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DEVELOPMENT OF SINKHOLE MODEL USING ANN (EASYNN-PLUS) FOR UNDERGROUND COAL MINES IN INDIA

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ABSTRACT

Like an earthquake, sinkhole subsidence can strike with little or no warning and can result in damage to infrastructure and loss of human life without admonition. Sinkhole subsidence is sudden and abrupt fall of the surface into the void created due to mining activity. It cannot stop, but can be controlled in different ways where complete strata deformation may be dangerous or costly effects. In recent years at South Eastern Coalfields Limited (SECL) several sinkholes have been reported and to study the various influencing parameters which triggering the sinkhole, this study has taken up. The parameters which are causing to sinkhole have been collected & compiled based on parametric analysis to this parameters model was developed in Artificial Neural Network (ANN) by using EasyNN-plus software for sinkhole depth prediction. The same developed model has been validated by randomly selected four different mines with model results matching to ± 10 % of error.

Keywords: underground coal mining, sinkhole subsidence, artificial neural network.

1. INTRODUCTION

The underground extraction of minerals leads to deformations on the surface which can be further classified into trough and sinkhole subsidence. The subsidence may either be deep or shallow and accordingly it is called as trough and sinkhole subsidence respectively (Figure-1). When the overlying strata suddenly collapse, it leads to an unexpected formation of an underground cavity. This mechanism usually leads to the sinkhole subsidence. (Lokhande *et al*., 2013).

Subsidence of the ground can be stated as vertical movement of the ground which occurs due to the extraction of mineral resources. From the environment point of view, it is a typical consequence of underground mining activities. In the broader perspective, it reflects those movements which occur above the exploited area. It is a matter of concern because, subsidence can and does have serious effects on surface structures, environment as well as social-life (Genske *et al*., 2000).

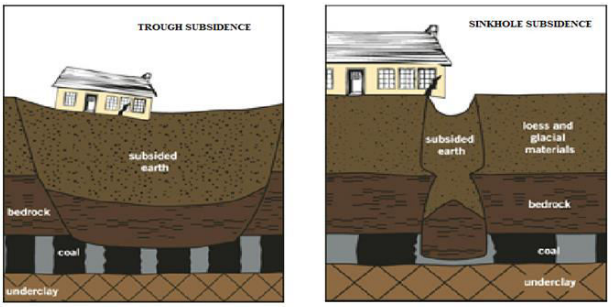

Figure-1. Trough and sinkhole subsidence (Anon, 2017).

Sinkholes cause severe damage to surface landmarks due to the collapse of houses; in addition to it, severe cracks are developed on walls and floors. Social life too may be hampered due to the likelihood of risk of falling into the sinkholes. Due to the inflow of surface runoff in mines and emission of a large quantity of mine gases and breathing in the mines becomes difficult. Thus sinkholes deteriorate the underground mining conditions (Lokhande *et al*., 2015). Sinkhole subsidence, hampers the economic assets in the form of loss of surface and underground property, discontinuity of work, loss of production, cleaning of the sinkhole affected area and filling of the sinkhole, is a significant issue in many cases (Lokhande *et al*, 2013) (Figure-2).

Figure-2. Impact of sinkhole on surface structure (Anon[1], 2017).

The paper mainly highlights the parametric analysis of influencing parameters responsible for sinkhole subsidence and based on this parametric analysis, an ANN (By using Easy NN-plus software) model has been developed for prediction of sinkhole depth.

2. PREVIOUS WORK ON SINKHOLE SUBSIDENCE

Previous research on sinkhole subsidence is presented briefly in this section. In the past, several sinkholes were reported across the globe due to underground coal mining, particularly, at shallow depth. In India, several mines suffer this challenge of unsafe conditions due to sinkholes, stoppage of work and mining losses particularly, at shallow depth. Thus, the present study assumes a significant importance. Sinkhole

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subsidence was reviewed for understanding the parameters which are prone to their occurrences.

Atkinson et al. (1975) model is based on limit equilibrium analysis, in model the vertically collapse configurations may give real representation of that collapse. According to Gray *et al*. (1978) the most probable cause of the development of a sinkhole is the collapse of a mine roof, especially over mine junctions where the exposed roof is more. Singh and Atkins (1983) have provided some suggestions which are similar to Kendorski model, this model refined by introducing different strains zones. In their earlier developed model carrying the large water bodies restricted for10 mm/m strains value to protect the surface structure. According to Karfakis (1986) the sinkhole can also be present to an extent further by self-choking action. The natural bulking of caved roof rock may cease the further extension of sinkhole subsidence. If, however at shallow cover or presence of weak rock in overlying strata or presence of water in overlying rock allowing caved material to flow into the cavity. The subsurface cavities which create tension cracks or fracture in overlying strata may create weak planes through which impact or caving may reache to surface. Abdullah and Goodings (1996) model explain a complete picture of stability of overlying rock particularly sand layer above the cavity. Sheorey P.R *et al*. (2000) have worked in India on shallow depth working and its impact on surface. In study it includes subsidence behaviour in caved roof rock and uncaved rock due to underground extraction. Vaziri *et al*. (2001) have given an analytical model for ascertaining the stability of an axisymmetric region of roof rock. Singh *et al*. (2008, 2011) have given a theory of trough and sinkhole subsidence on shallow depth working in underground coal mines. In study it is concluded that sinkhole subsidence affected mostly to low strength strata, fault and fissures, amount of rainfall. Saro *et al*. (2012) studied more than 824 cases in South Korea related to trough and sinkhole subsidence and model developed using Ground Subsidence Susceptibility (GSS), Artificial Neural Network (ANN) and Geographic Information System (GIS). In their study this emphasis has been given to subsidence affected area and slope, cover, distance from pit, presence of water reservoirs, RMR, impact of fault and its distance, geology of area and land use. Lokhande *et al*. (2014) gave an in-depth understanding of various parameters which influence the occurrence to formulating the basis of different predictive models. These critical parameters have been compiled and analysed, further a multiple regression model was developed to calculate sinkhole depth under different conditions. Strzalkowski and Tomiczek (2015) mostly studied the sinkhole formation due to at shallow depth which creates danger to social-life and available infrastructure.

3. FIELD INVESTIGATIONS

Field investigations work was carried out in three different areas, namely, Jamuna Kotma, Korba and Bisrampur area of South Eastern Coalfields Limited (SECL) which is one of the subsidiaries of Coal India Limited (CIL), India (Figure-3). This investigation was done in ten different mines of these three areas. Geo-mining & geological parameters are needed for carrying out detailed analysis and out of which the parameters having more influence has been selected for further development of the model.

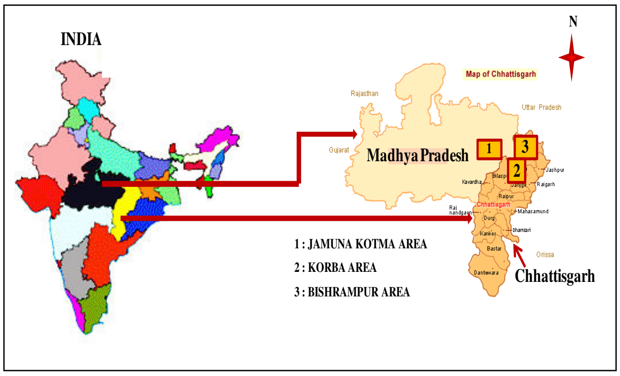

Figure-3. Location of the study area (Anon, 2016).

A total 41 sinkholes were studied from the view of geo-mining and geologic aspects. The extraction height varied from 1.7 to 3 m & depth of working varied from 15.1 to 58.05 m. Out of 41 sinkholes, nine were circular in shape with diameter 2 m and 20 m respectively and 32 sinkholes were oval in shape with different dimensions occurred over the working at shallow depth. The data related to field investigations and laboratory testing is given in Table-1.

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Table-1. Data related to field investigations and laboratory testing.

Method of working	Geo-mining parameters			Physico-mechanical parameters				Geological parameters		SD (m)
	HE (m)	Depth of working (m)	RTS	WCS (MPa)	WTS (MPa)	WD (kN/m^3)	WBF	Presence of fault	Presence of water	
Development	2.8	32.80	9.75	5.47	0.36	19.05	9.75	84 m	140 m	5.0
Development	2.8	47.61	0.84	5.81	0.42	17.57	0.84	4 m	-	12.0
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	72 m	40 m	1.4
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	30 m	104 m	1.8
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	182 m	50 m	2.5
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	110 m	42 m	2.5
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	280 m	24 m	5.0
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	460 m	172 m	2.5
Depillaring	2.6	27.95	8.16	5.30	0.41	18.83	8.16	-	-	2.8
Development	2.3	23.08	5.26	5.84	0.42	19.45	5.26	Fault plane	176 m	9.0
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	20 m	4.0
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	4.3
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	3.0
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	3.5
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	2.5
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	4.7
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	3.3
Depillaring	2.8	38.60	11.65	9.00	0.71	20.90	11.65	-	-	2.5
Development	2.5	49.59	12.35	6.09	2.40	23.37	12.35	Fault plane	44 m	2.0
Development	2.5	49.59	12.35	6.09	2.40	23.37	12.35	40 m	-	2.0
Development	2.5	49.59	12.35	6.09	2.40	23.37	12.35	-	-	2.0
Development	2.0	48.20	15.26	6.42	0.93	22.93	15.26	26 m	100 m	1.7
Development	3.0	29.00	2.17	6.20	0.89	22.90	2.17	30 m	-	2.5
Development	3.0	29.00	2.17	6.20	0.89	22.90	2.17	12 m	-	2.8
Development	3.0	29.00	2.17	6.20	0.89	22.90	2.17	4 m	-	2.5
Development	3.0	29.00	2.17	6.20	0.89	22.90	2.17	16 m	-	3.5
Development	1.8	15.10	0.65	3.10	0.28	16.40	0.65	300 m	Y	12.0
Depillaring	1.7	58.05	24.57	3.24	0.36	17.69	24.57	-	-	3.0
Depillaring	1.7	58.05	24.57	3.24	0.36	17.69	24.57	-	60 m	3.0
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	3.0
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	2.0
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	2.5
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	4.5
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	3.0
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	4.0
Development	2.7	41.87	12.97	3.35	0.26	23.47	12.97	-	-	8.5
Development	2.7	36.45	17.22	4.06	0.47	20.24	17.22	-	128 m	4.8

HE-Height of Extraction
RTS-Rock to soil ratio
WCS-Weighted compressive strength
WTS-Weighted tensile strength
WD-Weighted density
WBF-Weighted bulk Factor
SD-Sinkhole depth

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Field investigations work was done for the collection of various parameters which directly or indirectly influence the triggering of sinkhole subsidence. Investigations included the collection of geo-mining and geological data where sinkholes have developed. Geological discontinuities and presence of water bodies in the areas adjacent to sinkhole occurrence were given a major focus and importance in this study. Based on the literature review, field investigations and laboratory testing, the following parameters which have produced significant influence on sinkhole formation were identified. The parameters are, namely, depth of working (cover), height of extraction, thickness of hardcover (rock) in overburden, thickness of soft cover (soil) in the overburden, compressive strength of the overburden rock, tensile strength of the overburden rock, density of overburden rock and bulking factor of overlying strata.

Strength, density and bulk factor of rock are represented as a weighted average. The overlying rocks extended up to the surface excluding soil.

After an in-depth understanding of influencing parameters on the occurrence of sinkhole, it forms the basis of preparing prediction model. These parameters have been initially analysed on the basis of regression analysis and then used in development for of ANN model.

4. PARAMETRIC ANALYSIS

Seven parameters were studied to develop the model, namely, depth of working, height of excavation, rock to soil ratio (overlying rock till topsoil layer), weighted density of overburden, weighted compressive strength of overlying rock, weighted tensile strength of overlying rock and weighted bulk factor of overlying rock. Initially, these seven parameters were correlated with sinkhole depth to comprehend their impact consecutively and further model development.

4.1 Depth of working (cover)

At higher depth; the impact of working takes time to reach on surface and deform, whereas at shallow depth the immediate deformation reflected on the surface (Sahu & Lokhande, 2015). In the deeper cover, sinkhole trigger probabilities are less as in respect to shallow cover (Lokhande *et al*., 2013). Shallow cover is most dominating factor in terms of sinkhole incidence in different parts of globe and was broadly used by different researchers in their predictive models, namely, Price and Malkin (1969), Atkinson and Potts (1975), Grey *et al*. (1978), Piggott and Eyon (1977), Kendorski (1979), Dunrud and Osterwalk (1980), Singh and Atkins (1983), Muhlhaus (1985), Karfakis (1986), Whittaker and Reddish (1989), Abdullah and Goodings (1996), Singh and Dhar (1997), Dyne (1998), Tharp (1999), Sheorey *et al*. (2000), Vaziri *et al*. (2001), Soni *et al*. (2007), Singh (2007), Tajdus and Sroka (2007), Lokhande *et al*. (2005, 2008), Prakash *et al*. (2010), Singh *et al*. (2008, 2011), Saro *et al*. (2012), Lee *et al*. (2013), Swift (2014), Strzalkowski and Tomiczek (2015), Lokhande *et al*. (2013, 2014, 2015).

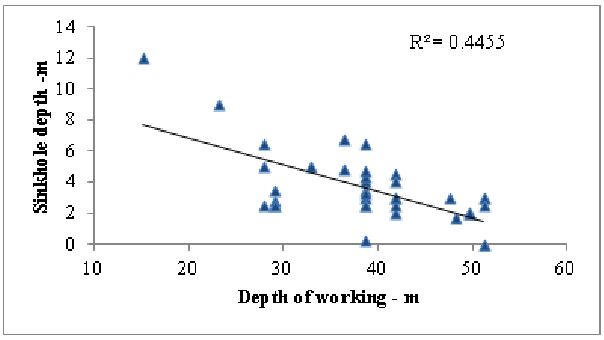

Figure-4. Influence of depth of working on sinkhole depth.

Parametric analysis was done between depth of working and sinkhole depth. The cover varied from 15.1 m to 51.15 m. From the Figure-4, it has been observed that at lesser depth the occurrence of sinkholes is more than at larger depth. The coefficient of determination (R^2) between depth of working and sinkhole depth was found to be 0.45.

4.2 Height of excavation

Lower the extraction percentage lowers the rate of subsidence. Height of extraction is important parameters causing sinkhole on the surface. Opinion differs from the effects of height of extraction on the magnitude of sinkhole subsidence. Researchers namely, Price and Malkin (1969), Grey *et al*. (1978), Piggott and Eyon (1977), Dunrud and Osterwalk (1980), Karfakis (1986), Whittaker and Reddish (1989) Abdullah and Goodings (1996) , Dyne (1998), Tharp (1999), Vaziri *et al*. (2001), Lokhande *et al*. (2005), Tajdus K and Sroka (2007), Singh *et al*. (2008, 2011) and Salmi *et al*. (2017) have used this parameter in their developed models.

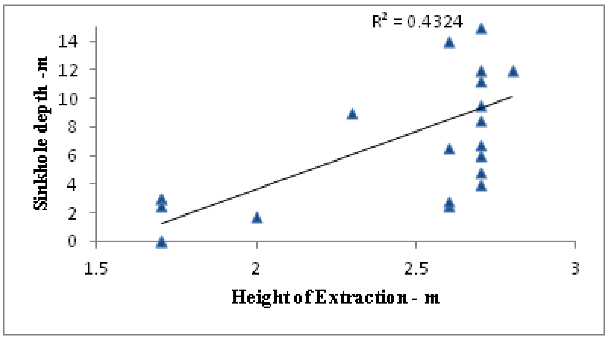

Figure-5. Influence of height of extraction on sinkhole depth.

Parametric analysis was done between height of extraction and sinkhole depth. The extraction height was varying from 1.7 m to 2.8 m. From Figure-5, it has been seen that sinkhole depth is less at less extracted height and increased relatively as height of extraction increased. The coefficient of determination (R^2) between Height of extraction and sinkhole depth was found to be 0.43.

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4.3 Rock to soil ratio

The soil is the uppermost layer of the earth's surface and important in terms of mining activities. The changes to the permeability and porosity of the rock (Anon[2], 2017). Competent rock in immediate roof and floor may avoid sinkhole through their arresting action. Singh (2007) and Lokhande *et al*. (2013) have used rock to soil ratio parameter in their work for the development of sinkhole subsidence models. Sinkhole involves failure and collapse of bedrock, and where soil cover is flushed into stable rock fissures Waltham (2005).

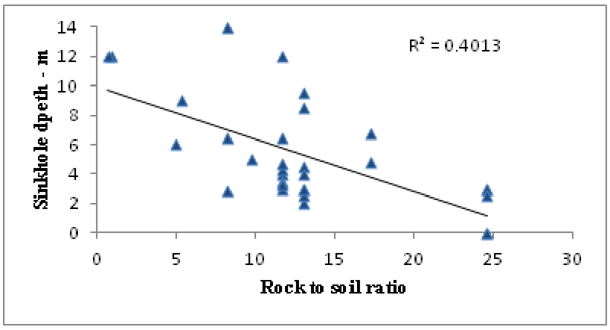

Figure-6. Influence of rock to soil ratio on sinkhole depth.

Parametric analysis was done between rock to soil ratio and sinkhole depth. The ratio of rock to soil is varying from 0.84 to 24.57. It has been observed from Figure-6, that at lower rock to soil ratio higher is the sinkhole depth and vice versa. The R^2 value was found to be on lower side (0.40).

4.4 Weighted density of overburden

The rock density is an important parameter for the prediction of sinkhole subsidence. Rock at higher density is difficult to cave and if it gets cave then due to lower density. And if it caved at higher density the created void will not be filling up but at low density, this process is reversed due to its bulking process. Cracks and fissures may develop and constitute further weak zones from which processes of mass movement start (Lokhande *et al*. 2014). This parameter was used by researchers, namely, Whittaker and Reddish (1989), Singh K B (2000), Strzalkowski and Tomiczek (2015) in their research.

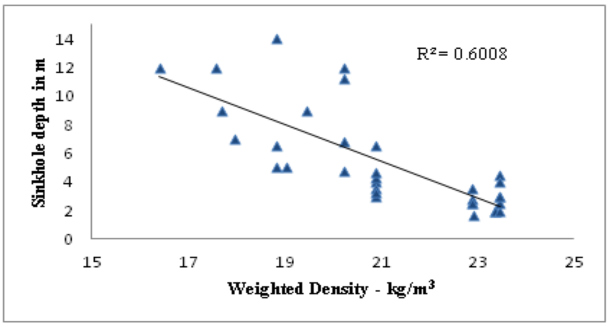

Figure-7. Relationship between weighted density and sinkhole depth.

The parametric analysis is shown in Figure-7, it was found that at low density the sinkhole depth is high because of weak strata and as density is increasing the sinkhole depth get reduces. The coefficient of determination (R^2) between weighted density and sinkhole depth was found to be 0.60.

4.5 Weighted compressive strength

In underground coal mining extraction, strength factor of immediate roof playing a vital role and it is calculated from the compressive strength. As the underground extraction takes place, the immediate roof gets disturbed and a load of overlying rocks may lead to failure of the roof rocks. The rocks present in the overlying layers have to withstand this load else it may collapse and increase the chances of sinkhole Abbasnejad *et al*. (2016). This parameter is very important in term of strength of strata is concerns and has been used widely by researchers, namely, Forster (1995), Abdullah and Goodings (1996), Vaziri *et al*. (2001,) Singh (2007), Singh *et al*. (2008, 2011), Parise and Lollino (2011), Saro *et al*. (2012), Lokhande *et al*. (2013, 2014, 2015), Salmi *et al*. (2017).

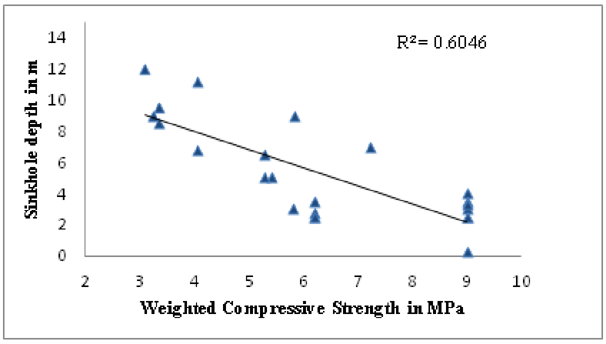

Figure-8. Influence of weighted compressive strength on sinkhole depth.

The parametric analysis is shown in Figure-8, it has been observed that at low compressive strength the sinkhole depth is high because of low competence and as compressive strength is increased the sinkhole depth gets reduce. The R^2 between weighted compressive strength and sinkhole depth of rock mass was found to be 0.60.

4.6 Weighted tensile strength of overlying rock

The disturbance produced by one gallery failure often leads to the weakening of adjacent areas particularly on the roof, resulting in the development of cracks that decrease tensile strength and allow the entry of water into weakened zones between blocks (Varnes 1984). Failure in coal mine roof is dominated by either tensile or shear stress developed due to the extraction of coal. Researcher Singh (2013), Forster (1995), Abdullah and Goodings (1996), Vaziri *et al*. (2001), Booth and Greer (2011), Parise and Lollino (2011), Lokhande *et al*. (2013, 2014, 2015), Potvin *et al*. (2016) and Salmi *et al*. (2017) have incorporated this parameter in their prediction models.

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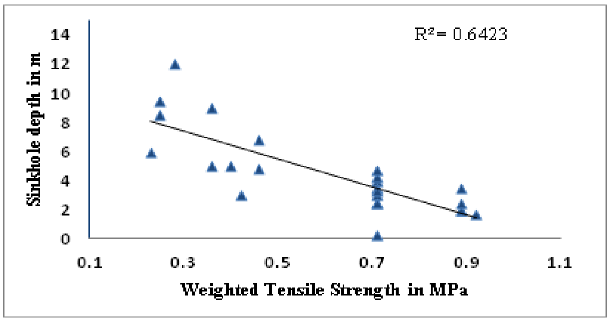

Figure-9. Influence of weighted tensile strength on sinkhole depth.

The parametric analysis is shown in Figure-9; it has been observed that at lower tensile strength the sinkhole depth was on higher side. The R^2 value between weighted tensile strength and sinkhole depth of rock mass was found to be 0.64.

4.7 Weighted bulk factor of overlying rock

In shallow working depth, bulking factor plays an important role. During depillaring the strata get caved immediately and its impact reaches to the surface which leads to the formation of sinkhole. But if the strata caved slowly and impact of this caved takes times to reach on the surface then bulking factor is playing a major role because the rock break gets swell and occupied more area. So the cavity is less and if less cavity then the intensity of sinkhole is less. This parameter was widely used by researchers, namely, Piggott and Eyon (1977), Bell and Bruyn (1999), Dunrud and Osterwalk (1980), Karfakis (1986), Whittaker and Reddish (1989), Tajdus and Sroka (2007) in their research.

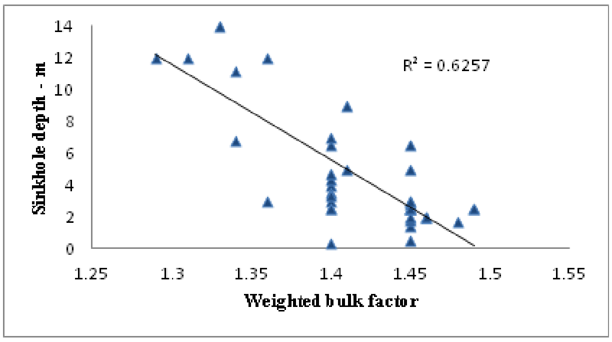

Figure-10. Influence of weighted bulk factor on sinkhole depth.

The regression analysis is shown in Figure-10; it was found that when the bulking factor increases the sinkhole depth decreases. The coefficient of determination (R^2) between weighted bulking factor and sinkhole depth was found to be 0.63.

5. DEVELOPMENT EASYNN MODEL

ANN is a pivotal form of artificial intelligence which exists for an input layer, hidden layer, and an output layer. It acts like a digital mathematical model for the nonlinear mapping between inputs and outputs which play a crucial role in the forecasting of sinkhole model. The characteristics of self-learning, self-organizing, nonlinear dynamic process and high fault tolerance, as well as associative inference and adjusted capacity and its particular application for processing various kinds of nonlinear problems makes it prominent and distinguished (Tomaz and Turk, 2003). Hundreds of single units, artificial neurons or processing elements (PE), linked with coefficients (weights), which comprise the neural structure organised layer wise are its constituents. The coefficients (weights) of these connecting elements and their arrangements are adjusted by a process of "training" for model graduation (Kustrin and Beresford, 2000).

5.1 Methodology

The development of sinkhole subsidence prediction model can be evolved through the Easy NN-plus software. The relative importance and relative sensitivity are represented by coefficients (weights) of different input parameters in the networks which were considered to select important influencing factors for prediction of sinkhole. During training, software assigns a weight to the various inter-related parameters and attempts to limit the error. This process is repeated until the error converges to the set limits. The final weight is obtained after training. A feed forward, a back-propagation neural network has been used where the learning process is achieved using the generalised delta rule or the back-propagation learning rule (Lokhande *et al*., 2014).

5.1.1 Parameters used for model development

The parameters which have significant influence on sinkhole formation were identified and used in development of ANN model are depth of working, height of extraction, thickness of hardcover (rock) in overburden, thickness of soft cover (soil) in the overburden, weighted compressive strength of the overburden rock, weighted tensile strength of the overburden rock, weighted density of overburden rock and weighted bulk factor of overlying strata.

5.1.2 Data sets for the ANN model

Total 34 data sets were selected for development and training of the neural network and five data randomly were used for the validation of model (Figure-11).

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Day 20	Height of +	Depth of w+	Rock to so+	Weighted c+	Weighted t+	Weighted d+	Bulk Factor	Sinkhole D+
A1	2.8000	32.8000	9.7500	5.4700	0.3600	19.0500	1.4100	5.0000
J2	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	1.4000
J3	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	1.8000
J4	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	2.5000
J5	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	2.6200
J6	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	5.0000
J9	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	2.5000
J10	2.6000	27.9500	8.1600	5.3000	0.4100	18.8300	1.4500	2.8000
B1	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	4.0000
B4	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	3.0000
B5	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	3.5000
B6	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	2.7300
B8	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	3.3000
B9	2.8000	38.6000	11.6500	9.0000	0.7100	20.9000	1.4000	2.5000
S1	2.5000	49.5900	12.3500	6.0900	2.4000	23.3700	1.4600	1.8300
S2	2.5000	49.5900	12.3500	6.0900	2.4000	23.3700	1.4600	2.0000
S3	2.5000	49.5900	12.3500	6.0900	2.4000	23.3700	1.4600	2.0000
C1	2.0000	48.2000	15.2600	6.4200	0.9300	22.9300	1.4800	1.7000
BL1	3.0000	29.0000	2.1700	6.2000	0.8900	22.9000	1.4900	2.5000
BL2	3.0000	29.0000	2.1700	6.2000	0.8900	22.9000	1.4900	2.8000
BL3	3.0000	29.0000	2.1700	6.2000	0.8900	22.9000	1.4900	2.5000
BL4	3.0000	29.0000	2.1700	6.2000	0.8900	22.9000	1.4900	3.7900
K1	1.7000	58.0500	24.5700	3.2400	0.3600	17.6900	1.4900	3.0000
K2	1.7000	58.0500	24.5700	3.2400	0.3600	17.6900	1.4900	3.0000
BR1	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	3.0000
BR2	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	2.0000
BR3	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	2.5000
BR4	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	4.5000
BR7	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	3.4300
BR8	2.7000	41.8700	12.9700	3.3500	0.2600	23.4700	1.4500	4.0000
BR11	2.7000	36.4500	17.2200	4.0600	0.4700	20.2400	1.3400	4.8000
BR14	2.7000	21.2300	4.9400	3.1400	0.2400	23.4900	1.4400	6.0000
BR15	2.7000	58.0500	24.5700	3.2400	0.3600	17.6900	1.4900	2.5000
Bt1	1.8000	46.2000	14.4000	7.2300	1.0000	17.9700	1.4000	7.0000

Figure-11. Training and validation data sets used in the neural network development.

5.1.3 Training of the Neural Network

For preparing a model only one hidden layer was used for learning purpose by setting a target error 0.05%. The model learning was controlled to stop when all the estimated error obtained below than the set targeted error. The learning and momentum rates were fixed to 0.7 and 0.8 respectively. After 904 cycles the learning was completed an average error computed was 0.019558 with the maximum and the minimum values of 0.049029 and 0.002343 (Figure-12). For training of the model seven input neurons, five hidden neurons and one output neuron were considered (Figure-13). Hidden neurons are used to avoid overfitting in the function approximation and based on the target error value. Optimizing the number of hidden neurons to use without a pre-set target for accuracy is one of the major challenges for a neural network (Geman *et al*., 1992). The thickness of the connections represented the weights of different processing elements.

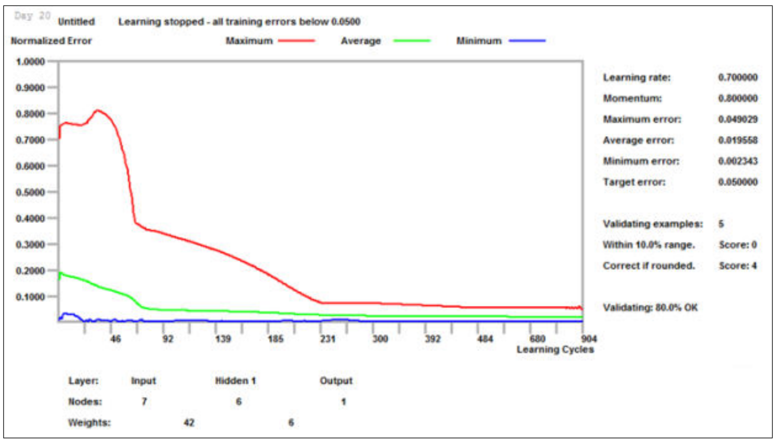

Figure-12. Learning of model.

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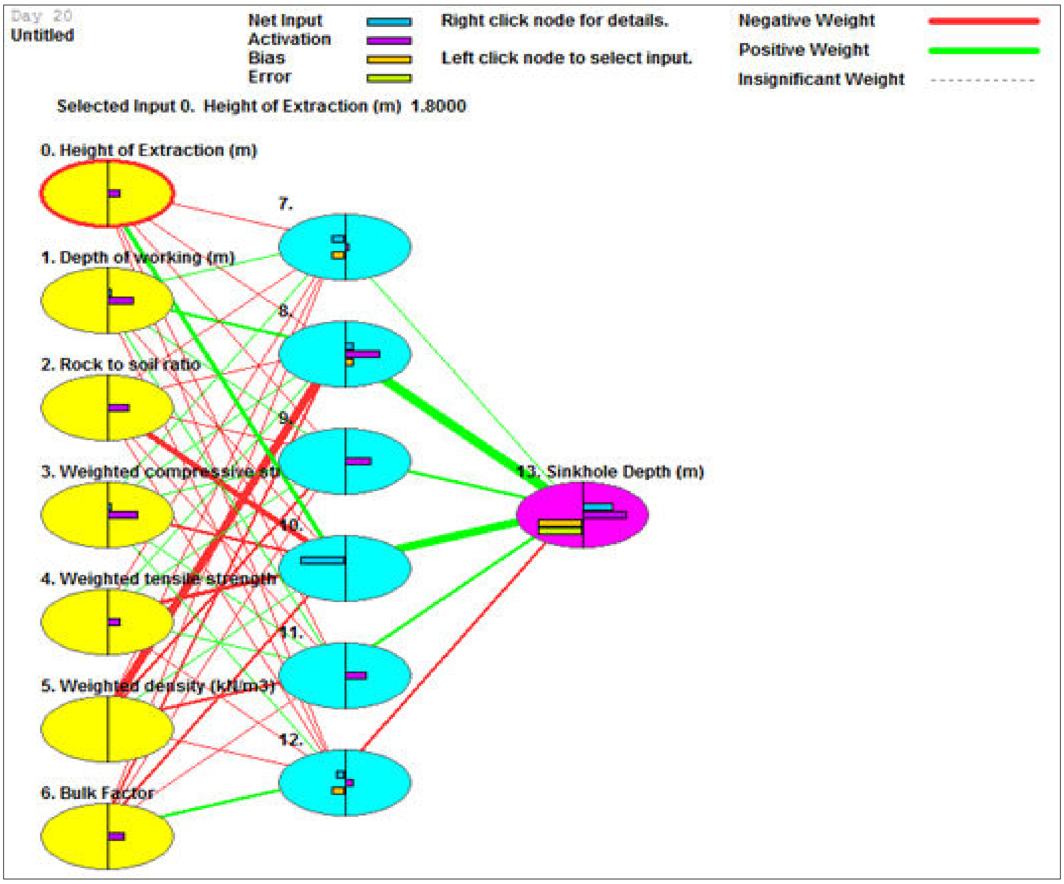

Figure-13. Neural network after model development.

The normalised and relative errors with respect to targeted and average error value of different sinkholes are depicted in Figure-14.

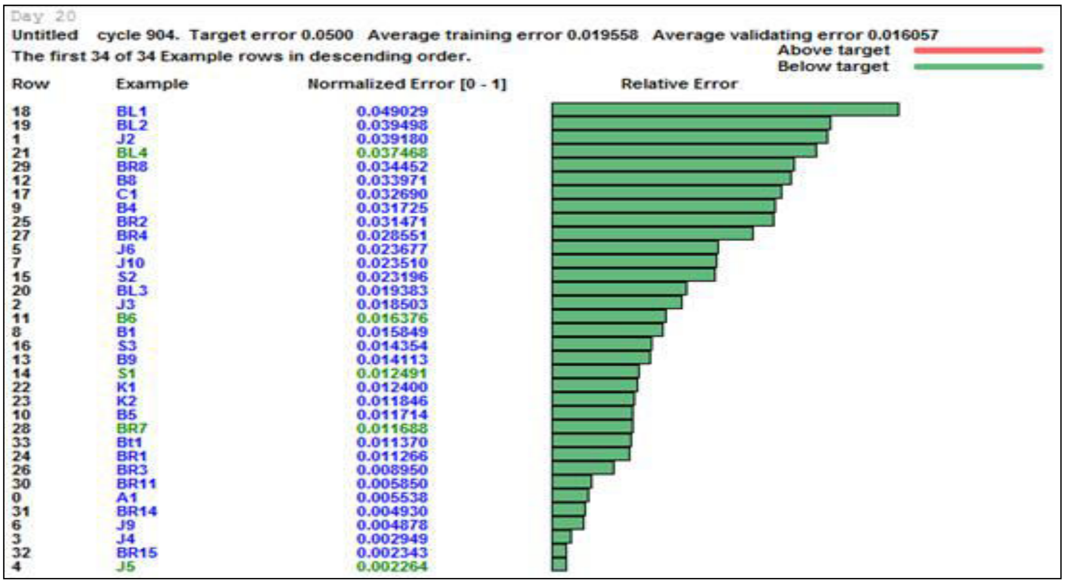

Figure-14. Normalised and relative error with respect to targeted and average error.

In the trained network, weights of input parameters and their relative importance in terms of percentage are shown in (Figure-15 a & b). Similarly, sensitivity of inputs parameters is shown in (Figure-16 a & b). The sensitivity value was obtained by setting all the input values to a median value and then each in turn was increased from the lowest value to the highest value.

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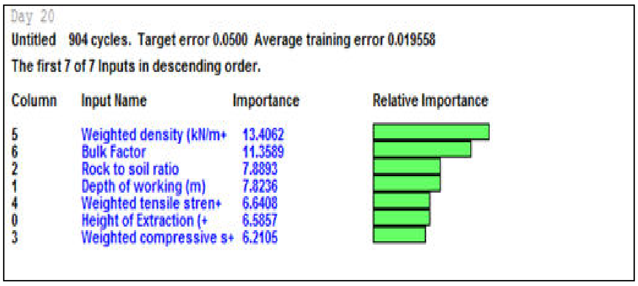
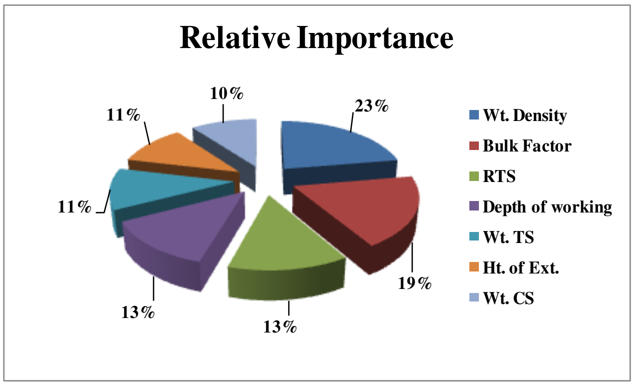
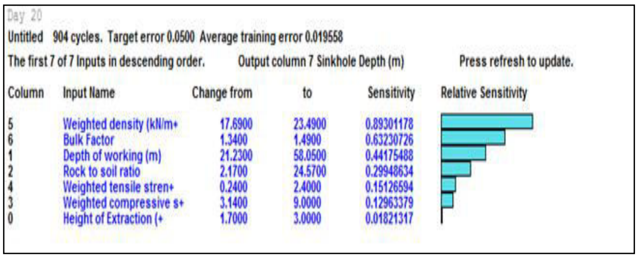


(a)

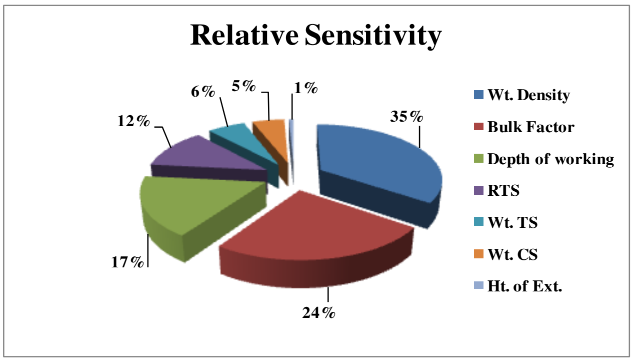


(b)

Figure-15 (a & b). Weights of input parameters and their relative importance in terms of percentage.



(a)



(b)

Figure-16 (a & b). Relative sensitivity of input parameters.

6. MODEL VALIDATION

ANN model was validated by using data of four various coal mines, namely, Jamuna 1 & 2 incline, Bhadra 7 & 8 Incline, Surakachhar main mine, Balgi 1 & 2 mine and Balrampur 10 & 12 Incline. It was found that total ± 10 % of the variation in observed and the predicted data of sinkhole depth (Table-2) (Figure-17). The developed model is of self-learning and with the availability of more number of data will help to fine tune the model.

Table-2. Observed and the predicted sinkhole depth.

Mine	Observed sinkhole depth (m)	Predicted sinkhole depth (m)	Percentage difference
Jamuna 1 & 2 incline (J5)	2.5	2.62	4.8 %
Bhadra 7 & 8 Incline (B6)	2.5	2.73	9.2 %
Surakachhar main mine (S1)	2.0	1.83	-8.5 %
Balgi 1 & 2 mine (BL4)	3.5	3.70	5.7 %
Balrampur 10 & 12 Inclines (BR7)	3.0	3.43	14.34

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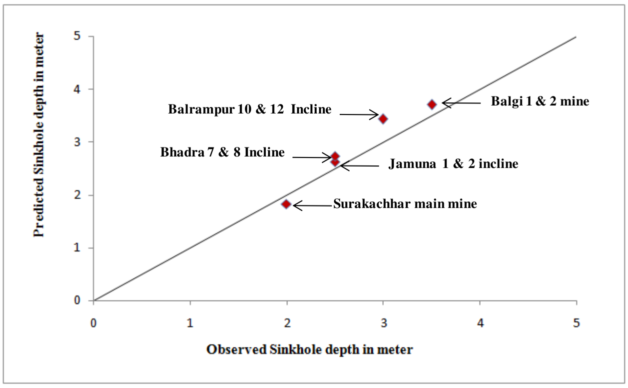

Figure-17. Comparison between measured and predicted sinkhole depth EasyNN-plus.

7. RESULTS AND DISCUSSIONS

The model is developed by carrying out correlation analysis between dependent and independent variables. These variables are studied under different conditions and are chosen on the basis of significant influence of them on the formation of sinkholes. Development & depillaring, presence & absence of faults and influence of water bodies are the major conditions were considered for the study. No parameter can individually determine the formation of sinkholes; hence ANN model was developed with a view of analysing and studying the combined influence of all these parameters.

From (Figure-15 a & b) and (Figure-16 a & b), it was observed that weighted density is having the highest relative importance and sensitivity among the other parameters. It was also observed that the relative importance of different input parameters is not in the same order to that of their sensitivities except weighted density and bulk factor. The model was validated against the data of four sinkholes which were not used in the training. The percentage of error in these cases was about 10%.

It was observed from Figure-17 that Balrampur 10 & 12 Incline (BR7) yielded maximum training error of 14.34 %, in this case, the observed sinkhole depth was 3.0 m and predicted depth given by Easy-NN is 3.43 m.

8. CONCLUSIONS

Sinkhole occurrence is influenced by combination of the various parameters. Each parameter has its own relative degree of influence under different conditions. Rigorous literature review and filed investigations have revealed seven board parameters which are depth of working, height of excavation, rock to soil ratio, weighted density of overburden, weighted compressive strength of overlying rock, weighted tensile strength of overlying rock and weighted bulk factor of overlying rock. The developed ANN model was used to predict the depth of sinkhole subsidence.

The ANN results depict that among the influencing parameters weighted density have the highest relative importance and sensitivity on the formation of sinkhole depth. The deviation of the sinkhole depth predicted by ANN model from the observed sinkhole depth was found that total ± 10 %. This confirms the utility of developed ANN model.

The mining industry will have a great assistance for the sinkhole depth assessment from this model. The model can be more refined and fine tune with the involvement of varied geo-mining conditions covered in various case studies.

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