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## CHARACTERIZATION OF TABLETS MADE FROM MIXTURE OF CHARRED AGRICULTURAL RESIDUES WITH AND WITHOUT EMBEDDED FERTILIZER

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Densification of biochar can reduce transportation and handling costs, as well as significantly decrease loss of biochar during soil application. Although the nutrient-rich biochar tablets may be a potential cost-effective slow-release fertilizer in soil, there is a lack of information on characterization of mixtures of rubber tree twigs and rice residues tablets with embedded NPK fertilizer. Objective of this work was to determine the physical and chemical properties of biochar tablets with and without embedded fertilizer. Biochar tablets were produced by blending of charred rice husk, rice straw, rubber tree twigs, and starch and followed by tableting. Their production with embedded fertilizer was similar to production process of tablets without it, except adding the NPK fertilizer to blending phase prior to tableting. Fourier-transform infrared spectra analysis indicates was utilized for determination of presence of ammonium and phosphorus substances in the biochar tablets with embedded fertilizer (BFs). The NPK fertilizer significantly increased tablet density and total contents of nitrogen, phosphorus, potassium, calcium and magnesium. The presence of higher amount of nutrients in BFs suggests that it could release nutrients for plant use.

Keywords: biochar; carbon; nutrient; rice husk; rubber tree twigs

Malaysia is one of the world top producers of natural rubber (Department of Statistics Malaysia, 2016). Oil palm and rubber dominate the agricultural land utilization in Malaysia; rice is in the third place. Rice cultivation covers an area of nearly 209,300 ha (Karim et al., 2004). Approximately 4 million tons of rice straw had been produced by 2015 and 0.48 million tons of rice husk is produced annually in Malaysia (Shafie et al., 2014).

Rubber tree twigs and rice residues generated from rubber pruning and rice production are commonly left to decompose on the ground or burned in the field with consequent negative impact on the environment (Rondon et al., 2007). These agricultural residues represent the lowcost renewable resources, which should be reused and valorised. An alternative to agricultural residue management is thermal conversion of rice residues and rubber tree twigs to biochar, while simultaneously generating the energy during heating (Dhaundiyal and Hanon, 2018). Biochar can be utilized as an efficient long-term C sink in terrestrial systems for mitigation of climate changes. Moreover, it is a suitable soil amendment as it increases water and nutrient retention (Vaughn et al., 2013). Nevertheless, the brittle and low density biochar hinder the process of storage, transportation, and even soil application. Husk and Major (2008) reported that 25% of biochar applied was lost during the field application. Approximately 20-53% of biochar incorporated into soil was also lost by surface runoff during

heavy precipitation events (Major et al., 2010). High amount of ash is also produced during the biochar production process (Dróżdż et al., 2016). Densification of biochar is one of the potential ways to decrease the high costs associated with transport and application rates during soil application, as it is challenging to handle the light density of biochar.

The addition of lignocellulosic biomass-derived biochar into the soil complements mineral fertilizers, increasing crop yield. Several researchers have suggested that supplementing of biochar with NPK fertilizer and bentonite clay boosted rice yields by 15-30% compared to chemical fertilizers applied at a rate of 500 kg·ha<sup>-1</sup> (Joseph et al., 2013; Qian et al., 2014). This could minimize the chemical inputs and the polluting effect of overutilization. BFs will have lesser amounts of voids and higher density, facilitating its handling. Although the nutrient-rich biochar tablets are suggested to be better than conventional fertilizer in terms of supplying the plant nutrition demand throughout the specific plant's lifespan, there is lack of information on characterization of mixtures of rubber twigs and rice tablets embedded with NPK fertilizer. In presented study, biochar derived from thermal decomposition of rice straw, rice husk and rubber tree twigs was blended with commercial fertilizer and subsequently densified into tablets. The physio-chemical properties of biochar tablets with and without embedded fertilizer were investigated for the assessment of being an environmentally friendly slow-release fertilizer.

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### **Material and methods**

#### Sample collection and preparation

Rubber tree twigs and rice residues were collected from a rubber plantation and a paddy field in Perlis (located at  $6.4449^{\circ}$  N, 100.2048° E). The samples were sun-dried for 3 days. Rubber tree twigs were chopped into 2 cm sections using a SIMA Model RC61605 wood chipper (with a capacity of 2,000–4,000 kg·hr<sup>-1</sup>, China). The rice straws were cut into pieces 15 cm long and kept in a gunny sack, whereas the rice husks were ground and sieved into size of 1 mm and kept in a sealed container. The rubber tree twigs, rice straws and rice husks were charred separately prior to the production of the biochar tablets.

#### **Biochar production and preparation**

Biochar was produced using a stainless-steel kiln fabricated locally at the Department of Mechanical Engineering Technology, Universiti Malaysia Perlis, Perlis, Malaysia. The temperature was measured using Lutron Model TM969 handheld infrared thermometer (measurement up to 1,000 °C, adjustable emissivity value from 0.1 to 1.00) every 30 minutes during the combustion. During the charring, a maximum temperature of 500 °C was attained after 1 hour of ignition. The average temperature of the kiln throughout the charring process was approx. 340 °C. The charring process was completed in 3 hours, after which the charred product was collected and weighed to determine the percentage yield of the charring process. The result indicates that the percentage yield was approx. 34%. The charred materials were ground and sieved to pass a 1 mm sieve prior to their blending with and without fertilizer.

#### **Biochar tablet (BT) production**

The biochar tablets (BTs) consisted of 50% charred rice husk, 30% charred rice straw and 20% charred rubber twigs. Subsequently, biochar was blended with 20 wt.% of starch and 30 wt.% of water as a binder using a mixer. Thereafter, the mixture was heated at 100 °C for 5 minutes using a water bath. Afterwards, the biochar mixture was densified using a single press tablet with punch weight of 0.4 t. Tablets with dimensions of 6 mm in height and 10 mm in diameter were generated. BTs were oven dried at 60 °C for 1 hour. After oven-drying, the biochar tablets were cooled and kept in air-tight container.

# Biochar tablets with embedded fertilizer (BFs) production

Biochar derived from rice straw, rice husk and rubber tree twigs was blended with 20 wt.% of starch and 30 wt.% of water as binder using a mixer. The mixture was then heated at 100 °C for 5 minutes using water bath. Subsequently, 5:3:3 NPK fertilizer was mixed into the biochar. The sources of NPK fertilizer were ammonium sulphate, triple superphosphate, and muriate of potash, respectively. The mixture ratio of fertilizer to biochar was 1:2. The mixture was densified using a single press tablet. The biochar tablets embedded with fertilizer (BFs) were then dried at 60 °C for 1 hour in the oven. After oven-drying, BFs were left to cool down and stored in an air-tight container.

#### Physical properties test

## Unit density and tablet durability

The unit density of the BTs and BFs was measured by weighing the individual tablets and calculating their volume based on their length and diameter as per the following equation (Eq. 1):

$$\rho = \frac{m}{V} \tag{1}$$

where:

 $\rho$  – density of individual tablet (g·cm<sup>-3</sup>)

*m* – weight of individual tablet (g)

V – volume of individual tablet (cm<sup>3</sup>)

Tablet durability was measured by weight loss upon vibration. Initial weight of both the BTs and BFs was recorded. Afterwards, tablet durability was tested using a vibrating screen size 4 mm sieve. After 10 minutes, they were weighed again and the final weights were recorded. The tablet durability was calculated using the following equation (Eq. 2):

$$Pd = 100 - \left(\frac{mi - mf}{mi}\right) \times 100\%$$
 (2)

where:

Pd – tablet durability (%)

*mi* – initial weight of samples (g)

*mf* – final weight of the samples (g)

#### Chemical properties test

#### pH and electrical conductivity

By mixing the sample with deionized water at a 1 : 10 ratio for 24 hours, the pH and electrical conductivity (EC) of BTs and BFs were determined using Sartorius Model PB10 pH meter (measuring pH range: 0–14; accuracy:  $\pm 0.01$ ) and Model EC3000 conductivity meter (measuring range: 0–200 mS; accuracy:  $\pm 2\%$ ) respectively.

#### Total macronutrient

Dry ashing was adopted for the content determination of phosphorus (P), potassium (K), calcium (Ca) and magnesium (Mg). Approx. 1 g of sample was weighed into crucible and then initially ashed at 300 °C for 1 hour in a DAIHAN model FHP03 muffle furnace (WiseTherm, Korea, resolution: 1 °C, 1 min). Later, the temperature was increased to 500 °C and maintained until the samples became grayish in colour. Afterwards, the samples were left to cool down. Few drops of distilled water were added to the samples, followed by 2 ml concentrated hydrochloric acid (HCl). Samples were evaporated to dryness on a hot plate. A 10 ml of 20% nitric acid (HNO<sub>3</sub>) was added to the samples and placed in a water bath for 1 hour. Subsequently, samples were filtered through Whatman no. 2 filter paper into volumetric flask of 100 ml and diluted to this volume.

#### Total carbon and nitrogen analysis

Total carbon (TC) and total nitrogen (TN) of the BTs and BFs were determined using a LECO model TruMac CNS analyzer (LECO Corporation, USA).

#### Fourier transform infrared spectra (FTIR) analysis

The BTs and BFs were analysed using the Perkin-Elmer FTIR Spectrometer Spectrum 2000 (measuring range: 7,800–400 cm<sup>-1</sup>, resolution: starting with 0.5 cm<sup>-1</sup>) with a Perkin-Elmer Universal Attenuated Total Reflectance (ATR) sampling accessory to obtain their FTIR spectra. Data collection and processing were performed by Spectrum version 6.2.0.0055 software (Leng et al., 2011).

#### Statistical analysis

Pair-samples *T*-test was used to detect significant differences in the chemical and physical properties between BTs and BFs. Statistical Analysis System (SAS) software version 9.2 was used for the statistical analysis.

### **Results and discussion**

#### Unit density, tablet durability and moisture content

Density is a fundamental physical property which controls the movement and interaction of biochar in the soil. Low density (0.25–0.3 g·cm<sup>-3</sup>) has been reported for soft wood biochar (Brewer et al., 2014). This density makes it challenging for biochar to be handled and transported. Furthermore, significant amount of biochar with such density is lost during soil application (Husk and Major, 2008). Unit density of BFs (0.90 g·cm<sup>-3</sup>) was significantly higher than that of BTs (0.70 g·cm<sup>-3</sup>). This difference could be attributed to the pores being filled with the NPK fertilizer (BFs), resulting in the density increase of BFs. The densities of BTs and BFs were higher than that of softwood biochar reported by Brewer et al. (2014). This indicates that tableting enables binding and compressing of the biochar particles to increase the densities of BTs and BFs.

Handling, transporting and storing of biochar are influenced by its durability (Weber and Quicker, 2018; Macák et al., 2015). The tablet durability of BTs and BFs fall in the range of high durability reported by Adapa et al. (2003). Higher durability of BTs and BFs indicates that they do not easily crack and the mass loss during their transportation can be reduced.

# pH, EC, total content of phosphorus, potassium, calcium, and magnesium

Biochar has a significant impact on the physicochemical processes in soils that may influence the microbial communities and this aspect strongly depends on the soil pH (Sheng et al., 2016). The alkalinity of biochar increases the soil pH with a simultaneous increase in growth of soil microorganism, as well as bioavailability of soil organic carbon (Sheng and Zhu, 2018). The BT showed a high pH (9.34) and this finding was similar with the pH of biochar obtained by Leng et al. (2011), who also studied biochar production by combustion at low temperature and long residence time. On the contrary, fertilizer addition to biochar tablets significantly decreased the pH value to 5.92 (Table 1). When the charred rice residues and rubber tree twigs were mixed with ammonium sulphate, the dissociation of protons from oxygenated functional groups of biochar surfaces and ammonium sulphate released free hydrogen ions (Xue et al., 2017; Singh et al., 2017). Sulphuric acid was generated after the binding reactions of free hydrogen ions and sulphate ions, thereby reducing the pH of the BFs.

Electrical conductivity (EC) is a predominant factor for controlling seed germination and plant growth (Andreasen et al., 2014). The EC of biochar greatly depends on the combustion conditions and the biomass type used to produce it (Mandal et al., 2018). The EC value of BTs was 3.78 ms·cm<sup>-1</sup> and it was in the range of biochar EC value reported by Limvikran et al. (2018). A significantly higher value of EC of BFs (41.16 ms·cm<sup>-1</sup>) can be attributed to the deposit of mineral salts thanks to addition of NPK fertilizer. Blending of fertilizer with the BFs led to significantly higher concentration of total phosphorus, potassium, and calcium (Table 1). It is essential for the BFs to contain ample amounts of essential plant nutrients, which could substitute or supplement conventional fertilizers. Total content of magnesium in BTs (0.20%) was significantly higher than in BFs (0.17%). It appears that embedding with fertilizer led to lower magnesium content in the BFs. Increase in potassium and calcium content in the BFs might have caused competition with the magnesium in terms of binding with

Table 1	pH, electrical conductivity (EC), total content of phosphorus, potassium, calcium, and magnesium of tablets
	produced from charred rice residues-rubber tree twigs mixture embedded with (BFs) and without fertilizer (BTs)

Element	Types of biochar tablets			
	without fertilizer (BTs)	with fertilizer (BFs)		
рН	9.34 <sup>*a</sup> ±0.01	5.92 <sup>b</sup> ±0.02		
EC (ms⋅cm <sup>-1</sup> )	3.78 <sup>b</sup> ±0.04	41.16 <sup>a</sup> ±0.76		
Phosphorus (%)	0.07 <sup>b</sup> ±0.01	0.36 <sup>a</sup> ±0.01		
Potassium (%)	1.23 <sup>b</sup> ±0.09	2.45 <sup>a</sup> ±0.06		
Calcium (%)	$0.73^{b} \pm 0.06$	1.09 <sup>a</sup> ±0.04		
Magnesium (%)	0.2 <sup>a</sup> ±0.01	0.17 <sup>b</sup> ±0.01		

\* – means (n = 3) within a row with the same letter indicate no significant difference between the treatment means at lpha = 0.05

the negative biochar surface charge. The magnesium most probably precipitated with the phosphate and ammonium, formed magnesium ammonium phosphate, which was easier to decompose thermally during the tableting processing (Chen et al., 2015).

## Total content of carbon and nitrogen

Total content of C in BTs (48.49%) was lower than the C content in biochar reported in literature (Yi et al., 2016; Gonzaga et al., 2017). This could be caused by higher amount of ash in the rice husk, resulting in a lower total C concentration in the BTs. This is consistent with the observation made by Claosten et al. (2014), who also discovered that the lower C content of rice husk (38.10%) was because rice husk is composed of much higher amount of ash in contrast to other agricultural residues. In comparison to C content of BTs, the reduced C content in BFs (32.35%) is related to the added mineral salt embedded in the tablet with fertilizer. This agrees with Dunnigan et al. (2018), who also observed that high mineral salt content reduced the C content in rice husk-derived biochar.

Total *N* content (0.75%) in BTs was comparable to the reported *N* content of rice husk biochar produced at low temperature (Yi et al., 2015; O'Connor et al., 2018). The blending of ammonium sulphate fertilizer with the BFs significantly increased the concentration of total *N* content (4.96%). Nitrogen is an important element required for successful plant growth, development, and reproduction. Application of BFs can result in increase in the plants' absorption of inorganic nitrogen compared to the BTs.

#### **FTIR Analysis**

Fig. 1 shows the bands present in the spectra of tablets made of charred rice residues-rubber tree twigs mixture embedded with (BFs) and without fertilizer (BTs). As expected, significant changes occurred in the charred rice residues-rubber tree twigs tablets after their embedding with NPK fertilizer. The absorption band between 1,400.75–1,614.25 cm<sup>-1</sup> for aromatic C ring and C–O stretching (1,080.16 cm<sup>-1</sup>)



Fig. 1 FTIR spectra of tablets made of charred rice residues-rubber tree twigs mixture embedded with (BFs) and without fertilizer (BTs)

are observed in both BFs and BTs. The presence of aromatic C ring and primary alcohol C-O stretching are typical chemical groups of biochar (Armynah et al., 2018). The chars consist of aromatic C compounds that are degraded slowly by microorganisms. The formation of C–O stretching indicates that the biomass was partially decomposed during the combustion. These findings are consistent with Leng et al. (2013), who also discovered that the presence of primary alcohol C-O stretching in the char was due to the partial oxidation of cellulose in the charring process. This indicates that ability of BFs and BTs to release the nutrients slowly is attributed to the presence of easily degradable aliphatic and oxidized compounds, as well as the aromatic compounds.

Broad absorption at 3,420.56 cm<sup>-1</sup> indicates the presence of alcohol and phenolic groups in the charred rice residues and rubber tree twigs mixture pellet. Fig. 1 shows the appearance of NH stretch (3,137.25 cm<sup>-1</sup>) in the BFs, suggesting the sorption of ammonium substances to the char. In contrast to BTs, strong stretch occurs at 650 cm<sup>-1</sup>, suggesting the presence of sulphonic acids in the BFs. This is attributed to higher amount of ammonium sulphate added to the charred rice residues and rubber tree twigs mixture Phosphorus pellet. compounds (1,400.75 cm<sup>-1</sup>) were also observed in the BFs due to the addition of rock phosphate fertilizer.

## Conclusion

process increases the Tableting densities and durability of BTs and BFs. In terms of quality, higher amount of nutrients in BFs makes it a potential nutrient supplier for plants. The blending of ammonium sulphate fertilizer with the biochar tablets significantly increased the concentration of total N, which is essential element required for successful plant growth, development, and reproduction. Therefore, application of BFs can increase the amount of inorganic nitrogen absorbed by plants. BFs are not only made up of aromatic compounds but they also include easily degradable aliphatic and oxidized C compounds. Therefore, it has the potential to slowly release the nutrients and to serve as a replacement of the inorganic fertilizer. Further investigation is also needed to determine the decomposition rate and nutrient release of biochar with and without embedded fertilizer.

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## MONITORING OF GAS PRODUCTION DURING THE BIOWASTE COMPOSTING

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The aim of this paper was to monitor the production and composition of gases from the biowaste landfill in terms of the utilized composting process technology. Processing technology of biowaste in the reference sample V1 was without modification; process optimization technology – material homogenization by overturning and irrigation – was used for the second sample V2. Gas measurements (methane, carbon dioxide, ammonia, nitrous oxide) were conducted during the first and sixth weeks after their establishing. At the same time, samples were taken for laboratory determination of the dry matter content of examined materials, pH and C/N ratio. It has been statistically proved that there was a significantly higher gas production in V2, which was overturned and irrigated, than in V1. The measured  $CO_2$  values were 2.5 times higher in V2 in comparison to V1. The mean  $CH_4$  production in the stack V1 was 96.35 mg·m<sup>-3</sup> and 235.9 mg·m<sup>-3</sup> in the stack V2, which is 2.5 times more. Due to overturning and irrigation of composted material in the stack V2, the decomposition of microorganisms was faster, which also affected the amount of released gases.

Keywords: biological waste; municipal waste; landfill gases; composting

The issue of waste management is one of the biggest environmental challenges in Slovakia. Generally, municipal waste in Slovakia contains a large amount of waste suitable for sorting and recovery. It includes e.g. plastics, paper, glass, metals and biodegradable waste. Landfilling each of these components is economically disadvantageous and represents a major health risk (Hrabčák, 2013). Biodegradable waste (BDW) accounts for 40% of the mixed waste in average. It might seem that biodegradable waste does not represent a risk to the environment. However, BDW needs the optimal conditions for its decomposition, recovery and utilization of nutrients in the form of compost (Demirbas, 2011). Landfills do not provide these conditions and biowaste is compressed together with other kinds of waste in the landfill. Thereby, decomposition occurs without air and causes putrescence process. The harmful gases (such as methane) are released into the air during rotting and groundwater is polluted by landfill leachates. Numerous waste management activities are carried out in the exterior or in front of operating halls and thus they become the source of surface or fugitive emissions (Hroncová and Ladomerský, 2017). Gaseous emissions in the air represent probably the largest share of negative environmental impact of municipal waste landfilling. These are mainly methane (CH<sub>4</sub>), nitrogen oxides, hydrogen sulphide and volatile non-methane organic compounds (Hrabčák, 2017). Biowaste can be composted either as municipal waste (35 to 70% of its total weight deposited in the Slovak Republic at landfills is currently represented by biowaste) or incinerated in

waste incinerators. Biowaste composting is considered by experts to be one of the most efficient means of CO<sub>2</sub> production reduction in human activities and thus also a method exploitable in fight against global warming. Due to the implementation of the European Union landfill directive to divert the biodegradable waste fraction from the municipal solid waste stream (CEC, 1999), composting has received widened interest as a means of addressing the current waste management challenges. During composting, fugitive emissions primarily depend on the compost feedstock, as well as on process and operating conditions (Amlinger et al., 2005; Amlinger et al., 2008). In addition to the composting operation, the C/N ratio, texture of the input material, humidity and temperature conditions are the essential parameters influencing the greenhouse gas production (He et al., 2001; Eklind et al., 2007; Amlinger et al., 2008). Globally, biogas production for energy use is considered to be active step towards climate protection and sustainable life technology, in which waste from animal production, livestock excrements, residues of various crops (Kažimírová et al., 2018) can be used as starting materials.

The aim of the experiment was to monitor the production and composition of landfill gases and investigate the impact of the used bio-waste recovery process on landfill gas production.

Hypotheses:

H0: There is no significant difference between gas production at stacks V1 and V2 at the start of the biodegradation process (week 1).

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- H1: There is no significant difference between gas production at stacks V1 and V2 on week 6 of the biodegradation process.
- H2: There are no significant differences in gas production between week 1 and 6 of the biodegradation process at each stack.

## **Material and methods**

The composting plant for biodegradable waste, where the experiment was carried out, is located in the cadastral area of Výčapy-Opatovce at an altitude of 155 m. This village belongs to the area of lowland climate with slight temperature inversion. Total landfill capacity is 5,000 tonnes per year of biodegradable waste for composting. Two stacks of biowaste (V1 and V2) at the same time and with the same volume (10 m<sup>3</sup>) were needed to set up the experiment with implementation of a different technological process for composting waste at each pile. In terms of technology of biowaste processing, reference sample V1 was untreated and the second sample V2 was optimized by homogenization of material by overturning and irrigation. Each stack was equipped with a shaft for exhaustion of landfill gases. During the experiment, the temperature inside each pile was monitored daily in order to determine the need to overturn and irrigate the waste in V2. Gas production measurements (methane, carbon dioxide, ammonia, nitrous oxide) at each stack were conducted during the first and sixth weeks after their establishing. Simultaneously, samples from V1 and V2 were taken for laboratory determination of the content of dry matter, pH and C/N ratio of the materials examined. Considering the processing of collected data, programme Statistica 10 was utilized for statistical analysis of significant differences. Pfeuffer GT 1 needle thermometer was used to measure compost temperature, allowing measurements at a depth of up to 1.5 m, as well as on the surface. Determination of compost moisture, pH and C/N nutrient ratio was performed at a certified laboratory. These physical and chemical properties are important for comparison of two biowaste recovery technologies, by which the decomposition rate and the correct recovery method can be assumed for further use. Multigas Monitor

1312 gas analyser, together with the Multipoint Sampler 1309 sampler were used to measure emissions.

Measuring points:

- V1 measuring in the shaft fitted in a stack without modification of technological process;
- V2 measuring in the shaft fitted in a stack with optimization of technological processes.

## **Results and discussion**

Table 1 shows the results of a 24-hour gas production measurement in both V1 and V2 stacks monitored on week 1 after sample creation. During the first week, mean CO<sub>2</sub> content reached values of 46,335.58 mg·m<sup>-3</sup> in V1, and 5,2551.29 mg·m<sup>-3</sup> in V2. Mean N<sub>2</sub>O content, production of which slightly decreased in both piles during the measurement, reached value of 55.69 mg·m<sup>-3</sup> in V1, and 64.00 mg·m<sup>-3</sup> in V2. Recorded mean NH<sub>3</sub> content was 471.19 mg·m<sup>-3</sup> in V1, and 436.93 mg·m<sup>-3</sup> in V2. With moderate fluctuations, mean CH₄ production reached 862.19 mg·m<sup>-3</sup> and 750.63 mg·m<sup>-3</sup> in V1 and V2, respectively. During week 1, production of landfill gases at monitored bio-waste piles V1 and V2 did not differ significantly (Table 1) despite the fact that they contained identical material and volume of each stack and gas contents were measured immediately three days after creation of samples. Both samples were without any intervention at that time. From the material samples taken during the week 1, the same values of pH (6.13) and moisture (68.42%) were found in both V1 and V2 stacks (Table 3).

The gas production results obtained in the 24-hour measurement during the week 6 after establishing of V1 and V2 are shown in Table 2. It was statistically proven that there was recorded significantly higher gas production in V2, which was overturned and irrigated, than in V1 (Table 2). The CO<sub>2</sub> content was 2.5 times higher and the N<sub>2</sub>O content was almost 3 times higher in V2 in comparison to V1. Mean NH<sub>3</sub> content in V1 was 12.74 mg·m<sup>-3</sup>; mean NH<sub>3</sub> content in V2 was 58.35 mg·m<sup>-3</sup>, making it almost 5 times higher. Mean CH<sub>4</sub> production was 96.35 mg·m<sup>-3</sup> in V1 and 235.9 mg·m<sup>-3</sup> in V2 – 2.5 times higher. The amount of gases released depends on microbial activity; therefore, it can be concluded that microorganisms decomposed the composting material in

Gas	Measurement points – stack	Number of meas.	Average $\pm$ stand. dev.	P-value
60	V1	466	46,335.58 ±3,380.66 <sup>a</sup>	0.06
CO <sub>2</sub>	V2	466	52,551.29 ±3,000.82 <sup>a</sup>	0.06
NO	V1	466	$55.69 \pm 10.68^{\circ}$	0.00
N <sub>2</sub> O	V2	466	64.00 ±11.13 <sup>a</sup>	0.08
NH <sub>3</sub>	V1	466	471.19 ±30.55 <sup>a</sup>	0.00
	V2	466	436.93 ±28.62 <sup>a</sup>	0.08
CH₄	V1	466	862.19 ±48.27 <sup>a</sup>	0.06
	V2	466	$750.63 \pm 38.40^{a}$	0.06

**Table 1** Gas production at measurement points V1, V2 – week 1 ( $mg \cdot m^{-3}$ )

<sup>a</sup> the same upper indices indicate – there is no significant difference in gas production between V1 and V2 at *p* <0.05

Gast	Measurement point – stack	Number of meas.	Average $\pm$ stand. dev.	P-value	
<u></u>	V1	462	6,481.49 ±802.72 <sup>a</sup>	0.00000	
CO <sub>2</sub>	V2	462	16,135.51 ±1,852.36 <sup>b</sup>	0.00009	
NO	V1	462	$4.45 \pm 0.50^{a}$	0.00008	
N <sub>2</sub> O	V2	462	13.00 ±1.57 <sup>b</sup>	0.00008	
NH <sub>3</sub>	V1	462	$12.74 \pm 1.10^{a}$	0.00008	
	V2	462	58.35 ±5.45 <sup>b</sup>	0.00008	
CH₄	V1	462	96.35 ±15.33ª	0.00000	
	V2	462	235.90 ±35.00 <sup>b</sup>	0.00009	

**Table 2** Gas production at measurement points V1, V2 – week 6 (mg $\cdot$ m<sup>-3</sup>)

 $^{ab}$  different upper indices indicate significant difference in gas production in V1 and V2 at p <0.05

Table 3 Analysis of material samples from stacks V1	and V2
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Time of		V1		V2			
sampling	рН	moisture (%)	C : N	рН	moisture (%)	C:N	
Week 1	6.13	68.42	9.12 : 1	6.13	68.42	9.12:1	
Week 6	7.29	27.45	23.59 : 1	8.22	46.9	12.7 : 1	

V2 more rapidly thanks to overturning and irrigation. As reported by other authors (Sundberg and Jonsson, 2007), it is possible to shorten the time needed for production of a stable compost product and thus to increase the efficiency of composting plants by increasing the aeration and adding water to compensate for drying. The same results were achieved by Hrad et al. (2014), who reported that emissions were higher during the overturning and thus the frequency of shovelling appears to be a key factor in regulation of emissions during biowaste composting.

There were also observed different pH values in V1 and V2 – namely 7.29 and 8.22, respectively – different moisture contents in material samples taken from V1 (27.45%) and V2 (46.9%) on week 6 (Table 3).

From the initial values of the gas concentrations measured at week 1, the gas concentrations at week 6 in each stack decreased to significantly



lower levels (Figs. 1 and 2). However, in V2, this decrease was smaller since the decomposition process taking place inside the stack was supported by aeration as a result of overturning, making the composting an aerobic process. However, aeration caused the compost drying. Therefore, irrigating was needed in order to increase the temperature, allowing thus the faster degradation of composted material, since moisture facilitates the movement of microorganisms and serves as a medium for chemical reactions.

The maximum CO<sub>2</sub> concentrations observed during the week 1 correspond to the maximum temperatures recorded during the first days of composting; as the temperatures gradually dropped, the amount of CO<sub>2</sub> produced also decreased. These results are consistent with the findings of several other authors (Plíva et al., 2006; Jiang, 2011), who reported that the amount of released  $CO_2$ decreases with compost maturation time; furthermore, they observed that material temperature, pH and C/N nutrient ratio have also significant impacts on CO<sub>2</sub> compost production. Fig. 3 shows the course of temperature during the entire process, indicating the time of overturning and irrigating the stack V2. The temperature rose rapidly at the start of the experiment, a maximum temperature of 70 °C was







Fig. 3 Temperature profile of samples in V1 and V2

observed on the third day, causing a short mesophilic phase followed by a slight decrease in temperature to 45 °C. After adjusting by means of overturning and irrigating, the temperature rose close to 70 °C. However, the temperature inside the pile is also affected by the external temperature, which varied from 7 to 27 °C. Hellmann et al. (1997) and Osada et al. (2010) observed similar results in a system of composting in rows. These temperature variations were caused by the degradation of partially decomposed materials that were transferred from anaerobic to aerobic areas (Jiang, 2011).

Considering the measurement results recorded during the week 6,

it is obvious that the production of the monitored gases was higher in V2 compared to V1. During the first week, the C/N ratio of samples V1 and V2 was equal, 9.12 : 1. During the week 6, the C/N ratio of samples V1 and V2 was 23.59 : 1 and 12.7 : 1, respectively. Table 3 shows that the observed gas concentrations in sample V2 were higher. The C/N ratio is an important factor in controlling microbiological metabolism (Godwin et al., 2017). As reported by Amlinger et al. (2008), the amount of CO<sub>2</sub> released also depends on the C/N ratio. CO<sub>2</sub> emissions are lower when the C/N ratio of processed raw materials is higher. However, a low C/N ratio is responsible for higher NH<sub>3</sub> emissions, especially at good aeration

and high compost temperatures. Therefore, a C/N ratio >25 will help to minimize NH<sub>3</sub> and N<sub>2</sub>O emissions. However, a C/N ratio >35 may result in the available nitrogen pool limiting the proper decomposition and humification process (Amlinger, 2008). Jiang (2011) states in his study that a lower C/N ratio resulted in a higher production of methane emissions by reduction in the air spaces. High aeration rate can reduce the CH<sub>4</sub> emissions, whereas the emissions of N<sub>2</sub>O and NH<sub>3</sub> increase. As the author further states, the moisture content can affect the methane and ammonia emissions during the composting period. However, he does not consider the moisture impacts significant.

For the purpose of reference, monitoring report of gas measurement emitted from the body of municipal solid waste mixed with biodegradable waste using degassing shafts is provided (Potyš, 2018). The author observed the average CO<sub>2</sub> content of 15.6 vol. %, which is 28,6681.2 mg·m<sup>-3</sup>, and average  $CH_4$  content of 21.4 vol. %, which is 142,257.6 mg·m<sup>-3</sup>. Although these data are not comparable with experiment presented, because the amounts and compositions of gaseous emissions depend on moisture, temperature, etc., by application of anaerobic decomposition stage, it can be assumed that the municipal waste mixed with biowaste produces higher amounts of harmful gases than biodegradable waste composted separately. However, this will be the subject of further investigation.

#### Conclusion

Gaseous emissions (especially methane) from composting can be a significant source of anthropogenic greenhouse gases emissions and air pollution. An experiment was conducted to estimate the effects of aeration by means of overturning and moisture content on the gas production during composting. A 24-hour measurement method was used and the gas production was compared in two open stacks located at two waste piles with different processing technology of composted material. Results showed that the production of all monitored gases was the highest at the beginning of composting process and the amount

of gases gradually decreased during the process. By comparing the two technological compost treatments, it has been shown that the higher gas production and faster decomposition of microorganisms occur when compost material is overturned and irrigated, resulting in reduction of time necessary for achieving of a stable compost product and increasing compost efficiency. On the basis of the evaluated data in the first week, the H0 hypothesis can be accepted, since the production of landfill gases in the monitored biowaste stacks V1 and V2 did not differ significantly at the beginning of the process. Hypothesis H1 proved to be false, because statistical analysis of significant differences has shown that the gas production in V2, which was overturned and irrigated, was significantly higher than in V1 in the sixth week. Furthermore, this is also true for H2 hypothesis, since by analysing significant differences in gas amounts produced during the first and sixth weeks, it was statistically proven that landfill gas production differs significantly at the significance level  $\alpha$  = 0.05. Directive of the European Parliament and Council 2008/98/EC on waste, as well as Council Directive 1999/31/EC on the landfill of waste, clearly prioritize the use of biodegradable waste according to the waste hierarchy - material recovery before energy recovery and waste disposal (Jensen et al., 2017). Consequently, all biowaste that is not contaminated with foreign substances and other unsuitable ingredients should be used primary for compost production.

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# APPLICATION OF COMPUTATIONAL INTELLIGENCE METHODS FOR PREDICTING SOIL STRENGTH

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The aim of this study was to make predictions for soil cone index using artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and a regression model. Field tests were conducted on three soil textures and obtained results were analyzed by application of a factorial experiment based on a Randomized Complete Block Design with five replications. The four independent variables of percentage of soil moisture content, soil bulk density, electrical conductivity and sampling depth were used to predict soil cone index by ANNs, ANFIS and a regression model. The ANNs design was that of back propagation multilayer networks. Predictions of soil cone index with ANFIS were made using the hybrid learning model. Comparison of results acquired from ANNs, ANFIS and regression models showed that the ANFIS model could predict soil cone index values more accurately than ANNs and regression models. Considering the ANFIS model, a novel result on soil compaction modeling, relative error ( $\varepsilon$ ), and regression coefficient ( $R^2$ ) were calculated at 2.54% and 0.979, respectively.

Keywords: artificial neural network; ANFIS; cone index; modeling; Levenberg-Marquardt algorithm

Soil compaction is an index that displays the soil structure's physical deterioration and is defined as increased soil bulk density or reduced porosity. Certain methods, standards, and indices are used to determine the soil compaction, such as soil color index (compression recognition by means of observation), measurement of soil bulk density, penetrating the soil with radars and evaluation of the soil cone index (Hemmat et al., 2014; Raper et al., 1990; Upadhyaya et al., 1994). In terms of these methods, cone penetrometers were determined as the most reliable (Abbaspour-Gilandeh and Rahimi-Ajdadi, 2016; Clark, 1999; Mulqeen et al., 1977).

The advantage of using an artificial neural network is that it can create a connection between input and output parameters without any theory of predetermined mathematical relations (Goh, 1995; Kushwaha and Zhang, 1998; Levine et al., 1996). The reason for using ANNs and ANFIS for soil cone index predictions in this study is that they show high prediction capability and no mathematical relationship between dependent and independent variables.

Research has demonstrated a correlation between evaluations of the soil cone index and soil bulk density as parameters related to soil compaction and compression (Bayat et al., 2017; Henderson et al., 1988) and between the soil cone index and moisture content (Faure and Da Mata, 1994).

Abbaspour-Gilandeh et al. (2006) reported that soil electrical conductivity (EC) data were highly correlated to soil texture (% clay content) with a correlation coefficient of 0.916 and that there was a strong linear correlation between soil EC and draft force across a field. The soil cone

index could also be a function of soil electrical conductivity (Abbaspour-Gilandeh et al., 2011).

Santos et al. (2012) used statistical analyses and ANNs for predicting soil penetration resistance based on the soil bulk density and water content. Results showed that ANNs architecture 2-2-2-1 presented an RMSE (Root Mean Square Error) of value less than 0.085, an  $R^2$  equal to 0.98 and a global mean error of approximately 6.75%, whereas the model obtained from statistical analyses presented an RMSE of 0.951 and an  $R^2$  of 0.92.

The aim of this study was to develop models based on computational intelligence methods and the regression method for predicting soil cone index. For the purposes of modeling of the soil cone index, artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and multiple range regression methods were utilized. Finally, performances of these models were compared with each other.

## **Material and methods**

## Field experiments

Field experiments were conducted at the Educational and Experimental Farm of the University of Mohaghegh Ardabili, Ardabil, Iran (latitude 38° 19' N, longitude 48° 20' E). Tests were done on three types of soil texture (loam, loamy sand and sandy loam). The effects of three soil moisture content levels (dry, semi-humid and humid), three sampling depths (0–10, 10–20 and 20–30 cm) and three numbers of tractor passes (0, 10 and 20 passes) on soil cone index were

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investigated by application of a factorial experiment based on a Randomized Complete Block Design (RCBD) with five replications using MSTATC Version 2.0.0 statistical software. Considering each test plot, evaluations were made for soil cone index, percentage of soil moisture content, soil bulk density and soil electrical conductivity.

A tractor-mounted cone pernetrometer (Abbaspour-Gilandeh et al., 2010) was used to measure the strength of the soil. Calculations for cone index were based on measurements of the force required to press a cone with a 130 mm<sup>2</sup> base area and 30° point angle into the soil according to the ASAE standard S313.2.

Soil moisture content percentage was measured utilizing Eq. 1; soil samples were extracted from the given depths and subsequently weighed with a precise scale.

$$MC = \left(\frac{W_w - W_d}{W_d}\right) \times 100 \tag{1}$$

where:

 $W_w$  – weight of wet matter (g)  $W_d$  – weight of dry matter (g)

To determine the soil bulk density, undistributed soil samples were taken from various depths in the range of 0-30 cm from the test field. Samples were oven dried at 105 °C for 24 hours, weighed and measured for weight of dry soil and soil volume. Then, soil bulk density was determined by dividing the weight of sample by its volume. An electrical conductivity meter device was used to evaluate electrical conductivity. The electrical conductivity of a solution should be determined at the temperature of 25 °C. Eq. 2 was used to correct the values of soil electrical conductivity (Abbaspour-Gilandeh et al., 2011).

$$EC_{25} = EC_t - 0.02(t - 25) EC_t$$
 (2)

where:

t

 $EC_{25}$  – electrical conductivity of solution at 25 °C ( $\mu$ S·cm<sup>-1</sup>)

 $EC_t$  – measured electrical conductivity of solution at the actual temperature of the solution ( $\mu$ S·cm<sup>-1</sup>)

 actual temperature of the solution (°C)

#### Design of the Artificial Neural Networks (ANNs) model

A multilayer back propagation network was used for making soil cone index predictions in the network designed in this research. Fig. 1 shows layers and connections of the designed feedforward back propagating artificial neural network. The three algorithms of descent gradient algorithm with momentum, Levenberg-Marquardt algorithm and scaled conjugated gradient algorithm were used to train the network with MATLAB version R2017a (Matlab, 1994).

Selecting the number of neurons in a middle layer is made by "trial and error". In this study, selection for the





number of hidden layers and the number of neurons in the middle layers was made by comparing the performance among different networks. Moreover, the type of function used between input and middle layers was sigmoid tangent and linear was used between middle and output layers.

Data were divided into three subcategories including training, validation and testing in such a way that one fourth of data (25%) were considered for testing, 25% for evaluation and half (50%) for training. The best method of training for data and performance of the developed networks was determined by calculating the mean square error (MSE), sum of square errors (SSE), coefficient of determination ( $R^2$ ), and prediction accuracy (PA) (Gautam et al., 2003; Matlab, 1994).

#### Design of adaptive neuro-fuzzy inference system (ANFIS)

By combining the fuzzy inference system (FIS) with ANNs that is termed ANFIS, it is possible to acquire both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic for predictions. The goal of ANFIS was to determine a model for correct associating of input values with the target. The ANFIS model proposed in this study was a multilayer neural network-based fuzzy system. Its topology is shown in Fig. 2 and the system had a total of five layers. The hidden layers consisted of nodes functioning as membership functions (MFs) and rules. In this model, to estimate soil cone index, 80% of total data was used for training and 20% of the data was used for validation. Triangular shaped membership functions were used as input variables because of their accuracy. The hybrid learning model was selected for soil cone index prediction with ANFIS.

Fig. 3 shows the data set used to train and check the soil cone index model with ANFIS. Training data were marked with the (○) sign and the check data were indicated with the plus sign (+) in Fig. 3. To initialize FIS using ANFIS, two partition methods were used – grid partitioning and subtractive clustering. The main difference between these two methods is related to how the fuzzy



Fig. 2 ANFIS architecture for soil cone index prediction



Fig. 3 Loading training and checking data in ANFIS

Table 1         The results of analysis of variance of soil co	ne index
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Variation source	Degree of freedom	Mean square	
Replication	4	15,949.515 <sup>ns</sup>	
Soil texture	2	6,125,782.724**	
Moisture content	2	430,853.772**	
Texture × moisture	4	555,545.556**	
Tractor traffic	2	1,823,290.459**	
Texture × tractor traffic	4	32,189.957 <sup>ns</sup>	
Moisture × traffic	4	43,466.475*	
Texture × moisture × traffic	8	107,463.83**	
Depth	2	6,029,325.987**	
Texture × depth	4	135,206.146**	
Moisture × depth	4	57,439.856**	
Texture × moisture × depth	8	50,648.257**	
Traffic × depth	4	121,767.287**	
Texture $\times$ traffic $\times$ depth	8	161,720.162**	
Moisture × traffic × depth	8	58,766.067**	
Texture $\times$ moisture $\times$ traffic $\times$ depth	16	79,912.831**	
Error	320	14,879.165	
Total	404	_	

\*\*, \* significant at probability levels of 1% and 5%, respectively and <sup>ns</sup>: no significant

membership function is selected. Considering the grid partitioning method, type and number of the input membership function vector was determined by the user.

## **Results and discussion**

#### Analysis of variance of data

Results of Analysis of Variance for the soil cone index are given in Table 1. Results of ANOVA show that the main effects of soil texture, tractor traffic and sampling depth individually had significant impact on soil cone index (P <0.01). Furthermore, interaction effects of moisture content and tractor traffic on soil cone index was significant (P < 0.05). However, the interaction effect of soil texture and tractor traffic on soil cone index was determined as not significant. This shows that effects of these two factors on soil cone index were independent of each other. The results of this section indicate that effects of the four parameters - soil texture, moisture content, tractor traffic and sampling depth - should be considered in modeling soil cone index (Varga et al., 2013).

## Presenting a regression model for soil cone index

To determine the mathematical model of soil cone index as a dependent variable in relation to the percentage of soil moisture content, data from soil bulk density, electrical conductivity and sampling depth were used as independent variables (Bayat et al., 2017). The multiple-regression model was used for statistical operations. Linear model used as a mathematical model of soil cone index is shown in Eq. 3:

Cl = 26.2(SD) + 1,298.6(BD) - 28.8(MC) + 133.3(logEC) - 1,026.6 (3)

where:

- CI cone index (kPa)
- *SD* sampling depth (cm)
- *BD* bulk density (g·cm<sup>-3</sup>)
- EC electrical conductivity ( $\mu$ S·cm<sup>-1</sup>)

# Soil cone index prediction using artificial neural network

Table 2 shows results from the designed neural networks for soil cone

The number of	Network parameters		Network statistical parameters		Network's determination coefficients			The mean simulation	Correlation coefficient
neurons	learning rater	momentum	MSE	SSE	training	validation	test	accuracy test (%)	
28-30	0.3	0.3	0.072	16.2	0.96	0.76	0.83	87.98	0.88
30-30	0.3	0.3	0.0669	15.1	0.97	0.68	0.84	88.04	0.89
30-32	0.3	0.3	0.119	26.7	0.91	0.83	0.85	88.09	0.87
32-32	0.3	0.3	0.0741	16.7	0.94	0.82	0.83	87.76	0.87
32-34	0.3	0.3	0.0895	20.1	0.95	0.74	0.86	88.78	0.88
34-34	0.3	0.3	0.0875	19.7	0.95	0.83	0.85	88.29	0.89

 Table 2
 Quantitative evaluation standards of made networks by using the Levenberg-Marquardt training algorithm

Table 3

**le 3** Designed networks utilizing 3 training algorithms each having the optimized number of neurons in their hidden layer (layers)

Training algorithm	Transfer function	The optimizedMean squaresDetermination coefficients of the network			ts of the	The mean simulation	Correlation coefficient	
		structure of network		training	evaluation	test	accuracy of the network (%)	
	Ciaton	20 + 1	0.131	0.87	0.86	0.86	88.97	0.86
Scaled	Sig tan	12 + 12 + 1	0.128	0.88	0.86	0.85	87.77	0.86
gradient	<u>Cia loa</u>	13 + 1	0.137	0.86	0.87	0.86	88.71	0.86
	Siglog	12 + 12 + 1	0.13	0.87	0.86	0.85	87.97	0.86
Descent	Sig tan	6 + 1	0.141	0.86	0.85	0.85	88.07	0.85
gradient		6+6+1	0.14	0.85	0.85	0.84	87.44	0.85
with momentum	Sig log	12 + 1	0.126	0.87	0.86	0.85	87.78	0.86
		6+6+1	0.116	0.88	0.87	0.86	88.37	0.87
Levenberg-	Ciaton	25 + 1	0.0974	0.92	0.85	0.85	87.98	0.87
	Sig tan	12 + 13 + 1	0.0981	0.93	0.85	0.87	88.81	0.88
Marquardt	<u>Cia loa</u>	24 + 1	0.102	0.94	0.82	0.87	86.48	0.88
	Sig log	34 + 34 + 1	0.0875	0.95	0.83	0.86	88.29	0.89



**Fig. 4** The regression chart for evaluation step of the network to predict the soil cone index quantities

index prediction using the Levenberg-Marquardt algorithm with a middle layer (middle layers) and a different number of neurons in the middle layer (layers). The sigmoid tangent function was used between the input and middle layers and a linear type was used between the middle layers and the output layer. As shown in Table 2, the network containing 34 neurons in each middle layer for predicting the soil cone index quantities had the lowest value for mean square error, the least sum of squares error, the highest correlation coefficient, the maximum simulation accuracy and the highest determination coefficient. Therefore, this topology was selected for the network design.

A diagram indicating the best fitted line between real data (7) and predicted data by the network (Y) is shown in Fig. 4. The regression coefficients for soil cone index prediction between the data groups were extracted by as much as 0.94 for the built network with 34 neurons in each middle layer for predicting soil cone index quantities. The highest gradient and the maximum correlation coefficient were extracted for this structure. These quantities for prediction of the soil cone index were 0.9195 and 0.9419, respectively.

Type of membership functions		Number of me	embership functions	Learning	DMCE	- (0/ )	D <sup>2</sup>
input	output	input	epoch	method	method	٤ (%)	ň
triangular	linear	5	30	hybrid	0.621	2.54	0.979

 Table 4
 Characteristics of ANFIS model and its evaluation based on statistical parameters



Fig. 5 Changes in the training and checking data error



Fig. 6 Comparison of predicted data with training data



Fig. 7 Comparison of predicted data with checking data

Table 3 shows a summary of the results of built networks utilizing the 3 aforementioned training algorithms and a comparison of their statistical parameters and accuracy. As shown in Table 3, Levenberg-Marquardt training algorithm presented better results in simulation and training of the artificial neural network compared with the other training algorithms. The Levenberg-Marquardt training algorithm associated to sigmoid logarithm transfer function containing 2 hidden layers and 34 neurons in each hidden layer had a lower mean square and higher determination of coefficients in training, validation and test steps of the network in comparison to the similar single-layer network.

#### Prediction of soil cone index using ANFIS

Fig. 5 shows the relationship between the root mean square error (RMSE) and epochs for training and checking data. Training data error and checking data error are marked with (\*) and (◆), respectively. Fig. 5 shows how the training and checking error decreased to a certain point. After training and checking the ANFIS model, predicted values of model were obtained and compared with the training and checking data. Results are shown in Figs. 6 and 7. Root Mean Square Errors were obtained at 0.621 and 0.436 for training and checking, respectively.

Table 4 shows characteristics of the model and its evaluations based on statistical parameters of RMSE, percentage of relative error ( $\varepsilon$ ) and coefficient of determination ( $R^2$ ). These results show that the ANFIS model was capable of estimating and predicting soil cone index with high accuracy.

#### Conclusion

The Analysis of Variance of soil cone index revealed that effects of the four parameters of soil texture, soil moisture content, tractor traffic and sampling depth were significant on soil cone index and should be taken into account in soil cone index modeling using artificial neural networks or a multiple-regression modeling (Ozoemena et al., 2018; Varga et al., 2013). The developed multiple-regression model was evaluated by normality assumption, assumption of constant variance and the Leverage index. Acceptable results were obtained from the multiple regression models to predict soil cone index values. The effects of independent variables had significant impact on soil cone index as a dependent variable (P < 0.01). Multilayer network back propagation with Levenberg-Marguardt algorithm showed better results in comparison to other algorithms utilized in data simulation and training of artificial neural networks. In terms of ANFIS model for the soil cone index estimation, novel result on soil cone index modeling, relative error ( $\varepsilon$ ), and regression coefficient  $(R^2)$  were calculated at 2.54% and 0.979, respectively. Comparison of the results achieved by ANFIS model with ANNs and regression models showed that ANFIS managed to model the soil cone index with high accuracy (Abbaspour-Gilandeh and Abbaspour-Gilandeh, 2019).

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# SELECTED PHYSICAL PROPERTIES ASSESSMENT OF SUNFLOWER AND OLIVE OILS

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Presented paper is focused on comparison of certain physical properties of selected vegetable oils. Physical properties, such as density, dynamic, kinematic viscosity and fluidity, were experimentally determined. All experiments were conducted on two samples of vegetable oils: sunflower and extra virgin olive oils with approximate temperature range of 5–32 °C. Density of oils was determined by oscillation method utilizing digital densimeter Anton Paar DMA 4500M at different temperatures. Dynamic viscosity was measured by means of rotational viscometer Anton Paar DV-3P. The rest of rheological parameters were determined on the basis of their definitions. Obtained results are depicted as graphical dependencies of rheological parameters and density on temperature. These dependencies of vegetable oils on dynamic and kinematic viscosity showed decreasing exponential shape, which is in compliance with Arrhenius equation; temperature dependencies on fluidity showed an increasing exponential shape for both samples. Density dependencies of samples on temperature were characteristic with decreasing linear function within measured temperature range. Similar results were achieved by other researchers. On the basis of measured values, it is evident that dynamic viscosity of extra virgin olive oil shows higher values than sunflower oil viscosity, which is a result of different composition of oils.

Keywords: sunflower oil; olive oil; physical parameters; temperature dependency; comparison

Accurate knowledge of physical quantities of materials represents an essential aspect in controlled processes in terms of manufacturing, handling, and holding. In order to assess the quality of food materials, it is vital to be familiar with physical properties of materials, especially mechanical, rheological and thermophysical characteristics (Božiková and Hlaváč, 2010).

This paper deals primarily with rheological properties that are considered to be complex material characteristics. Rheological properties have been measured for different food materials: milk (Hlaváč and Božiková, 2011; Kumbár and Nedomová, 2015), strawberry mash (Bukurov et al., 2012), quince puree (Bikić et al., 2012), chocolate (Glicerina et al., 2013; Kumbár et al., 2018), mixture of apple pomace and wheat flour (Diósi et al., 2014), honey (Hlaváč and Božiková, 2012), liquid egg products (Kumbár et al., 2015), wort (Hlaváč et al., 2016), etc. Viscosity is significant rheological property in terms of liquid products. It primarily affects the engine operation, since a higher fuel viscosity can result in malfunctions in feeding system and deposit formation in combustion chamber, filters, etc. (Corsini et al., 2015). Viscosity can be expressed as fluid resistance to flow and usually related physical unit to it is Pa·s. Temperature highly affects viscosity. Molecular structure causes the differences in temperature effect on viscosity of fluids and gases. With increment in temperature, it is possible to observe decreasing trend in liquid viscosity. Liquid molecules continuously move into the vacancies, and although this process allows the flow, it still requires energy (Bird et al., 1960). Fluid flows

easily at higher temperatures and activation energy is better observable in such cases. Temperature impacts on viscosity can be expressed by means of an Arrhenius type equation (Eq. 1):

$$\eta = \eta_0 e^{\frac{E_A}{RT}} \tag{1}$$

where:

Т

η – reference value of dynamic viscosity

 $E_A$  – activation energy

*R* – gas constant

absolute temperature (Figura and Teixeira, 2007)

Liquid molecules are closely spaced and attracted by strong cohesive forces and temperature impacts on viscosity can also be explained by these forces (Munson et al., 1994). Increase in temperature will cause decrease in these forces and liquid can flow more easily. Due to this fact, liquid viscosity decreases with temperature rise. Viscosity of majority of liquids is constant until the pressure reaches value of 10.134 MPa. However, by exceeding this value, viscosity increases with each increment in pressure (Sahin and Sumnu, 2006).

Ratio of dynamic viscosity  $\eta$  to fluid density  $\rho$  at identical temperature is called kinematic viscosity and can be expressed as follows:

$$v = \frac{\eta}{\rho}$$
(2)

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Physical unit of this ratio is  $m^2 \cdot s^{-1}$ . Reciprocal value of dynamic viscosity  $\eta$  is fluidity  $\varphi$  and its unit is  $Pa^{-1} \cdot s^{-1}$ .

$$\varphi = \frac{1}{\eta} \tag{3}$$

Oils extracted from plants have been utilized for millennia. Vegetable oil production includes oil removal from plant components - seeds in the majority of cases. This process can be performed either by mechanical or chemical extraction. The former is carried out by means of oil mill; the latter utilizes solvent. Subsequently, extracted oil is purified. Furthermore, it can be refined or chemically altered if necessary. Many vegetable oils are consumed directly or indirectly as ingredients in food. Moreover, they can be utilized in cooking of meals and this process includes their heating. Vegetable oils consist of triglycerides (Rafiq et al., 2015). Properties of different vegetable oils were examined by numerous authors. Stedile et al. (2015) compared physical properties and chemical composition of various bio-oils. Moser et al. (2009) analysed composition and physical properties of selected vegetable oils (cress, field pennycress and soybean). Impacts of composition on vegetable oils oxidation using differential scanning calorimetry was studied by Qi et al. (2016). Eight vegetable oils were subjected to examination: refined palm, olive, grapeseed, sunflower, corn, soybean, safflower and sesame oils. Activation energy of measured oils was also determined. Purification of vegetable oils by application of metal-organic frameworks was described by Vlasova et al. (2016). Authors found out that application of metal-organic frameworks enhances the physicochemical properties of unrefined vegetable oils (more pleasant taste and odour), because free fatty acids and peroxide compounds are bound in such manner. Selected physical properties of brominated vegetable oil as function of temperature were investigated by Thomas et al. (2015). They found out that it showed significantly higher values of density and dynamic viscosity than natural oils. This is probably a result of enhanced dispersion forces, rather than enhanced polarity upon bromination. Electrical properties of pumpkin seed oil were investigated by Prevc et al. (2015). They found out that typical roasted pumpkin seed oil shows higher electrical conductivity in contrast to unrefined extra virgin olive oils and refined sunflower oils. It is due to the fact that electrical conductivity tends to correlate with concentration of phospholipids and metals in oil. Pillai et al. (2016) have described structure, chemical composition and physical properties of metathesized palm oil and novel polyol derivatives. Kelly et al. (2014) have observed physical properties of spray-dried dairy powders mixed with various vegetable oils (sunflower oil, palm oil and its mixtures). Thermal properties of oils extracted from raspberry and blackberry seeds using differential scanning calorimetry were studied by Micić et al. (2014).

Vegetable oils are frequently included as an ingredient in multiple manufactured products. Vegetable oils functioning as additives in biodegradable films and coatings in terms of active food packaging were examined by Atarés and Chiralt (2016). Chen et al. (2014) have dealt with impacts of waste edible vegetable oil on rejuvenation of aged asphalt binders considering the physical, chemical and rheological properties. The results show that it can efficiently soften the aged asphalt. Both physical and rheological properties of aged asphalts can be improved to that of their original state if they are treated with optimum waste edible vegetable oil dosage. Bounding of masonry units with waste vegetable oil was analysed by Heaton et al. (2014). Physical quality and moisture content of wooden pellets blended with waste vegetable oil were analysed by Mišljenović et al. (2015). The results indicate that energy content of wooden pellets was significantly increased by adding oil. On the other hand, pellet strength was reduced by oil addition due to the lower friction on the pellet-die wall contact area. Padmini et al. (2016) have investigated a potential of vegetable-oil-based nanofluids as cutting fluids in machining. Production of alcohol from several vegetable oils was described by Dumont et al. (2013). Authors have also determined certain specific physical and chemical properties of obtained alcohols. Mello et al. (2013) have analysed certain low-toxic metal compounds produced during soybean oil polymerization in order to produce bio-based resins that could be exploited as a binder in printing inks.

Vegetable oils are frequently utilized as alternative fuels or lubricants. The tribological, rheological properties, as well as microstructure of oleogels on the basis of vegetable oils for lubrication purposes were analysed by Martín-Alfonso and Valencia (2015). Emberger et al. (2015) have studied chemical composition and physical properties of ten vegetable oils (coconut, palm, high oleic sunflower, rapeseed, sunflower, camelina, linseed, soybean, corn, jatropha). Furthermore, they also investigated their ignition and combustion behaviour after injecting them into a constant volume combustion chamber. Ashraful et al. (2014) have compared fuel and emission properties, as well as engine performance characteristics of biodiesel fuels made of several non-edible vegetable oils (karanja, polanga, mahua, rubber seed, cotton seed, jojoba, tobacco neem, linseed and jatropha). Various biodiesel types with different vegetable oils (soybean, rapeseed, mustard, canola, palm, sunflower, rice bran, jatropha, karanja and used cooking oil) have been analysed by Issariyakul and Dalai (2014). Electrochemical impedance spectroscopy was utilized in research of biodiesel fuels made of different vegetable oils (canola, soybean, sunflower, and corn) by M'Peko et al. (2013). Authors have presented correlations between electric properties (resistivity and dielectric constant) and dynamic viscosity. Utilization of vegetable oils as a fuel in burners was studied by San José et al. (2015). During the investigation, authors used four vegetable oils made of rapeseed, soya, sunflower and refined seed. For the optimal combustion process, knowledge of physical properties (density, viscosity, etc.) and composition of the fatty acids is essential. Cermak et al. (2013) have compared properties of oils made of modern crops (lesquerella, field pennycress, meadowfoam and cuphea) with common commodity vegetable oils. They found out that all oils showed unique preconditioning them for lubrication purposes. Certain blended aviation biofuels made primarily of esterified Jatropha curcas with addition of waste vegetable oils were analysed by Baroutian et al. (2013).

## **Material and methods**

Measurements were carried out under laboratory regime (temperature - 20 °C; atmospheric pressure - 1,013 hPa; relative air humidity - 45%) on two samples of vegetable oil purchased at local market. The first sample was sunflower oil and other one was extra virgin olive oil. Rheological parameters - dynamic viscosity, kinematic viscosity, fluidity and density - were subjected to analyses during experiments. At first, samples were cooled to temperature of 3 °C. Subsequently, dynamic viscosity and density were measured at particular temperature values during the temperature stabilisation in approximate temperature range 5-32 °C. Dynamic viscosity was recorded utilizing digital rotational viscometer Anton Paar (DV-3P). This device works on principle founded on dependency of sample resistance to the probe rotation. Moreover, density of vegetable oils was measured utilizing densimeter Anton Paar DMA 4500 M and was recorded at the same temperatures as dynamic viscosity. Together with recorded dynamic viscosity values, obtained density values were utilized in kinematic viscosity calculation (Eq. 2). Reciprocal value of dynamic viscosity (fluidity) was also determined (Eq. 3). Correlations between rheological parameters and temperature were observed and properties of vegetable oils were compared.

It is possible to depict the temperature dependencies of dynamic viscosity for observed oils in form of decreasing exponential functions (Eq. 4). The same is true for temperature dependencies of kinematic viscosity (Eq. 5). Considering the temperature dependencies of fluidity, trends can be shown by increasing exponential functions (Eq. 6). Decreasing linear function (Eq. 7) described the trends in terms of temperature dependencies of density:

$$\eta = Ae^{-B\left(\frac{t}{t_o}\right)}; \quad \nu = Ce^{-D\left(\frac{t}{t_o}\right)}; \quad (4, 5)$$

$$\varphi = E e^{F\left(\frac{t}{t_o}\right)}; \quad \rho = -G\left(\frac{t}{t_o}\right) + H \quad (6,7)$$

where: *t* – temperature

t<sub>o</sub> – 1 °C; A, B, C, D, E, F, G, H – constants dependent on material type and methods of processing and storage

## **Results and discussion**

Considering the vegetable oils dynamic viscosity and density, obtained temperature dependencies of observed vegetable oils are shown in Fig. 1 and Fig. 2. It is evident from Fig. 1 that dynamic viscosity of oils shows decreasing trends with increments in temperature. It is possible to visualise this progress by means of decreasing exponential function, which is in compliance with Arrhenius equation (Eq. 1). Similar conclusions were made by authors Diamante and Lan (2014) and Thomas et al. (2015). Regression coefficients and coefficients of determination are shown in Table 1. Furthermore, Fig. 1 shows that values of dynamic viscosity of extra virgin olive oil were higher than those of sunflower oil, which could have been caused by different composition of oils.

Dependencies of oil density on temperature are presented in Fig. 2. It is evident that values of density are decreasing with increasing temperature for both samples. Linear decreasing function was utilized for description of the progress at given temperature range. Thomas et al. (2015) deployed the identical dependency type. Density of sunflower oil was higher in contrast to extra virgin olive oil sample. Similar results for sunflower oil were obtained by Emberger et al. (2015), San José et al. (2015), and for olive oil by Tanilgan et al. (2007).

Table 1	Coefficients A, B, C,	D, E, F, G, H of regression eq	uations (4, 5, 6 and 7) an	d coefficients of determinations $(R^2)$
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	Regression equations (4, 5, 6, 7) Coefficients				
Sample	A (mPa·s)	B (1)	R <sup>2</sup>		
Sunflower oil	251.491	0.028017	1.000000		
Olive oil	261.117	0.022905	0.999958		
Sample	C (mm <sup>2</sup> ·s <sup>-1</sup> )	D (1)	R <sup>2</sup>		
Sunflower oil	269.187	0.027260	0.999999		
Olive oil	281.934	0.022151	0.999960		
Sample	E (Pa <sup>-1</sup> ·s <sup>-1</sup> )	F (1)	R <sup>2</sup>		
Sunflower oil	3.98038	0.027965	0.999996		
Olive oil	<b>re oil</b> 3.82843		0.999937		
Sample	H (kg⋅m <sup>-3</sup> )	G (kg⋅m⁻³)	R <sup>2</sup>		
Sunflower oil	933.866	0.682059	0.999997		
Olive oil	926.042	0.684142	0.999996		







**Fig. 2** Temperature dependencies of density for vegetable oils • – sunflower oil; × – extra virgin olive oil



**Fig. 3** Temperature dependencies of kinematic viscosity for vegetable oils • – sunflower oil; × – extra virgin olive oil

Fig. 3 and Fig. 4 depict temperature dependencies of kinematic viscosity and fluidity observed in analysed samples. For both samples, decreasing function describes dependencies of kinematic viscosity on temperature. Table 1 provides values of regression coefficients and coefficients of determination. In contrast to extra virgin olive oil, sunflower oil showed higher values of kinematic viscosity (Fig. 3). This is most likely due to same reason as in case of dynamic viscosity. Temperature dependencies of fluidity are depicted in Fig. 4. It is obvious that with increase in temperature, there is also an increase in fluidity. Ultimately, Table 1 provides values of regression coefficients and coefficients of determination. It is possible to explain the proportion of curves shown in Fig. 4 in similar manner as in previous dependencies.

It is evident from Table 1 that coefficients of determinations showed very high values in the given range (0.99993–1.0) in all cases.

#### Conclusion

properties Physical of food materials must be analysed individually due to the very complex composition of these materials. Properties of these materials can be influenced in multiple ways (e.g. manipulation, external conditions, etc.). Rheological properties of selected vegetable oils were observed and subjected to analysis in this paper. Impacts of temperature on measured samples of vegetable oils were investigated and their properties were compared.

In terms of dynamic and kinematic viscosities, temperature dependencies of vegetable oils had decreasing shape (Fig. 1 and Fig. 3). Considering the temperature dependencies of fluidity, there have been observed an increasing shape (Fig. 4). In order to stay in line with Arrhenius equation exponential functions were (1), utilized for expression of temperature dependencies of rheological properties. Similar results were also achieved by other authors (Diamante and Lan, 2014; Thomas et al., 2015).

Linear decreasing functions were utilized for expression of temperature dependencies of density for observed oils in the given temperature range (Fig. 2). Several other authors



**Fig. 4** Temperature dependencies of fluidity for vegetable oils • – sunflower oil; × – extra virgin olive oil

(Emberger et al., 2015; San José et al., 2015; Tanilgan et al., 2007) achieved similar results for density of vegetable oils.

It was observed that values of dynamic and kinematic viscosities for extra virgin olive oil were higher than for sunflower oil, which could have been caused by different composition of oils. Fluidity and density of extra virgin olive oil showed lower values most likely for the same reason as well.

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# STOCHASTIC ANALYSIS OF MULTI-REACTION MODEL FOR NON-LINEAR THERMAL HISTORY

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This paper investigates the effect of non-linear thermal profile on the numerical solution of the multi-reaction model. According to the practical perspective, the temperature distribution at a different section of pyrolysis reactor is not necessarily following the ideal thermal history; therefore, it is necessary to predict the behaviour of the system for the higher degree of freedom. TG thermogram is obtained by the thermal degradation of pine needles sample in the thermogravimetric analyser (TGA). The activation energy, frequency factor, reaction order and the scale, shape and location parameters of a stochastic function are estimated for the non-linear parabolic thermal profile. The conventional Laplace integral is used to approximate the multi-reaction model. Activation energy obtained for the non-thermal profile lies in the range of 57.5–60 kJ·mol<sup>-1</sup>, whereas the frequency factor varies from  $10^3-10^5$  min<sup>-1</sup>. The obtained value of reaction order (*n*) lies in the domain of (0.9, 1.6).

Keywords: biomass pyrolysis; kinetic parameters; the Laplace method; the multi-reaction model

Apart from the basic thermal applications of pyrolysis, certain other aspects of it must be addressed properly. For the same purpose, there is a need for a robust modelling scheme which can efficiently describe the pyrolysis phenomenon. At the elementary level, the thermal degradation of material (Li et al., 2009; Yan et al., 2009) (biodegradable or non-biodegradable) is performed by the thermogravimetry technique. This technique measures the extensive, as well as intensive properties of materials such as the mass, heat flux, and temperature variation of material with respect to the reference material. However, one of the most inherent parts of pyrolysis is the yield of secondary fuels, which can be further processed to get energetic biofuels. Therefore, the kinetic analysis of conversion process plays a major role in the determination of characteristics of the final products obtained from thermal degradation.

Method of assessing the kinetics of any process depends on the condensed phase reactions, as they guide the formulation of absolute rate theory without the involvement of momenta or ballistic motion. They signify position probability of particles (if the number of steps increases, probability follows the Gaussian distribution). Moreover, it also leads to an important approximation that activities of the reactants and products can be assumed to be one, or it would not be part of the equilibrium constant (Burnham, 2017). Mathematical schemes, iso-conversional and model-fitting methods, are used to simplify the kinetic mechanism of pyrolysis, but they have certain merit and demerit over each other. Inconsistent values of Arrhenius parameters and their hypothesis make them depart from the realistic overview of the problem. Chemical kinetics of material is determined by the reactivity of any given set of reactions. It becomes difficult to tackle a situation where one can compromise with the intrinsic behaviour of biomass pyrolysis. Therefore, there is a need to approximate the rate equation by using an asymptotic approach.

In this paper, the emphasis is laid on the effect of kinetic parameters on the approximated solution of the multireaction model. Several simplifications and approximations to the multi-reaction model are performed for an ideal thermal profile. Therefore, the heating rate is considered to vary with time. Furthermore, the effect of altering the sample temperature profile is also examined to determine the trend of the mass-loss curves. Thereafter, a comparative sketch of temperature non-linear variation is drawn against the results obtained from the isothermal and non-isothermal conditions.

## **Material and methods**

#### Mathematical modelling of biomass pyrolysis

It has been assumed that the activation energies of concurrent reactions could be represented through the continuous normal distribution function (Anthony and Howard, 1976). However, the same model is tested for the different density functions, and it is reported that the modelling of biomass pyrolysis can be can be rather precisely described by the Rayleigh distribution than the Gaussian distribution (Dhaundiyal and Singh, 2018a).

Contact address: Alok Dhaundiyal, Szent István University, Doctoral School of Mechanical Engineering, Gödöllő, Hungary, e-mail: <u>alok.dext@hotmail.com</u> The Gamma and the Gaussian distributions, on the other hand, provide a good insight into the constant thermal history. A detailed study of assumption and restriction is reported in the literature (Dhaundiyal and Tewari, 2017). The material of interest is having a variety of reactivity; hence, it is reasonable to distinguish the set of independent parallel reactions by the differential equation for *i*<sup>th</sup> number of reactions. The solid-state reaction rate equation can be represented by Eq. 1:

$$\frac{d(1-\alpha_i)}{dt} = -k_i(T)f(\alpha_i) \tag{1}$$

where:

 $k_i(T)$  – the rate constant,  $(1 - \alpha_i)$  denotes the remaining mass fraction

t – time

 $f(\alpha_i)$  – the conversion function

The sum of the initial  $(1 - \alpha_i)$  should not be more than one. Parallel reaction model can be generalised from a set of discrete reactions to a continuous distribution. The final solution of differential equation (Eq. 1) is provided by Eq. 2. It is evident from Eq. 2 that the integral has no analytical solution; therefore, it requires some approximation schemes.

The mathematical expression of non-isothermal  $n^{tn}$  order multi-reaction model equation derived from the Eq. 1 is:

$$(1-\alpha) = \begin{cases} \int_{0}^{\infty} D(T)G(E)dE, First order (n = 1) \\ \int_{0}^{\infty} \left[1 - (1-n)\ln(D(T))\right]^{\frac{1}{1-n}}G(E)dE, n^{\text{th}} order (n \neq 1) \end{cases}$$
(2)

where:

G(E) – the continuous distribution function n – represents the reaction order D(T) – the double exponential term T – temperature  $E (kJ \cdot mol^{-1})$  – denotes the activation energy.

To simplify the integral Eq. 2, the arbitrary unitless variable 'z' and the energy correction scale y are assumed to:

$$z_0 = \frac{E}{RT_0}; = \frac{E}{R(al^2 + T_0)}; z_m = \frac{E}{R(at^2 + T_0)} \text{ and } y = \frac{E}{\chi}$$

where:

 $z_0$  and  $z_m$  – lower and upper limits of the double exponential function R – a universal gas constant  $\chi$  (kJ·mol<sup>-1</sup>) – the threshold parameter

Eq. 2 denotes the distributed activation energy model equations for the first, as well as  $n^{\text{th}}$  order reactions. It comprises two components. One of the components refers to the double exponential term D(z), which is a function of non-linear thermal history encountered by the sample of biomass, whereas the other term denotes the continuous distribution function of varying activation energies of

the overlapped concurrent reactions. To demonstrate the approach, the temperature depending term is simplified as Eq. 3:

$$D(z) = \exp\left[\int_{z_o}^{z_m} \frac{AE}{\Theta R} z^{-2} \exp(-z) dz\right]$$
(3)

Deciding an appropriate density function should be accomplished with serious attention. In the stochastic modelling of biomass pyrolysis, density function represents the probabilistic behaviour of all those overlapped parallel reactions which differ in activation energies by a small margin. It is difficult to quote the superiority of one form over another, despite there being various other schemes proposed to describe the biomass with good accordance between experimental and predicted solution. The most common distribution function is Gaussian (Dhaundiyal and Tewari, 2017), but it is not necessary that thermo-analytical data follow the symmetrical pathway. There are also some other ways of analysing the problem of biomass pyrolysis (Dhaundiyal and Singh, 2017a). The function G(E) is considered to follow three parametric forms (3-P) of Weibull distribution, where ' $\chi$ ' (kJ·mol<sup>-1</sup>) represents the minimum barrier of the energy required to initiate the reactions. Here,  $\mu$  and  $\beta$  (kJ·mol<sup>-1</sup>) denote the shape and scale parameters of the Weibull distribution function respectively:

$$G(y) = \frac{\mu}{\beta} \delta^{\mu-1} (y-1)^{\mu-1} e^{-\left((\delta(y-1))^{\mu}\right)}$$
(4)

The practical value of dimension-less ratio  $\delta = \frac{\chi}{\beta}$  is always  $\delta >> 1$ .

The major drawback of the computational mechanism is to solve two distinct components simultaneously. Therefore, it requires a lot of resources to evaluate it for multiple times. In the previous approximation, Miura (1995) proposed the relationship for the effective disparity between activation energies of reactions by replacing the double exponential term with its approximations without paying heed to their influence on the value of the conversion ( $\alpha$ ) at the point of discord. His approach is latterly rebutted by Cai and Liu (2011). Assessment of Miura's approximation led to the miscellaneous value of frequency factor when the predicted solution is synchronised with the Gaussian distribution. Mathematically, with some assumption, the double exponential term can be approximated by the conventional Laplace scheme rather than the hit and trial methods. Hence, it is crucial to estimate the behaviour of the exponential term by demarcating the passive domain from the active ones.

To demonstrate the approach, ramping profile of temperature is assumed to follow the course of the parabolic temperature programme:

$$T(K) = al^2 + T_0(K)$$
(5)

where:

rate ( $\theta$ ).

$$l(\min)-$$
 an instant of time  
 $a(^{\circ}C \cdot \min^{-2}) = \frac{1}{2}\frac{d\theta}{dt} -$  represents the rate of change of heating

Boundary conditions for non-linear thermal history is Let v = (y - 1) be integral form transformed into: given as:

$$T(0) = T_0; T(t) = T_m$$

The expression for double exponential term is expressed as:

$$D(z) \equiv \exp\left[\int_{z_0}^{z_m} \frac{AEe^{-z}dz}{2\left(z\sqrt{azR(E-RzT_0)}\right)}\right]$$
(6)

Applying the Laplace approximation to Eq. 6, we get:

$$D(z) = \exp\left(\frac{-AE}{2\left(z_m\sqrt{az_mR(E-Rz_mT_0)}\right)}e^{-z_m}\right) \text{ as } \frac{-E}{R(at^2+T_0)} \to \infty (7)$$

It is obvious from Eq. 7 that the function D(z) leaps from zero to one as y increases by stepwise width of  $y_w$  around the neighbourhood of the mean value of energy correction factor,  $y_s$ , thus it can be approximated through the Taylor series expansion about  $y = y_s$ :

$$J(y) \sim J(y_s) + (y - y_s) J'(y_s) + \dots$$
(8)

where:

$$(y) = \frac{y_s - y}{y_w}$$

Using the following conditions,  $J(y_s) = 0$  and  $J'(y_s) = \frac{-1}{y_{ws}}$ we get the values of:

$$y_{s} = \frac{RT_{m}y_{s}}{\chi}W(\tau) \text{ and } y_{w} = \frac{RT_{m}y_{s}}{(\chi y_{s} + RT_{m})}; \ \tau = \frac{A}{\sqrt[2]{\frac{a\left(1 - \frac{Z_{m}}{Z_{0}}\right)}{T_{m}}}}$$

where:

τ – a time scale factor

 $W(\tau)$  – represents the Lambert W function

Note: The ratio of  $\frac{Z_m}{Z_0}$  lies in domain of (0,1), therefore,  $\tau$  will always be positive real number. Since  $\frac{z_m}{z_0} \ll 1$ , then  $0 < \left(1 - \frac{z_m}{z_0}\right)$ .

Eq. 2 demarcates two different set of reactions for the first and  $n^{\text{th}}$  order reactions, hence they are solved and programmed separately. Thereafter, the mutually exclusive effect of them on the numerical solution is graphically demonstrated.

#### Case 1: The first order reaction scheme

All the parallel reactions that follow the first order reactions are represented by Eq. 2:

$$1 - \alpha = \int_{1}^{\infty} \mu \delta^{\mu} (y - 1)^{\mu - 1} D(z) e^{-\left\{ (\delta(y - 1))^{\mu} \right\}} dy$$
 (9)

$$1 - \alpha = \int_{1}^{\infty} \mu \delta^{\mu} v^{\mu - 1} e^{-\{(\delta v)^{\mu} + D(z)\}} dv$$
 (10)

The term  $S(v) = v^{\mu-1} e^{-\{(\delta v)^{\mu}\}}$  in Eq. 10 is assumed to be negligibly small everywhere except at the vicinity of  $y_{sr}$ therefore, it is to be evaluated by the Taylor expansion about  $y = y_s$ .

To demonstrate the approximation scheme of  $n^{\text{th}}$  multi reaction model equations, application of Heaviside step function H(x) is introduced to differentiate the distribution of activation energies for two different intervals of x.

After incorporating the step function H(x), Eq. (10) can be represented in the form:

$$1 - \alpha \sim \mu \delta^{\mu} \left[ \left\{ (v_{w} + 1) \left( \int_{-\infty}^{\infty} e^{-\left\{ e^{-x} - H(x) \right\}} S(v) dx \right) \right\} + \left\{ 1 - \left( \int_{0}^{v_{s}} G(v + 1) dv \right) \right\} \right]$$
(11)

Further simplification yields:

$$1 - \alpha \sim \mu \delta^{\mu} \left[ (v_{s})^{(\mu-1)} \exp\left(-(\delta v_{s})^{\mu}\right) (v_{w} + 1) \left\{ I_{0} - \frac{(v_{w} + 1)}{v_{s}} \right]^{(12)} \right] \\ \left( \mu - \mu (\delta v_{s})^{\mu} - 1 \right) I_{1} + \left( \frac{(v_{w} + 1)}{v_{s}} \right)^{2} I_{2} \left( \mu^{2} \left( -3(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 1 \right) + 3\mu \left( (\delta v_{s})^{\mu} - 1 \right) + 2 \right) - \left( \frac{(v_{w} + 1)}{v_{s}} \right) I_{3} \left( \delta^{2} \mu^{4} \right) (-v_{s}^{2}) \left( (\delta v_{s})^{\mu} - 1 \right) + \mu^{3} \left( -(\delta v_{s})^{2} - 7(\delta v_{s})^{\mu} + 3(\delta v_{s})^{2\mu} + 1 \right) - 3\mu^{2} \left( -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \right) + R(y_{s}) \left[ -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \right] + R(y_{s}) \left[ -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right] - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \left( -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \left( -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \left( -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( -6(\delta v_{s})^{\mu} - 1 \right) - 6 \left( -6(\delta v_{s})^{\mu} + 1 \right)$$

Eq. 12 represents the required expression for the first order reactions.

The parameter  $I_i$  is an unbiased parameter that needs to be computed once, so the first few computed values are:

 $I_0 \approx -0.5772, I_1 \approx -0.9890, I_2 \approx -1.8149, I_3 \approx -5.8903$ 

To improve the accuracy of the given numerical solution, the other integral terms can be evaluated through integral equation:

$$I_{j} \equiv \lim_{x \to \infty} \int_{-\infty}^{x} x^{j} \left( e^{-e^{-x}} - H(x) \right) dx j = 0, 1, 2...$$

## Case 2: The *n*<sup>th</sup> order reaction scheme

Similarly, the numerical solution for n<sup>th</sup> order multi reaction model can be derived through the Binomial expansion of Eq. 13 as:

$$(1-\alpha)_{n} = \int_{1}^{\infty} \left[ \left\{ 1 - (1-n) \ln(D(z)) \right\} \right]^{\frac{1}{1-n}} G(y) dy$$
(13)

Rearrangement and simplification of Eq. 13 yields the desirous expression for *n*<sup>th</sup> order reactions:

$$(1-\alpha)_{n} \sim 1 + \left[ \left( \frac{n-5}{6} \right) R(y_{s}) - (v_{s})^{(\mu-1)} (v_{w} + 1) \exp\left(-(\delta v_{s})^{\mu} + \left( \left( U_{0} - \frac{n}{2} V_{0} + \left( \frac{2n-1}{6} \right) W_{0} \right) - \left( \frac{(v_{w} + 1)}{W v_{s}} (\mu - \mu (\delta v_{s})^{\mu} - 1 \right) \right) \right]$$

$$\left( U_{1} - \frac{n}{2} V_{1} + \frac{(2n-1)W_{1}}{6} \right) + \left( \left( \frac{(v_{w} + 1)}{v_{s}} \right)^{2} \left( \mu^{2} \left( -3(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 1 \right) + 3\mu \left( (\delta v_{s})^{\mu} - 1 \right) + 2 \right) \right) \left( U_{2} - \frac{n}{2} V_{2} + \frac{(2n-1)W_{2}}{6} \right) - \left( \left( \frac{(v_{w} + 1)}{v_{s}} \right)^{3} + \left( \delta^{2} \mu^{4} (-v_{s}^{2}) \left( (\delta v_{s})^{\mu} - 1 \right) + \mu^{3} \left( -(\delta v_{s})^{2} - 7(\delta v_{s})^{\mu} + 3(\delta v_{s})^{2\mu} + 1 \right) - 3(\delta v_{s})^{2\mu} + 1 \right) - 3\mu^{2} \left( -6(\delta v_{s})^{\mu} + (\delta v_{s})^{2\mu} + 2 \right) - 11\mu \left( (\delta v_{s})^{\mu} - 1 \right) - 6 \left( U_{3} - \frac{n}{2} V_{3} + \frac{(2n-1)W_{3}}{6} \right) + \dots \right\}$$

Eq. 14 represents the required expression for  $n^{th}$  order reactions.

Here, the first few values of independent parameters ( $U_{kr}$ ,  $V_{kr}$ ,  $W_k$ ) are given below:

 $U_0 \approx -0.3678, U_1 \approx -0.2357, U_2 \approx -0.1727, U_3 \approx -0.1360,$   $V_0 \approx -0.5676, V_1 \approx -0.3515, V_2 \approx -0.2525, V_3 \approx -0.1964,$  $W_0 \approx -0.6832, W_1 \approx -0.4110, W_2 \approx -0.2906, W_3 \approx -0.2238.$ 

#### Modelling and simulation of prototype model

MATLAB R2015a software is considered for the computation and simulation process. The non-linear thermal history experienced by the biomass sample is programmed for iterative loops. The objective functions of the computational problem are expressed by Eq. 12 and Eq. 14. Each allocated value goes through a common checkpoint for evaluating the acceptable range of permissible error. Until and unless the value qualifies itself as a suitable member of the permissible range, the iterative loop keeps looking for another assigned value to the input system. Eventually, thermo-chemical parameters are examined on the criterion of constraints imposed on the given pyrolysis problem. As the root mean square error and coefficient of regression is the foundation of grey box modelling, comparative tabulation of the nonlinear regime with linear ramping thermal history is given in Table 1.

#### Application of pine waste

Chemical analysis is performed through the CHNO-S analyser, whereas the higher heating value of pine waste is recorded with the help of a bomb calorimeter. Thermal evaluation of pine waste is based on thermogravimetricdifferential thermal analyser (Diamond TG/DTA, Perkin Elmer, and USA). The sample of 5.68 mg is heated in a crucible pan of alumina from 303 K to 923 K. To circumvent the obnoxious error of buoyant effect at the high temperature, horizontal differential type of prototype analyser is considered for experimentation. Thermocouple type 'R' is involved to measure the temperature inside the furnace. The volumetric flow rate of inert gas inside the chamber is fixed to 200 mL·min<sup>-1</sup>. Indium and tin are used as reference materials for the differential thermograms. Thermoanalytical data of pine needles sample is used for the qualitative assessment of multi-reaction model through a physically distinct regime of temperature. Elemental composition of pine needles is illustrated in Table 2.

 Table 1
 Comparative error of different non-isothermal profile

Distribution type	Ramping profile (non-isothermal)	Root mean square error (RMSE)	$R^2$ (coefficient of regression)
Weibull distribution	linear	0.11	0.822
	parabolic	0.070	0.960

 Table 2
 Elemental composition of pine needles

С%	<b>H%</b>	N%	0%	<b>S%</b>	Ash content (%)	Higher heating value (MJ·kg <sup>-1</sup> )
53.7	5.21	0.61	32.13	0.22	4.72	19.5























**Fig. 6** The effect of upper limit of activation energy ( $E_{\infty}$ ) on the predicted result a – first order; b –  $n^{\text{th}}$  order ( $\chi = 1.10 \text{ kJ} \cdot \text{mol}^{-1}$ ;  $\mu = 0.70$ ;  $\beta = 0.85 \text{ kJ} \cdot \text{mol}^{-1}$ ;  $T_0 = 290 \text{ K}$ ;  $a = 0.0135 \text{ °C-min}^{-2}$ ;  $A = 10^3 \text{ min}^{-1}$ )



**Fig. 7** Comparative sketch of experimental and predicted *n*<sup>th</sup> order pattern for non-linear thermal history

## **Results and discussion**

The effects of various parameters on the pyrolysis problem are embedded together, and it is graphically illustrated. The effect of frequency factor (A) for the non-linear regime is shown in Fig. 1a, b. At the onset of the pyrolysis process, the remaining mass fraction which is denoted by  $(1 - \alpha)$  is approximately equal to one and as temperature increases with time, it decreases unless it reaches its residual mass  $(m_r)$ . It seems that undulation in the remaining mass curves decreases as the decreasing trend in the frequency factor value has been encountered. Consequently, the curves get shifted in the right direction. Although the stochastic modelling through non-linear approach is perfectly depicting the initiating point of evaporation (the sunken segment of the curves), the rate of change of  $(1 - \alpha)$  with time is very subtle with the molecular collision of reactants. Therefore, the validation of the predicted model is suitable within the given range of  $10^3 < A(\min^{-1}) < 10^5$ . If the value exceeds 10<sup>5</sup>, the condition of 'no-solution' arises as it is impossible for  $(1 - \alpha)$  to be negative or more than one unless the surface oxidation affects the chemical affinity of the pyrolytic reactions. On the other hand, the domain of frequency factor less than 10<sup>5</sup> makes pyrolysis process slow, and the higher level of residual weight is obtained through the stochastic model, which overrides the possibilities of occurrence of proper devolatilization process. Observance for both cases (first-order, as well as n<sup>th</sup> order reactions) states the rate of conversion ( $\alpha$ ) decreases at a low value of A. The influence of variation of activation energy  $(E_{\infty})$  on the numerical solution is illustrated in Fig. 2a, b. The increase in

the upper limit of activation energy causes shift of  $(1 - \alpha)$ curves to the left direction. The domain of activation energies for higher and the first order reactions has a variant effect on the shape, as well as thermochemical attributes for the non-linear regime of thermal decomposition. the difference between activation energies of As reactants gets wide up, the rate of conversion changes with time. For the activation energies of the first-order reactions  $E_{\infty} > 60 \text{ kJ} \cdot \text{mol}^{-1}$ , the conversion of biomass is relatively faster than all those reactions that take place at  $E_{\infty}$  >60 kJ·mol<sup>-1</sup>. Unlike the case of the first order,  $n^{\text{th}}$  order reactions add up the concrete values to the outcome of the stochastic modelling. The interval of 55 kJ·mol<sup>-1</sup>  $\leq E_{\infty}$  <60 kJ·mol<sup>-1</sup> gives a promising result to the numerical solution. Inequality holds good for the given experimental conditions, else the solution converges to the isothermal conditions of pyrolysis (Dhaundiyal and Singh, 2017b). The values obtained through stochastic modelling exhibit the compensatory effect amongst Arrhenius parameters, especially for activation energies (Burnham, 2014).

The effect of scale parameter  $\beta$  (kJ·mol<sup>-1</sup>) of distribution function on the numerical solution is depicted in Fig. 3a, b. The domain of  $\beta$  unanimously agreed for the higher and first-order reactions. The condition of no solution is imposed for all the values of  $\beta \leq 0.70$ , therefore, the defined domain of the scale parameter to get the desirous result is  $0.90 \leq \beta < 1.075$ . Unlike the Arrhenius parameters, the slope of conversion remains the same, but the temperature scale shifted up for the given domain of  $\beta$ .

The influence of the shape  $\mu$  and the location parameters  $\chi$  (kJ·mol<sup>-1</sup>) of distribution function on the numerical solution is depicted in Fig. 4a, b and Fig. 5a, b, respectively. Likewise, to the activation energies variation, the first and  $n^{\text{th}}$  order reactions are inconsistent to each other. The magnitude of the shape parameters  $\mu$  for  $\mu \leq 0.85$  is asymptotically stable and provides solution to the experimental solution except for some infringement at the outbound of  $(1 - \alpha)$ , however, the first-order reaction prediction defied the solution outright at  $\mu \leq 0.85$ . Therefore, the common solution for both reaction regimes lies in the domain of  $0.75 < \mu < 0.85$ . The value of the shape parameter causes the conversion  $\alpha$  to increase drastically and shift of the  $(1 - \alpha)$  curves downward. On the other hand, the decrease in the location or threshold parameter initiates the pyrolysis process spontaneously, and the conversion  $\alpha$  becomes independent of the temperature scale for a certain time. The domain of threshold parameter

for the precise solution of the predicted solution varies from 0.90 <  $\chi \le$  1.11.

The relevance of physically different regime of thermal history and its effect on the predicted remaining mass proposition is depicted in Fig. 6a, b. With the increasing initial temperature ( $T_0$ ), the remaining mass fraction curves shifted towards the left, therefore, the temperature scale is reduced for the same conversion value. The behaviour of the curve changes rapidly to exponential decaying function as temperature elevates for the same initial time. The predicted solution converges swiftly at the vicinity of 284 K, therefore, the initial experimental parameter ( $T_0$ ) must exist in an open interval of 284 < T < 289.

On the other hand, the precise solution for the first order reactions is obtained for all the values of  $T_0(K) \ge 289$ . This implies that the first order reaction requires a high-temperature range to maintain the same conversion than that of the  $n^{\text{th}}$  order reactions at the same instance of time l (min). At the onset of pyrolysis process, the inflexion points are visible, which demarcates evaporation of water content in the biomass, but as the temperature decreases, the inflexion point changes at the same time for different initial temperature ( $T_0$ ). The domain of 'a' for the first- order reaction suggests the numerical solution  $\forall a < 0.014 \,^\circ \text{C} \cdot \text{min}^{-2}$ .

It is worth mentioning that quantitative analysis of linear ramping problem (Dhaundiyal et al., 2019; Dhaundiyal et al., 2018b) of non-linear thermal history provided the qualitative insight of the same problem through better fitting of predicted model to the given thermo-analytical data (Table 1). It is observed through linear ramping that the activation energy is increased for the same experimentation when the linear thermal history is executed, therefore it is sure that frequency factor and activation energy vary simultaneously with thermal history. Sensitivity and attributes of curves largely rely upon scale, threshold and shape parameters.

#### Conclusion

Through predicted data of non-linear thermal history, 57.5 kJ·mol<sup>-1</sup> can be incorporated as the upper limit of activation energies, which is a bit lower than the expected ones (Dhaundiyal and Singh, 2018a) due to the mutually compensatory effect. On the other hand, the frequency factor lies in the range of  $10^3$  to  $10^5$  min<sup>-1</sup>. The initial temperature should be more than 289 K. The value of 'a' lower than 0.014 °C·min<sup>-2</sup> violates the boundary condition, therefore the value of 0.014 °C·min<sup>-2</sup> is considered as the minimum permissible value of the parameter 'a'. The value lower than 11 kJ·mol<sup>-1</sup> exhibit (1 –  $\alpha$ ) curve becomes asymptotic to the isothermal lines. The reaction order should be within the domain of 0.9 < n < 1.6 for numerical prediction of the non-linear ramping profile. The derived results provided good information about variation of the heating rate with time and the effect of initial temperature on the different reaction orders.

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## THEORETICAL RESEARCH OF THE DESIGN AND TECHNOLOGICAL PARAMETERS OF A DEVICE FOR LIFTING OF DEEP-SEATED TABLE ROOT CROPS

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Due to the high energy intensity of lifting of deep-seated table root crops, their growth develops mainly in light sandy-loam soils, in which it is possible to transfer a heap of root crops to the separating devices in order to facilitate the qualitative separation. Therefore, issue of lifting of deep-seated table root crops at minimal energy consumption and labour costs is an important scientific and practical task, which would allow expansion of cultivation of deep-seated table root vegetables to heavy soils. Research was conducted by means of a theoretical method utilizing elements of theoretical mechanics with subsequent processing of results by means of PC. Mathematical model and resulting energy cost dependences were constructed on the basis of the device parameters for soil loosening and lifting of deep-seated table root crops. Refined mathematical model of the process of lifting of deep-seated root crops made it possible to find out scientific and technical preconditions for the development of lifting devices with minimal energy consumption.

Keywords: root crops; lifting devices; soil, energy consumption; mathematical model

Table root crops represent valuable group of products and their cultivation is an important branch of agriculture (Chloupek, 2004; Bulgakov et al., 2015). However, cultivation and especially harvesting of the root crops is generally a labour-consuming and expensive process that largely determines the prime cost of the product (Anar et al., 2019; Bulgakov et al., 2016). Considering the stage of lifting of deepseated root crops, several scientific and production issues arise in terms of increased energy intensity of lifting of these crops in heavy soils, and low process efficiency (Pavlocky, 2015; Bulgakov et al., 2013; Vilde and Rucins, 2012). There used to be a tradition of digging out deep-seated table root crops with diggers and their manual pickup. Energy costs reached 7 kW per 1 row and overall efficiency of the pickup process did not exceed 0.2–0.3 ha $\cdot$ h<sup>-1</sup> in such case. Taking into account the aforementioned circumstances, mass cultivation of the deep-seated table root crops is possible only in the light sandy-loam soils, in which it is possible to transfer the heap of the root crops to the separating devices in order to carry out high-quality separation. Therefore, issue of lifting of deep-seated table root crops with minimal energy consumption and labour costs is an important scientific and practical task that allows for expansion of the area of growing deep-seated table root crops in heavy soils.

Solution to this issue is proposed as follows. Technological process of lifting of root crops was divided into two stages: loosening of a soil layer using special soil-tillage device and pickup of this layer using a digger with subsequent separation (Pavlov et al., 1975). As the preliminary tests of the machine operation according to this technological scheme showed, separation of the heap of root crops becomes efficient also in heavy soils in this case. Furthermore, an important task is to reduce the energy consumption of the devices (Rucins and Vilde, 2005; Gao et al., 2013; Formato et al., 2017; Aulin et al., 2018). Therefore, goal is to investigate the soil loosening process while lifting the root crops and substantiate the device parameters for its implementation.

## **Material and methods**

To implement the soil loosening process, a new device has been developed (Fig. 1).

During the device movement, toothed rotors, rotating on axes, penetrate the soil to the depth of the deep-seated roots simultaneously with the ploughshare. Rotor teeth concentrate the forces of interaction on the soil layer, resulting in soil crumbling together with partial lifting of root crops. Due to the selected rotation direction of the working body relative to the movement direction, process of soil release occurs predominantly as a result of soil tensile stress and ensures minimal energy consumption. Loosened part of the soil is additionally deformed on the ploughshare back side and root crops with the soil remnants are transferred to the separating conveyor for final cleaning. Therefore, design and geometry of the proposed device provide crumbling of soil around the root crops to the depth of their bedding,

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Fig. 1 Device for lifting of deep-seated table root crops a) general view of the device; b) structural scheme: 1 – toothed rotors, 2 – rotor axle, 3 – ploughshare, 4 – rotor teeth

reducing the energy costs for their lifting and cleaning from soil.

In order to assess the energy efficiency of work of toothed rotors in the process of lifting of deep-seated table root crops, a scheme of a mathematical model of its functioning will be constructed. For this purpose, fixed system of Cartesian coordinates *XOY* and movable  $X_1O_1Y_1$  connected with the centre of the rotor  $O_1$ , which returns at an angle  $\varphi$  together with the rotor (Fig. 1), will be considered.

Let the aggregate move in a straight line and uniformly at speed V. Simultaneously, it is rotating around its axis according to the law  $\varphi = \omega t$ , where  $\omega = \text{constant}$  (angular velocity of the rotor).



Fig. 2 Equivalent scheme of the interaction between rotor and soil layer

Let us consider the movement of the tooth tip (point *K* in Fig. 2). It is easy to see that the point *K* at tooth top (located at a distance *R* from the rotation centre  $O_1$ ) describes the cycloid, which, in turn, is described by well-known formulas (Fox and Pratt, 1982):

$$x = \pm R \sin \omega t + V \tag{1}$$

$$y = \pm R(1 - \cos\omega t) \tag{2}$$

In order to determine the energy intensity, interaction of rotor teeth with soil layer must be taken into account. To determine the energy costs, dependencies of consumed power on time will be in a form:

$$N(t) = M(t) \frac{30 \cdot \omega}{\pi} \tag{3}$$

where:

M(t) – torque on the rotor shaft (N·m)

Unknown component M(t) can be defined from the expression:

$$S(t) = S(t) \cdot P(t) \cdot h(t) \tag{4}$$

where:

- S(t) dynamic cross-sectional area of interaction between teeth and soil layer (m<sup>2</sup>)
- P(t) specific forces of soil deformation (N·m<sup>2</sup>)
- h(t) arm of an equivalent concentrated soil reaction acting upon the tooth (m)

Let the tooth interact with a soil layer of thickness equal to -a (Fig. 3). In case when a tooth penetrates the soil and has previously removed a layer of soil, there occurs a shape confined by lines 1 and 2. Considering the first assumption, it is assumed that the tooth has a straight shape, and interaction area of tooth with soil layer will be as depicted in Fig. 2:

$$S(t) = bk \tag{5}$$

where:

k

*b* – tooth width (m)

tooth penetration degree through the soil (m)

Value *k* expresses the distance between the two points on a plane according to the known formulas from the course of analytic geometry (Fig. 4):

$$M_{1}M_{2} = k = \sqrt{(x_{M_{1}} - x_{M_{2}})^{2} + (y_{M_{1}} - y_{M_{2}})^{2}}$$
(6)

Since the analytical expression of the coordinates of point  $M_2$  is related to the solution of transcendental equations and is not expressed by elementary functions,



Fig. 3 Scheme for determination of rotor teeth interaction area with a soil layer



**Fig. 4** Scheme for determination of soil reaction force arm upon the tooth

these will be defined by means of a numerical method using the KOMPAS 3D program.

Furthermore, it is necessary to find the arm of equivalent concentrated soil reaction acting upon the tooth. It is evident from Fig. 4 that the arm *h* is equal to segment *AB* and it is parallel to segment  $M_1M_2$ . *AC* is a segment connecting the centre of the rotor to the point of application of the concentrated soil reaction; subsequently, segment *AB* is the arm of indicated reaction. Angle  $\alpha$  represents the angle between segment *AC* and arm *AB*.

Value of segment AB is determined from the expression:

$$AB = \cos\alpha \cdot AC \tag{7}$$

Since the segments AB and  $M_1M_2$  are parallel, it is possible to anticipate that angle  $\alpha$  is equal to angle  $\alpha'$  (Fig. 4) and can be found as an angle of two directing vectors of the straight lines containing segments AC and  $M_1M_2$ :

$$\alpha = \arccos\left(\frac{x_{ac} \cdot x_{m1m2} + y_{ac} \cdot y_{m1m2}}{\sqrt{x_{ac}^{2} + y_{ac}^{2}} \cdot \sqrt{x_{m1m2}^{2} + y_{m1m2}^{2}}}\right)$$
(8)

where:

 $x_{acr}$   $y_{ac}$  and  $x_{m1m2}$ ,  $y_{m1m2}$  – the coordinates of the directing vectors of straight segments AC and  $M_1M_2$ , respectively

To find out the coordinates of these vectors, it is necessary to find the coordinates of point *C* at first by means of the following formulas:

$$x_{c} = x_{m1} + \left(\frac{x_{m2} - x_{m1}}{2}\right)$$
(9)

$$y_{c} = y_{m1} + \left(\frac{y_{m2} - y_{m1}}{2}\right)$$
(10)

The coordinates of directing vector of straight line containing segment AC will then be equal to:

$$x_{ac} = x_c - V \cdot t \tag{11}$$

$$y_{ac} = y_c - R \tag{12}$$

Considering Eqs. 9 and 10, it is possible to re-write as follows:

$$\boldsymbol{x}_{ac} = \left(\boldsymbol{x}_{m1} + \left(\frac{\boldsymbol{x}_{m2} - \boldsymbol{x}_{m1}}{2}\right)\right) - \boldsymbol{V} \cdot \boldsymbol{t}$$
(13)

$$y_{ac} = \left(y_{m1} + \left(\frac{y_{m2} - y_{m1}}{2}\right)\right) - R \tag{14}$$

The coordinates of the directing vector of straight line containing segment  $M_1M_2$  will be equal to:

$$x_{m1m2} = x_{m2} - x_{m1} \tag{15}$$

$$y_{m1m2} = y_{m2} - y_{m1} \tag{16}$$

Subsequently, length of segment AC can be determined; it will be equal to:

$$AC = \sqrt{(Vt - x_c)^2 + (R - y_c)^2}$$
(17)

#### **Results and discussion**

Using the obtained dependencies (Eqs. 8–17), Eq. 7 will obtain the final form:

$$h = \frac{\left(\left(x_{m1} + \left(\frac{x_{m2} - x_{m1}}{2}\right)\right) - V \cdot t\right) \cdot \left(x_{m2} - x_{m1}\right) + \left(\left(y_{m1} + \left(\frac{y_{m2} - y_{m1}}{2}\right)\right) - R\right) \cdot \left(y_{m2} - y_{m1}\right)}{\sqrt{\left(\left(x_{m1} + \left(\frac{x_{m2} - x_{m1}}{2}\right)\right) - V \cdot t\right)^{2} + \left(\left(y_{m1} + \left(\frac{y_{m2} - y_{m1}}{2}\right)\right) - R\right)^{2}}} (18)}{\sqrt{\left[Vt - \left(x_{m1} + \left(\frac{x_{m2} - x_{m1}}{2}\right)\right)\right]^{2} \cdot \left[R - \left(y_{m1} + \left(\frac{y_{m2} - y_{m1}}{2}\right)\right)\right]^{2}}}{\sqrt{\left(x_{m2} - x_{m1}\right)^{2} + \left(y_{m2} - y_{m1}\right)^{2}}}$$

Eq. 18 is, in fact, a mathematical model that allows one to make an assessment of the energy efficiency of the device work in terms of soil loosening and lifting of deep-seated table root crops.

Aforementioned methodology for the power determination was implemented as a computational model in the Octave 4.0 software environment. Additionally, specific soil stretching efforts were taken at the level of 6,700 N·m<sup>-2</sup>. As a result



**Fig. 5** Dependence of power *N* consumed by the tooth as a function of time *t* and rotor angular velocity  $\omega$ 





of simulation, a response surface was constructed, which reflected the dependence of energy consumed by a rotor tooth at angular velocity  $\omega$  and time t from penetrating the soil to the tooth leaving it.

It is evident from Fig. 5 that with an increase in time, the power consumption increases, which is explained by an increase in the tooth soil penetration degree and, accordingly, the interaction area of its cutting surface. The decrease in power at the end, before the tooth leaves the working area, is due to a decreased soil reaction force upon the tooth. With increasing angular velocity, the power increases from 500 to 650 W.

In order to test the theoretical model adequacy, an experiment was conducted to determine the power consumed by the working tool teeth. A graph of tooth power consumption N dependent on time t at a rotor angular speed  $\omega = 40$ rad·s<sup>-1</sup> (Fig. 6) was obtained. Acquired experimental data were compared with the theoretical model. Statistical processing utilizing Fisher criterion showed that the theoretical model adequately describes the real process at a significance level of 5% (Dospehov, 2012). Nature of the dependence generally replicates the theoretical model, and differences observed in comparison to experimental data, skewing towards the larger side, can be explained by an unaccounted factor, i.e. friction force of the tooth lateral surface in contact with soil.

It is advisable to investigate the device power consumption case when several teeth interact with soil at the same time in the future. Moreover, it would be also worthy to pay attention to changes in power consumption depending on the inclination angle of tooth working area in relation to the radial direction. Therefore, aforementioned scientific tasks will become subjects of our further research.

#### Conclusion

This paper describes successful refined mathematical model for determining the energy consumption of the process of lifting of deepseated roots. Dependence of device power for soil loosening and lifting of deep-seated table root crops in the kinematic operational mode was established. It was found out that with an increase in the tooth penetration degree, the power consumption increases to a maximum of 500–600 W. Power decreases before the tooth leaves the soil, which can be explained by a decreased soil reaction force acting on tooth.

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