APPLICATION OF SOFT COMPUTING TECHNIQUE FOR MINING MACHINERY TO OPTIMIZE PRODUCTIVITY –AN APPRASAL

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ABSTRACT

Excavation on the mother earth has been increased due to high demand of raw materials all over the world in last decade. To optimize the time frame for any project, utilization of HEMM machines has been introduced in open pit mines in the country. Till date there is no full scale soft computing technique available for hundred percent utilization of HEMM machines in the country. Technological innovation in soft computing techniques has brought automation capabilities to a whole new level. Process control is an important application of any industry for controlling the complex system parameters, which can greatly benefit from such advancements. Conventional control theory is based on mathematical models that describe the dynamic behavior of process control systems.Exponential growth in soft computing technologies has marked new milestones in powerful representation, modeling paradigms and optimization mechanisms for solving modern controller issues. Soft computing has provided sophisticated methodology for the development of industrial process controllers. It is considered to be a state-of-art approach to artificial intelligence. With the emergence of high performance computing power, design engineers have applied artificial intelligence techniques to a wide spectrum of real-world problems in intelligent and autonomous control.This paper presents critical review of application of soft computing technique for mining machinery to optimize productivity using fuzzy logic and genetic algorithm for maximum utilization of modern HEMM equipment's in opencast mining operations in the country.

INTRODUCTION

Exponential growth in soft computing technique has marked new milestones in powerful representation, modelling paradigms and optimization mechanisms for solving modern controller issue. In today's world, improving reliability, maintainability and thus availability of industrial products become a challenging task for many companies. Reports indicated that performance and availability largely depends on reliability and maintainability. There are many solutions to improve the maintenance of complex system. One solution is corrective action, including the required repair and maintenance activities after the occurrence of failure and downtimes. Because of high cost, risks and time consumptions, this method is not appropriate. Another solution is to use systematic and planned repair methods. Although this method prevents from serious failures, but it could be very expensive.

Given the issue above, to reduce costs and increase availability more effectively, it is better to predict errors before occurrence using data analysis. In companies, growing data volume is the main issue such that it is a major need to process data in real time. Even in high production rate technology makes it possible to obtain the data from different resources. Soft computing has provided sophisticated methodology for development of industrial process controllers. It is considered to be a state-of-art approach to artificial intelligence. With the emergence of high performance computing power, design engineers have applied artificial intelligence technique to a wide spectrum of real world problems in intelligent and autonomous control. Within last decade substantial amount of growth has been noticed on the application of soft computing technique in engineering. The pervasive use of this technique in various engineering applications makes it an indispensable tool. The principleconstituent of this tool includes theory of neurons, fuzzy logic, evolutionary computing, genetic algorithms, caustic system and probabilistic reasoning. Out of which the two emerging technique viz. fuzzy logic and genetic algorithms are considered in this research work to control the process of the systems.

Soft computing techniques have been recognized as attractive alternatives to the standard, well established hard computing paradigms. Soft computing techniques, in comparison with hard computing employ different methods which are capable of representing imprecise, uncertain and vague concepts. Soft computing technique is able to handle non linearity and offers computational simplicity.A fuzzy logic is a universal approximation of any multivariate function because it can be used for modelling highly non-linear, unknown or partially known controllers, plants or processes. Fuzzy logic helps an engineer for solving non-linear control problems in process control applications. It emulates human reasoning and provides an intuitive way to design functional block for an intelligent control system.

Genetic algorithms (Gas) have emerged as potential robust optimization tools in the last decades. Genetic algorithm (Gas) is a search heuristic that mimics the process of natural evolution. Genetic algorithms (Gas) can be applied to the process control for their optimization using natural operator viz. mutation and crossover. Well established methodologies have been discussed in literature for integrating soft computing techniques to realize synergistic or hybrid models with which better results could be obtained.

AN OVERVIEW OF SOFT COMPUTING TECHNIQUES

Soft computing is an approach to computing which parallel the remarkable ability of human mind to reason and learn in an environment of uncertainty and imprecision. In an attempt to find out reasonably useful solutions, soft computing –based methods acknowledge the presence of imprecision and uncertainty present in machining. Soft computing technique such as fuzzy logic, genetic algorithm, neural network, simulation have received a lot of attention of researcher due to their potentials to deal with highly non-linear, multidimensional, and ill-behaved complex engineering problems. A brief overview of various soft computing techniques is presented here.

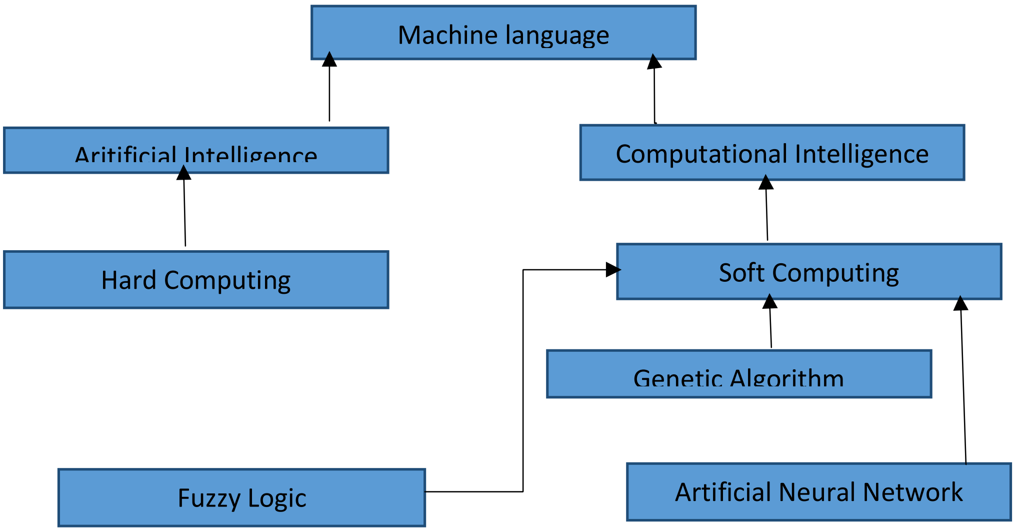

Fig 1. Artificial intelligence and computational intelligence

Fuzzy Logic

Fuzzy logic attempts to systematically and mathematically emulate human reasoning and decision making. It provides an intuitive way to implement control systems, decision making and diagnostic systems in various branches of industry. Fuzzy logic explains an excellent concept to close the gap between human reasoning and computational logic. Variables like intelligence, credibility, trustworthiness, and reputation employs subjectively as well as uncertainty. They cannot be represented as crisp values, however their estimation is highly desirable. Fuzzy systems are emerging technologies targeting industrial application and added promising new dimension to the existing domain of conventional control systems. Fuzzy logic allows engineer to exploit their empirical knowledge and heuristics represented in the IF-THEN rules and transfers it to a functional block. Fuzzy logic systems can be used for advanced engineering application such as control systems, process diagnostics, fault detection, decision making and expert systems.

Neural Network

Neural networks are the system that can acquire, store, and utilize knowledge gained from experience. An artificial neural network (ANN) is capable of learning from an experimental set to describe the non-linear and interaction effect with great success. It consists of an input layer used to present data to the network, output layer to produce ANN's response, and one or more hidden layers in between. The input and output layers are exposed to the environment and hidden layers do not have any contact to the environment. ANN's are characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. A neural network is trained with a number of data and tested with other set of data to arrive at an optimum topology and weights. Once trained, the neural networks can be used for prediction.

Genetic Algorithms (Gas) Controllers:

Analytical genetic algorithm (Gas) is deployed for optimal selection of antecedents and consequent in fuzzy system. Genetic algorithms (Gas) have been proven to be powerful in optimization, design and real time implementation. Genetic algorithms (Gas) which are modeled on natural evolutionary strategies are a methodology that has been introduced as a leaning and optimization technique for solving complex problems. Furthermore, genetic algorithm (Gas) search hasaninherent parallelism which enables rapid identification of high performance region of complex domains without experiencing problems with high dimensionality. Thus, genetic algorithm (Gas)have found exponential growth in many control applications especially while integrating the fuzzy logic, where they have applied to the process of learning control rules, selection of rules and their membership functions. The theory of genetic algorithm (Gas) is based initialization of chromosomes, giving fitting values to the chromosome according to their performance criteria, reproduction based on probability, crossover which divides the binary coding of each parent into or more segment and then combines to give a new offspring that has inherited part of its coding from each parent, mutation process in which the coding of offspring is done with low probability.

These optimization algorithms perform a stochastic search by iteration of populations of solutions according to their fitness. In control application, fitness is related to performance measures of the process controllers. Performance of fuzzy logic controllers can be improved if fuzzy reasoning model is supplemented by genetic algorithm mechanism. The genetic algorithm (Gas) enables us to generate an optimal set of parameters for fuzzy logic model.

APPLICATION OF SOFT COMPUTING TO VARIOUS MACHINING PROCESSES

In this section, application of major soft computing tools to various machining processes is discussed. Soft computing tools can be used for prediction of the performance parameters of machining as well as for the optimization of the process. Figure a, b schematically depict the application of soft computing techniques for these tasks.

Turning process

In turning processes, a single point cutting tool moves along the axis of a rotating work piece. The peripheral speed of the work piece called cutting speed, movement of the tool along the axisofjobfor onerevolutionofjob calledfeed,andradial depth of cut of the tool are the process parameters. These parameters may be optimized for obtaining the minimum cost of machining and minimum production time. However, for optimization, performance of the process has to be predicted.

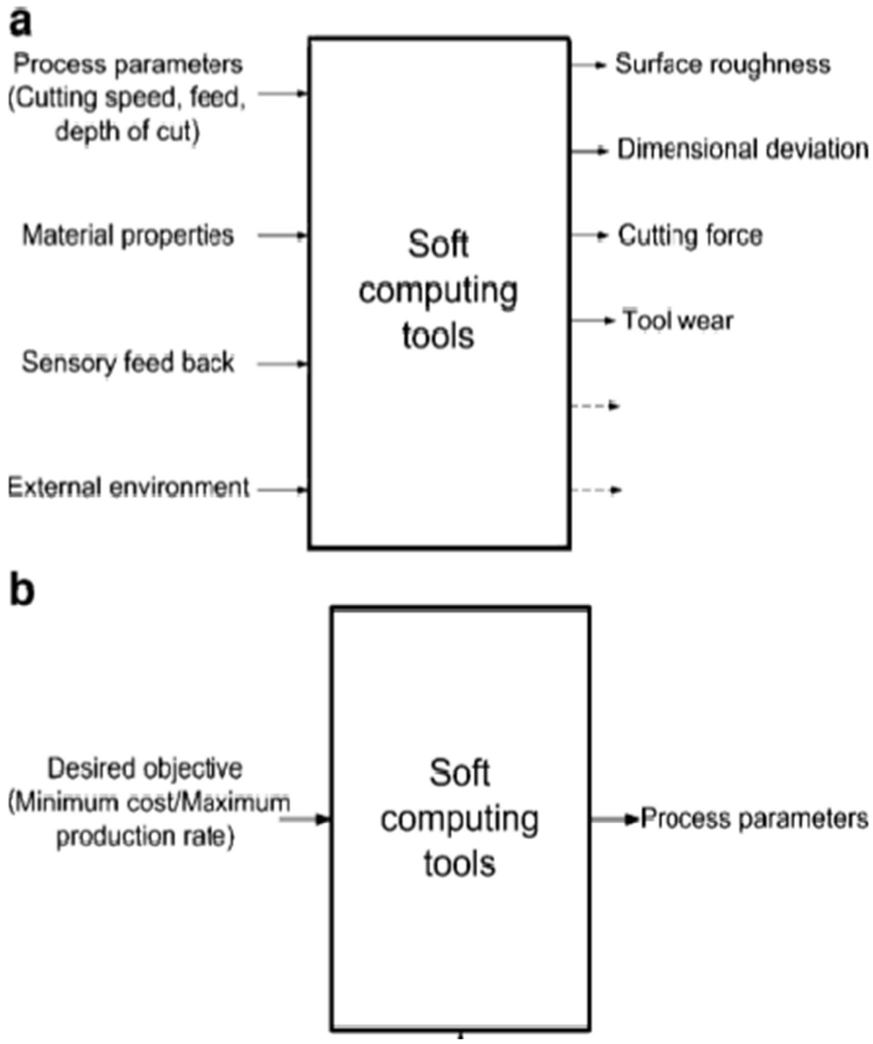

Fig 2: Two applications of soft computing in machining: a) performance prediction b)optimization

Surface finish and dimensional deviation

Two main attributes of quality of turned job are surface finish and dimensional deviation. Surface finish is defined as the degree of smoothness of a part's surface after it has been manufactured. Surface finish is the result of the surface roughness, waviness, and flaws remaining on the part. Dimensional deviation is defined as the radial difference between the set depth of cut and the obtained depth of cut. Researchers studied the effect of number of factors such as feed rate, cutting speed, depth of cut, work material characteristics, unstable built up edge, tool nose radius, tool angles, stability of material, tool and work piece setup, use of cutting fluids, radial vibration, tool material, etc. on surface finish. For modeling of machining processes, researchers used four main methods, viz., multiple regression, mathematical modeling based on physics of process, fuzzy set theory, and neural network. The review in this paper will focus on last two techniques.

A nearly work for the prediction of machining performance using neural networks is by Rangwala and Dornfeld. The authors utilized a feedforward network model to predict the cutting performance in turning process. The network is trained using a number of patterns of input variables, viz., cutting speed, feed rate, and depth of cut, and the output variables, viz., cutting force, power, temperature, and surface finish. Rangwala and Dornfeldand many later researchers used MLP neural network for machining performance prediction. An MLP neural network consists of input layer, output layer, and one or more hidden layers. Each layer consists of a number of neurons. Neurons in the hidden and output layers get input from the neurons of the preceding layers. Neurons in the input and hidden layers emit the output to be received by the neurons of the succeeding layer.

Azouzi and Guillotproposed neural network model to predict surface finish and dimensional deviation of the job based on the feedback from various sensors. They developed several network models to find out the influence of feedbacks from a number of sensors. The author observed that feed, depth of cut, radial force, and feed force provide the best combination to build a model for online prediction of surface roughness and dimensional deviation.

Several researchers have compared the effectiveness of the neural network model with statistical regression models. Chryssolouris and Guillot observed the superiority of neural network model compared to regression model. On the other hand, Feng and Wang found multiple regression analysis and neural networks equally effective in predicting surface roughness for a finish turning process.

Tool life and tool wear

Tool life and tool wear play a major role in the economic aspects of metal cutting operations. Most of the time, tool life is considered as a time lapse between two successive regrinds of tool when operating under specified cutting conditions. In an early work on tool wear estimation using neural networks, Ezugwu et al. predicted tool life and failure mode in machining of gray cast iron with ceramic cutting tools. The tool failure based on average and maximum flank wear, crater depth, notch depth, surface roughness, and catastrophic failure of the tool have been considered. The experimental data have been used to train the MLP neural network using backpropagation algorithm. However, the authors had limitation of having just 25 data. With these data, they could predict the correct tool life (within 20%) in 58.3% cases and tool failure mode in 87.5% cases. Dutta et al. studied the application of neural network with different learning schemes for faster processing of data which is a major criterion in online tool condition monitoring. Speed, feed, depth of cut, and three components of cutting forces were inputs of the neural networks and flank wear was output of the network. The authors found that the modified backpropagation algorithm converge faster than standard backpropagation algorithm.

Tool life in hot machining of high magnesium steel has been modeled by Tosun and Ozler using an MLP neural network. The turning was carried out at four temperatures— room temperature, 200°C, 400°C, and 600°C. The neural network model predicted the tool life with better accuracy as compared to a regression model.

Ojha and Dixit proposed an economic and quicker method of tool life estimation and predicted low, most likely, and higher estimates of tool life using neural networks. In their approach, the tool life is estimated by fitting a best-fit line for the data falling in steady wear zone and finding the time till tool fails by extrapolation. For predicting the lower and upper estimates of the tool life, they used the backpropagation (BP) algorithm of Ishbuchi and Tanaka , as was earlier done by Kohli and Dixit. The neural network model was found superior to the multiple regressions model. Quiza et al. carried out an experimental investigation on tool wear prediction on ceramic cutting tools used for turning hardened cold rolled tool steel. They predicted tool wear with the help of neural network and regression models. The neural network model was found superior to the regression model.

Soft computing optimization techniques, viz., genetic algorithm, particle swarm optimization, and simulated annealing, were used for optimizing neural network model parameters. For tool life estimation, Natarajan et al.employed a neural network model that was optimized by PSO. The use of PSO resulted in reduction of training time by 50%.

Tool wear monitoring has been other widely investigated research topic. Tool wear monitoring is of two types: direct and indirect. Direct methods measure the actual values of size of wear parameters with optical instruments, while indirect methods measure parameters such as cutting forces or vibrations that are correlated with tool wear. A number of tool wear monitoring schemes have been proposed that employ vibrations, ultrasonic, torque, power, velocity, and temperature sensors and sensor fusion. Sick has reviewed a number of research papers dealing with online and indirect tool wear monitoring in turning using artificial neural networks. Mainly, vibrations, acoustic emission (AE), torque, power, velocity, and temperature sensors were employed for obtaining the feedback for indirect estimation of tool wear. Some of the representative work is as follows: Das et al. developed a backpropagation neural network model for the reliable online tool condition monitoring based on cutting force measurement. The ratio of cutting force components have been found as a better indicator of the tool wear. Silva et al. developed neural network based online tool condition monitoring for turning process using signals from five sensors. They used two types of neural network learning algorithms—adaptive resonance theory (ART) and self-organizing map (SOM) to classify statistical and frequency domain features of the sensor signals. The ART2 creates and classifies tool wear with less number of sampled data and has the ability to respond immediately. The SOM is a method of mapping a high-dimensionalinputspaceontoaone-ortwo-dimensional output space by using an unsupervised neural model. The authors found that the NN with the SOM perform better than the ART2 in classifying unseen sampled data. Nadgir and Ozel employed a neural network to model tool condition monitoring system. Online cutting forces were measured by a piezoelectric tool dynamometer and used as inputs to the network. Data obtained from several machining test with use of different cutting speed, feed, and a constant depth of cut were used to train the network. Chungchoo and Saini proposed an online fuzzy neural network to predict tool wear. Cutting forces, acoustic emission signals, skew and kurtosis of force bands, and total energy of forces were taken as input parameters of the neural network.

Cutting force

Cutting force is one of the important characteristic variables to be monitored during machining process. Tool breakage, tool wear, and work piece deflection are mainly due to abnormal cutting force developed during machining process. To predict and monitor cutting forces, various models were proposed using soft computing techniques. Khanchustambham and Zhang used neural network to predict cutting force as well as surface finish during machining of ceramic material. Feed, depth of cut, and spindle speed are used as input parameters for the network. The network is trained by cutting force signal and measured surface finish for online monitoring of turning process. Lee et al. used feedforward neural network to predict cutting force components. The network is trained using undeformed chip thickness, chip width, cutting speed, and tool rake angle as input parameters. The authors found the predicted results are in good agreement with experimental data. Luong and Spedding developed neural network model to find cutting conditions for a given work material and required depth of cut to predict the cutting forces, surface roughness, and tool life. They trained the network using data from Machining Data Handbook and have shown that the neural network establishes a correlation from empirical data. Szecsi used neural network model for cutting force estimation in turning process. Process parameters, tool geometry, work piece material, and flank wear were taken as input parameters of the network. The author used 3,200 training and 1,500 testing data to train the network and found very good prediction accuracy. However, there is no discussion about the statistical variation of the cutting forces. Lin et al. used radial basis function neural network and multiple regression analysis to predict machining forces–tool wear relationship in machining of aluminum metal matrix composites. Besides process parameters, feed and cutting forces were used to estimate tool wear. The authors obtain better correlation of tool wear with feed force data than with cutting force.

In high speed turning, the correlations between various cutting parameters play an important role while model building. Ezugwu et al. used an ANN approach to model the correlation between five process parameters, viz., speed, feed rate, depth of cut, cutting time, and coolant pressure, with seven performance parameters, viz., tangential force, feed force, spindle motor power consumption, surface roughness, average flank wear, maximum flank wear, and nose wear. The developed model agrees well with experimental data and can be used to analyze and predict the relationship between process and performance parameters.

Hao et al. proposed multilayer perceptron neural network model for predicting cutting force in self-propelled rotary tool in turning. Cutting speed, feed rate, depth of cut, and tool inclination angle were input parameters and thrust force, radial force, and main cutting force are output parameters of the network. The authors applied hybrid of GA and BP algorithm to improve performance of neural network model.

Lin et al. predicted surface roughness and cutting force using abductive neural network during turning of high carbon steel with carbide inserts. Abductive networks are composed of a number of polynomial functional nodes organized into several layers. Unlike general neural network, abductive neural network generate optimal network architecture automatically and take less iterations in training. The network is trained with cutting speed, feed, and depth of cut as input parameters. Predicted results are found more accurate compared to regression analysis. Li et al. used neurofuzzy techniques to estimate feed cutting force by measuring motor current using current sensor in CNC turning center. Motor current and feed rate were used as input parameters. The authors found that the estimated force was within an error of 5%.

Process optimization

The machining optimization problem is highly nonlinear and possesses multiple solutions. In multi-objective optimization, cutting parameters is of great concern in manufacturing environment. Researchers considered various input (cutting) parameters like cutting speed, feed rate, depth of cut, cutting time, coolant pressure, etc. and output (process) parameters like tangential force, axial force, radial force, feed force, spindle power consumption, surface roughness, tool life, average and maximum flank wear, and nose wear, etc. for modeling. Optimization of singlepass turning has been attempted in early works. However, in general, a turning operation involves a number of rough cuts and a final finish cut. In manufacturing industries, multipass turning is widely used than single-pass turning. The highest possible metal removal is aimed in rough passes, where surface finish is not an important consideration. However, in finish turning process, surface finish is the most important consideration. Researchers have used soft computing optimization techniques, viz., fuzzy logic, neural network, simulated annealing, genetic algorithm, ant colony optimization, and particle swarm optimization to optimize both single and multi-pass turning problem.

Karpat and Ozel developed a multi-objective optimization model for single pass turning to model surface roughness and tool wear. They used PSO-based neural network optimization scheme to optimize finish hard turning processes using cubic boron nitride tools. NN model predicts surface roughness and tool wear during machining and PSO is used to obtain optimum cutting speed, feed rate, and tool geometry. The authors found that PSO takes less number of iterations to reach optimal conditions.

Neural network used in fuzzy decision environment have been reported in literature. Wang uses feedforward neural network using manufacturer’s fuzzy preferences to determine the optimum cutting parameters by solving the multi-objective problem with the help of a neural network model. The objectives considered were productivity, operation cost, and cutting quality. Lee et al. presented fuzzy nonlinear programming model to optimize cutting conditions for a turning process. Subsequently, a neural network model is trained based on the results of the optimization model. The trained neural network is able to predict the cutting speed accurately. The readers may note that these authors have used the term "machinability" for "material removal rate". Hashmi et al. developed a fuzzy logic model for selection of cutting conditions for machining.

GAs are very suitable for solving multi-objective problems. Based on representation of design variables, they are of two types: binary-coded genetic algorithm and realcoded genetic algorithm (RGA). In machining optimization, RGAs are more precise, more consistent, and lead to faster convergence. Abburi and Dixit developed an optimization methodology which is a combination of a RGA and sequential quadratic programming (SQP) to obtain Paretooptimal solutions to minimize production cost. The major advantage of the methodology is that various Paretooptimal solutions are generated without the knowledge of the cost data. The optimization is carried out with equal depths of cut for roughing passes and the authors found that RGA combined with SQP is very efficient in reaching up to global optima. Kim et al. also explored the applicability of RGA in machining optimization. In their work, RGA has been compared to SA, continuous SA, GA, and generalized reduced gradient method.

CONCLUSIONS

Neural network models have been effectively employed for predicting the surface roughness of machined components in turning and drilling. However, most of the models do not predict the surface roughness as a function of time, concentrating on the time zone when surface finish changes only slightly with time.

Soft computing tools have been used for estimating the tools wear and tool life. However, the results are not as impressive as in the case of surface roughness prediction. This is due to highly statistical nature of tool life and tool wear and difficulty in identifying a measurable parameter with which the tool wear can be well-correlated. Most of the authors have used cutting force components as input parameters in their soft computing-based models. Several other signals such as acoustic emission, vibrations, and temperatures have also been tried. It is observed that instead of raw data from sensors, features extracted from the signals are more effective in modeling the tool wear and tool life. Soft computing optimization methods like GA have been used in machining area for two purposes—(a) for optimizing the internal parameters of neural networks, fuzzy sets, and neurofuzzy systems and (b) for machining optimization. Application of GA for machining has attained maturity. PSO, a relatively newer technique, may emerge as a better alternative to GA. The best strategy is to use a combination of fuzzy and neural network for performance prediction and soft computing optimization tool like GA or PSO for optimization. However, some important issues need urgent attention. These are (a) acquisition of data in an economical and efficient way, (b) filtering of noisy data, and (c) extracting the statistical feature of the data. If these issues are addressed, the industrial application of these techniques will become an easy and fruitful task. It is proposed to conduct detailed studies for some of the mining machinery at MOIL in near future by application of soft computing technique to optimize productivity.

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