A Review of Recent Advances and Applications of Machine Learning in Tribology

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Table S2. A tabular representation of applications of ANN to design lubricant materials. Accuracy measure: R^2=1, MSE = 0, RMSE = 0, and MAE = 0: perfect fitting and accurate predictions can be achieved.

Oil (s) Mixtures	Modifiers	Input	Output	ANN accuracy	Ref
Perfluoropolyether (PFPE)	Different types of PFPE	Sliding speed, distance, viscosity, applied load, CoF, and temperature	Wear rate	R^2 = 0.93	[1]
Castor oil (NCO), Glycerol	Cashew nut shell liquid (CNSL)	Contents of NCO, CNSL, and glycerol	CoF, WSD	-	[2]
Vegetable oil	Rapeseed oil	Contents of sunflower	CoF	RMSE	[3]

		oil and rapeseed oil		=0.00099876	
Mineral oil	Polytetrafluoroethylene (PTFE)	Applied load, sliding velocity, PTFE content	CoF	98 %	[4]

Table S3. A tabular representation of applications of ANN to design polymeric composite materials.

Polymers	Modifiers	Input	Output	Ref
Polyether ketone (PEK)	Short glass fiber (SGF)	Impact angle, impact velocity, fiber content	Erosion rate	[5]
Polyamide (PA) 4.6	Short carbon fibers (SCFs), PTFE, graphite	Compressive strength, compression modulus, contraction to failure, tensile strength (T_s), strain to failure, impact strength, environmental testing temperature, starting load, average load, average velocity	Wear volume	[6]
PA 4.6	PTFE, SCF	Polyamide volume, Fiber volume, PTFE volume, compression modulus, compression strength, hardness, fracture toughness, temperatures, normal force, wear speed	Coefficient of determination (B) of CoF and wear	[7]
Polyethylene (PE), polyurethane (PUR), Epoxy	Hygrothermally decomposed polyurethane (EP-PUR)	PE: Erosive impact angle, Young's modulus (Y), yield stress, yield strain and fracture energy, as well as the crystallinity (6-25-1) PUR: T_g, damping at T_g, hardness, density, thermal expansion coefficient EP-PUR: wt. % of epoxy and PUR, impact angle, mass flow rate and	Wear rate	[8]

		velocity of erodents.		
PA 4.6	Glass fiber (GF), CF, PTFE, Graphite	Content of polymer, fiber and filler, temperature, normal applied force and sliding speed	Compressive modulus, compressive strength, T_s, Flexural strength (F_s), and SWR, CoF	[9]
PA 4.6 and PA 6.6	GF, CF, PTFE, Graphite	Content of polymer, fiber and filler, temperature, normal applied force and sliding speed	Compressive modulus, compressive strength, T_s, F_s and SWR, CoF	[10]
Polyphenylene sulfide (PPS)	SCFs, TiO_2 particles, Graphite, PTFE	PPS content, Volume of SCF, TiO_2, PTFE, Graphite	SWR	[11]
PPS	SCFs, TiO_2 particles, Graphite, PTFE	Material composition (volume fraction of matrix, fillers, reinforcing agents and lubricants), pressure, sliding speed, tensile and compressive properties	SWR and CoF	[12]
PPS	SCFs, TiO_2 particles, Graphite, PTFE	Content of polymer, SCF, TiO_2, PTFE, and graphite, normal applied force and sliding speed	SWR and CoF	[13]
PPS	SCFs, TiO_2 particles, Graphite, PTFE	-	SWR and CoF	[14]
PTFE	CF, TiO_2	Content of PTFE, CF, TiO_2, sliding speed, applied load, hardness, compressive strength	Wear	[15]
Polyetheretherketone composite (PEEK)	30 wt. % CF	*pv* factor, sliding temperature	CoF, Wear weight loss	[16]
Epoxy (Araldite	Pine wood dust (PWD)	Filler content, sliding speed, and distance, applied normal load	SWR	[17]

LY 556)				
Epoxy (LY 556)	Rice husk (RH)	RH content, sliding velocity, applied load	SWR	[18]
Epoxy (LY 556)	SGF, Microsized blast furnace slag (BFS) particles	Filler content, sliding speed, and distance, applied normal load	SWR	[19]
Polyester	Betelnut fiber	Applied load, sliding distance and fiber orientation	CoF	[20]
Polyester	Chopped strand mat GF	Applied load, sliding speed, time of test and fiber orientation	CoF	[21]
Polyester	Cotton fiber, fly ash	Content of polyester, cotton fiber, 3 wt. % fly ash and 5 wt. % fly ash	SWR	[22]
Polyester	Waste marble dust (WMD)	Applied load, sliding speed and distance and fiber orientation	SWR	[23]
Polycarbonate	Graphene (GR), Boron carbide (B_4C)	Vol. content of polycarbonate, GR, and B_4C, applied load, and sliding speed	SWR and CoF	[24]
Polypropylene	Blast furnace slag (BFS)	BFS content, sliding velocity, sliding distance and applied load	SWR	[25]
Ultra high molecular weight polyethylene (UHMWPE)	Carbon nanotube (CNT), CF, graphene oxide (GO), wollastonite	UHMWPE, ZnO, zeolite, CNT, CF, GO, wollastonite, size of ZnO and zeolite, applied load, and sliding speed	Wear volume	[26]
PEEK	Silica Carbide (SiC)	Applied load, and sliding speed	CoF and SWR	[27]

Table S4. A tabular representation of applications of ANN to design metallic composite materials.

Metals/Alloy	Modifiers	Input	Output	Ref

Aluminum	Al_2O_3	Operating conditions: Applied load, sliding speed, temperature Material: Hardness, Vol. fraction of Al_2O_3 and densityfraction of	SWR	[28]
Aluminum (AA2014) alloy	B_4C	Sliding time, B_4C volume fraction	Volume loss, SWR, and surface roughness	[29]
Co-30Cr-4Mo-1Ni alloy	Tungsten	Applied load, sliding velocity, sliding distance, tungsten content	Wear loss	[30]
Aluminum (AA1100) alloy	Rice husk ash (RHA), bagasse ash, coconut shell ash, zinc oxide (ZnO), egg shell particles	Applied load, sliding speed, sliding velocity, cumulative time, 6 % Content of one of the ash	SWR and CoF	[31]
Titanium	GR, Si_3N_4	Applied load, density, reinforcements	SWR	[32]
Aluminum (AA 7075) alloy	Silicon carbide (SiC), Al_2O_3	Applied load, sliding speed, material composition	SWR and CoF	[33]
Aluminum (AA 6082) alloy	SiC, TiC, Al_2O_3, WC, B_4C	Friction stir welding (FSW) process: Rotational speed, traverse speed, groove width, and ceramic particle	SWR	[34]
Aluminum-silicon alloy	Titanium carbide (TiC)	Applied load, sliding speed	Wear volume loss, Rise in temperature	[35]
Aluminum A380 alloy	Fly ash	Peak current, pulse on, pulse off, Fly ash content %, particle size	Surface roughness, material removal rate, tool wear rate	[36]
Copper surface	SiC, TiC, Al_2O_3, WC,	FSW process: Rotational speed, traverse speed, groove width, and	SWR	[37]

	B_4C	ceramic particle		
Aluminum	RHA	Applied load, sliding speed, RHA particle size, and weight percentage of RHA reinforcement.	SWR and CoF	[38]
Aluminum	Red mud nanoparticle	Composition and deformation of composite, sliding velocity, and applied load	Volumetric wear	[39]
Zinc–aluminum ZA27	Alumina fiber	Fiber volume, fiber orientation, and applied load and	SWR and CoF	[40]
Aluminum (A380)	Fly ash	Applied load, sliding speed, fly ash particle size and content (wt. %)	SWR and CoF	[41]
Aluminum alloys	Copper, SiC	Copper content (wt. %), SiC content (wt. %), Cumulative testing time	Wear mass loss	[42]
Aluminum alloys (A356)	Copper, SiC	Manufacturing furnace temperature, applied load, sliding distance, wt. % of SiC	Wear mass loss	[43]
Aluminum alloys (A356)	B_4C	Sliding distance, particle size and volume percent of B_4C, and From FEM: Temperature gradient, cooling rate	Weight loss, Variation of porosity	[44]
Aluminum silicon alloy (A356)	SiC	SiC wt. %, SiC particle size,	SWR	[45]
Aluminum alloys (Al7075)	Al_2O_3	Al_2O_3 wt. %, applied load, sliding distance, density	SWR	[46]
Aluminum alloys (Al6061)	Al_2O_3	Al_2O_3 wt. %, applied load, sliding distance, density	SWR	[47]
Magnesium alloy (RZ-5)	TiC	Applied load, Sliding distance	CoF	[48]
Nickel-free stainless steel (NFSS)	Hydroxyapatite (HA)	Applied load, HA content (vol. %), Sliding distance	Wear volume loss	[49]

Table S5. A tabular representation of applications of ANN combined with ANOVA statistical analysis to design composite materials.

Material	Modifiers	ANN model parameters	Input	Output	Ref
Polyester	SGF	4-10-1	Filler content, sliding speed, and distance, applied normal load	SWR and CoF	[50]
Epoxy resins	Castor oil fiber (Ricinus communis)	3-9-13-9-3	Applied load, fiber length, sliding distance	Gravimetric wear, CoF, and interfacial temperature	[51]
Copper	Tungsten	4-7-4-3	Tungsten weight content, applied load, sliding distance, and sintering temperature	CoF, SWR, and hardness	[52]
Copper	Tungsten	4-140-3	Tungsten weight content, applied load, sliding distance, and sintering temperature	CoF, SWR, and hardness	[53]
Aluminum	Micro SiC, nano Zirconia	4-10-1	Sliding speed, zirconia content, applied load, sliding distance	Wear loss	[54]
Copper (Cu)	Aluminum nitride, Boron nitride	4-7-1	Volumetric fractions of particles, sliding speed, applied load, and sliding distances	SWR	[55]
Al-Si alloy (A356)	SiC (10 wt. %), Graphite	3-20-30-2	Applied load, sliding speed and graphite content	SWR and CoF	[56]
Aluminum (LM6)	Powder -chip	2-5-1	Sliding distance, Reinforcement	SWR	[57]
Aluminum alloy (Al25Zn)	SiC	4-8-1	SiC wt. %, applied load, sliding speed, testing temperature	SWR	[58]
Copper	Multi-walled carbon nanotubes	3-7-1	MWCNT wt. %, sliding distance and applied load	Wear loss	[59]

	(MWCNTs)				
Magnesium (AZ31) alloy	Reduced graphene oxide (r-GO)	4-7-1	Applied load, r-GO weight content, sliding distance, sliding velocity	SWR	60
Magnesium (AZ31) alloy	r-GO, SiC	5-8-1	Applied load, r-GO and SiC weight content, sliding distance, sliding velocity	SWR	61

Table S6. A tabular representation of applications of ANN with other ML and optimization algorithms to design composite materials.

Oil (s) Mixtures	Modifiers	ML/Optimization algorithm with ANN	Output	Ref
PTFE resin	Aramid pulp, mica, copper (Cu), nano-SiO_2, potassium titanate whisker (PTW)	Monte-Carlo (MC)	CoF and SWR	62
ZA-27 alloy	Marble dust particles (MDp)	Improved bat algorithm (IBA)	Wear	63
UHMWPE	CNT, GR	Non-sorted Genetic Algorithm (NSGA-II)	Y, T_s	64
Coconut oil, castor oil, palm oil	MWCNT and GR	Genetic Algorithm (GA)	CoF, WSD	65
Castor oil (NCO), mineral oil (CMO)	MWCNT, GR, graphite, ZnO particles	Genetic algorithm (GA)	CoF	66

Polyester	E-glass fiber, cement by-pass dust (CBPD), alumina (Al_2O_3), SiC	Genetic algorithm (GA)	Wear rate	67

Table S7. A tabular representation of applications of other ML technqies to design processes or novel materials.

Aim/Test/Process	Material	ML algorithm	Accuracy	Output	Ref
Dry and base oil bath lubricated Fretting test	Chromium steel	Recurrent Neural Network (RNN), PCA-ANN	RNN: PCA-ANN:		68
Identify defects in ball bearing		Adaptive resonance theory (ART-2) based ANN, BPNN	ART-2-ANN: BPNN		69
Transesterification process	P50S50 biodiesel	Extreme Learning Machine (ELM)	ELM		70
FSW	AA7075 aluminum alloy	Adaptive neuro-fuzzy inference systems (ANFIS)	RMSE: 9.331	Tool pin profile, tool rotary speed, welding speed, and welding axial forces	71
FSW	Aluminum alloy joints	ANFIS	ANFIS - (RMSE: 29.7 MPa, MAPE: 7.7%); ANN - (RMSE:36.7 MPa, MAPE: 10.9 %)	Ultimate tensile strength (UTS)	72
Designing ceramic pairings	-	Decision trees	$R^2 = 0.89$	CoF	73
Sliding	-	Random Forests	Accuracy: 0.939	States of	74

experiments in oscillatory and translatory motion				operation	
Gas face seal status	-	Support Vector Machines (SVM)	$\frac{RSS}{TSE} \leq 0.1$	Eccentric load on the stator of the seal	[75]
FSW	Aluminum alloy AA1100	SVM	Absolute error: (i) SVR: 0.53 (ii) BPNN: 3.08 (iii) General regression: 13.55	UTS	[76]
Brakes	-	Isotonic regression, SMO, simple linear, linearm pace, gaussian least median squared regression	RMSE: 0.0014 Correlation coefficient: 0.9999	CoF	[77]
Thin film synthesis	Alumina (Al_2O_3), TiO_2, molybdenum disulphide (MoS_2), and aluminum (Al)	MLP-ANN, DT and RF, SVR, age-layered population structure (ALPS), grammatical evolution (GE), and symbolic regression multi-gene programming (SRMG)	-	-	[78]
Aluminum base alloy	SiC	KNN, SVM, ANN, RF, and GBM	MSE of SWR 1. ANN = 0.0009 2. RF = 0.00001 3. kNN = 0.0008 4. SVM = 0.0007 5. GBM = 0.00002 MSE of CoF 1. ANN = 0.0055 2. RF = 0.0028 3. kNN = 0.0028 4. SVM = 0.0007	SWR and CoF	[79]

			5. GBM = 0.0030		
Aluminum-graphite	SiC	KNN, SVM, ANN, RF, and GBM	MSE of SWR 1. ANN = 0.0031 2. RF = 0.0014 3. kNN = 0.0017 4. GBM = 0.0016 MSE of CoF 1. ANN = 0.0037 2. RF = 0.0037 3. KNN = 0.0066 4. SVM = 0.0064 5. GBM = 0.0028	SWR and CoF	[80]

Table S8. A tabular representation of ML used in combination with computational modeling techniques like MD and DFT.

Aim/Test/Process	Material	ML algorithm	Research outputs	Ref
High throughput screening	Soft matter monolayer films	RF	CoF and adhesion force	[81]
Elastohydrodynamic lubrication	Squalane	PCA with NEMD simulations	-	[82]
2D materials	-	Bayesian Model with MD and DFT	Maximum energy barrier	[83]
Lubricants screening (with surface sliding MD simulations)	Toy model of fluids	Gaussian mixture model and bayesian neural network with MD	Shear rate	[84]

Abbreviation List:

AE	Acoustic emissions
AIREBO	Adaptive intermolecular reactive empirical bond order
GDX	Adaptive learning rate

ANFIS	Adaptive neuro-fuzzy inference system
ART-2	Adaptive resonance theory
Adj SS	Adjusted sum of squares
ASTM	American society for testing and materials
ANOVA	Analysis of variance
ANN	Artificial neural network
BPNN	Back propagation neural network
BA	Bat algorithm
BNN	Bayesian neural network
BFS	Blast furnace slag
BFGS	Broyden-Fletcher-Goldfarb-Shanno
CF	Carbon fiber
CNT	Carbon nanotube
CNSL	Cashew nut shell liquid
CBPD	Cement by-pass dust
CVT	Centroidal Voronoi tessellation
CMC	Ceramic matrix composite
CG MD	Coarse grained molecular dynamics
CoF	Coefficient of friction
CMO	Commercial mineral oil
CNN	Convolutional neural network
CC	Correlation coefficient
CFPC	cotton fiber polyester composite
DT	Decision trees
DFT	Density functional theory
DBSCAN	Density-based spatial clustering of applications with noise

DOE	Design of experiments
DLC	Diamondlike carbon
DTAB	Dodecyl trimethyl ammonium bromide
EHL	Elastohydrodynamic lubrication
EFI	Empirical force index
EBP	Error back propagation
ELM	Extreme learning machine
FEM	Finite element method
FF	Force field
FM	Friction modifier
FSW	Friction stir welding
FGM	Functionally graded materials
GA	Genetic algorithm
T_g	Glass transition temperature
GBM	Gradient boosting machine
GR	graphene
GO	graphene oxide
GRA	Gray relational analysis
HA	Hydroxyapatite
IBA	Improved bat algorithm
KNN	K nearest neighnours
LFM	Lateral force microscopy
LOO	Leave one out
LJ	Lennard Jones
LM	Levenberg–Marquardt

LED	Light emitting diodes
ML	Machine Learning
MDp	Marble dust particles
MEB	Maximum energy barrier
MAE	Mean absolute error
MRE	Mean relative error
MSE	Mean squared error
MF	Membership function
MMC	Metal matrix composite
MNN	Modular neural network
MD	Molecular dynamics
MOSDeF	Molecular Simulation and Design Framework
MC	Monte carlo
MWCNT	Multi walled carbon nanotube
MoGA	Multi-objectives Genetic Algorithm
MRA	Multiple regression analyses
NCO	Neutralized castor oil
NFSS	Nickel-free stainless steel composites
Neural network	NN
NEMD	Non-equilibrium molecular dynamics
NSGA	Non-sorting genetic algorithm
PAES	Pareto-archived evolution strategy
PFPE	Perfluoropolyether
POD	Pin-on-disk
PWD	Pine wood dust
PEEK	Poly ether ether ketone

PA	Polyamide
PEK	Polyetherketone
PE	Polyethylene
PMC	Polymer matrix composite
PPS	Polyphenylene sulfide
PTFE	Polytetrafluoroethylene
EP-PUR	Polyurethane
PTW	Potassium titanate whisker
PES	Potential energy surface
CGB	Powell–Beale conjugate gradient algorithm
PC	Principal component
PCA	Principal component analysis
QSTR	Quantitative structure tribo-ability relationship
RBFNN	radial basis function neural network
RF	Random forests
REBO	Reactive empirical bond order
ReaxFF	Reactive force field
RMD	Reactive molecular dynamics
RNN	Recurrent neural networks
r-GO	Reduced graphene oxide
RSM	Response surface methodology
RH	Rice husk
RHA	Rice husk ash
RMSE	Root mean squared error
RPM	Rotations per minute
SCG	Scaled conjugate gradient

SCF	Short carbon fiber
SGF	Short glass fiber
SWR	Specific wear rate
SPEA	Strength pareto evolutionary algorithm
SVM	Support vector machine
SVR	Support vector regression
SRGM	Symbolic regression multi-gene programming
T_s	Tensile strength
TTCF	Transient-time correlation function
TMDC	Transition metal dichalcogenide
T-BFRP	Treated betelnut fiber polyster
UTS	Ultimate tensile strength
UHMWPE	Ultra high molecular weight polyethylene
UA	United atom
WMD	Waste marble dust
WSD	Wear scar diameter
Y	Young's modulus

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