1. The drawbacks of the GRG were resolved by the fuzzy logic approach.

The fuzzy logic approach involves the following steps (i) fuzzification of input values, (ii) rule inference and (iii) defuzzification to obtain better values. The excellent prediction accuracy can be achieved by the comparison of values of input with a defuzzification output value. The fuzzification is a procedure which is employed for making a crisp quantity fuzzy by the application of the linguistic variables. The fuzzy system is applied for answering the ambiguous and unclear questions, and it is also used for describing the certainty level of the answers. The membership values could be mapped to the fuzzy variables in number of ways based on logical operations [32]. From the results of previous findings, it was found that the various assignment process available.
are intuition, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithm and fuzzy statistics. The membership function can be either triangular, trapezoidal or Gaussian.

The rule inference system finds solution based on set of rules formed or by opinions from the experts or based on intuition. The following condition gives the rules which are developed based on the structure as shown below

**IF premise (antecedent), THEN conclusion (consequent)**

The representation can be termed as shallow knowledge, and it can be suitable for linguistic variables. There are different techniques for obtaining the membership function of values of fuzzy relation with the use of fuzzy implication operation. The implication method of inference applied in this research work is Mamdani’s implication method. It was applied for yielding aggregation of fuzzy rules, and it was termed as max-min inference method. The next step is the defuzzification, which was carried out by the max—min membership method.

The application of fuzzy logic results in enhanced GRG, which consists of reduced uncertain output when compared with the output of GRA. Hence the output from grey fuzzy logic will always be higher than GRG. Thus the increment in the values of grey fuzzy logic can be applied to different types of applications.

In general, ANOVA is employed for finding the percentage of contribution concerning, every input and output factors \[33\]. In this study, ANOVA was used for studying the effect of input abrasive wear characteristics with the output characteristics of SWR and COF.

### 4. Results and discussions

The abrasive wear experiments were carried out, and the results are discussed in the following section. The experimental values are also optimised according to GRA and grey fuzzy logic.

#### 4.1. Weight loss, COF and SWR of PP/C3B/EAC nanocomposites

The weight loss concerning C3B (wt%), sliding distance (m) and load (N) are shown in table 3. The main effect plots considering the COF and SWR are shown in figure 5(a) and (b). When 1 wt% of C3B was added to PP matrix nanocomposites the weight loss was maximum when compared to other wt% addition of C3B. There was further reduction in weight loss on further addition of C3B. The weight loss was found to be lesser in case of 5N for all addition of C3B, and it got increased with increase in load.

The values of SWR was maximum up to 150 m sliding distance, and on further increase in the values, there was a reduction in SWR. When the sliding distance was less, the outer layer of PP /C3B/EAC nanocomposites were exposed, which also increased SWR values. When the abrading distance was at 150 m, there was less clogging of material in 320 grit surface, and when it was further increased, the clogging of materials was more in the 320 grit surface. When the sliding distance was more, the PP/C3B/EAC nanocomposite pin slid over the same surface again and again for more amount of time, which leads to the formation of the transfer layer. The transfer layer formed on the surface leads to the reduction of SWR values. When the load was increased, the SWR values get decreased. At 20N load, the PP/C3B/EAC nanocomposite get detached from the surface due to the production of heat at the contact surface. When C3B was added at a low level, the value of SWR was more, and on further addition of C3B, the values of SWR get decreased.

| SL.No | C3B (wt%) | Load (N) | Sliding distance (m) | Coefficient of friction (µ) | Weight loss (g) | Specific wear rate (mm³/Nm) |
|-------|-----------|----------|----------------------|-----------------------------|----------------|-----------------------------|
| 1     | 1         | 5        | 75                   | 0.298                       | 0.0023         | 0.007032                    |
| 2     | 1         | 10       | 150                  | 0.292                       | 0.0091         | 0.006810                    |
| 3     | 1         | 15       | 225                  | 0.27                        | 0.0099         | 0.003492                    |
| 4     | 1         | 20       | 300                  | 0.245                       | 0.0148         | 0.002735                    |
| 5     | 2         | 5        | 150                  | 0.281                       | 0.0047         | 0.007032                    |
| 6     | 2         | 10       | 75                   | 0.268                       | 0.004          | 0.006000                    |
| 7     | 2         | 15       | 300                  | 0.251                       | 0.0143         | 0.003492                    |
| 8     | 2         | 20       | 225                  | 0.249                       | 0.0112         | 0.002735                    |
| 9     | 3         | 5        | 225                  | 0.246                       | 0.0048         | 0.004680                    |
| 10    | 3         | 10       | 300                  | 0.241                       | 0.0112         | 0.004100                    |
| 11    | 3         | 15       | 75                   | 0.239                       | 0.0103         | 0.00500                     |
| 12    | 3         | 20       | 150                  | 0.246                       | 0.0108         | 0.003950                    |
| 13    | 5         | 5        | 300                  | 0.243                       | 0.0093         | 0.004043                    |
| 14    | 5         | 10       | 225                  | 0.236                       | 0.008          | 0.003860                    |
| 15    | 5         | 15       | 150                  | 0.241                       | 0.007          | 0.003530                    |
| 16    | 5         | 20       | 75                   | 0.229                       | 0.0041         | 0.003023                    |
C3B and the PP matrix majorly share the load. The values of COF was maximum at 1wt% of PP/C3B/EAC and it get decreased with an increase in the addition of C3B with PP matrix. The other plausible cause for the reduction in values of COF was due to the rise in values of thermalstability at 5wt% of PP/C3B/EAC nanocomposites, which were confirmed by thermogravimetric tests \[2\]. The COF value get decreased when the load was increased. This was due to the temperature change at the PP/C3B/EAC nanocomposite specimen at the contact zone. At 20N load condition, heat is accumulated at the interface, which leads to the partial melting of the PP/C3B/EAC nanocomposite surface, which lubricates the surface and also reduces COF value. The values of COF get increased upto a sliding distance of 150 m and get decreased on further increase in sliding distance. When the sliding distance was high, the COF values declined due to clogging of PP/C3B/EAC nanocomposite on the 320 grit surface.

4.2. Grey relational analysis for abrasive wear characteristics
Lower-the-better performance characteristics were employed in this study for analysing the output characteristics. Table 4 indicates the grey relational coefficients of abrasive wear characteristics of PP/C3B/EAC nanocomposites in terms of weight loss, SWR and COF as outputs. The grey relational coefficient values do not have the same value for all the experiments. Hence there was a need for calculation of grey relational grade for abrasive wear characteristics.

The GRG was calculated by taking the average of every input parameters as listed in table 4. The optimum condition which was achieved from the response table showed that the C3B addition must be at 5wt%, with 20 N load and sliding distance of 75 m. Figure 6 shows the main effect plot of calculated GRG. Table 4 also reveals that all the three output abrasive wear characteristics have a GRG value above 0.5.

4.3. Grey fuzzy reasoning analysis for abrasive wear characteristics
The values of grey fuzzy output were calculated using MATLAB R2010. Figure 7 shows the triangular membership function employed for the output characteristics like weight loss, COF and SWR and figure 8 shows...
Table 4. The grey relation coefficient and grey relational grade for abrasive wear responses.

| SL.No | C3B (wt%) | Load (N) | Sliding distance (m) | Grey relational coefficient for Coefficient of friction (μ) | Grey relational coefficient for weight loss | Grey relational coefficient for specific wear rate (mm³/Nm) | Grey relational grade | Rank |
|-------|-----------|----------|---------------------|-------------------------------------------------------------|-------------------------------------------|----------------------------------------------------------|----------------------|------|
| 1     | 1         | 5        | 75                  | 0.333                                                       | 1.000                                     | 0.333                                                    | 0.555                | 12   |
| 2     | 1         | 10       | 150                 | 0.354                                                       | 0.479                                     | 0.345                                                    | 0.392                | 16   |
| 3     | 1         | 15       | 225                 | 0.457                                                       | 0.451                                     | 0.739                                                    | 0.549                | 14   |
| 4     | 1         | 20       | 300                 | 0.683                                                       | 0.333                                     | 1.000                                                    | 0.671                | 4    |
| 5     | 2         | 5        | 150                 | 0.399                                                       | 0.723                                     | 0.333                                                    | 0.484                | 15   |
| 6     | 2         | 10       | 75                  | 0.469                                                       | 0.786                                     | 0.397                                                    | 0.350                | 13   |
| 7     | 2         | 15       | 300                 | 0.611                                                       | 0.342                                     | 0.739                                                    | 0.564                | 11   |
| 8     | 2         | 20       | 225                 | 0.633                                                       | 0.413                                     | 1.000                                                    | 0.681                | 2    |
| 9     | 3         | 5        | 225                 | 0.670                                                       | 0.714                                     | 0.525                                                    | 0.636                | 6    |
| 10    | 3         | 10       | 300                 | 0.742                                                       | 0.413                                     | 0.611                                                    | 0.588                | 8    |
| 11    | 3         | 15       | 75                  | 0.775                                                       | 0.439                                     | 0.487                                                    | 0.566                | 10   |
| 12    | 3         | 20       | 150                 | 0.670                                                       | 0.424                                     | 0.639                                                    | 0.577                | 9    |
| 13    | 5         | 5        | 300                 | 0.711                                                       | 0.472                                     | 0.622                                                    | 0.601                | 7    |
| 14    | 5         | 10       | 225                 | 0.831                                                       | 0.523                                     | 0.656                                                    | 0.670                | 5    |
| 15    | 5         | 15       | 150                 | 0.742                                                       | 0.571                                     | 0.730                                                    | 0.680                | 3    |
| 16    | 5         | 20       | 75                  | 1.000                                                       | 0.776                                     | 0.882                                                    | 0.885                | 1    |
The typical nine fuzzy subsets which have been used for grey fuzzy reasoning grade. The Fuzzy Interface System (FIS) was activated by writing rules, and it was used for the prediction of values of the grey fuzzy reasoning grade for all abrasive wear experiments.

The obtained grey fuzzy grade values are listed in table 5, which were predicted from FIS. The values in table 4 were compared with values in table 5. The grey fuzzy reasoning grade was improved when compared with GRG value. The uncertainty in the experiment was decreased at the 16th experiment, and the maximum grey fuzzy relational grade was noted there. The increased values of grey fuzzy reasoning grade increased when compared with GRA are shown in tables 4 and 5. There was a reduction in fuzziness, and the grey relational grade value moves to the reference value 1.

The main effect plot of the grey fuzzy reasoning grade of the abrasive wear characteristics is shown in figure 9. The best parameter combination was obtained from the response table of grey fuzzy approach in experiment sixteen indicates that C3B and load were maintained at level 4 and sliding distance at level 1.

The prediction of grey fuzzy reasoning grade theoretically was a vital one once the optimal conditions were found out. The calculation of fuzzy reasoning grade was carried out using the equation (14).

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**Figure 6.** Main effect plots for grey relational grade.

**Figure 7.** The triangular membership applied for output characteristics like weight loss, COF and SWR.

**Figure 8.** The nine fuzzy subsets used for grey-fuzzy reasoning grade.
where $\eta_{om}$ — grey fuzzy reasoning grade mean value, $\eta_{opt}$ — grey fuzzy reasoning grade at the optimal level, and K — the number of influential parameters which determine the several performances of abrasive wear outputs like weight loss, SWR and COF. The results of the confirmation experiment are shown in table 6. The values of the grey fuzzy relationship were found to be higher when compared with GRG.
4.4. ANOVA for grey fuzzy grade

The values of ANOVA for the grey fuzzy grade are shown in table 7. ANOVA was applied to reveal the significance of each input abrasive wear characteristics concerning output abrasive wear characteristics. The results of ANOVA showed that the addition of C3B played a dominant role in determining the abrasive wear characteristics followed by load and sliding distance.

| Source          | DOF | Adj. SS  | Adj. MS  | F_cal | F_table |
|-----------------|-----|----------|----------|-------|---------|
| C3B (wt%)       | 3   | 0.071249 | 0.02750  | 5.58  | 3.28    |
| Load (N)        | 3   | 0.062266 | 0.020755 | 4.88  | 3.28    |
| Sliding Distance (m) | 3   | 0.033279 | 0.011093 | 2.61  | 3.28    |
| Error           | 6   | 0.025540 | 0.004257 | —     | —       |
| Total           | 15  | 0.192334 | —        | —     | —       |

4.5. Worn surface morphology

The worn surfaces were examined using SEM, and the images are mentioned in figures 10(a), (b). All SEM images were taken at 5 N and 20 N load conditions irrespective of sliding distance. White arrows represent the sliding direction, which is depicted in figures 10(a) and (b).

Figure 10(a) depicts the worn surface of 5 wt% PP/C3B/EAC nanocomposite sliding at 5 N and 20 N. When the C3B was added at 5 wt% in PP/C3B/EAC nanocomposites there was an enhanced abrasive wear resistance. The abraded surfaces of 5 wt% PP/C3B/EAC nanocomposites was relatively smooth with less surface damage with an evidence of PP/C3B/EAC nanocomposites. The formation of the agglomerated structure during the processing of PP/C3B/EAC nanocomposites obstruct the removal of matrix from the surface. The patches of C3B can be seen on the abraded surface, which also upsurges the wear resistance. The abraded surface was smooth, and there was less amount of damage, as shown in figure 10(a). The enhanced thermal stability at 5 wt% PP/C3B/EAC nanocomposites was also a significant cause for the increase in wear resistance [2].

The worn surface of 1 wt% PP/C3B/EAC nanocomposites is shown in figure 10(b). When C3B was added at 1 wt% there was more damage to the abraded surface when compared to all other additions of C3B to PP matrix. Figure 10(b) shows ductile fracture as the primary failure mode, and the extent of damage to the matrix was severe in comparison with all other manufactured PP/C3B/EAC nanocomposites. In figure 10(b) the presence of wide, deep grooves are evident in the longitudinal direction of the worn surface due to surface fatigue by repeated abrasion. A governing feature observed on the surface of 1 wt% PP/C3B/EAC nanocomposites were the micro-ploughing and micro-cracking, which are evident from figure 10(b), which was also due to lower thermal stability. When the network of cracks intersects, the C3B particle tends to become loose and was removed in the form of wear debris. Thus a higher degree of wear was found at 1 wt% PP/C3B/EAC.
nanocomposites, which can be attributed to lower matrix ductility, which deforms the matrix by surface disintegration. The wear mechanisms found in the current study were micro-cracking and micro-ploughing.

5. Conclusion

The manufacturing of PP/C3B/EAC nanocomposites was carried out using a twin screw extruder. The manufactured PP/C3B/EAC nanocomposites were characterised based on two-body abrasive wear tests. The output of the abrasive wear tests was optimised using GRA and Grey-Fuzzy logic. The conclusions drawn are as follows:

- The two-body abrasive wear tests were carried out with concern to multiple performances to attain excellent abrasive wear characteristics. The outputs of two-body abrasive wear tests were optimized based on GRA and Grey fuzzy.
- The load at 20 N, C3B addition at 5 wt% and sliding distance of 300 m were identified as an optimal combination which provided an enhanced value of grey fuzzy reasoning grade and a higher fuzzy reasoning grade of 0.901 which was close to the reference value.
- ANOVA studies showed that the amount of (wt%) addition of C3B played a dominant role in determining the abrasive wear characteristics followed by load and sliding distance.
- The worn surface morphology of abraded wear surfaces showed less damage when C3B was added at 5 wt% due to the more amount of exposed C3B during the abrasive wear test. The abrasive wear mechanisms found were micro-cracking and micro-ploughing.

ORCID iDs

Jafrey Daniel D
https://orcid.org/0000-0001-5319-8610

Panneerselvam K
https://orcid.org/0000-0002-9231-7122

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