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Advanced machine learning and experimental studies of polypropylene based polyesters tribological composite systems for sustainable recycling automation and digitalization

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A B S T R A C T

Digitalization and automation are emerging solutions to the complex problems of recycling. In this research work, the experimental and Python based Archard deep learning wear rate models are introduced regarding recycling automation and composite tribological systems optimization. The optimum polyester fibers (PESF) of length of 3–3.5 mm were used for fabrication of polypropylene (PP)-PESF composite systems. The deformation, high texture, asperities, and micro-cracks were observed during scanning electron microscope and machine-learning studies. The lowest experimental value of abrasive wear of 3.0×10^{-6} mm^3/Nm was observed for PP. Comparatively, higher experimental values of abrasive wear of the PP-PESF composites are found in the range of 4.35×10^{-6} to 4.7×10^{-6} mm^3/Nm due to presence micro-defects on the surface of composites. The experimental values of Coefficient of friction (COF) of PP and PP-PESF are found in the range of 0.70–0.8 and 1.1–1.3, respectively. The experimental values of abrasive wear and COF are found compatible with literature. Similarly, the simulated values of abrasive wear of PP and PP-PESF composites are predicted in the range of 4.8×10^{-7} to 3.75×10^{-7} mm^3/Nm, respectively. The predicted values of PP and PP-PESF composite show better resistance towards abrasive wear. The proposed experimental and simulated (in terms of Python coding, machine learning, image processing, artificial intelligence, and deep learning studies) research work can be introduced industrially for automation as well as digitalization of grinding of PES waste, processing, tribological testing, and SEM characterization evaluations.

1. Introduction

Tribological investigations play an important role in surface evaluations during engineering design of recycled products. The recycling of polymeric waste helps to transform open into closed loop manufacturing [1,2]. The primary, secondary, tertiary, and quaternary recycling technologies assist to process pre-consumer, post-consumer, end-waste, and end-of-life waste, respectively. However, primary recycling (mechanical) is considered economical for manufacturing of post-consumer reinforced composites materials. Mostly, pre-consumer and post-consumer wastes are used as a raw material [3,4]. This waste contained higher levels of valuable material and low impurities. The utilization of waste in manufacturing enhances the level of sustainability of the environment. Sustainability relies on areas of human, social, economic, and environment. The enhancement in degree of sustainability assists in meeting the needs of people, protecting the well-being of the

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environment, ensuring financial stability, and growth of the future [5,6]. Mechanical recycling utilized waste as an initial raw material. The utilization of waste as a raw material lowered the carbon emissions and other environmental effects [7,8]. The extrusion, injection, compression molding, pultrusion, thermoforming, additive manufacturing can be utilized as closed loop processing techniques [9–12]. The polyesters, polycarbonates, polyether ether ketones, polystyrene, polyvinyl chlorides, polyethylene (low, linear low, high density), polyamides, and polyurethanes are the most common commercial polymers and produce large waste [13,14].

Polyesters are very common polymeric materials used in the automotive, aerospace, textile, and medical industries. The 75 % of resin for composite industries is derived from polyester [15]. The saturation and unsaturation nature of polyester formulate diverse properties and applications [16]. The extensive utilization of polyester produces waste. The polyester waste can be reutilized after the steps of collection, sorting, separation, and grinding for fabrication of fiber reinforced composites (FRC). The additional steps include mixing, recycling, and quality testing [17]. The FRC consists of matrix and reinforced phases. The matrix phase helps in transfer of load, dispersion of phase in exact place, protection from environmental impacts, net shape to design, and surface quality. The fiber phase enhances the tensile strength, stiffness, and performance quality [18,19]. However, physical parameters like operating temperature, applied pressure, torque, presence of moisture, and nature of materials also affect the tribological properties of composite materials [20,21]. The utilization of polymeric materials during service life lowers service life and performance. Therefore, optimization of operating parameters assists in enhancing the surface performance and overall quality of recycled products [22,23]. The abrasive wear testing can be introduced to check the useability, suitability, stability, and service life of recycled composite products [24–26].

Tribological studies are mostly considered for checking the surface performance of composites. The fatigue, abrasion, and erosion are the most used techniques to measure wear rate, weight loss, creation of plastic deformation, and material removal [24,25,27]. The tribological properties fundamentally rely on the nature of matrix, fiber materials, binders, manufacturing techniques, orientation, and length of reinforced fibers [24,25,28]. Physical parameters like applied force, operating temperature, speed, time, matrix-fiber interfacial adhesion, presence of micro defects, and surface roughness also affect surface performance of composites [25,29,30]. The determination of experimental values of abrasion wear rates, deformation, and weight loss helps to optimize the surface performance regarding service life. The abrasive wear rate is considered resistance of the surface of soft materials (like polymers etc.) against hard counter-bodies (like silica alumina, zirconia, and tungsten carbide etc.). The tribological properties of recycled polymer products can also be enhanced by surface modification (using hard coatings) of various machinery parts [31–33]. The surface modification of machinery parts provides higher hardness regarding better grip and lower surface roughness to avoid the process of formation of textures. However, knowledge of tribological behavior of recycled polymer products is required in advance. Therefore, software tools like MATLAB, analysis of variance (ANOVA) artificial neural network (ANN), and machine learning studies can be introduced to predict the behavior of recycled products [34–36].

The Python based artificial intelligence (AI) and deep learning (DL) coding studies can help in modernization of manufacturing systems [34–36]. The application of machine learning tools provides a proven technical path for implementing the concepts of the fifth industrial revolution [37]. In manufacturing engineering, it can help for sustainable open into closed loop transformation of industrial production. The manufacturing of polymeric products consists of different steps. However, utilization of polymeric waste produces complexities during recycling [33,38]. The experimentation of fabrication of polymeric composites assists in finding the technical solutions to engineering problems faced during manufacturing. Besides evaluation of virgin raw materials, processing, and testing, the recycling of polymeric waste includes collection, separation, sorting, washing, grinding, and mixing as additional steps during production of polymeric products. Therefore, besides prediction of various physical parameters, the AI and DL can assist in optimization of steps of recycling. The optimization can be introduced using analysis of physical parameters like fiber length, speed of grinding, scanning electron microscope (SEM) characterization, artificial image processing, abrasive wear rates, plastic deformation, and coefficient of friction (COF). These physical parameters present the quality and performance of recycled

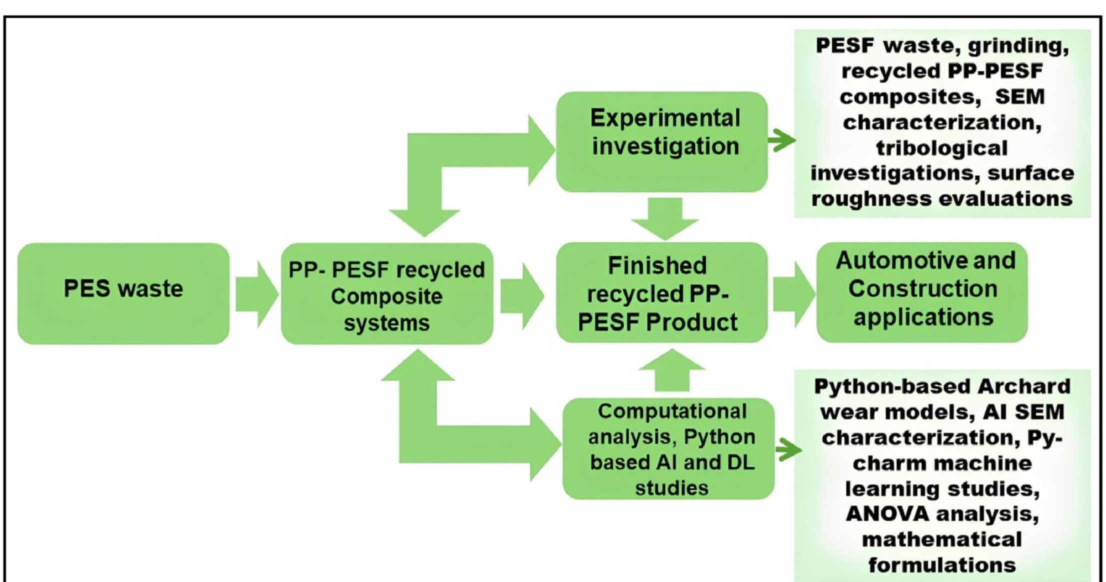


Fig. 1. Flow chart of experimentation and computational analysis of research.

products. The AI and DL can also help in the transformation of open into closed loop manufacturing [28,34,39].

In this research work, in the first step, the polyester (PES) waste was ground using a direct grinding process. The fiber length is optimized using experimental, mathematical formulation, and AI and DL results. The developed polypropylene (PP)-polyester fiber (PESF) reinforced composite materials are used to investigate the experimental abrasive wear, COF, and plastic deformation. The SEM characterization of PP and PP-PESF composites was done to study the abrasive wear, deformation, and micro defects before and after tribological investigations. The Ra (average surface roughness) was measured regarding the relative surface roughness of PP and PP-PESF composites.

In the second step of research, the AI and DL studies of PES waste, grinding process, PP-PESF tribological composite systems are carried out to predict the optimization of abrasive wear and wear depth. Python-based Archard deep learning wear rate mathematical models are used. The AI and DL SEM images (in terms of textures) are compared with experimental SEM characterization regarding quality and performance of recycled composites. The experimental and machine learning outcomes (SEM characterization, experimental abrasive wear rates, COF values, simulated abrasive values, and wear depths) are compared with the literature. Collectively, the direct extrusion and injection molding manufacturing methods are considered as sustainable closed loop recycling techniques for processing of PES waste. Similarly, AI and DL studies can assist in the implementation of recycling automation and digitalization (coding inputs, programming). Finally, the experimental and machine learning research studies are

Fig. 2. Materials for fabrication of PP-PESF composites: (a) Pure virgin PP and (b) fibers of PES waste.

Table 1
Fabrication scheme of PP-PESF composites.

Composite code	Real amount of PESF (wt.%)	Real amount of PP (wt.%)	Net weight of PP (g)	Net weight of PESF (g)
PP	0	100	500	0
PP-PESF-10	10	90	450	50
PP-PESF-30	30	70	350	150
PP-PESF-40	40	60	300	200

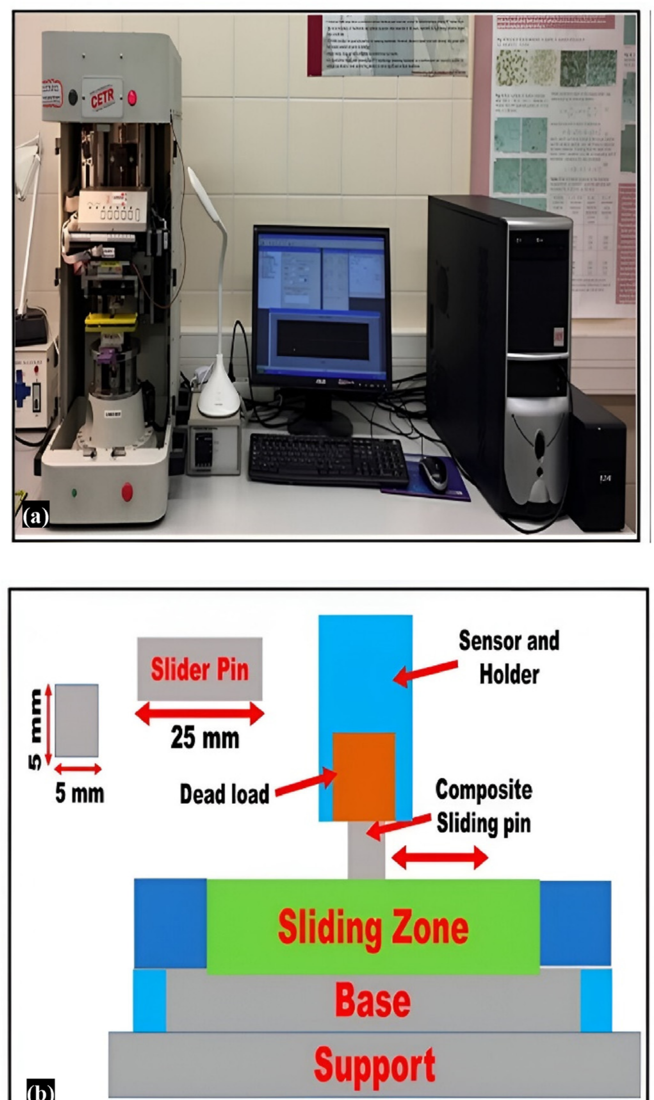


Fig. 3. Experimental setup for tribological investigations: (a) CETR Bruker UMT-2 tribometer and (b) working principle.

formulated for initial pilot production trials in small and medium commercial recycling industries. The Python-based AI and DL studies are carried out to compare experimental and computational results regarding automotive and structural applications.

2. Materials and methods

2.1. Planning of experimentation and computational analysis

The research was planned according to the flow chart shown in Fig. 1 The experimentation includes grinding of the PES waste, PESF fiber size SEM characterization, tribological investigations of PP-PESF composites, SEM characterization of composites before and after abrasive testing, determination of abrasive wear, surface roughness, and COF values, see Fig. 1.

The results and technical data produced during experimentation were used for computational analysis. The computational analysis involved development of Archard wear rate, depth models, DL studies, mathematical formulation of fiber length, and AI SEM characterization. The ANOVA tests were performed to analyze the yielding effect of each parameter, see Fig. 1.

2.2. Polymer waste and composites materials

The semi-crystalline PP thermoplastic was used as a matrix phase due to good adhesion, interfacial strength, moisture resistance, and fiber wettability. The poly-1.4 cyclohexyl-di-methylene terephthalate (PCDT) synthetic polyester post-consumer waste was used as a reinforced phase [40], see Fig. 2a and b.

The PES waste was ground into fine fibers. The PP and PESF were mixed and extruded into pellets of size 2–3 mm. Finally, the PP-PESF fiber reinforced composites were fabricated using injection molding. The 0, 10, 30, and 40 % of PESF fiber loadings were used [41]. The composites coding and formulation were shown in Table 1. The already sustainable manufactured PP-PESF composites were utilized for tribological investigations, surface analysis, SEM evaluations, and computational optimization. The PP-PESF composites were fabricated at Department of Mechanical and Industrial Engineering, Laboratory of Recycling and Materials Testing, Tallinn University of Technology.

2.3. Tribological investigations and SEM characterization

The composite sheets were cut into pins of 5 (thickness) x 5 (width) x 25 mm (length). The pins of PP of the same dimensions were used as a reference. For experimentation, a CETR Bruker UMT-2 tribometer was utilized to calculate the abrasive wear, coefficient of friction, and plastic deformation. The experimental setup is shown in Fig. 3a and b. The sliding speed, distance, and applied force were 0.1 m/s, 18 m, and 1 N, respectively. The volumetric wear rate was calculated using the following formula [26]:

$$W = \frac{V}{L \times S} \tag{1}$$

Where W, V, L, and S are volumetric wear rate, wear loss, applied force, and sliding distance, respectively.

The values of coefficient of friction (COF) were calculated using UMT Viewer software. The silicon carbide (SiC) P150 grade sandpaper was used as an abrasive medium against composite materials [26]. The average values of Ra of PP and PP-PESF composites were measured using mechanical profilometer (Mahr Perthometer PGK120). The PESF waste, PP, and PP-PESF composites were characterized using SEM before and after testing. All samples were coated with 2 nm thin films of gold. The PESF average length was measured digitally using SEM and installed software. All tests were performed at temperature and relative humidity of 25 °C and 50 %, respectively.

2.4. Python computational and ANOVA statistical analysis

The Python-based (Python 3.12) programming is performed to find out the critical PESF length for composite fabrication. The PyCharm 2023.3.5 software Package was introduced to develop the optimum relationship between grinding medium (grinding wheel) and PES waste, see Fig. 5c. The bunch of 100 fibers was considered

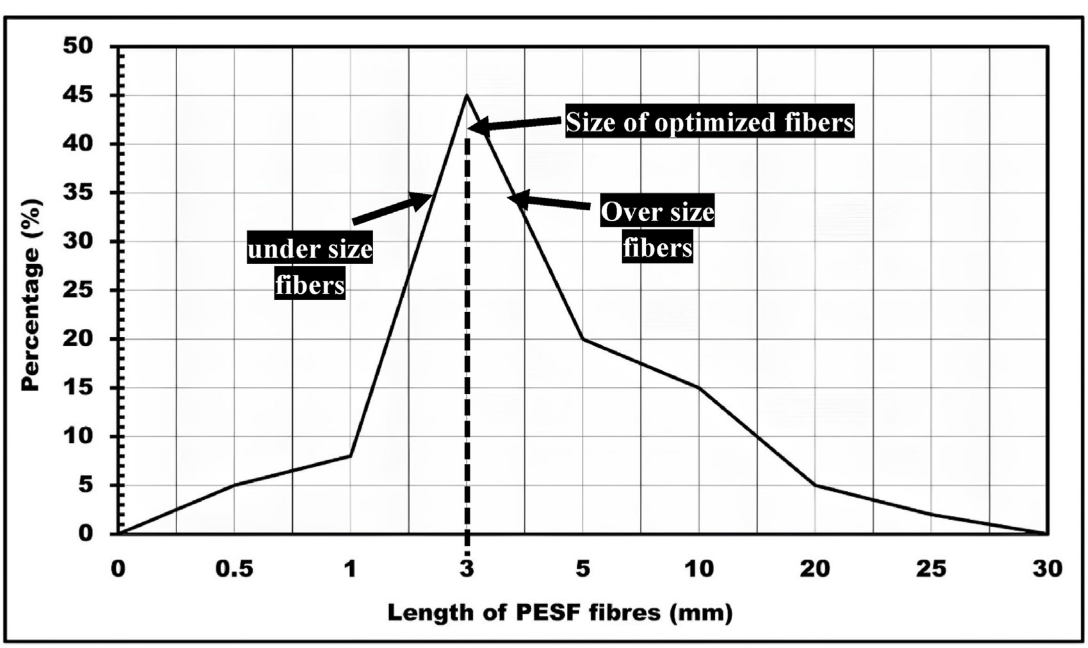


Fig. 4. Size distribution of PESF after grinding.

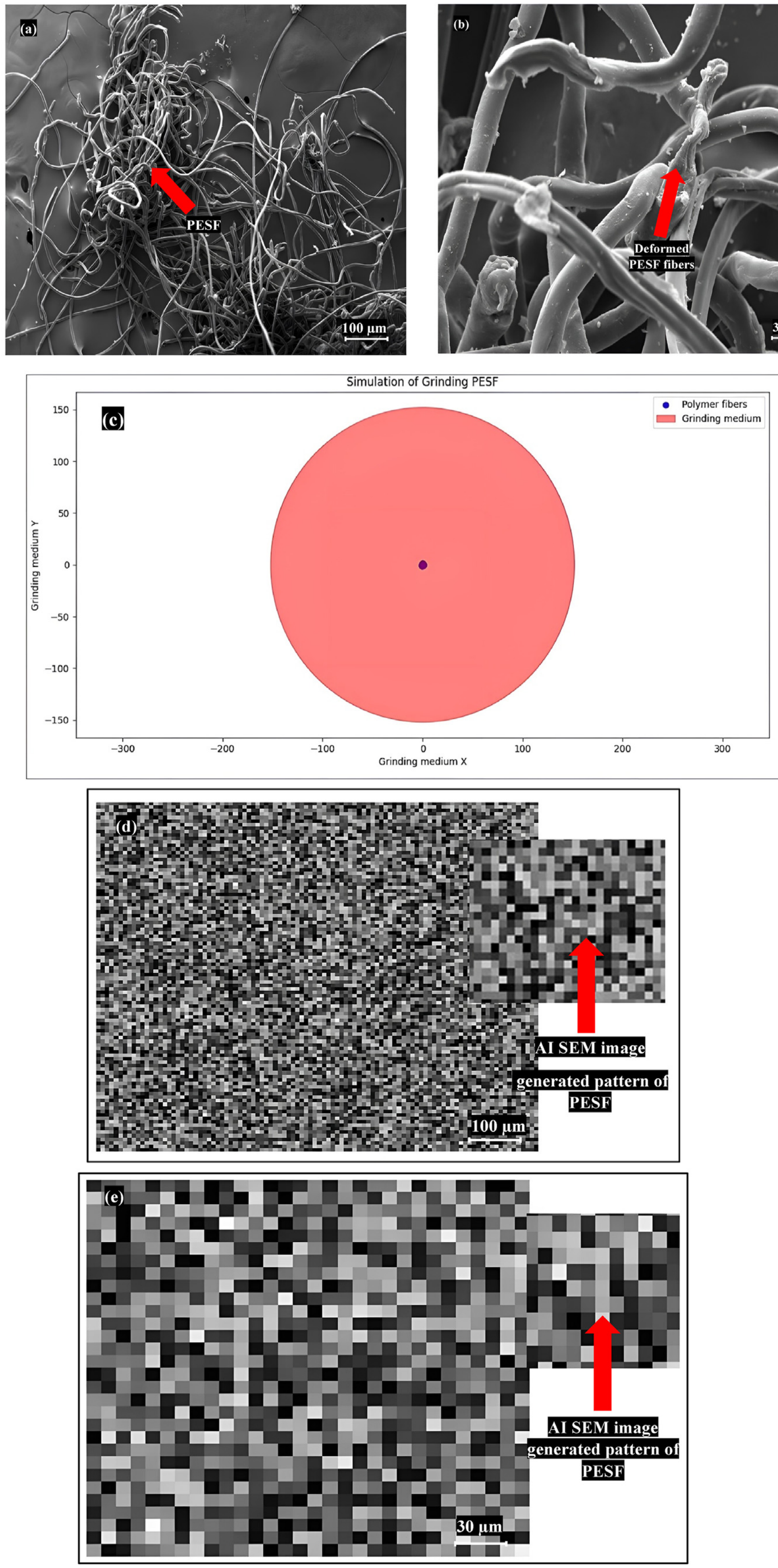


Fig. 5. SEM characterization and AI and DL studies of PESF: (a) SEM images of PESF at lower, (b) higher magnifications, (c) 2D simulation of grinding medium and PES fibers, (d) AI image of PESF at lower magnification, and (e) AI PESF image at higher magnification.

for AI and DL studies. The presence of the PESF within the grinding medium is a sign of good quality and performance of waste. The artificial SEM images of PESF were also studied; see Fig. 5d and e. The images were generated for 100 μm of width, 100 μm of height, 3.5 mm of the PESF length, and 0.09 μm of diameter (Fig. 5d). However, 30 μm of width and 30 μm of height were utilized for the generation of artificial PESF SEM image (Fig. 5e).

The Archard wear rate model (mathematical formulation and equation (3)) was utilized to simulate the results using the Python 3.12 coding system Py-Charm 2023.3.5 machine learning software package. The wear depth was also determined; see Figs. 8 and 9, respectively. The artificial SEM images of PP and PP-PESF composites were also studied before and after abrasion testing; see Fig. 6c and d. The images were generated at 100 μm width and 100 μm height. At higher magnification, the images were generated at 2 μm width and 2 μm in height. Additionally, after tribological testing, the AI SEM image of the representative sample was generated at 20 μm width and 20 μm height with respect to experimental data using the gray scale, see Fig. 7d. The formed pixels represents white, black, and gray micro square blocks corresponding to constructive, destructive, and overlapping of the interference, respectively. Therefore, these AI SEM images (Figs. 5d, e, 6c, 6d, and 7d) are corresponding to experimental SEM images (Figs. 5a, b, 6a, 6b, and 7c) of PESF, PP and PP-PESF composites, respectively. Collectively, the AI and DL studies were carried out to predict the PESF waste and PP-PESF composite behavior for industrial recycling and commercial use. A single test ANOVA was carried out to study the yielding effect of wear rate on PP and recycled PP-PESF composites.

3. Results and discussion

The optimum size of PESF is shown in Fig. 4. The under and oversize of PESF cause the decrease in PP-PESF composite interfacial adhesion, see Fig. 4. The optimum size for fabrication of PP-PESF composites was in the range of 3.00–3.50 mm.

The effective length of PESF was calculated using the following formula:

$$L_c = \frac{\sigma_f . D}{2 . \tau_c} \tag{2}$$

where L_c, σ_f, D, and τ_c were critical length, design strength (450 MPa), diameter (0.021 mm), and design shear strength (25 MPa) of the PESF [42].

The calculated critical length was 2.75 mm. The best results were found for a critical length of 3.50 mm, see Figs. 2b, 4 and 5. The optimization of fiber length was done through optical, SEM characterization, and sieve analysis [43]. The bunch of 20 fibers was considered for microscopic evaluation. The SEM images in Fig. 5a and b shows the plastic deformation on the surface of PESF. Fig. 5c demonstrates the two dimensional (2D) simulation of the grinding of the PESF. The grinding of the PESF (assuming the 0.01 mm cylindrical radius of the PESF) shows highest compatibility with grinding medium (grinding wheel with radius 152 mm). The bunch of 100 fibers was considered for AI and DL studies [44]. The presence of the PESF within the grinding medium is a sign of good quality and performance of waste. The artificial SEM images of PESF were also studied, see Fig. 4d and e. The images were generated for 100 μm of width, 100 μm of height, 3.5 mm of the PESF length, and 0.09 μm of diameter (Fig. 5d).

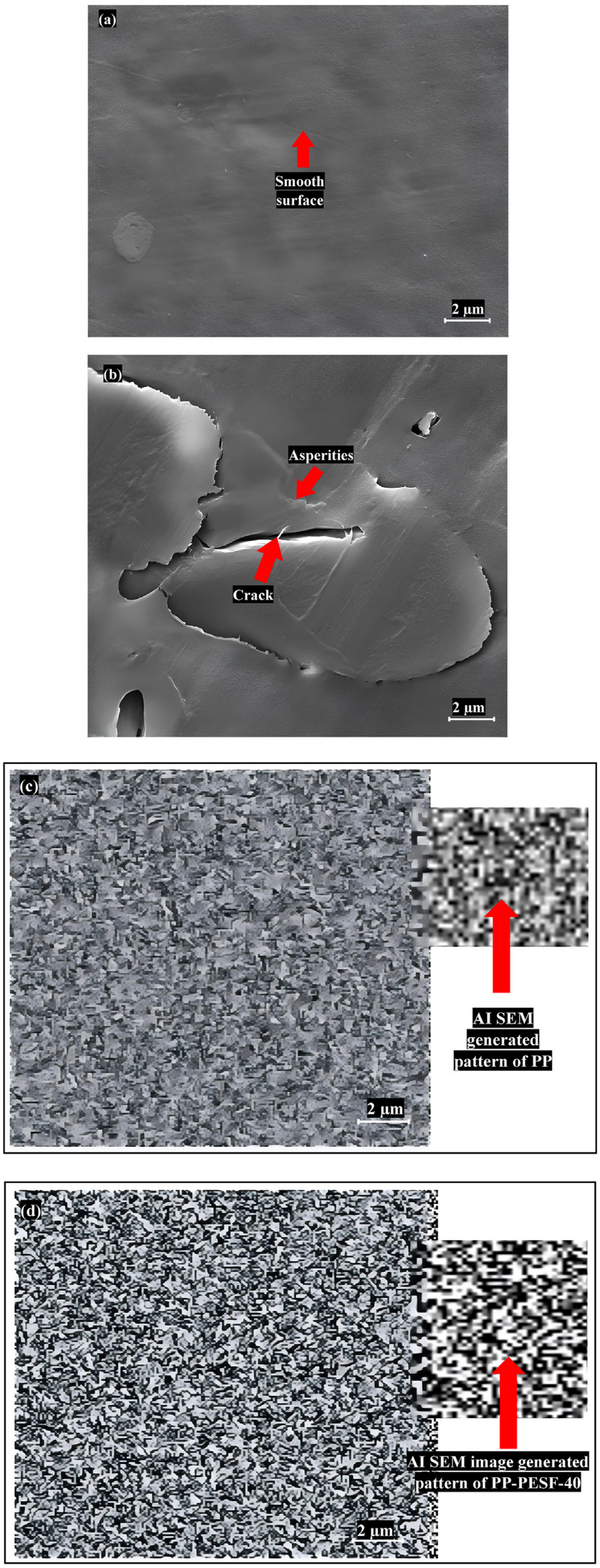


Fig. 6. SEM characterization and AI and DL studies of PP and PP- PESF composite: (a) SEM images of PP, (b) PP-PESF-40 composites, (c) AI image of PP, and (d) PP-PESF-40 Composites.

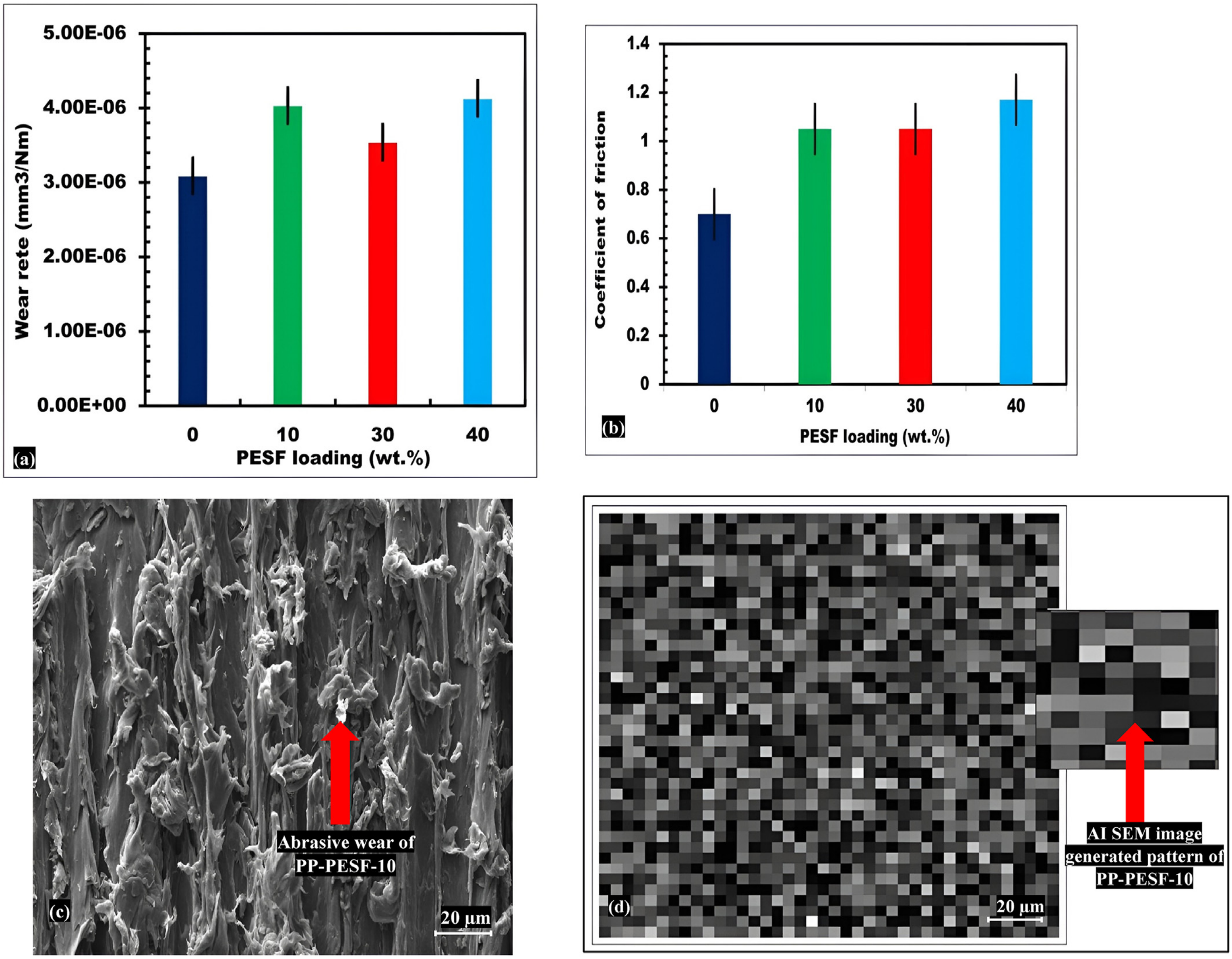


Fig. 7. Experimental investigations of tribological systems and SEM characterization of pure PP and PP-PESF composites: (a) abrasive wear rates, (b) COF, and (c) SEM characterization of PP-PESF-10, (d) AI SEM image of PP-PESF-10 composite.

However, 30 μm of width and 30 μm of height were utilized for the generation of artificial PESF SEM image (Fig. 5e). The diameter (Fig. 5e) of PESF was constant. The AI image shows the highest level of texture (in terms of roughness) due to the deformed surface of PESF (Fig. 5d). The degree of deformation becomes the highest and AI image results in a drop in resolution. The other possible reason may be the lowering in performance and quality of PES waste [45,46]. Therefore, the pattern of pixels appeared in the form of small white, black, and gray micro pixels due to constructive, destructive, and overlapping of interference. The presence of plastic deformation and micro defects can cause the increase in width of square blocks (pixels). This increment appeared in the form higher surface texture, see Fig. 5e.

Before tribological investigations, SEM characterization of PP and PESF was done, see Fig. 6a and b. The PP reference materials exhibit a smooth surface (Fig. 6a). However, asperities, micro cracks, voids, and highly rough regions were detected on the surface of PP-PESF-40 composites (Fig. 6b). The artificial SEM images of PP and PP-PESF composites were also studied, see Fig. 6c and d. The images were generated at 100 μm width and 100 μm height. The images were generated at 2 μm width and 2 μm in height. Fig. 5c resembles Fig. 6a with uniform distribution of texture (in terms of roughness). Similarly, Fig. 5d resembles Fig. 6b with non-uniform texture of black and white regions (in terms of roughness). The non-uniform texture resembles the presence of micro defects mentioned in Fig. 6b. The PP-PESF-10 and PP-PESF-30 also exhibit similar behavior (as of PP-PESF-40 related to Fig. 6b and d). The constuctive, destructive, and overlapping of interference produce special AI image patterns. These patterns exist in the form of white, black, and gray regions. Irregular shapes of grains (crystals), amorphous, and crystalline phases individually increase the final surface texture of PP and PP-PESF composite families, see Fig. 6c and d, respectively.

The results of tribological PP and PP-PESF composite systems are shown in Fig. 7. The abrasive wear rates and COF results are shown in Fig. 7a and b, respectively. Pure PP exhibits the lowest value of abrasive wear. However, PP-PESF composites show relatively higher values of wear rates due to micro defects, see Figs. 5, 6 and 7a. Mostly, these defects are present in the form of microcracks and asperities. The interactions between silicon carbide hard particles, PP, and all PP-PESF composites decrease adhesion. The lowering in adhesion can cause an increase in the values of wear rates and COF. According to Fig. 7b, the highest value of COF was found for the PP-PESF-40 composite. The PP-PESF-10 and PP-

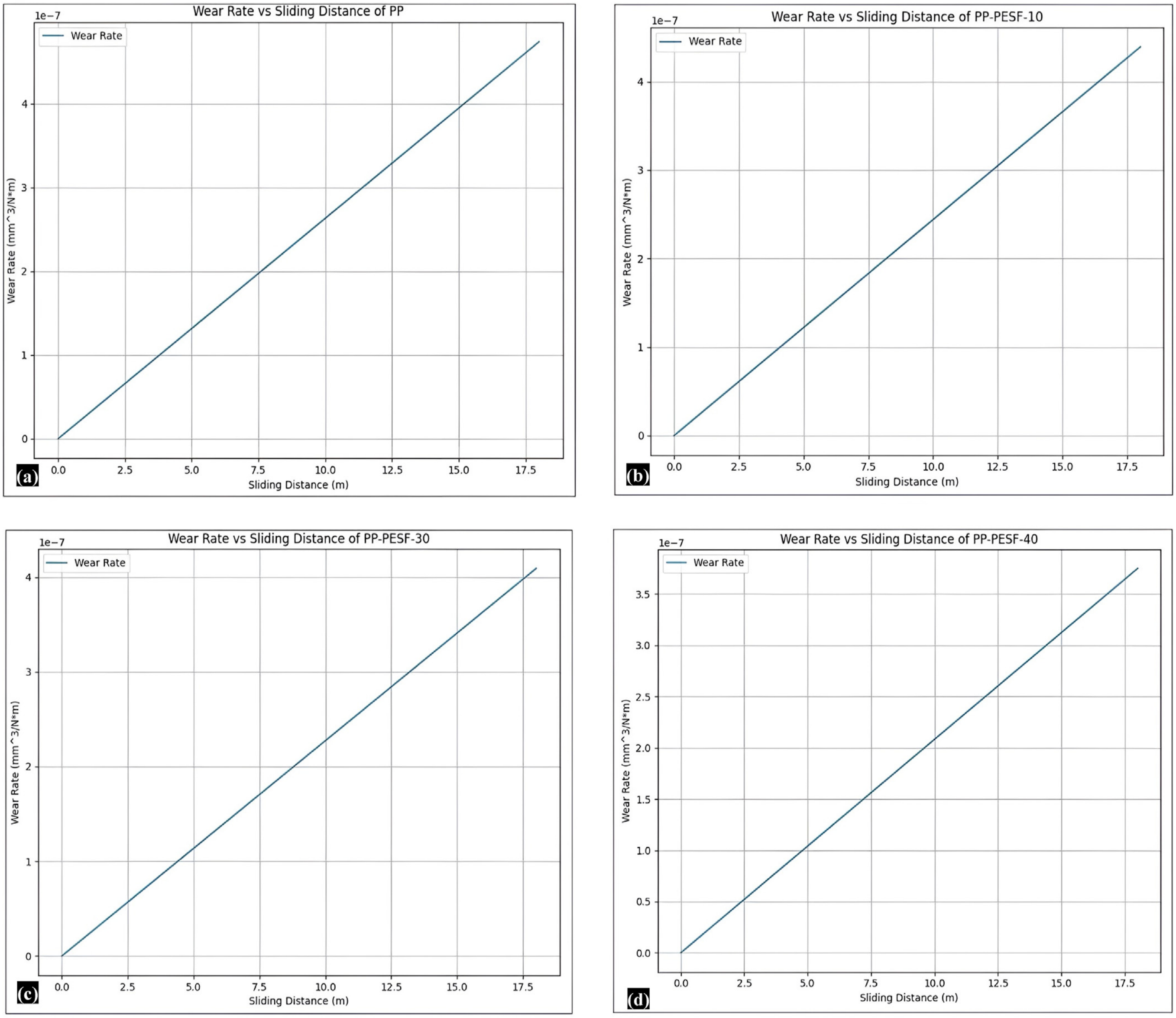


Fig. 8. Python machine learning studies of wear rates: (a) pure PP, (b) PP-PESF-10, (c) PP-PESF-30, and (d) PP-PESF-40 composites.

PESF-30 exhibited almost the same behavior regarding values of COF. The pure PP offered the highest resistance to COF due to a smooth surface and good inter-granular bonding. The values of COF of PP, PP-PESF-10, PP-PESF-30, and PP-PESF-40 were 0.70, 1.15, 1.17, and 1.26, respectively. The interactions between hard particles of silicon carbide, PP and composites produce softening effects due to increase in temperature during tribological tests. Finally, these effects cause the removal (abrasive wear) of the PP and the PP-PESF composite materials (Fig. 7c) due to collective shear, cutting, and tearing processes. According to Fig. 7d, image study show that, those micro-square blocks of pixels appeared with higher width. The higher width of micro-square blocks corresponds to increase in surface roughness. Additionally, higher non-focus of resolution (see specific pattern in Fig. 7d) can tell about the removal of the respective PP-PESF-10 composite material during abrasive testing.

The Archard wear rate model is used to study the tribological behavior of PP and PP-PESF composite materials [34]. The Python machine learning coding was utilized to simulate the results [35]. The Mathematical formulation of Archard model is given by:

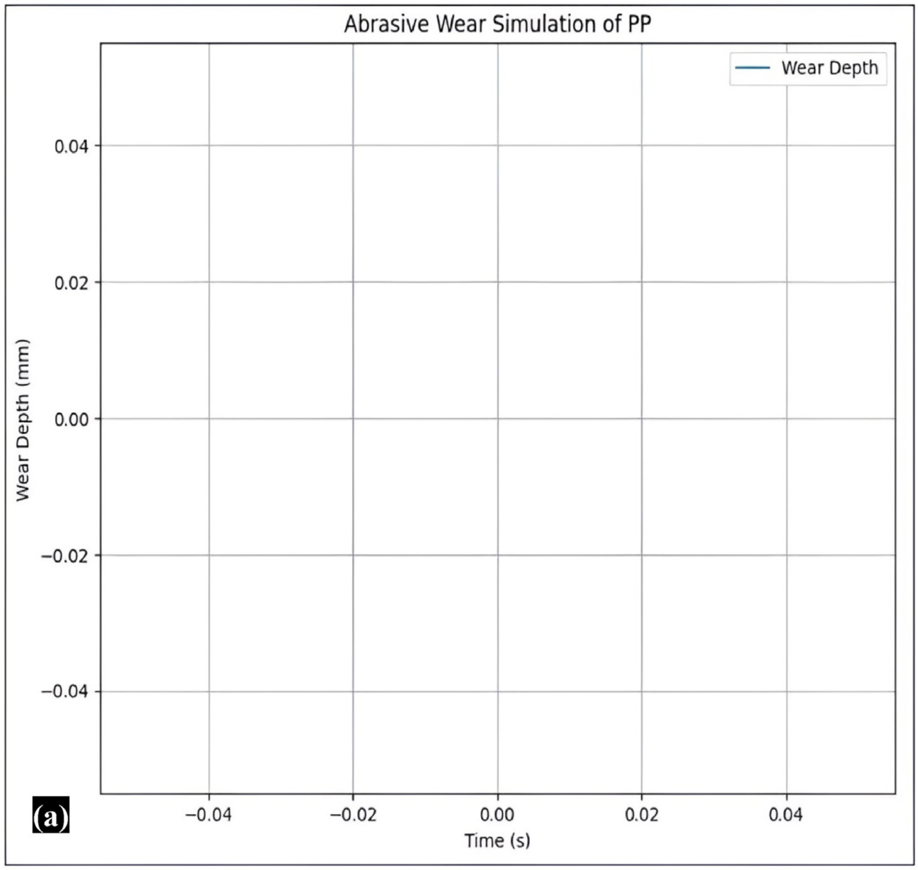
$$Q = \frac{KPS}{H} \quad (3)$$

where Q, K, P, S, and H are volumetric wear rate removal, dimensional constant, normal load, sliding distance and hardness of the material [47,48].

According to the equation, the Q is directly proportional to applied load, design constant, and sliding distance. However, Q is inversely proportional to the hardness of the composite materials [49].

The integral load (p) affected by micro defects area (a) is given below:

$$\delta P = p\pi a^2 \quad (4)$$



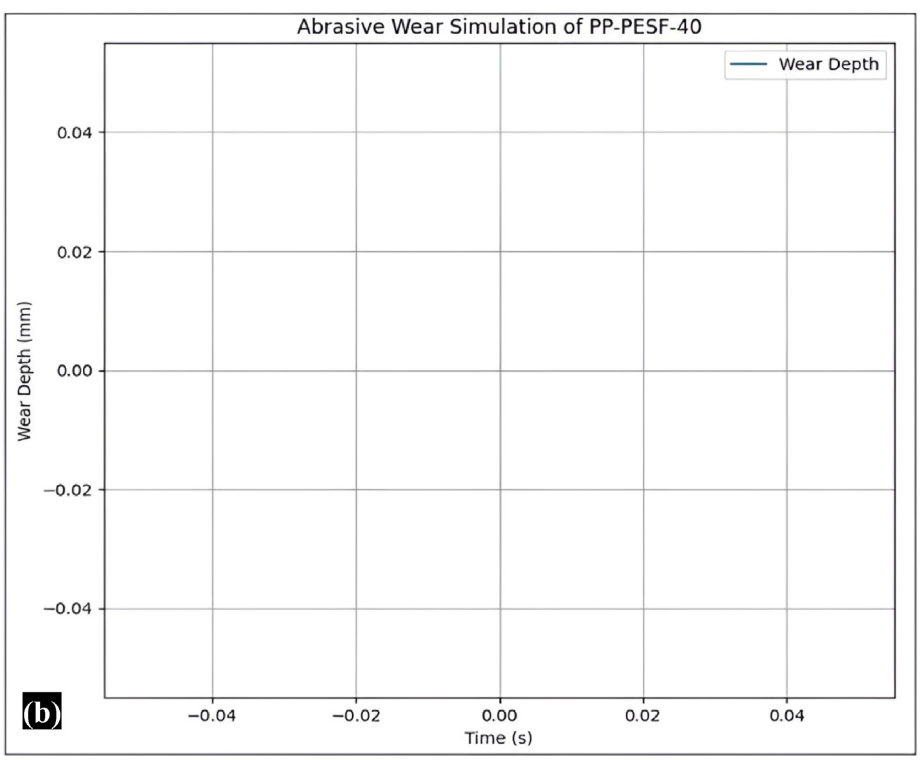


Fig. 9. Python machine learning studies of wear depth: (a) pure PP, (b) PP-PESF-40 c omposites.

Similarly, the volumetric loss is derived from the following mathematical equation:

$$\delta V = \frac{2}{3}\,\pi a^3 \tag{5}$$

Assuming $p \approx H$, the mathematical formulation can be written as:

$$\delta Q = \frac{\delta V}{2a} = \frac{\pi a^2}{3} = \frac{\delta W}{3P} \approx \frac{\delta W}{3H} \tag{6}$$

The dimensional constant K is affected by product design. The value of K for mild and severe wear rates exists in the range of $K \approx 10^{-8}$ and $K \approx 10^{-2}$, respectively.

In comparison, the values of experimental (Fig. 7) and deep learning studies (Fig. 8) were found compatible. The experimental values of PP and PP-PESF composite systems were in the range of 3.09×10^{-6} to 6.21×10^{-6} mm^3/Nm. The values of experimental abrasive wear rates of PP were lower than the values of abrasive wear rates of PP-PESF composites (Fig. 7a) due to the presence of micro defects (Fig. 6) [50]. The COF results of PP and PP-PESF exhibit similar behavior. According to Fig. 7b, the values of COF enhanced with increase in fiber loadings. However, the abrasive wear rate and COF values of PP-PESF show complex behavior. However, simulated results show that PP and PP-PESF recycled composites are more resistive towards abrasive wear [51]. The wear rates of simulated results of PP and PP-PESF composites were in the range of 4.8×10^{-7} to 3.75×10^{-6} mm^3/Nm. The highest and lowest values were recorded for PP (see Fig. 8a) and PP-PESF-40 composite materials (Fig. 8d). The variation in properties is due to change in values of the hardness and dimensional constant of PP and composite materials. Additionally, no variations between experimental and simulated values of COF of PP and PP-PESF composites were found. The creation of plastic deformation and material removal can be seen on the surface of PP-PESF-10 composites (Fig. 7c). The plastic deformation and material removal appeared in the form of an increase in surface texture (Fig. 7d) [52–54]. The addition of PESF as reinforcement affects the mechanical properties of recycled PP-PESF composites.

The values of average surface roughness of Ra of PP, PP-PESF-10, PP-PESF-30, and PP-PESF-40 were 0.21, 0.51, and 0.96 μm, respectively. The increase in surface roughness parameter was due to the presence of surface defects and plastic deformation, see Figs. 1–7. According to Fig. 9a and b, no signs of wear depth were detected. The PP-PESF-10 and PP-PESF-30 show similar results regarding wear depth. The presence of no wear depth is an indication of good surface performance and quality [55,56]. Furthermore, during single factor ANOVA test the p- and F- values of abrasive wear rate creates a sequential effect 98.7 % and 0.23, respectively.

4. Technical applications of results

The separation, sorting, grinding, mixing, processing, and testing are fundamental steps of recycling. The image processing and deep learning studies of steps of grinding, processing, SEM characterization, and tribological testing abets in automation and digitalization of recycling. Besides separation and sorting of PES waste, AI and DL studies of PES grinding assist in optimization of fiber length and diameter, see Figs. 4 and 5. The automation and digitalization of PP-PESF composite systems were proved using experimentation. The industrial extrusion and injection molding techniques were utilized to manufacture PP-PESF composites with various fiber loadings. The presence of micro defects can cause the decrease in surface performance of composites, see Fig. 6. The values of experimental abrasive wear rates and COF of PP and PP-PESF composites were in accordance with literature research. Similarly, the higher AI and DL simulated abrasive wear resistance rates of the PP-PESF composites indicate the signs of improvements in tribological properties.

The application of AI and DL in fiber length optimization, image processing, wear rate determination, wear depth evaluation can help in digitalization and automation of extrusion and injection molding recycling processes. Machine learning studies help to enhance the productivity, quality, precision, and performance of manufacturing systems. The proposed research work can be used directly for digital laboratory recycling of PES waste as well as automatic pilot small and medium industrial recycling.

5. Conclusions

We have presented innovative research and a technical path for digitalization and automation of mechanical recycling of polyester waste including grinding, processing, SEM characterization, and tribological testing. The average critical length of PESF was in the range of 3.0–3.5 mm. The PP-PESF composites were recycled successfully using extrusion and injection molding. The plastic deformation on PESF, micro cracks and asperities were observed during SEM characterization. These micro defects corresponded to the respective AI SEM textures of PESF, PP, and PP-PESF composite systems. The experimental abrasive wear rates (3.09×10^{-6} to 6.21×10^{-6} mm^3/Nm) of PP and PESF composites were higher than the AI and DL simulated values (4.8×10^{-7} to 3.75×10^{-6} mm^3/Nm). Comparatively, the experimental and simulated values of abrasive wear rates of PP and the PP-PESF composite showed 1 to 10 times good resistance towards silicon carbide hard particles, respectively. The PP and PP-PESF composites exhibited lower and higher values of COF in the range of 0.65–0.70 and 1.15–1.30 due to presence of smooth surface and micro-defects, respectively. The surface roughness (in the range of 0.21–0.96 μm) evaluation and ANOVA analysis indicate the compatibility of PP and PP-PESF composites with experimental and simulated tribological values. During single factor ANOVA test the p- and F- values of abrasive wear rate creates a sequential effect 98.7 % and 0.23. In conclusion, the presented research work can be considered for digitalization and automation of Polyester recycling industries.

6. Future works and recommendations

The following research work is proposed to improve the performance of PP-PESF composite materials:

- The industrial automation and digitalization of injection molding to enhance productivity.
- Application of AI and DL studies to evaluate the mechanical properties of PP-PESF composite materials.
- Industrial trials and experiments for commercial production of PP-PESF composite materials regarding automotive and structural applications.

CRediT authorship contribution statement

Abrar Hussain: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Project administration, Validation, Visualization. **Jakob Kübarsepp:** Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Fjodor Sergejev:** Validation, Supervision, Resources, Funding acquisition, Formal analysis, Conceptualization. **Dmitri Goljandin:** Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Irina Hussainova:** Validation, Supervision, Formal analysis. **Vitali Podgursky:** Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Kristo Karjust:** Validation, Supervision, Resources, Funding acquisition. **Himanshu S. Maurya:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis. **Ramin Rahmani:** Writing – review & editing, Methodology, Investigation. **Maris Sinka:** Validation, Supervision, Formal analysis. **Diāna Bajāre:** Validation, Supervision, Methodology. **Anatolijs Borodiņecs:** Resources, Supervision, Validation, Visualization.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that there is no conflicts of interest.

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Abbreviations

PESF	Polyester fibers
PP	Polypropylene
m	Meter
%	Percentage
ANOVA	Analysis of variance
AI	Artificial intelligence
SEM	Scanning electron microscope
Ra	Average surface roughness
wt	Weight
s	Second
V	Wear loss
S	Sliding distance
nm	Nano-meter
L_c	Critical length
D	Diameter
MPa	Mega Pascal
Q	Volumetric wear rate removal
P	Normal load
p	Integral load
mm	millimeter
N	Newton
COF	Coefficient of friction
FRC	fiber reinforced composites
ANN	Artificial neural network
DL	Deep learning
PES	Polyester
PCDT	Poly-1.4 cyclohexyl-di-methylene terephthalate
g	Grams
W	Volumetric wear rate
L	Applied force
SiC	Silicon carbide
μm	Micrometer
σ_f	Design strength
τ_c	Design shear strength
2D	Two dimensional
K	Dimensional constant
H	Hardness
a	Micro defects area

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