1 INTRODUCTION

1.1 Background

Coal remains a cornerstone of India's energy sector, fulfilling 75% of the country's electricity needs and 51.65% of its total energy demand as of December 31, 2021, according to the Central Electricity Authority of India. Despite consistent growth in its domestic production—from 532.7 million tonnes (Mt) in 2010-2011 to 893.2 Mt in 2022-2023, reflecting a compound annual growth rate (CAGR) of 4.4%—India's coal demand continues to exceed supply, as shown in Figure 1.1. This discrepancy has led to a sharp rise in coal imports, which increased from 68.9 Mt to 237.7 Mt over the same period, with a CAGR of 10.9% (MOC, 2023; MOP, 2023). The persistent supply-demand gap highlights challenges of meeting production targets, particularly in opencast coal mines that contribute 95% of India's total coal output (CIL, 2023).

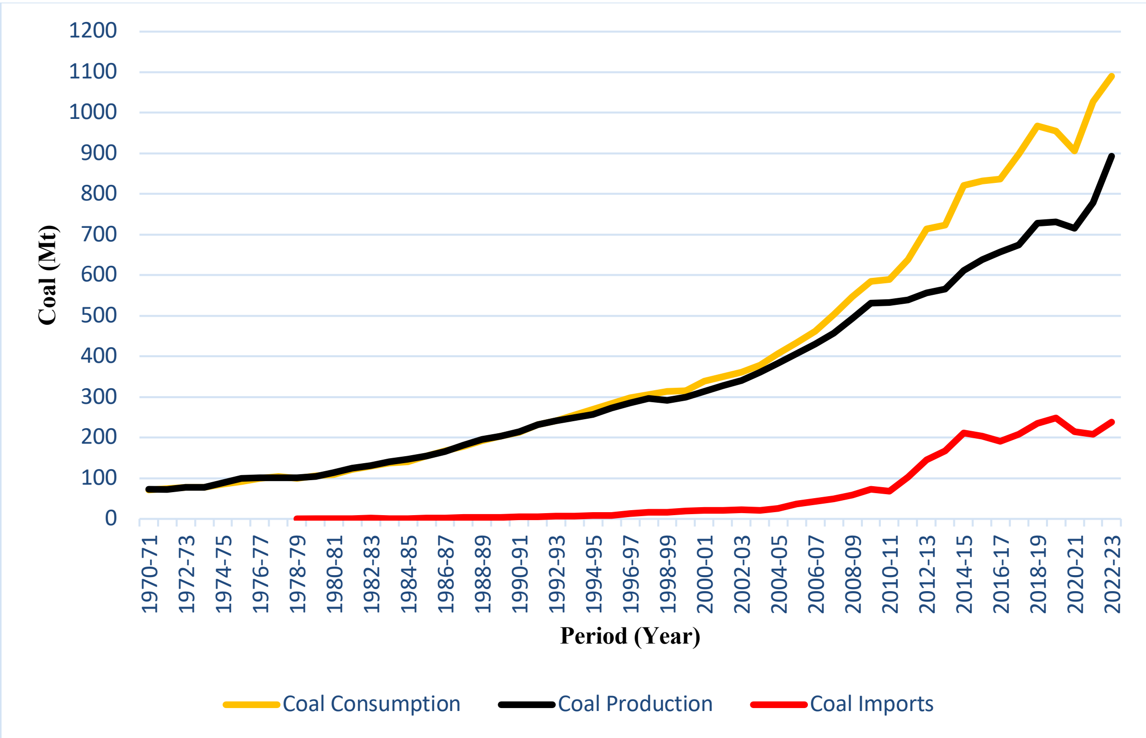

Figure 1.1: Annual Scenario of coal in India

Technological advancements have been introduced to address these challenges. Surface miner (SM) as state-of-the-art technology has gained significant traction in India's opencast coal mines over the past two decades due to its continuous, selective, cost-effective and eco-friendly coal mining capabilities. It is a crawler-mounted machine equipped with a cutting drum, which is fitted with multiple conical picks to cut coal into specified sizes, eliminating the need of conventional drilling, blasting, and primary crushing for coal production. It restrains ground vibrations, fly rocks, toxic emissions and land degradation due to blasting and improves coal quality as well as recovery percentage (Dey and Bhattacharya, 2012; Volk, 2016; Ali, 2022). It ensures stable, steep, and compact highwall profiles without cracks and fissures, thereby minimising the risk of fire and slope stability issues. Presently, 105 SMs are operating across 36 opencast coal mines under Coal India Limited (CIL) to produce approximately 378 Mt of coal, accounting 53.75% of company's total coal output, as shown in Figure 1.2 (CIL, 2023).

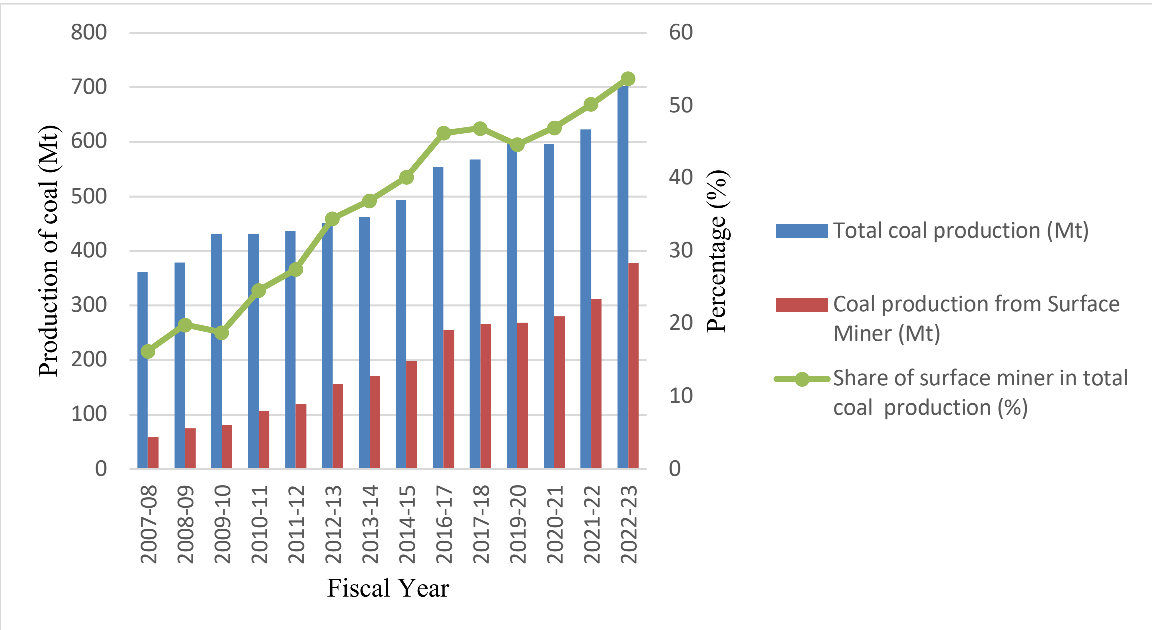

Figure 1.2: Annual applicability trend of surface miner in Coal India Limited

Selecting an optimal SM model is crucial to improve coal production. In this study, five SM models, namely, KSM 303 (Machine A), KSM 304 (Machine B), KSM 403

(Machine C) from L&T and 2200 SM (Machine D) and 2200 SM 3.8 (Machine E) from Wirtgen are selected to facilitate meaningful comparisons across SM models based on energy productivity. Energy productivity is defined as a ratio of rated production to the energy consumed during coal cutting in a fixed period. Diaz *et al.*, (2011) has evaluated energy consumption as the product of average power demand and cutting time dictated by the control factors of machine. Goktan and Gunes (2005) cutting force model for conical picks is used to evaluate the power demand of cutting drum, whereas, cutting time is dictated by the rated production capacity of SM given in Wirtgen (2008).

In addition, industries may not have financial resources to acquire the most productive machine. Thus, an improvement of energy productivity becomes necessary at the level of existing machine (Hanafi *et al.*, 2012). Several studies have been conducted to optimise the machining process parameters at different conditions using swarm optimisation technique (Gupta *et al.*, 2015) or response surface methodology based desirability approach (Gupta and Sood, 2017).

However, Taguchi based signal-to-noise (S/N) ratio analysis is one of the mostly used and reliable techniques utilised in various investigations to save significant amount of resources by practicing optimum process parameter settings (Dvivedi and Kumar, 2007; Lin and Chou, 2008; Datta *et al.*, 2009; Rao and Padmanabhan, 2012; Ezoddin *et al.*, 2014; Zerti *et al.*, 2016; Mia and Dhar, 2017; Cetin *et al.*, 2020; Singh *et al.*, 2023f). It minimises variation around a target value using experiment design system and designs process to be robust to environmental conditions and component variations. Kumar *et al.* (2020) embraced Taguchi S/N ratio and ANOVA to determine the optimal cutting parameters subjected to an objective function of minimum pick tip temperature and to assess the impact of parameters on temperature, respectively.

In this study, Taguchi method is used to optimise the control factors of SM, namely, cutting depth (D), cutting speed (V) and drum speed (v) by serving energy productivity as a characteristic response. Taguchi L25 orthogonal array is utilised to statistically analyse the effect of control factors on energy productivity. Taguchi, multiple linear regression (MLR) and artificial neural network (ANN) models are developed to predict energy productivity based on control factors. Meanwhile, one way ANOVA is used to assess the contribution of control factors in the variability of energy productivity, resulting cutting speed as the most influencing factor with a substantial contribution of 66%. Cutting speed models are also developed based on coal tensile strength at specified cutting depths for machine E, indicating that cutting speed followed an exponential decline with increased coal tensile strength.

The prediction of key productivity indicators of an excavator can prevent the excessive material consumption (Tiryaki and Dikmen, 2006). Coal, machine and operational parameters significantly affect key productivity indicators of SM, namely, machine productiivty, pick consumption and diesel consumption in opencast coal mines (Wirtgen, 2008; Dey and Ghosh, 2011; Prakash *et al.*, 2013). Coal properties, *i.e.*, uniaxial compressive strength (Jones and Kramadibrata, 1995; Origliasso *et al.*, 2014), tensile strength (Thuro, 1997; Kahraman *et al.*, 2003), ash content (Foster *et al.*, 2004; Bhatt, 2006) and moisture content (Spero, 1990; Mammen *et al.*, 2009) affect the machine productivity during coal cutting. Machine specifications, namely, cutting width (Wirtgen, 2008), rated power (Dey and Ghosh, 2011), cutting depth (Wirtgen, 2008), cutting area (Prakash *et al.*, 2015) and cutting speed (Wirtgen, 2008) affect the cutting performance of SM. Meanwhile, operating conditions, such as, face length (Wirtgen, 2008; Dey and Ghosh, 2011) and machine utilisation (Raghavan *et al.*, 2021) limit the machine productivity of SM.

To predict key productivity indicators of SM, a dataset consists of 47 field-scale SM coal production trials is observed from eight Indian opencast coal mines using middle cutting drum-type SM for coal cutting. Two set of data points are excluded from the dataset as outliers for having standardised residuals of 2.3 and 2.6 based on bivariate regression analysis between machine shift time and coal production using the criterion of being more than two standard deviations away from the mean of residuals (Hunasigi *et al.,* 2023). Meanwhile, laboratory tests are done to assess factors related to coal parameter, whereas, field investigations are administered to measure machine and operational parameters along with corresponding key productivity indicators.

Bearing in mind various parameters affecting key productivity indicators and complex interaction among factors related to those parameters, it is imperative that variable selection techniques must be used to select only the critical factors for predicting the same. To this end, the prominent and widely accepted techniques, such as correlation coefficient analysis (CCA) and principal component analysis (PCA) is used in analysis and interpretation of key productivity indicators. Tiryaki and Dikmen (2006) has investigated the strength and direction of linear relationship between specific energy and textural, compositional, and engineering properties of sandstones based on Pearson correlation coefficient. Meanwhile, PCA technique is utilised as a dimension reduction method to obtain predictor variables vis-à-vis more comprehensive insights into complex processes (Cacho, 1997; Bengraine and Marhaba, 2003; Loska and Wiechula, 2003; Martínez *et al.*, 2008; Majdi and Beiki, 2010).

The main concern of principal component analysis is to understand mode of action or behaviour of components of a system and its subsystem (Petersen *et al.*, 2001; Yang *et al.*, 2021). It reduces the complexity of multidimensional system by maximisation of component loadings variance and elimination of invalid components (Jolliffe and Cadima, 2016; Louloudis *et al.*, 2019; Fan *et al.*, 2023). It explains the variance–covariance structure of original variables to extract the interpretable information of a predictor variables system. PCA employs either alone or in combination with other methods to model mining processes (Chen and Mynett, 2003; Paurush *et al.*, 2021; Zhang *et al.*, 2022; Yang *et al.*, 2023).

A dataset of 39 field-scale SM coal production trials is observed to select critical factors affecting key productivity indicators based on correlation coefficient and principal component analysis, respectively. Seven critical factors are selected out of eleven identified influencing factors for better imitation of the interaction of coal, machine and operational parameters in predicting key productivity indicators of SM. MLR models are developed key productivity indicators based on selected critical factors. It can handle any unsystematic noise by selecting new values of regression coefficients and formula (Silhavy *et al.*, 2017). The performance of these models is validated using coefficient of determination between actual and predicted values and standardised residual analysis for normal distribution of residuals with zero mean and constant variance (Singh *et al.*, 2023b).

To simplify the relationships within the MLR models, a unified index, termed as Surface Miner Productivity Index for Coal ($SMPI_C$) is developed as a composite of coal, machine and operational parameters to predict key productivity indicators. This technological index can capture the complexity of coal behaviour during cutting, depending not only on the coal properties but also on the interacting mechanism (Prakash *et al.*, 2015). It would not only make the machine productivity prediction easy but also the estimation of pick and diesel consumptions for a given coal, machine and operational parameters. Empirical models based on $SMPI_C$ index are validated using 6 field-scale SM coal production trials dataset.

Moreover, MLR and $SMPI_C$ index-based models are further verified outside the statistical domain using artificial neural network (ANN) technique. ANN based modelling technique has found its application in various engineering fields (Tsen, *et al.*, 1996; Patel *et al.*, 2007; Chavan *et al.*, 2012; Patil-Shinde *et al.*, 2014). ANN technique has the ability to handle data non-linearity and interdependability between variables for predicting key productivity indicators through the precised training of model without considering thorough information about mechanistic phenomenon on which the system works (Hunasigi *et al.*, 2023). A confirmation test based on the sum of squared errors (SSE) is used to compare the efficacy of developed key productivity indicators prediction models using statistical and ANN approach. The average SSE value was observed as 0.68 for MLP-ANN models as compared to 0.90 and 1 for MLR and $SMPI_C$ index-based models at a significance level of 0.05, respectively.

The productivity change in a mechanical excavation system can be attributed to the structural change in production process like expansion of labour force or shift to the more classical reasons of growth like long-term effects of capital accumulation or change in production technology (Kulshreshtha and Parikh, 2001). Drawing from empirical observations, Cobb and Douglas (1928) proposed that production could be linked to inputs, such as, labour, capital, and technology through a multivariate non-linear function to offer a comprehensive framework capable of elucidating various production activities. It has found extensive application in measuring total factor productivity (Szwilski, 1988; Ghobadian and Husband, 1990; Pendharkar *et al.*, 2008, Hassani 2012).

Meanwhile, machine shift time (MST) is the most commonly used input to develop machine utilisation index, as a measure of changes in machine productivity (Ghobadian and Husband, 1990). However, MST-based productivity index indicated changes only in machine utilisation efficiency and did not account for changes in machine cost efficiency. In this study, machine shift cost (MSK) is developed as a production factor in terms of ownership and operating (O&O) costs to investigate the relationship between coal production and capital input of SM using modified 'Corps of Engineers' method. It utilises one-time initial capital cost of machine purchase, annual fixed costs related to depreciation, interest, tax and insurance, and variable costs related to manpower, repair, maintenance, fuel, lubricating oil, grease, picks, holders and administrative overhead.

SM coal production (Q) in a 24-hour scheduled shift is aggregated on monthly basis as an output, to examine whether it follows the Cobb-Douglas production function (CPDF) with respect to the production factors, *i.e.*, MST as a 'labour' input and MSK as a 'capital' input. A confirmation test based on root mean squared error (RMSE) is conducted to compare the efficacy of CDPF model against bivariate exponential production function (BEPF) model at 0.05 significance level. Meanwhile, the isoquant curves representing a unique production level for each curve are developed to categorise SM coal production based on SM total factor productivity.

1.2 Statement of problem

Following a 1997 mandate by the Directorate General of Mines Safety, Government of India, residential and sensitive areas require restricted blasting operations, which set the threshold limit value for ground vibration at the foundation level of sensitive structures at less than 2 mm/s for dominant excitation frequencies below 8 Hz (Singh *et al.*, 2023d). Consequently, it generates the necessity for the deployment of SM, aiming to improve coal production and productivity in these areas. The development of an index is essential for selecting the most productive model of SM in terms of energy, currently available in the market. Optimised control factors of SM are necessary to prevent overloading of the SM's engine at a given tensile strength of coal during coal cutting.

The combined effect of coal, machine and operational parameters affecting machine productivity, pick consumption, and diesel consumption of SM in opencast coal mines is imperative to investigate for the development of models which can be used to predict key productivity indicators of SM without deploying them into opencast coal mines. Lastly, the development of coal production model for SM based on 'labour' as well as 'capital' inputs is inevitable while selecting SM as a coal mining technology for Indian opencast coal mines. The problem definition is outlined in Figure 1.3.

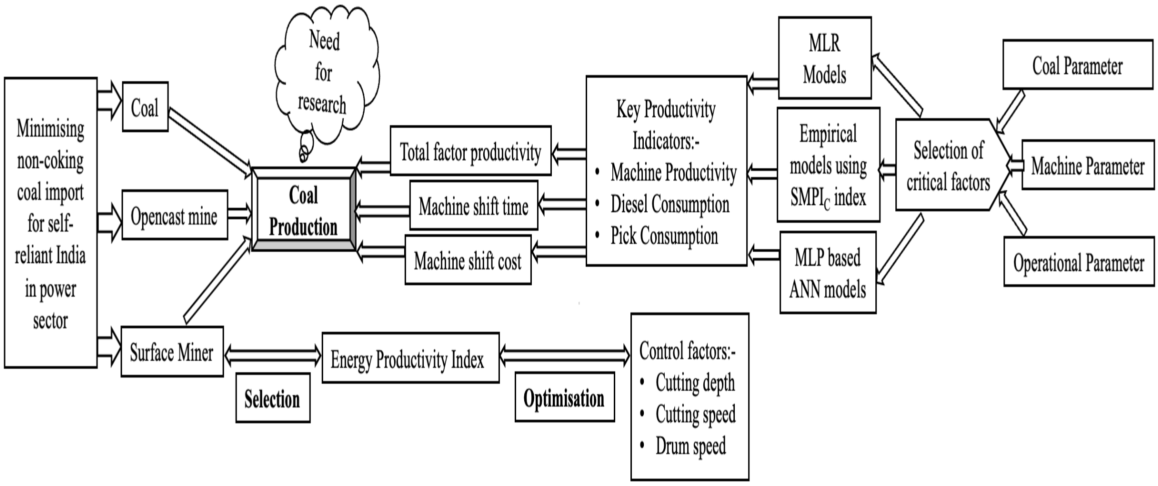

Figure 1.3: Outline of problem definition

1.3 Research objectives

Objectives of the thesis are mentioned as follows:

1. Selection of the most productive SM model in terms of energy.
2. Optimisation of control factors for optimum energy productivity of SM during coal cutting at specified coal tensile strength using Taguchi method.
3. Selection of critical factors affecting machine productivity, pick consumption and diesel consumption of SM in opencast coal mines.
4. Development of multiple linear regression models, SMPI$_C$ index-based models, and multilayer perceptron-based artificial neural network models to predict key productivity indicators of SM in opencast coal mines.
5. Development of coal production model based on SM total factor productivity, machine shift time and machine shift cost using Cobb-Douglas production function.

1.4 Scope and methodology

1.4.1 Scope of work

This research addresses the following issues:

1. Selection of the most energy-efficient SM model for coal cutting.
2. Parametric analysis of control factors, namely, cutting depth, cutting speed, and drum speed with respect to energy productivity during coal cutting.
3. Parametric analysis of coal, machine, and operational factors with respect to key productivity indicators of SM in opencast mines.
4. Parametric analysis of coal production with respect to machine shift time and machine shift cost for SM operating in Indian opencast coal mines.

1.4.2 Work plan

A comprehensive work plan has been developed to accomplish the objectives using a phased approach, as illustrated in Figure 1.4. This plan included both field and laboratory investigations in phase I. In phase II, experiments have been designed to analyse the collected data from phase I using analytical, empirical, MLR, and MLP-based ANN techniques. Finally, results of all analyses conducted in phase II are discussed in Phase III.

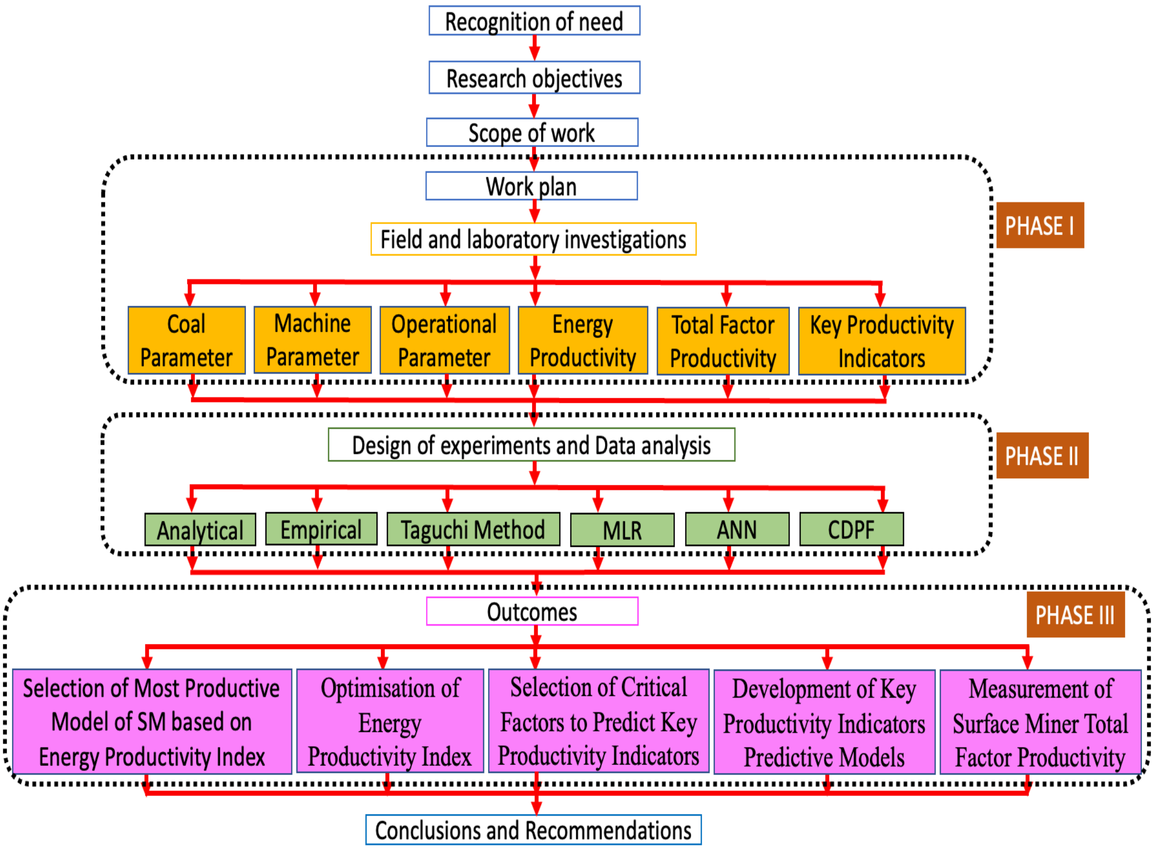

Figure 1.4: Flow chart of methodology

1.5 Organisation of thesis

The thesis is organised into eight chapters, which are discussed as follows:

Chapter 1 introduces the background, defines the problem statement, outlines the research objectives, and details the work scope and work plan.

Chapter 2 offers a comprehensive literature review regarding constructional and operational features of SM along with the cutting force models for conical picks, energy productivity models, machine productivity models, and total factor productivity models developed by different researchers, highlighting their features and limitations with year of publication in tabular form. Lastly, it details research gap and novelty of research work.

Chapter 3 details location, geology and mining system for selected Indian opencast coal mines based on deployment of SM for coal production. It describes procedures followed for field study and laboratory investigations to generate necessary data for building relationships between parameters. It summarises factors related coal, machine and operational parameters with corresponding values of key productivity indicators of SM.

Chapter 4 discusses optimisation and prediction techniques used in this study. It covers Taguchi method, orthogonal array, analysis using signal-to-noise (S/N) ratio, analysis of variance (ANOVA), multiple linear regression (MLR) and artificial neural network (ANN).

Chapter 5 presents optimisation of control factors for maximum energy productivity of selected SM during coal cutting using Taguchi method. It outlines the results of mean response plot, S/N ratios with delta values to rank control factors, ANOVA to determine the contribution of control factors on output response, energy productivity prediction models based on control factors at specified coal tensile strength with a confirmation test and cutting speed prediction models based on coal tensile strength at given cutting depths.

Chapter 6 covers the selection of critical factors related to coal, machine and operational parameters influencing key productivity indicators of SM in opencast coal mining using CCA and PCA. It outlines the development of MLR, surface miner productivity index for coal ($SMPI_C$)-based non-linear, and MLP-ANN key productivity indicators prediction models based on the selected critical factors and compares the efficacy of developed models based on sum of squared errors (SSE).

Chapter 7 presents the measurement of SM total factor productivity in Indian opencast coal mines based on monthly output (coal production), labour input (machine shift time), and capital input (machine shift cost) using Cobb-Douglas production function. The chapter concludes with recommendations and suggestions for future work.

Chapter 8 discusses conclusions, limitations and future scope of the research work that could not be undertaken due to time constraints. The references are provided in APA style by listing the author's last name and year of publication. Publication details arising from the research are mentioned at the end of the appendices.