8 CONCLUSION

8.1 Conclusions

8.1.1 Investigations into energy productivity to optimise control factors of SM

a) Machine E was selected as the most productive SM model in terms of energy.

b) The optimal settings for control factors of machine E was determined as D_5 = 0.35 m, V_5 = 30 m/min, ν_1 = 60 rpm at minimum tensile strength (1.5 MPa), D_4 = 0.3 m, V_4 = 25 m/min, ν_2 = 65 rpm at mean tensile strength (2.6 MPa) and D_2 = 0.2 m, V_2 = 10 m/min, ν_3 = 70 rpm at maximum tensile strength (3.7 MPa) for optimum energy productivity, facilitating the maximum utilisation of cutting power for peak coal production.

c) A confirmation test revealed that 29% of overall energy productivity was improved for machine E operating on a coal seam present at Bhubaneswari opencast coal mine by practicing optimum control factor settings as compared to the initial setting of control factors during coal cutting.

d) Taguchi, MLR, and ANN models predicted the energy productivity of machine E based on control factors with an acceptable accuracy at significance level of 0.05. A confirmation test revealed that Taguchi method provided a better outcome with minimum deviation.

e) ANOVA results indicated that cutting speed was the most significant factor affecting energy productivity, accounting for 66% of the contribution.

f) Cutting speed models were developed for machine E based on coal tensile strength at specified cutting depths, indicating that cutting speed followed an exponential decline with increased tensile strength of coal.

8.1.2 Evaluation of key productivity indicators of SM in opencast coal mines

a) Uniaxial compressive strength, tensile strength and ash content related to coal parameter; cutting depth, cutting area and cutting speed related to machine parameter; and face length and machine utilisation related to operational parameter were selected as critical factors for machine productivity based on Pearson's correlation coefficient. However, cutting depth was rejected as a critical factor for machine productivity using PCA.

b) Uniaxial compressive strength, tensile strength, ash content, cutting depth, cutting speed, face length and machine utilisation were selected as critical factors for predicting pick and diesel consumptions using CCA and PCA techniques. In summary, the result in case of both techniques were found to be in close agreement with each other.

c) Machine productivity followed an inversely proportional relationship with the coal parameter while sharing a directly proportional relationship with machine and operational parameters, respectively.

d) The MLR models and $SMPI_C$ index-based models were found to be statistically significant for predicting key productivity indicators of SM at the 0.05 significance level. These models were further validated beyond the statistical domain using the MLP-ANN technique. A confirmation test demonstrated that the MLP-ANN models exhibited the highest predictive accuracy, outperforming the MLR and $SMPI_C$ index-based models, with an average sum of squared errors (SSE) of 0.68, compared to 0.90 and 1.00, respectively. Furthermore, the MLP-ANN models developed using PCA-selected critical factors confirmed the compatibility and coherence between the statistical and artificial neural network approaches.

8.1.3 Surface miner total factor productivity

a) Coal production model based on two production factors, namely, machine shift time (MST) as 'labour' input and machine shift cost (MSK) as 'capital' input using Cobb–Douglas production function (CDPF) was found to be statistically significant for the measurement of SM total factor productivity at 0.05 significance level. The model was expressed as follows:

$$Q = 0.072 \times (MST)^{1.7162} \times (MSK)^{1.2537} \qquad \text{(Equation 7.11)}$$

b) The output elasticities of labour (α) and capital (β), i.e., 1.7162 and 1.2537, gauged the utilisation intensity of MST and MSK, respectively. A higher value of α than β suggested that SM leans towards the MST-intensive technology. Moreover, the sum of α and β exceeded unity, indicating an increasing return to scale economy. It highlighted the need for mine managers to exercise caution while utilising MST and MSK as production factors to avoid irregularities and cost overruns during SM coal production, since, doubling either or both factors shall increase the SM coal production for more than double.

Figure 8.1 shows the key outcomes for the quick appreciation of research on the impact of surface miner on production and productivity with special reference to coal mining.

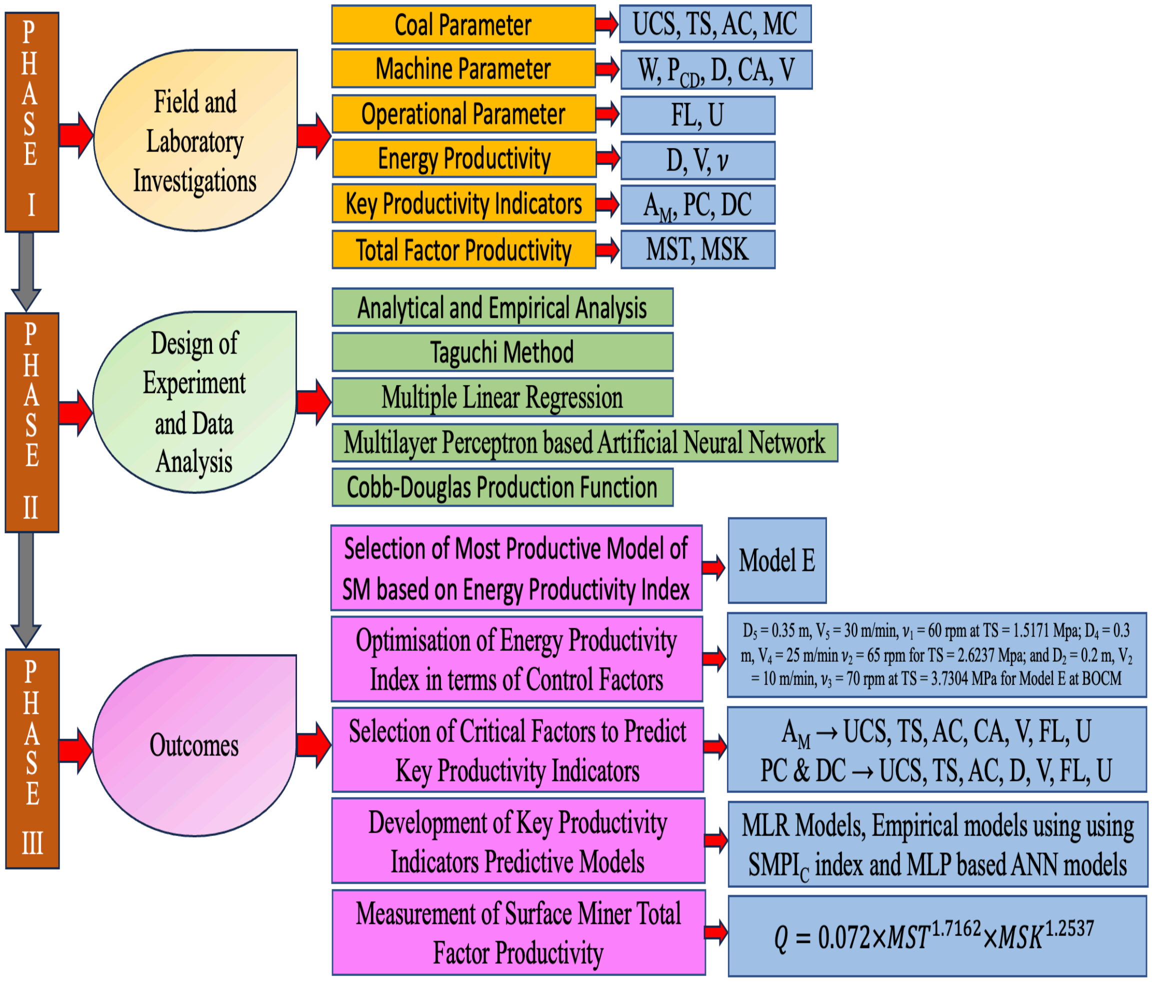

Figure 8.1: Key outcomes of the research work

8.2 Limitations of the study

a) Diversified field data collection, analysis, and validation can further refine the developed predictive models.

b) Given the constraints of field-oriented studies in a stressed environment, several assumptions regarding factors related to machine and operational parameters and key productivity indicators of SM in opencast coal mines might have caused variations in the model output. These variations can be addressed through more controlled experiments.

8.3 Future scope of research

a) Numerical modelling of coal cutting process may be used to investigate the energy productivity of SM in opencast coal mines.

b) This study considered only one artificial intelligence technique, namely, the MLP-ANN method, which paves the way for using other AI techniques like big data analytics and machine learning.

c) This study considered Cobb–Douglas production function to simulate SM coal production with multiple inputs and single output, which paves the way for using other production functions like translog production functions with both single output and multiple outputs. Moreover, application of data envelopment analysis (DEA) and heuristic rank aggregation approach like Borda method may address the well-known problem of ranking mines using SM for coal production.