# Significance of Neural Network Applications in Materials Researches

The generic nature of ANN was widely applied in materials related fields, covering mechanical [[15](#_ENREF_15)], wear [[16](#_ENREF_16)], hydrological [[17](#_ENREF_17)], atmospheric science[[18](#_ENREF_18)][[19](#_ENREF_19)], civil engineering [[20](#_ENREF_20)]and etc., for several application areas in which materials failures can occur, including pressurized water reactors[[21](#_ENREF_21)], quenching operation[[22](#_ENREF_22)],wrought application[[23](#_ENREF_23)], distribution and transmission electric energy lines[[24](#_ENREF_24)], aqueous chloride solution[[25](#_ENREF_25)], nuclear waste disposal [[26](#_ENREF_26)], aerospace and aviation sectors[[27](#_ENREF_27)], steel production lines[[28](#_ENREF_28)]and etc. ANN was established for predicting corrosionindifferent environments such asatmosphere[[29](#_ENREF_29)],water[[30](#_ENREF_30)],sea[[24](#_ENREF_24)], hightemperature[[31](#_ENREF_31)]and so on as well as forecasting materials performance as failure forms of fatigue[[32](#_ENREF_32)], crack[[21](#_ENREF_21)], pitting[[4](#_ENREF_4)], creep [[33](#_ENREF_33)], flow stress[[34](#_ENREF_34)], wear[[16](#_ENREF_16)], elasticity[[35](#_ENREF_35)], toughness and hardness[[36](#_ENREF_36)], hot deformation behavior [[37](#_ENREF_37)][[3](#_ENREF_3)], yield strength[[38](#_ENREF_38)], ultimate strength[[39](#_ENREF_39)], elongation to fracture[[23](#_ENREF_23)], etc.

Materials on researches were varied due to the intention materials researchers focused on. Several of them were steel[[40](#_ENREF_40)][[25](#_ENREF_25)], zinc[[41](#_ENREF_41)], aluminum[[42](#_ENREF_42)], copper[[24](#_ENREF_24)], iron and titanium[[43](#_ENREF_43)], magnesium[[44](#_ENREF_44)], other metal alloys [[21](#_ENREF_21)][[22](#_ENREF_22)][[26](#_ENREF_26)][[27](#_ENREF_27)][[34](#_ENREF_34)][[45](#_ENREF_45)][[46](#_ENREF_46)]and so on. The majority of materials related applications are focused on implementing feed forward backpropagation neural networks. Recent works on other powerful, complicated and efficient neural networks models, such as radial basic function neural network (RBFNN), convolutional neural network (CNN) and generalized regression neural network (GRNN) can also give satisfactory prediction. In materials science researches, it is important to know the role of variables affecting on material properties and determine which input variable is the most influencing factor on desired output variable. Some input ranking methods, such as change of MSE (COM), fuzzy curves and sensitivity analysis, have been applied to extract knowledge from trained ANN [[47](#_ENREF_47)]. Previous recent works have shown that integration of neural networks with other computing paradigms such as Bayesian framework [[48](#_ENREF_48)], genetic algorithm [[49](#_ENREF_49)][[50](#_ENREF_50)][[51](#_ENREF_51)], sensitivity analysis [[52](#_ENREF_52)][[41](#_ENREF_41)][[25](#_ENREF_25)] and fuzzy logic[[44](#_ENREF_44)] can effectively be used to make the performance of neural network models more efficient. The development of more than one ANN types, such as linear model (LM) (simplest form of ANN), multilayer perceptron (MLP), radial basis function (RBF) and so on, and their comparison results were also discussed in some researches in literature [[53](#_ENREF_53)][[54](#_ENREF_54)].

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