Research Article

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Wear Performance Evaluation of Nano Zirconium Diboride Developed ZK60 Nanocomposite

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ABSTRACT

This study intended to apply an artificial neural network (ANN) technique to forecast the wear rate (WR) of a ZK60- 8% ZrB_2 nanocomposite. The load, sliding velocity, and sliding distance on the pin and disc were all factors included during the development of the predictive model. The wear rate from the L16 full factorial tests was used as an input in the model. According to the data, the forecast for all wear rates demonstrated a level of accuracy. Thus, ANN enables the prediction of wear performance of the composite material. Applying the ANN model to the data results in effectiveness and precision. In addition, it has the potential to assist researchers in the development and execution of their discoveries, reducing the amount of time required for lengthy experimental initiatives.

Keywords: ANN; ZK60; Zirconium diboride; Sliding velocity; Sliding distance.

1. INTRODUCTION

The global rules focusing on reducing energy use in addition to carbon dioxide emissions and environmentally friendly composite materials have become a practical answer to the urgent need to lower the weight of the components. The green composite industry is actively seeking sustainable production techniques for environmentally sustainable composite materials that possess a high strength-to-density ratio and are efficient (Wasik *et al.* 2024). Engineered composites consist of multiple substances that possess distinct biological, chemical, and physical attributes from each other. The distinctive attributes of each component, together with their proportion and arrangement within the material system, collectively determine the properties of the composite (Egbo, 2021). Depending on the purpose of fabrication, one can customize composites to meet specific requirements in geometry, structure, mechanics, chemistry, and even aesthetics. Recently, sectors such as electronics, medical, aerospace, and defence have shown interest in magnesium and hybrid composites (Zhao *et al.* 2024; Thirugnanasambandham *et al.* 2024). Magnesium alloys and nanocomposites have gained popularity recently due to their low density and implementation of environmental laws regarding climate change and increased CO_2 emission.

Additionally, many efforts have been made to minimize the environmental consequences of processing, research, design, and manufacture, with the goal of improving the ecological sustainability of Mg-based materials (Kumar *et al.* 2020; Padmavathi *et al.* 2024). Metal matrix composites (MMCs) with homogeneous structures show better strength and toughness. This implies that the metal matrix randomly distributes uniform-size reinforcements, resulting in a uniform distribution of grain sizes. However, the technological applications of the composites remain severely limited. Moreover, this work explored the common uses of MMCs in the domains of transportation, aerospace, and aviation. Finally, it paved the way for advanced research on MMCs (Singh and Hashmi, 2020; Senthilkumar *et al.* 2024; Hossain *et al.* 2024). To get a deeper understanding of the properties of composite materials, this work offers a comprehensive overview of the many combinations of reinforcements used in the synthesis of composites with a matrix. Recently, the aviation, automobile, pharmaceutical, defence, offshore, and electronics industries have shown interest in using magnesium nanocomposites to meet their requirements (Khatkar, 2023; Aruna *et al.* 2024; Karthik *et al.* 2024). Recently, a variety of new metals with bioactive, compatible, and degradable properties have been utilized for application in orthopaedics. Magnesium alloy nanocomposites are an attractive material for use in medical applications due to their optimal toughness and exceptional compatibility (Bommala *et al.* 2019; Thangavel *et al.* 2019; Periyasamy *et al.* 2022).

The varying characteristics of the constituent materials impose limitations on the refining techniques of powder metallurgy and stir casting. The properties include the extent of plastic deformation, strength, melting point, and density. The purpose of this investigation is to identify the challenges associated with stir-casting in MMCs (Sankhla and Patel, 2022). This work fills a void in the existing corpus of knowledge by thoroughly examining how the addition of nano ZrB_2 enhanced the tribology of the ZK60 alloy. The application of a Taguchi approach, involving four design stages and three factorials, improved the wear resistance of a ZK60/12 Wt% ZrB_2 composite, which is characterized by its long-lasting durability and lightweight properties (Kumar and Mohananvel, 2024). Tayebi *et al.* (2020) chose the stir-casting method to produce these composite samples, followed by extrusion and ageing. They used extrusion to examine its effect on microstructure as well as mechanical behavior in cast ZK60 alloy and a mixture with 5% nano SiC. They used the liquid route method with SF6 in this respect to prepare reinforced composites. There was a new solution when a semisolid temperature occurred during production. For comparison purposes, this research took a closer look at the outcomes of experiments involving testing the strength and durability of unfilled ZK60 alloys and composites (Boztas *et al.* 2024). The crack behaviour in magnesium composites containing 5 and 10 wt. % SiC, specifically in the stir-cast AZ31 were subjected to different heating and cooling cycles ranging from 150 to 350 °C. A V-shaped notch specimen was used for testing, whereby the mode of crack propagation, its path and shape were studied (Mousavi *et al.* 2022). The durability and power efficiency of a system depend significantly on the performance of the sliding component. The development of MMMCs, which can enhance the resistance of the surface to erosion and friction, can greatly reduce energy loss. Consequently, there is a need for knowledge about the wear properties of newly developed Mg matrix composites. Different types of wear related to contact pressure, particle size, abrasive media, etc., may be observed in MMMCs, according to Aydin (2023). The aim was to investigate the literature on how composite materials are simulated using ANNs. There is a new generation of machine learning that is providing a new outlook for design. Recent works discuss on the future of data-driven composite design and analysis with reference to accuracy, robustness, and efficiency (Liu *et al.* 2021; Jayasankar *et al.* 2024). Another research article gives a brief overview of deep learning, including its basics as well as its origins. It provides many applications in composite research, such as prognosis, database mining and topology optimization, among others. Response Surface Methodology (RSM) and ANN techniques were used to predict and determine the major process parameters that affect the mechanical properties of stir-cast metal matrix composites statistically (Wang *et al.* 2022). An optimal approach for designing RSM and ANN, where the effects of stirring speed, duration, and weight fraction on composite properties were investigated (Saleh *et al.* 2023). Chukwuma *et al.* (2024) modelled the mechanical characteristics of materials using fuzzy logic and ANN. At the same time, the proportional content of particles served as the sole input. The ultimate goal of incorporating ANN is to enhance prediction accuracy and comprehend complex information (Kumar *et al.* 2022). These goals progress composite material research and help in improving efficiency and durability. In this study, we chose the ZK60 reinforced with 8 Wt% of nano zirconium diboride to execute an ANN with three inputs and two hidden layers, resulting in a total of 22 neurons. The motive is to predict the output responses; WR, for given input parameters by trained neurons of ANN and subsequently to verify the experiments response values obtained with that predicted and the error involved. If it is within acceptable range, the model is validated.

2. EXPERIMENTATION

2.1 Composite Preparation

The composites were prepared using ZK60 as matrix and 8 Wt% of nano ZrB_2 as reinforcement (50 nm) by stir casting process following the reported procedure (Kumar *et al.* 2024). The entire work of fabrication and testing schema is shown in Fig. 1.

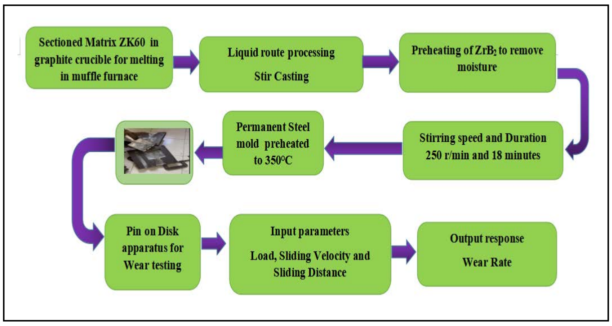

Fig. 1 Entire schema work of fabrication and testing

Table 1. Experimental WR

Exp. No.	Load	SV	SD	Experimental Wear Rate
1	5	1	750	0.047
2	10	2	1000	0.043
3	15	3	1250	0.05
4	20	4	1500	0.052
5	5	2	1250	0.065
6	10	1	1500	0.05
7	15	4	750	0.061
8	20	3	1000	0.052
9	5	3	1500	0.016
10	10	4	1250	0.038
11	15	1	1000	0.037
12	20	2	750	0.019
13	5	4	1000	0.015
14	10	3	750	0.026
15	15	2	1500	0.011
16	20	1	1250	0.013

The produced sample was machined with wire electrical discharge machining for the required dimension as per the ASTM G 99 standard for performing the wear test for each experiment. Table 1 displays the experimental wear rate.

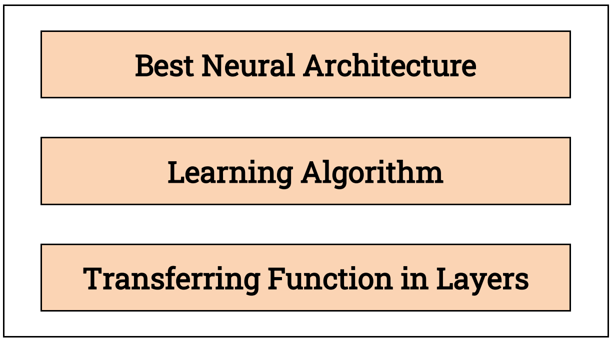

Fig. 2 Key factors for an ANN model

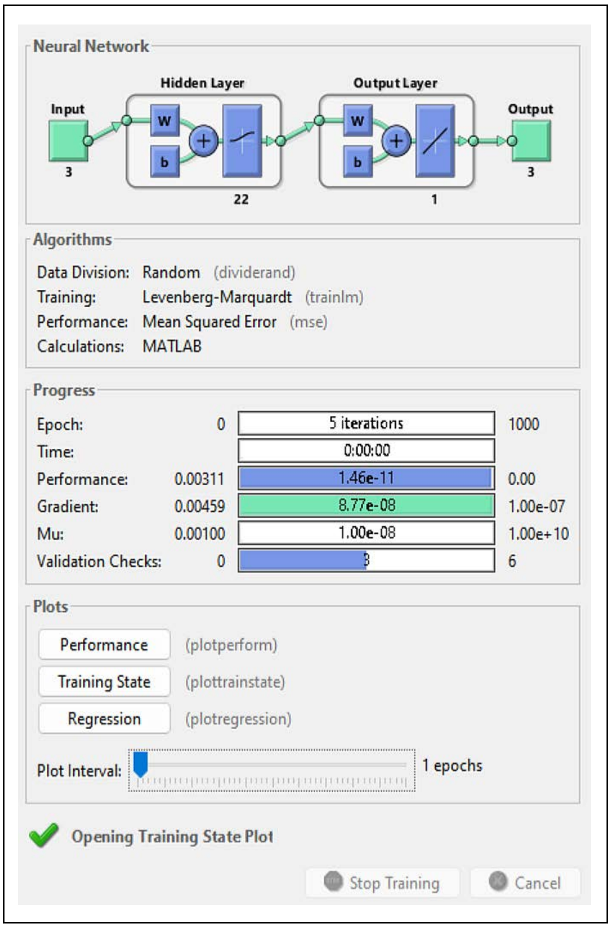

Fig. 3 Configuration of ANN architecture

2.2 ANN Modeling

A network of neurons is an ensemble of neurons that mimics the functioning of real-world neural systems. Neural networks connect several neurons, modifying their assigned weight values to perform specific tasks. Fig. 2 provides a thorough breakdown of the main factors that contribute to the development of a reliable ANN model. Researchers often use the chosen layer and neural network methods to understand the non-linear connection between the independent input factors and the dependent output variables. This study believes that the training technique and transfer function, which are linear in the hidden layer and the other layers, are the most effective for optimization. Most of the time, researchers used the hit-and-try method to determine the number of neurons in the hidden layer. Afterwards, researchers iterate to achieve the optimal number of neurons in the hidden layer (Roseline *et al.* 2022; Venkatesh *et al.* 2023). In the present work, the feed-forward, error backpropagation ANN technique was applied to predict the WR values using the neural network tool of MATLAB R2015a to train and analyze the network model.

Fig. 3 displays the architecture of the ANN, including epoch, gradient, and validations. The machine learning technique consists of three layers namely input, hidden, and output. Each of the layers has one neuron, which represents the input variables. This work used 22 neurons for the experimental data to establish the input and target parameters.

3. RESULTS AND DISCUSSION

Fig. 4 exploits the entire performance of ANN architecture with training and testing results. From the regression plot, it is found that ANN simulation for ZK60/8 wt.% nano ZrB_2 gave a correlation coefficient (R) of 0.89344 for WR.

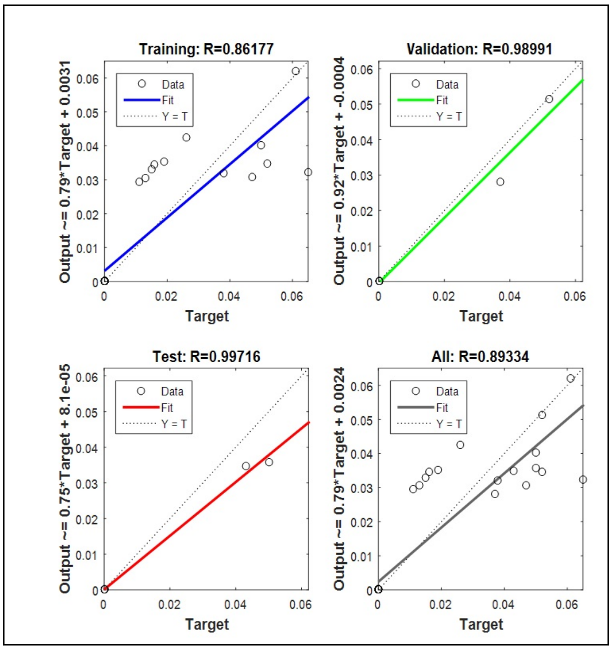

Fig. 4 Performance of ANN with training and testing (regression plot)

Deviation of experimental values from predicted values happens because of the small amount of sample data (Wiciak-Pikula *et al.* 2020), which makes it hard to figure out the most accurate results. The correlation coefficients of actual predicted data for WR showcased agreement between the experimental and ANN predicted.

Table 2. ANN predicted WR with error percentage

Exp. No.	Prediction	Error percentage
	Wear Rate	
1	0.030778	0.016222
2	0.034821	0.008179
3	0.04017	0.009831
4	0.034734	0.017266
5	0.032267	0.032733
6	0.035776	0.014224
7	0.062156	-0.00116
8	0.051379	0.000621
9	0.034568	-0.01857
10	0.032064	0.005936
11	0.028024	0.008976
12	0.035277	-0.01628
13	0.032957	-0.01796
14	0.042485	-0.01649
15	0.029454	-0.01845
16	0.030616	-0.01762

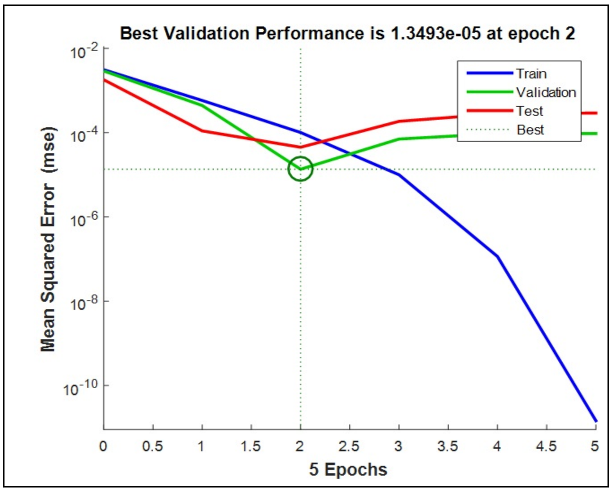

Fig. 5 Performance of ANN with validation plot

Neural network training forecasted the WR values as shown in Table 2. To measure the effectiveness of the developed ANN model, the predicted values were compared with the experimental data for each input pattern. The percentage error was determined by equation (1).

$$\%\ \text{error} = \left|\frac{\text{Response}_{\text{expt}} - \text{Response}_{\text{pred}}}{\text{Response}_{\text{expt}}}\right| * 100 \qquad \ldots (1)$$

Upon examining the predicted WR values, it was found that the actual WR values had a maximum error percentage inaccuracy of 0.032733 and a minimum of -0.01857.

The graph in the current investigation illustrates the highest level of achievement at epoch 2, as seen in Fig. 5, at the point where the horizontal and vertical dotted lines connect. Similar results were obtained by Venkatesh *et al.* (2023). Hence, the quality of the process responses can be improved by implementing the developed ANN model that is fast to converge. This system can reduce the computational cost and time.

4. CONCLUSIONS

After carefully examining the parameters, this study used the neural network prediction model to evaluate the wear rate of ZK60 with 8% nano ZrB_2 composites. The correlation coefficient in the artificial neural network is 0.89334 indicating a positive relationship between the variables in the ANN. The suggested ANN demonstrated accuracy and a fit over the data. The results measured were modelled using a feed-forward, error-back propagation artificial neural network. The prediction results matched the experimentally obtained, with a margin of error indicating the model can effectively predict the response variables by means of which better process control can be attained. Thus, ANN provides a substantial promise for addressing a wide range of concerns via the use of sophisticated approaches for predictive modeling and analysis.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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REFERENCES

Aruna, M., Mohana, K. A., Prabagaran, S., Priya, C. B. and Abul Kalam, M., Semisolid stir processing of AZ91/TiO_2 nanocomposite analysis with SiC exposure: behaviour measures, *Int. J. Cast Met. Res.*, 37(3), 159-166 (2024). https://doi.org/10.1080/13640461.2024.2327016

Aydın, F., Tribological aspects of magnesium matrix composites: a review of recent experimental studies. Tribology - Materials, *Surf. Interfaces.*,17(4), 1-10 (2023).
https://doi.org/10.1080/17515831.2023.2246809

Bommala, V. K., Krishna, M. G. and Rao, C. T., Magnesium matrix composites for biomedical applications: A review, *J Magnes Alloys.*,7(1), 72-79 (2019).
https://doi.org/10.1016/j.jma.2018.11.001

Boztas, H., Esen, I., Ahlatci, H. and Turen, Y., Microstructure Characterization and Wear Behavior of New ZK60 Alloy Reinforced with 5–10% SiC and 5–10% B_4C Particles, *J. Mater. Eng. Perform.*, 33, 7413-7427 (2024).
https://doi.org/10.1007/s11665-023-08469-1

Chukwuma, A., Godwills, C., Nwaeju, C. and Onyemachi, O., Artificial Neural Network and Fuzzy Logic Based Techniques for Numerical Modeling and Prediction of Aluminum-5%Magnesium Alloy Doped with REM Neodymium, *Int. J. Nonferrous Metall.*, 11, 1-19 (2024).
https://doi.org/10.4236/ijnm.2024.111001

Egbo, M. K., A fundamental review on composite materials and some of their applications in biomedical engineering, *J. King Saud Univ. Eng. Sci.*,33(8), 557-568 (2021).
https://doi.org/10.1016/j.jksues.2020.07.007

Hossain, I., Aruna, M., Mohana Krishnan, A., Prabagaran, S., Venkatesh, R., Priya, C. B. and Abul, K. M., Silicon carbide nanoparticles featured AZ63/BN alloy nanocomposite made by using liquid stir vacuum die cast: characteristics study, *Int. J. Cast Met. Res.*, 37(2), 148-157 (2024).
https://doi.org/10.1080/13640461.2024.2327015

Jayasankar, K. C., Anandhakumar, G. and Kalaimurugan, A., Advancements and Challenges in Solar Radiation Prediction: A Review of Machine Learning Approaches, *Environ. Technol.*, 13(2), 60-64 (2024).
https://doi.org/10.13074/jent.2024.06.242623

Karthik, R., Shiva, S. N. and Venkatesh, R. K., Characteristics performance evaluation of AZ91-fly ash composite developed by vacuum associated stir processing, *Int. J. Cast Met. Res.*, 2, 1–8 (2024).
https://doi.org/10.1080/13640461.2024.2364129

Khatkar, S. K., Hybrid magnesium matrix composites: A review of reinforcement philosophies, mechanical and tribological characteristics, *Rev. Adv. Mater. Sci.*, 2022, 0294 (2023)
https://doi.org/10.1515/rams-2022-0294

Kumar, P. M., Saravanakumar, R., Karthick, A. and Mohanavel, V., Artificial neural network-based output power prediction of grid-connected semitransparent photovoltaic system, *Environ. Sci. Pollut. Res.*, 29(7), 10173–10182 (2022).
https://doi.org/10.1007/s11356-021-16398-6

Kumar., Suresh, S. and Mohanavel, V., Investigations on physical, mechanical and metallurgical characteristics of ZK60/ZrB_2 composites produced by stir casting route, *Matéria (Rio de Janeiro)*, 29(3), 15-20 (2024).
https://doi.org/10.1590/1517-7076-RMAT-2024-0264

Kumar, S. S. and V. Mohanavel., Optimization of Tribological parameter of ZK60/12 Wt% ZrB_2 composite through Taguchi approach, *Interactions.*, 245, 208 (2024).
https://doi.org/10.1007/s10751-024-02054-1

Kumar, D., Phanden, R. K. and Thakur, L., A review on environment friendly and lightweight Magnesium-Based metal matrix composites and alloys, *Mater.*, 38, 359-364 (2020).
https://doi.org/10.1016/j.matpr.2020.07.424

Liu, X., Tian, S., Tao, F. and Yu, W., A review of artificial neural networks in the constitutive modeling of composite materials, *Compos. B. Eng*., 224, 109152 (2021).
https://doi.org/10.1016/j.compositesb.2021.109152

Mousavi, S. F., Sharifi, H., Tayebi, M., Hamawandi, B. and Behnamian, Y., Thermal cycles behaviour and microstructure of AZ31/SiC composite prepared by stir casting, *Sci. Rep.*, 12(1), 15191 (2022).
https://doi.org/10.1038/s41598-022-19410-2

Padmavathi, K. R., Devi, G. R. and Muthukumar, V., Synthesis and Characteristics Evaluation of SiCnp and SiCnp/CNT-Reinforced AZ91D Alloy Hybrid Nanocomposites Via Semisolid Stir Casting Technique, *Int. J. Met.*, 18(2), 1633–1643 (2024).
https://doi.org/10.1007/s40962-023-01137-z

Periasamy, K., Ganesh, S., Chandra Kumar, S., Nandhakumar, S. and Gurmesa, M. D., Appraisal of Thermomechanical Performance of Aluminum Metal Matrix Composites Using Stir Casting Technique, *Adv. Mater. Sci. Eng.*, 2022(1), 2381425 (2022).
https://doi.org/10.1155/2022/2381425

Roseline, J. F., Dhanya, D., Selvan, S., Yuvaraj, M., Duraipandy, P., Kumar, S. S. and Mohanavel, V., Neural Network modelling for prediction of energy in hybrid renewable energy systems, *Energy Rep.*, 8, 999–1008 (2022).
https://doi.org/10.1016/j.egyr.2022.10.284

Saleh, B., Ma, A., Fathi, R., Radhika, N., Yang, G. and Jiang, J., Optimized mechanical properties of magnesium matrix composites using RSM and ANN, *J. Mater. Sci. Eng., B.*, 290, 116303 (2023).
https://doi.org/10.1016/j.mseb.2023.116303

Sankhla, A. and Patel, K. M., Metal Matrix Composites Fabricated by Stir Casting Process–A Review,*Adv. Mater. and Pro. Tech.*,8(2), 1270-1291 (2022).
https://doi.org/10.1080/2374068X.2020.1855404

Senthilkumar, S., Revathi, K. and Sivaprakash, E., Enhancement of Magnesium Alloy (AZ31B) Nanocomposite by the Additions of Zirconia Nanoparticle Via Stir Casting Technique: Physical, Microstructural, and Mechanical Behaviour,*Int. J. Met.*, 18(2), 1465–1474 (2024). https://doi.org/10.1007/s40962-023-01116-4

Singh, R. and Hashmi, M. S. J., Metal matrix composite: a methodological review, *Adv. Mater. and Pro. Tech.*, 6(1), 13-24 (2020). https://doi.org/10.1080/2374068X.2019.1682296

Tayebi, M., Nategh, S., Najafi, H. and Khodabandeh, A., Tensile properties and microstructure of ZK60/SiCw composite after extrusion and ageing, *J. Alloys Compd.*, 830, 154709 (2020). https://doi.org/10.1016/j.jallcom.2020.154709

Thangavel, T. S., Jeyaseelan, C., Paramathma, B. S. and Mahadevan, K., Experimental Investigation of Silicon Carbide Nanoparticles Reinforced Magnesium Alloy (AZ91E) Metal Matrix Composite by Vacuum Stir Casting Method, *SAE Tech. Pap.*, 28, 0169 (2019). https://doi.org/10.4271/2019-28-0169

Thirugnanasambandham, T., Chandradass, J., Venkatesh, R., Sharma, P., Elahi, M. and Almoallim, H. S., Silicon carbide-embedded AZ91E alloy nanocomposite hybridized with chopped basalt fibre: performance measures, *Int. J. Cast Met. Res.*, 2, 1-11 (2024) https://doi.org/10.1080/13640461.2024.2395124

Venkatesh, R., Sakthivel, P., Selvakumar, G., Krishnan, A. M., Purushothaman, P. and Priya, C. B. Mechanical and thermal properties of a waste fly ash-bonded Al-10 Mg alloy composite improved by bioceramic silicon nanoparticles, *Biomass Convers. Biorefin.*, 14, 1-12 (2023). https://doi.org/10.1007/s13399-023-04588-w

Wang, Y., Soutis, C., Ando, D., Sutou, Y. and Narita, F., Application of deep neural network learning in composites design, *EJMSE.*, 2(1), 117-170 (2022) https://doi.org/10.1080/26889277.2022.2053302

Wąsik, A., Leszczyńska-Madej, B. and Madej, M., Sustainability in the Manufacturing of Eco-Friendly Aluminum Matrix Composite Materials, *Sustainability*., 16(2), 903 (2024). https://doi.org/10.3390/su16020903

Wiciak-Pikuła, M., Felusiak-Czyryca, A. and Twardowski, P., Tool wear prediction based on artificial neural network during aluminium matrix composite milling, *Sensors (Switzerland.)*, 20(20), 5798 (2020). https://doi.org/10.3390/s20205798

Zhao, L., Zheng, W., Hu, Y., Guo, Q. and Zhang, D., Heterostructured metal matrix composites for structural applications: a review, *J. Mater. Sci.*, 59, 9768-9801 (2024). https://doi.org/10.1007/s10853-023-09300-x