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AMA

AGRICULTURAL MECHANIZATION IN ASIA, AFRICA AND LATIN AMERICA

VOL.53, NO.2, SPRING 2022

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YOSHISUKE KISHIDA

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EDITORIAL

The Earth's population continues to grow, reaching over 8 billion and moving towards 10 billion. In particular, the population of many countries in Africa is increasing rapidly.

We must increase food production per unit of agricultural land to increase food production per capita in the world, that is, by increasing land productivity. For that purpose, new cultivation techniques and improved breeding are important, but agricultural mechanization is also a very big factor. In order to increase the yield, it is necessary to control the timing of farm work, meaning that it is impossible with human or animal power only. In other words, the progress of mechanization can make the timely operation possible. Also, the accuracy of farm work is required. For example, if the optimum seeding depth is known to be 10 cm, the seeds must be sown quickly and accurately to the prescribed depth. This is also impossible by hand and requires appropriate mechanization. It means that agricultural mechanization is indispensable for increasing land productivity.

Agricultural mechanization is witnessing major transformation to enter a new era. Advances in AI will promote the unmanned operations of agricultural machinery. Instead of simply increasing labor productivity by increasing the size, productivity can be increased by using a large number of small, unmanned agricultural robots. I believe that agricultural mechanization in developing countries will also enter the era of agricultural robots that anyone can easily use.

The world still has more than 800 million hungry people, and that number is increasing. People all over the world must work together to address these issues. Unfortunately, the world is seeing a tough time due to severe crisis in international politics. Ukraine hosts the world's leading agricultural lands and contributes significantly to the production of wheat and corn. Production there is expected to be significantly damaged by this truly man-made catastrophe. Why would such a ridiculous war occur when we have to cooperate in eradicating hunger all over the world? Some say that the history of mankind is the history of war. I think it's because humans can't control their desires properly.

The AMA was born for the purpose of working hand-in-hand with agricultural machinery engineers around the world to further advance the agricultural mechanization. I just hope that the global peace will be restored as soon as possible, and that the pace of agricultural growth will not be hampered for long.

Yoshisuke Kishida
Chief Editor
June, 2022

CONTENTS

AGRICULTURAL MECHANIZATION IN ASIA, AFRICA AND LATIN AMERICA

Vol.53, No.2, Spring 2022

NOTICE

The previous issue of AMA (Vol.53 No.1) contained the below-mentioned typo.
We regret the inconvenience caused.

<u>Errata in page 65</u>

Wrong: Optization of Developed Continuous Type Pomegranate Juice Extractor
Correct: Optimization of Developed Continuous Type Pomegranate Juice Extractor

Optimized Design of Gunpowder Tea Shaping Machine Using on ABC Algorithm

by
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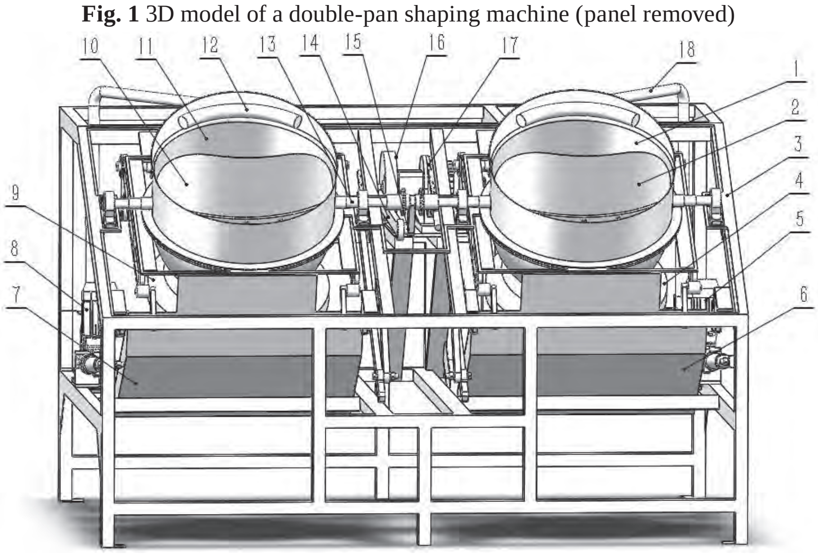
Abstract

Aiming at the problems of high labor intensity and low efficiency in artificial shaping Gunpowder tea, a kind of tea shaping machine with two pans, was designed. The machine used crank and rocker mechanism to realize the swing of the shaping plate and simulates the traditional process. In order to improve the smoothness of the machine running, to reduce vibration and noise, and to reduce the amount of broken tea, the ABC algorithm was used to optimize the design of the key kinematic parameters. The objective function was to maximize the minimum transmission angle. A three-dimensional nonlinear constrained mechanical optimization mathematical model was established. The program based on the ABC algorithm was developed by MATLAB. When the length of crank, connecting rod, rocker and the frame length were 180 mm, 420 mm, 421 mm and 450 mm respectively, the minimum transmission angle is increased from 30.1 to 37.4, and the noise is reduced from 78 dB to 71 dB, the forming rate of gunpowder tea increased from 81% to 93%. The rate of broken tea decreased from 8.7% to 7.3%. This research provides a theoretical basis for improving the performance of double-pan shaping machine.

Keywords: tea shaping machine; optimized design; ABC algorithm

Fig. 1 3D model of a double-pan shaping machine (panel removed)



Note: 1. Right frying pan, 2. Right frying plate, 3. Body frame, 4. Right electric heating unit, 5. Right electric push rod, 6. Right tea outlet, 7. Left tea outlet, 8. Left electric push rod, 9. Left electric heating unit, 10. Left frying plate, 11. Left frying pan, 12. Left hot air pipe, 13. Frying plate shaft, 14. Connecting rod, 15. Rocker, 16. Crank, 17. Motor, 18. Right hot air pipe

Introduction

Gunpowder tea is one of the Chinese roasted green tea. It is originated from Ping Shui Town, Shaoxing County, Zhejiang province, China. Refined export tea called Gunpowder tea or "Ping green". The main processes include finished fixing, rolling, shaping and baking. Shaping is the key process to form the unique shape and quality of Gunpowder tea. The traditional way of shaping Gunpowder tea is by hand, with good quality, but low production efficiency, only 0.6-0.7 kg/h by a skilled labor, and high labor intensity. In the 90s, with the increase of tea export, the production area of raw materials of pearl tea began to grow from Zhejiang, to Jiangxi, Anhui, Hubei, Sichuan and other places in China.

Material and Method

Structural Design and Working Principle

The structure of the machine is shown in **Fig. 1**. The technical parameters of the machine are shown in **Table 1**. The working process is as follows: The frequency conversion motor drives the active pulley to rotate, the driven pulley is rotated through the belt drive, and the crank is installed coaxially with the driven pulley to rotate uniformly. The crank rocker mechanism drives the arc plate fixed on the bracket of the arc plate board to swing. Using the swing of the arc plate simulates the process of artificial frying tea process. The tea is promoted to roast in the pan; under the action of the shaping pan and the extrusion of the pan wall, the internal friction between the tea leaves increases, and the tea leaves curl and gradually form spherical shape.

Table 1 Parameters of the tea shaping machine

Parameter	Value
Physical dimension (L × W × H) /mm	1860 × 850 × 1228
Structural weight /kg	178
Shaping speed /rpm	60-110
Shaping angle /º	80
Speed regulation mode	frequency control
Electric heating power /kw	13
Pan diameter /mm	700
Pan inclined angle/º	30
Productivity/ kg/h	6

ABC Algorithm

Artificial Bee Colony (ABC) algorithm is an optimization method, which imitates the behavior of bees. It is a concrete application of the idea of cluster intelligence. Its main characteristic is that it does not need to know the specifical information of the problem. It only needs to compare the advantages and disadvantages of the problem. Through the local optimization behavior of each artificial bee individual, it can finally make the global optimization in the colony. The value emerges has a faster convergence speed. To solve the problem of multivariable function optimization, Karaboga proposed the artificial bee colony algorithm (ABC) model. In recent years, ABC algorithm has been used in the field of mechanical and civil engineering areas, or in electrical engineering.

Unlike genetic algorithm and other swarm intelligence algorithms, role conversion is a unique mechanism of ABC algorithm. Bee colonies work together to find high-quality honey sources by changing the roles of employed bees, scouts and onlookers. In the search and optimization of ABC algorithm, the functions of the three kinds of bees are different: employed bees are used to maintain a good solution, scouts are used to increase convergence speed; onlookers are used to enhance the ability to get rid of local optimum. The location of the nectar source is abstracted as a point in the solution space, representing the potential solution of the problem. The nectar source i (i = 1, 2,..., SN), SN is the number of nectar sources. The quality of the honey source corresponds to the fitness value of the solution fiti. The initial location of the nectar source is randomly generated in search space according to equation (1).

$$x_{ij} = l_j + \delta \times (u_j - l_j) \quad (1)$$

Where $j \in \{1, 2,..., D\}$, D is dimension of the problem, l_j and u_j are the lower and upper bound of the parameter x_{ij}, and δ is a random number in the range [0, 1), i = 1..., SP/2.

Each employed bee produces a new solution according to equation (2).

$$v_{ij} = x_{ij} + \varphi \times (x_{ij} - x_{kj}) \quad (2)$$

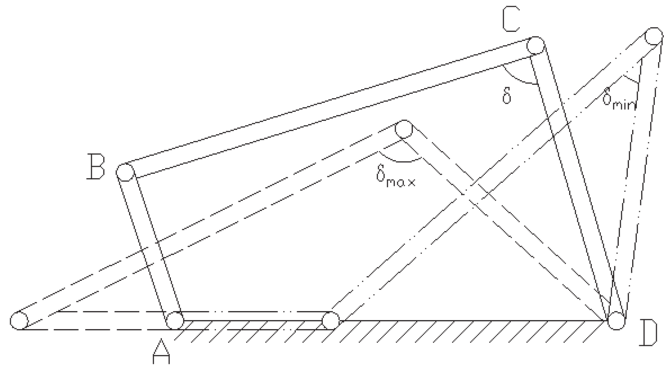
Where φ_i is random number in range [-1, 1), $k \in \{1, 2,...,SP/2\}$, $k \neq i$ is randomly chosen index, φ_i is randomly chosen real number in range [0, 1) and j = 1, 2,...,D, when new nectar source v_i = [v1, v2,..., vd]. The fitness is better than that of x_i.

Greedy election is adopted. The alternative method is v_i instead of x_i, otherwise, keep x_i. All employed bees complete operation (2), fly to the information exchange area to share the nectar source information. An onlooker bee chooses a nectar source depending on the probability value associated, p_i, calculated by equation (3), and the employed bees exchange their information with the onlookers in this way.

$$P_1 = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (3)$$

Where fit_i is the fitness value of the solution i evaluated by its employed bee, which is proportional to the nectar amount of the food source

Fig. 2 schematic diagram of crank rocker mechanism



in the position i and SN is the number of food sources which is equal to the number of employed bees. The scout bee chooses to employed bee by roulette, that is, to produce a uniformly distributed random number r at (0, 1). If the p_i is greater than r, the scout bee produces a new honey source around the honey source I, and identifies the reserved nectar source by the same greedy selection method as the employed bee.

During search, if the nectar source x_i is searched by trial iterations, the threshold limit is met, and no better nectar source is found; then the nectar source is x_i will be abandoned, and the corresponding employed bee role will be transformed into a scout bee, and it will randomly generate a new nectar source in search space instead of x_i. The process mentioned is executed according to equation (4).

$$x_{ij} = \begin{cases} lj + \delta \times (u_j - l_j) & \text{trial} \geq \text{limit} \\ x_{ij} & \text{otherwise} \end{cases} \quad (4)$$

For minimizing the optimization problem, the fitness of the solution fit_{ij} is calculated by equation (5).

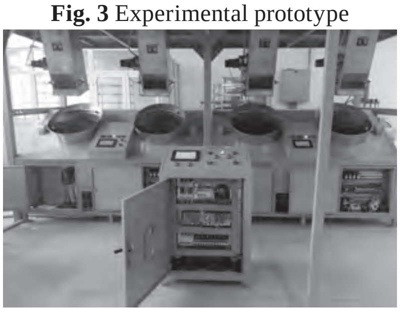
$$fit_{ij} = \begin{cases} 1/(1+f_i) & f_1 \geq 0 \\ 1 + abs(f_i) & \text{otherwise} \end{cases} \quad (5)$$

Where f_i is function of solution.

The pseudo-code of the ABC algorithm is:

1) Initialize the population solutions x_{ij} according to equation (1). Set parameters SN, limit and the maximum iterations; t = 1;
2) Produce a new solution v_i for each employed bee by equation (2).
3) Evaluate fitness value of the solution by equation (5).
4) Calculate the probability of nectar source being followed according equation (3).
5) Scouts searched in the same way as the employed bee, and reserved nectar source or not was determined according to the greedy selection method.
6) Judge whether the nectar source meets the conditions of abandonment. If satisfied, the employed bee role will become a scout bee, otherwise go to 8.
7) Onlooker bee founded new nectar source according to equation (4).
8) t = t + 1, if the termination condition is satisfied, the optimal solution is output. Otherwise go to 2.

Fig. 3 Experimental prototype



Optimal Design Model

The transmission mechanism of Gunpowder tea shaping machine is a crank-rocker mechanism, as shown in **Fig. 2**. The rocker and the frying plate bracket are coaxially installed to realize the swaying of the frying plate in a certain angle range for frying tea. It is a plane four-bar mechanism. The minimum transmission angle is one of the key parameters of the mechanical properties of the mechanism, which directly affects the smoothness and stability of the mechanism movement.

The length of the rod satisfies $l_{AB}^2 + l_{AD}^2 < l_{BC}^2 + l_{CD}^2$. When the crank AB is overlapped with the rack AD, the minimum transmission angle of the mechanism is equation (6):

$$\gamma_{min} = \cos^{-1}\frac{l_{BC}^2 + l_{CD}^2 - (l_{AD} - l_{AB})}{2l_{BC}l_{CD}} \quad (6)$$

The length of the rack bar in the double cooker l_{AD} is 450 mm. The design parameters are: crank length l_{AB}, connecting rod length l_{BC}, rocker length l_{CD} and rack bar length l_{AD}, that is equation (6),

$$X = [x_1, x_2, x_2]^T = [l_{AB}, l_{BC}, l_{CD}]^T \quad (7)$$

The objective function can mainly reflect the kinematic performance of the transmission mechanism. When the transmission angle is too small, it will cause the mechanism to be stuck, the vibration and noise are large, and the minimum transmission angle should be maximized. So the objective function is:

$$\min F(x) = \gamma_{min} \quad (8)$$

The mathematical model of optimal design is standardized as equations (9) to (22):

$$\min F(x) = \cos^{-1}\frac{x_2 + x_3 - (450 - x_1)^2}{2x_2x_3} \quad (9)$$

$$g_1(x) = x_1 + 450 - x_2 - x_3 < 0 \quad (10)$$
$$g_2(x) = x_1 + 450 + x_3 - x_2 < 0 \quad (11)$$
$$g_3(x) = x_1 + 450 + x_2 - x_3 < 0 \quad (12)$$
$$g_4(x) = x_1 - x_2 < 0 \quad (13)$$
$$g_5(x) = x_1 - x_3 < 0 \quad (14)$$
$$g_6(x) = x_1 - 450 < 0 \quad (15)$$
$$g_7(x) = x_1^2 + 450^2 - x_2^2 - x_3^2 < 0 \quad (16)$$
$$g_8(x) = 170 - x_1 < 0 \quad (17)$$
$$g_9(x) = x_1 - 285 < 0 \quad (18)$$
$$g_{10}(x) = 346 - x_2 < 0 \quad (19)$$
$$g_{11}(x) = x_2 - 487 < 0 \quad (20)$$
$$g_{12}(x) = 399 - x_3 < 0 \quad (21)$$
$$g_{13}(x) = x_3 - 432 < 0 \quad (22)$$

Results and Discussion

The optimum design program of crank-rocker mechanism of gunpowder tea shaping machine based on ABC algorithm is compiled by using MATLAB language. It runs on PC with Intel Pentium Dual E5200 and RAM of 4G. The crank length l_{AB}, link length l_{BC} and rocker length l_{CD} of the machine are calculated.

In order to verify the correctness of the results, a validation test was carried out in Huayang Tea Machine Co., Ltd. Xuancheng City, Anhui Province, as shown in **Fig. 3**. The test raw materials were rolled leaves with 65% moisture content of 14 kg. The experiments were carried out to obtain an average of 7 kg each time. The tea shaping machine before and after optimization was used to shaping tea. When the moisture content of tea was 20%, the procedure was completed.

This paper mainly examines the determination of gunpowder tea shaping rate, noise caused by vibration and broken tea rate before and after optimization design. The above indices were related to the motion performance of the machine. The prototype after optimization is shown in **Fig. 3**, and the finished tea before and after optimization is shown in **Fig. 4**.

Determination of Gunpowder Shaping Rate:

After a normal working procedure (40 min) of the tea shaping machine, the qualified products of gunpowder tea were sorted manually and weighed, and the average value was repeated 10 times. The forming rate of pearl tea was calculated according to the equation (23).

$$\xi_P = \frac{W_a - W_b}{W_a} \times 100\% \qquad (23)$$

Where ξ_P is gunpowder shaping rate, W_a is unqualified quality after sorting (g), W_b is total quality of tea Samples (g).

Noise Measurement:

Fluke 945 noise meter was used to measure the noise according to the machine noise measurement standard (DIN 45635-61-1990). Determination of broken tea rate: According to the standard GB/T 8311-2013, 100 g tea samples were weighed and screened by pouring the broken tea sieve with a diameter of 1.25 mm into the sieve hole. The quality of broken tea under the sieve was measured and calculated according to the equation (24).

$$\delta = \frac{m_1}{m} \times 100\% \qquad (24)$$

The test results are shown in **Table 2**. When the minimum transmission angle of the mechanism was small, the phenomenon of motion stuck will occur, resulting in increased vibration and noise, and the impact of frying plate on tea in produces will increase, resulting in excessive broken tea. After optimization, the minimum transmission angle of the tea shaping machine is increased, the motion smoothness was improved, the vibration and noise were reduced, and the quality of the finished tea was improved.

Table 2 Optimization parameters result of tea shaping machine

Item	Before optimization	After optimization
Length of the crank l_{AB}/mm	240	180
Length of the connecting rod l_{BC}/mm	410	420
Length of the rocker l_{CD}/mm	397	421
Length of the frame length l_{AD}/mm	450	450
Minimum transmission angle/°	30.1	37.4
Noise/dB	78	71
Shaping rate of gunpowder tea/%	81	93
Broken tea rate/%	8.7	7.3

Conclusion

A gunpowder tea shaping machine was designed in this research, based on ABC algorithm. Traditional experience or analogy method was used to design the relevant transmission mechanism, which has a high vibration noise and affects the reliability and durability of the machine. The minimal transmission angle maximization of double-pot millimeter crank was taken as the design objective, and the kinematics key parameters were taken as the design parameters. The optimization design model was established. ABC algorithm-based optimization design program was compiled by using MATLAB, and the verification test was carried out. The optimization results show that the crank length is 180 mm, the connecting rod length is 420 mm, the rocker length is 421 mm, and the frame length is 450 mm. Compared with before optimization, the minimum transmission angle increased from 30.1° to 37.5°, the noise decreased from 78 dB to 71 dB, the forming rate of Gunpowder tea increased from 81% to 93%, and the broken tea rate decreased from 8.7% to 7.3%. This study can provide theoretical reference for the design of tea machinery.

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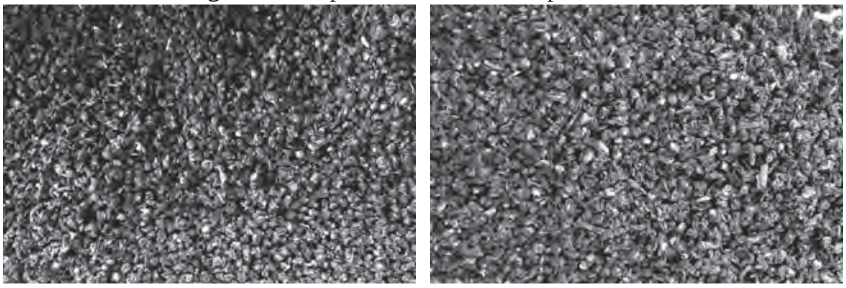
Karaboga, D. and B. Akay. Artifi-

Fig. 4 Tea samples before and after optimization



Note: 1. The right is the optimized and the left is the unoptimized.

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■■

ABSTRACTS

The ABSTRACTS pages is to introduce the abstracts of the article which cannot be published in whole contents owing to the limited publication space and so many contributions to AMA. The readers who wish to know the contents of the article more in detail are kindly requested to contact the authors.

2031

Sensing Soil Compaction Through its Vibratory Response to Impact Excitation: Arturo Martínez Rodríguez: armaro646@gmail.com, María V. Gómez-Águila: mvaguila@hotmail.com, Yeandy Graverán Valdés: arturo@unah.edu.cu, Ernesto Ramos Carbajal: erc670819@gmail.com, Julio C. Ayala López: arturo@unah.edu.cu, Lázara Rangel Montes Oca:lazarar@unah.edu.cu

In order to evaluate the vibratory response of soil to impact, as a way to develop a non-invasive method of sensing soil compaction, this research was conducted at Agricultural Mechanization Center of the Agrarian University of Havana. The experiment was carried out by exciting the soil by the impact of a mass with certain level of potential energy and taking readings from two accelerometers placed on the ground at different distances from the excitation point. Soil bulk density was taken as independent variable, measured at three levels to represent the soil compaction. Dependent variables were taken as: a) frequency that corresponds to the maximum peak of the Power Spectral Density of the accelerometer output signal, b) energy of the signal, and c) its damping ratio. As a result, it was found that both the frequency corresponding to the peak value of the power spectral density, as well as the energy of the signal and its damping ratio, showed a significantly strong relationship (R2 between 0.93 and 0.99) with the bulk density of a Red Ferralitic soil with an exponential adjustment model. This fact leads to the possibility of using these methods as a principle for non-invasive sensing of soil compaction.

Recent Trends in Measurement of Soil Penetration Resistance and Electrical Conductivity of Agricultural Soil and Its Management under Precision Agriculture

by

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Abstract

Soil compaction increases in agricultural fields with use of heavy machinery by the farmers to meet the growing demand of food for world population. Extreme soil compaction has negative impact on agriculture and the environment. It adversely affect soil structure, reduces crop production, increases runoff and erosion, accelerates potential pollution of surface water by organic waste and applied agrochemicals, and causes inefficient use of water and nutrients due to slow drainage. In field operations, high energy requirement and other land management treatments are performed to enrich undesirable soil compaction. Soil compaction is the process through which soil grains are rearranged to reduce void space and take them into closer contact with each other, so increasing the bulk density. Soil compaction is caused due to severe loads applied to the unsaturated soils surface. Electrical Conductivity (EC) of soil-water mixtures also helps us to predict much important information that indicates the aggregate of salts available in the soil. Salt present in the soil arises from the irrigation water, fertilizer, and dissolving soil minerals. A soil comprises some salts, which are very essential for plant growth. Although, excess salts will interruption plant growth by distressing the soil-water balance. Soil from the semiarid and western arid areas of the country are mostly affected by salt, where the rainwater is less yearly, allowing salts to accumulate in the soil profile. Electrical conductivity measurement indicates the number of cations and anions (salts) in solution, if more in the number of anions or cations, greater is the electrical conductivity.

Keywords: Soil Compaction, Penetration Resistance, Electrical conductivity, Cone Penetrometer, Compaction effects on soil.

Introduction

Compaction of soil is the compression of soil particles into a smaller volume, which reduces the size of pore space available for air and water. Soil compaction is a serious and unnecessary form of soil degradation that may result in increased soil erosion and decreased crop yield production. Compaction of soil equal to 80 kPa or greater can result in blocking of root of plants from emergence (Bowen and Goble, 1967). There are numerous important biological and chemical processes taking place within soil pores that require both water and air but the reduction in pore size hinders biological and chemical processes, such as the reduced cycling and release of plant available nutrients. Soil compaction impairs water infiltration into soil, water uptake, root penetration, crop emergence and crop nutrient, which results in overall decrease in crop yield (Anonymous, 2010). Compaction of agricultural soil may be caused due to tillage implements adopted during soil cultivation or as a result of other heavy weight of field equipment being used on agricultural soil or it can also be the result of natural soil forming processes. The compaction caused by tillage implement is also referred as "hard pan" or "plough pan" (Duiker, 2004). In the past several decades the concern of wheel traffic compaction has also increased due to the increasing size of farms, farm equipment and the time needed to complete farm operations at seeding and harvest (Poesse, 1992).

Evaluation of soil compaction is necessary to resolve its rigorousness and to make out suitable mechanical, chemical, or biological methods of interference suggested for eliminating or controlling soil compaction.

Compaction can also be measured directly from porosity, void ratio, dry specific volume and dry bulk density (Culley, 1993). However, other methods includes indirect measurements for detecting increase in soil compactions that rely on either decrease in unified pore spaces (fluid permeability) or increase in soil strength (mechanical impedance to penetrating objects), whereas, direct measurement measures the condition of soil compactness. The indirect method of measurement specifies only the changes in behaviour of soil response frequently which is not always related to soil compactness (Johnson and Bailey, 2002). In India, continuous high usage of heavy machinery, cropping pattern, pesticides and fertilizers has resulted in declining water table, increase in soil compaction and salinity of soil are some problems which are being faced by farmers (Narang et al., 2001). Excessive and prolonged usage of rotary ploughs especially with L-blade for many years has also caused increase in soil compaction and formation of hard pan in the top soil which affect the crop growth and production (Singh et al., 2015).

The objective of this paper is to collect the reviews of the different types of developed cone penetrometers for measuring soil penetration resistance and identify the major problems related to the soil due to soil compaction and electrical conductivity. To study its effects on soil physical properties and its relation with plant growth and yield, and the various instruments developed for measuring soil compaction and electrical conductivity of soil.

Penetrometer for Soil Compaction Measurements

Penetrometers are the instruments used for measurement of soil penetration resistance (SPR) values and consist of a rod or a shaft with a cone tip (Morrison and Lowery, 2002). Penetrometer penetrates into the soil by means of the vertical force and the SPR values of a cone are determined by measuring the force applied to the cone divided by its basal area (Bradford, 1986). The SPR values of the rod friction can also be calculated by dividing its surface area by the force applied to the rod, according to this same author. The design of the soil cone penetrometer probe tip and shaft and the procedure for the determination of SPR values are governed and standardized by the ASAE Standard S313.2 (ASAE, 1998) via ASABE, 2006a and ASABE, 2006b standards. According to the American Society of Agricultural and Biological Engineers (ASABE) there are two standard sizes used in design. Firstly for soft soils, 20.27 mm (0.798 in.) diameter base cone having 15.88 mm (0.625 in.) diameter shaft and secondly for hard soils 12.83 mm (0.505 in.) diameter base cone having 9.53 mm (0.375 in.) diameter shaft as shown in **Fig. 1**. The standard dimensions must be followed for designing different components of cone penetrometers and standardised procedure should be followed for accurate analysis and interpretation of results. Penetrometers also take SPR values in third dimension, while insertion into the soil at different angles of a soil layer (Lowery and Morrison, 2002). Therefore, for development of roots while monitoring mechanical impediment of different soil layers are important to characterize the evolution of agricultural management systems evaluation (Torres and Saraiva, 1999, Secco et al. 2009).

Researchers, for past decades, are trying to simplify the procedure of the soil cone penetrometer usage by improving the design. Many researchers have designed portable hand- operated recording penetrometers which can be inserted continuously into the soil and does not require a second person (Carter, 1967,

Fig. 1 Cone standards for penetrometers according to ASABE S.313.3 (Source: ASABE, 2006b)

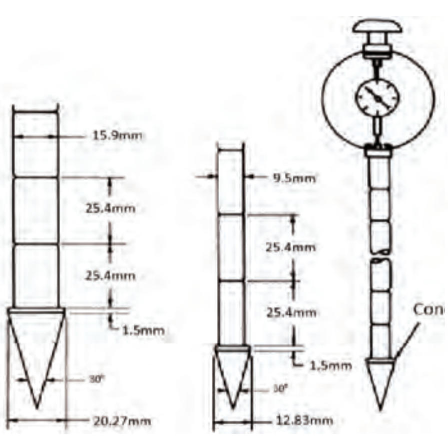
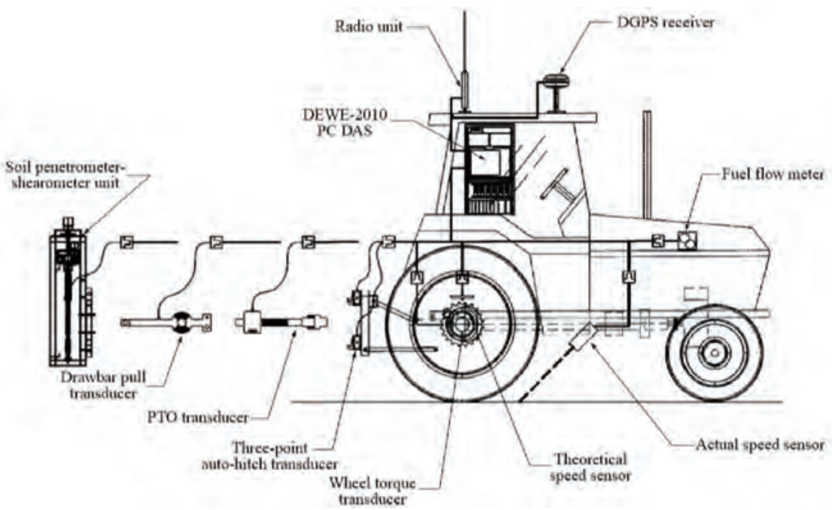


Fig. 2 Tractor mounted multiple probe soil cone penetrometer (Source: Gew et al., 2005



Hendrick, 1969, Prather et al. 1970, Hruby et al. 2014 and Rezae, 2017). Hand operated penetrometers are either dial gauge or digital display type generally used for measurement of compaction data are taken in India, which have certain limitations and more prone to error and not ergonomically correct (Kumar et al. 2015). To eliminate the manual labour requirements associated with obtaining these measurements, number of tractor-mounted multiple probe soil cone penetrometer were also developed by many researchers have according to ASAE Standard (Williford et al., 1972, Smith and Dumas, 1978, Wilkerson et al., 1982, Hooks et al., 1986, Raper et al., 2001, Jahn et al., 2002, Alimardani, 2005, Gew et al., 2005, Tekin et al., 2007, Sharabiani et al., 2009 and Onwualu et al., 2011) as shown in **Fig. 2**. Some researchers have developed GPS enabled cone pentrometers, which generate three dimensional data (Hemmat et al., 2005, Tekin et al., 2008, Topakci et al., 2010 and Mafra et al., 2010).

With advances in precision agriculture, spatial variation of soil compaction has been focused by many researchers in their investigation. It has been recognized that the recommended methods for direct measurement of a large amount of soil compaction using a hand penetrometer with high accuracy also requires more time and extreme effort in field conditions which is labour demanding and cost prohibiting for large scale field mapping. Therefore, determination of indirect measures along with their geographical coordinates has become a more appealing alternative (Gaultney, 1989). Soil penetration resistance depends on the water content present in the soil (VAZ et al., 2011 and Moraes et al., 2012). Different types of penetrometers are shown in **Figs. 3** and **4**.

Among the various factors that affect the determination of soil penetration resistance values, the angle of cone, diameter and roughness, and rate of penetration of the penetrometer is recommended to be cited (Bradford, 1986). The determination of Soil penetration resistance values also depends on soil bulk density (Otto et al., 2011), amount of water content present in the soil (Figueiredo et al., 2011 Assis et al., 2009, and Moraes et al., 2012), pore and water pressure of soil (Freudlund et al., 1978 and Kim et al., 2008), distribution of particle size (Vaz et al., 2011), clay content present in the soil (Molin et al., 2006), type of soil (Silva et al., 2004), compressibility of soil (Silva et al., 2002), and friction due to metal content present in soil (Dexter et al., 2007).

The problem that was observed from the studies on different types of penetrometers is the non-uniformity among the adopted penetration rates and it is difficult to establish relation among them a penetration rate as the rate of penetration may get increased or decreased depending upon percentage moisture content and other properties of the soil profile (Bradford, 1986, Bengough and Mullins, 1991). The classification of the SPR values was done by USDA (1993) based on a penetrometer described by Bradford (1986) into three main classes: small, intermediate, and large shown in **Table 1**. It is recommended that the SPR values should be offered with the description of the field conditions such as the amount of the soil water content and axis orientation. Another method for comparing the limits of SPR values for different classes were presented by Canarache (1990), as shown in **Table 2**.

Table 1 Penetration resistance classes according to the United States Dept. of Agriculture (Source: USDA, 1993)

Classes	Limits (MPa)
Small	< 0.10
Extremely low	< 0.01
Very low	0.01 – 0.10
Intermediate	0.10 – 2.00
Low	0.10 – 1.00
Moderate	1.00 – 2.00
Large	> 2.00
High	2.00 – 4.00
Very high	4.00 – 8.00
Extremely high	> 8.00

Effect of Soil Compactions on Agricultural Soil

Compaction of a soil mass causes an increase in dry density which depends on percentage of moisture

Fig. 3 Digital cone penetrometer

Fig. 4 Veris P4000B Penetrometer, USA

Table 2 Limits for penetration resistance classes according to Canarache (1990)

Penetration resistance classes	Limits (MPa)	Limitations for root growth
Very low	≤ 1.0	No limitations
Low	1.1 – 2.5	Weak limitations
Medium	2.6 – 5.0	Moderate restrictions
High	5.1 – 10.0	Critical restrictions
Very high	10.1 – 15.0	Virtually no root growth
Extremely high	> 15.0	No root growth

content. Soil compaction causes increase in bulk density, penetration resistance, and decrease in hydraulic conductivity, infiltration rate and porosity. Soil-plant-water relations are strongly affected by resisting the penetration of roots, its growth and development due formation of compact layer at any depth and further reduction in root growth and density also cause decrease in nutrient uptake and ultimately crop yield (Kaul et al., 2015). Increase in soil compactness decreases root size, lower rooting depth and a greater distance between the nearest roots and the higher concentration of roots in the upper soil (Lipiec et al., 2003). It also results in decrease in oxygen diffusion rates below critical values for all bulk densities due to which O_2 concentrations in roots form 0.10 to 0.25 m depths, due to soil compaction and bulk density (Smucker et al., 1989) and decreased Na and Cu uptake in this plant (Najafi et al., 2015).

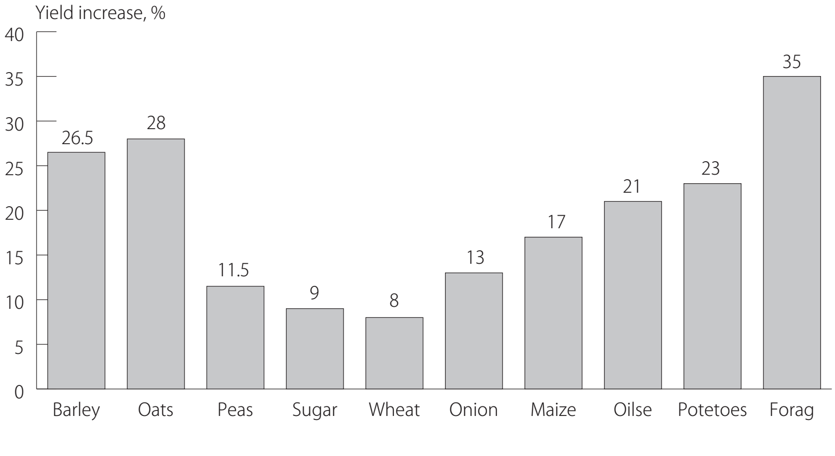
The effects of soil bulk density due to compaction causes decrease on soil microbial populations and enzyme activities during the growth of any crop. The greatest activities of most soil enzymes occur at a bulk density of 1.0 to 1.3 Mg m^{-3}, which is most advantageous for most field crops (Zhang et al., 2002, Brye et al., 2005, Jurisic 2013 and Moraes et al., 2014). Soil compaction is also induced with intensive use of machinery, especially for harvest affecting the crop development and control of agricultural traffic could be an alternative for management by preserving the soil physical quality and higher productivity and yield was also recorded in traffic control over no traffic control system (Araujo et al., 2014). Effect of non-trafficked and conventionally trafficked soils on crop yield has been shown in **Fig. 5**.

Effect of Soil Strength on Agricultural Soil

Soil strength is the resistance offered by soil itself which has to be defeated to obtain a given soil deformation, when submitted to external forces which largely depends on the characteristics of the internal stress tensor due to soil compaction (Guerif, 1994). Increase in soil strength can result in decrease shoot and shoot growth in pot (Masle and Passioura 1987, Atwell, 1990 and Passioura, 2002) experiments. However, it is not totally understood that to what extent high soil strength can be considered to effect crop growth. Understanding of plant responses is complex by the fact that soil strength and water stress are extremely correlated (Whalley et al., 2007b, Taylor and Ratliff 1969), making it difficult to recognize whether the plant responds to low availability of water or to high soil strength (Whalley et al., 2006).

Soil compaction or strength properties not only influence the crop growth but also its yield. If soil compaction/strength is found less than 1 MPa, then the roots grow through soil without any difficulty indicating good physical quality soil where as if the soil strength is between 1 to 3 MPa it may result in restricted root growth indicating moderate soil physical quality. Further soil strength greater than 3 MPa can stop the root growth to great extent and can drastically reduce crop yield. Hence, it is important to measure the soil properties to reduce their influence on crop yield.

Fig. 5 Yield increase attributed to non-trafficked compared with conventionally trafficked soils (Source: Chamen, et al., 2011)



Characterising Electrical Conductivity for Agricultural Soil

Soil electrical conductivity is the measurement that correlates with soil properties that directly affects crop productivity. Surplus amount of salts accumulation in the agricultural soil is easily detected by electrical conductivity. Some physical and chemical properties of soil can be indirectly measured from soil electrical conductivity. Further soil characteristics (soil moisture, silt, sand, organic carbon and organic carbon) are powerfully interrelated to electrical conductivity in some study fields but not in others, Sudduth et al. (2001). The yield of any crop is mostly affected by the water holding ability of soil which has strong correlation with the electrical conductivity of that particular soil. Electrical conductivity of soil provides very precious information about similarities and differences among different soil which makes it easy to divide the large or small field into smaller zones for management which can easily indicate the area where further exploration can be done. The Food and Agriculture Organisation published maps of soil threats on World Soil Day, 2016 as shown in **Fig. 6**.

Therefore electrical conductivity is the quick and economical way for estimation of soil quality measurements. Soil bulk density and cation exchange capacity are the most significantly correlated (r. 0.55) with electrical conductivity at the deepest sampling depth are positively correlated to yield, Motavalli et al. (2005). There is negative correlation between electrical conductivity and soil penetration resistance using classical statistics and geostatistics, (Gonzalez et al., 2010 and Krajco, 2009). It is found that there are significant correlations between physical parameters of soils and electrical conductivity and higher order correlations were observed between bulk density and texture of soil samples and inverse correlation was found between Electrical Conductivity and Bulk Density.

However, it is suggested that Regression equations may be used to determine the significant level of physical Constituents between Electrical Conductivity and Physical Parameters of Indian soils, Maity et al., 2014. However it was also observed from the literature that work has been done on measurements of soil electrical conductivity by many researchers (Sudduth et al., 2001, Sudduth et al., 2005, Motavalli et al., 2005, Gonzalez et al., 2010 and Maity et al., 2014) but for future it is suggested that soil electrical measuring sensors should be attached with tractor mounted cone-penetrometer to relief the researchers from separate analysis of electrical conductivity of soil. Soil compaction and electrical conductivity analysis is the future and first step of precision farming for variable rate technology.

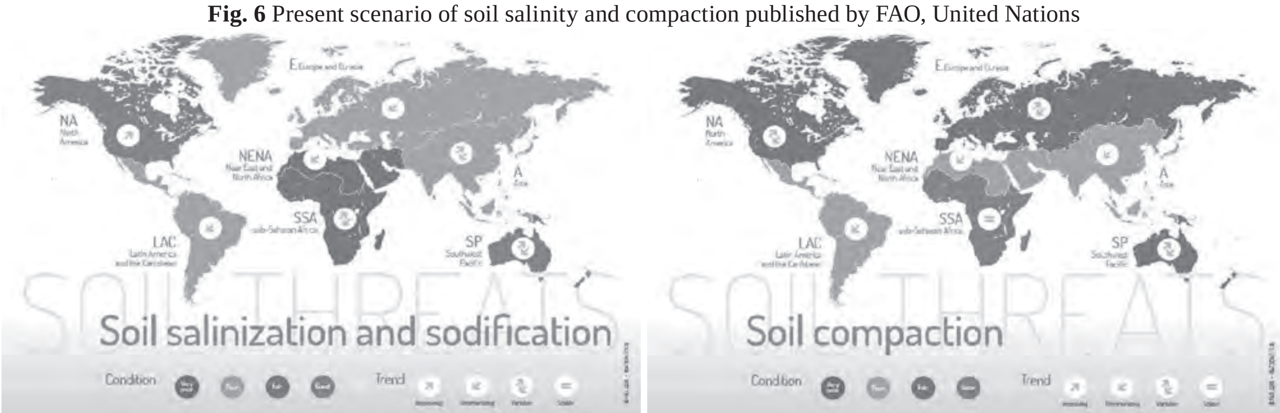
Sensors for Measurement of Electrical Conductivity of Soil

Many manufacturers in collaboration with different researchers have developed numerous soil sensors for measurement of electrical conductivity of soil out of which very there are less sensor systems that are commercially available in the market (Adamchuk, 2004 and Kumar et al., 2018). At present, there are mainly two types of soil sensors commercially available to measure electrical conductivity of soil in the field namely, contact or non-contact.

i. Contact Sensor Measurements: These types of sensors are most trendy and widely accepted for precision farming for large areas which can be mapped quickly and it can be used for small land holdings due to bulkier nature. These sensors use coulters as electrodes where one coulter acts as transmitting electrodes and other acts as receiving electrodes which makes contact with the soil for measuring the electrical conductivity (**Fig. 7**). Data collected is recorded in the data logger attached with global positioning system (GPS) for precise grid mapping.

ii. Non-contact Sensor Measurements: These types of sensors work on the principle of electromagnetic induction and do not make any direct contact with soil surface. These sensors are easy to handle individually and useful for small fields due to its light weight. These sensors are composed of transmitter and receiver coil which measures the electromagnetic field induced by current which is directly correlated with electrical conductivity of soil. The most popular models of non-contact sensors are GEM-2 (Geophex) and EM38 (Geonics Limited). GEM-2 is a digital and multi-frequency sensor that has the ability to measure electrical conductivity at different depths whereas EM-38 facilitates

Fig. 6 Present scenario of soil salinity and compaction published by FAO, United Nations



only fixed frequency which can take measurements up to 60 inches of depth in horizontal mode or 30 inches in vertical mode.

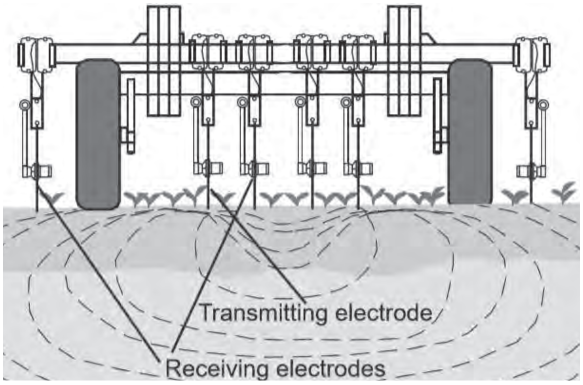
Management of Soil Compaction and Electrical Conductivity under Precision Agriculture

The management of soils should be done with the supposition that the use of agricultural machinery is expected to increase with the introduction of new machineries every year all over the world. For management two alternative approaches need to be followed i.e. either the use of machinery should be confined to tracks (controlled traffic) or it must be acknowledged that a degree of compaction is unavoidable. The risk of deeper subsoil compaction can only be achieved with proper engineering interventions; however some surface layer on the upper layers of soil compaction will still occur. There are well established techniques for loosening compact soil up to about 45 cm depth although there are many variations on experiment evidence. There is always a risk of deeper soil compaction problems under difficult soil conditions with the increased mass of tillage and harvesting machines. Therefore it is recommended that methods for evaluation of the degree of soil compaction should be improved up to 60 cm depth as there are no techniques available to loosen deep seated compaction efficiently and economically (Godwin et al., 2008).

Soil management and cropping practices should be ensured to prevent soil compaction such as direct seeding practices to optimize soil structure with increase in soil organic matter content, reducing traffic to increase crop water use efficiency and crop yield potential in fields and application of fibrous and tap rooted crops in a rotation which develops deep root channels and further leads to addition of organic matter to soil, (Glenk et al., 2010). GPS technology has been used to restrict all wheel tracks to precise routes has been developed into a cropping system on a more extensive scale (Tullberg et al., 2007). The best way for management of soil compaction is the standardization of equipment for soil penetration resistance and procedure for its determination, both in the field and laboratory for better understanding of crop conditions (Gew et al., 2005).

Soil electrical conductivity (EC) is principally determined by laboratory analysis methods by placing the soil solution between two electrodes of constant geometry and distance of separation (Bohn et al., 1985) which is time consuming process as large number of samples has to be taken for single field. Similarly, the measurement of soil strength process by manually pushing the cone into the hard compacted agricultural soil and recording individual data at constant and specified intervals with the help of cone penetrometer and manual penetrometers is also very laborious process. There are machines available in advanced countries for measurement of EC like soil EC mapper (Veris 3100) but it is bulky and costly. Tractor mounted EC mapper along with soil strength measurement can collect more information in lesser time which will be helpful for managing fields effectively.

Fig. 6 Contact type EC sensor with one electrode as transmitting and others as receiving electrodes. (Veris @ 3100 Technologies, Salina, Kansas)



Conclusion

Present review revealed that the soil penetration resistance and electrical conductivity are both important properties used to evaluate the physical properties of the cultivated soil, as it indicates many problems that occur due to soil compaction. More accurate soil sensors are needed to be developed to successfully implement precision farming to overcome high cost of traditional inadequate large sampling density. However, measurement of electrical conductivity with the latest sensor technologies has the potential to increase soil sampling density with reduced cost of soil maps which can be used to define small targeted management zones to treat them independently. It was also found in the literature that sometimes, it becomes difficult to compare the data observed from field as there is no proper procedure, standardization of the instruments and due to lack of the ability of the data interpretation. Standard procedures and management practices should be followed to minimize the negative effect of soil compaction and to reduce the environmental risks. In the era of precision agriculture for modern agriculture, soil compaction is a global challenge to increase crop yield and reduce expensive inputs such as fertiliser and energy. World farms can enhance the potential of productivity and reduce the environmental impact by reducing this harmful influence.

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Determination of Agricultural Farm Structure and Mechanisation Level in the Canakkale Region

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Abstract

This study was conducted to determine the current mechanisation level in agricultural farms of the Bayramic-Ezine-Kumkale agricultural plains, in Canakkale (*Dardanelles*) region of west of Turkey. For this purpose, a questionnaire was carried out for 401 farms capable of growing both field and horticulture crops. Results indicated that each farm having small size characteristic has at least one tractor, but 19.20% of farms included more than one tractor. The status of having one (91.67%) or more (41.67%) tractors per farm was higher in Bayramic, due to growing both field and horticulture crops. However, the highest number of tractors was recorded in Kumkale farms (60.00%), followed by Ezine (31.65%) and Bayramic (8.35%). Most of them are young, but 12.00% are older than 24-year, especially Massey Ferguson-135, Universal and Fiat (54C, 480). The most used tractor brand has been New Holland (32.15%), followed by Massey Ferguson (18.99%), Fiat (9.11%), John Deere (8.10%), Case IH (7.85%), Same (5.05%), Deutz (4.05%), Steyr (3.54%), Valtra (2.28%) and others (Ford, Hattat, Erkunt, Basak, Tumosan, Universal, Kubota and Landini). On average three plains, 77.03% of farms were preferred to purchase the new tractors, 22.97% preferred the second-hand. Tractor was 0.99 per farm, but it was the highest in Ezine (1.17). Agricultural area per tractor was 11.7 hectare on average three plains, the highest for Kumkale (13.6 hectare) and the lowest for Ezine (8.3 hectare per tractor). Machinery per tractor was 7.67 for all farms, but Kumkale (8.78) had the highest, and then followed by Bayramic (6.58) and Ezine (5.87).

Keywords: Mechanisation, Farmer Status, Crop Pattern, Farm Structure.

Introduction

Agriculture economy of Turkey is among the top ten in the world, with half of the country consisting of agricultural area and nearly a quarter of the population employed in agriculture. The country is a major producer of wheat, sugar beet, cotton, tomatoes, and it is the top producer in the world for apricot and hazelnut. Therefore, the agriculture sector is a raw material that provides the industry with an economic and social contribution to the national income and industrial sectors. In order to meet the needs of rapidly growing human communities, more qualified and quantitative production in agricultural areas is one of the main purposes of agricultural cultivation in nowadays. For this purpose, the use of technological facilities in agriculture such as agricultural mechanisation has become inevitable. In recent years, the necessity and tendency of reducing the labour directly affecting cultivation costs increases the importance and development of mechanisation in agricultural activities. Tractor is the main important indicator taken into consideration in the activities of agricultural areas for determining the mechanisation level. Canakkale region is one of those areas where many annual and perennial crops are grown throughout the country because of many agricultural locations. In the region, agricultural cultivation is carried out on 332 thousand hectare of agricultural area corresponding to 1.39% of the country level by 24 million hectares (TUIK, 2018). The current number of agriculture farms is around 49 thousand most of which are family farms employing by family labour corresponding to 2.45% of the national (over 2 million). However, 45.13% of them are only under Farm

Fig. 1 Location of Canakkale (*Dardanelles*) region in west of Turkey

Recording System which significant contributions to farmers, especially information flow and other services such as soil analysis, weather forecasts. The average size of farms is 6.6 hectare in the region which is lower than the country (7.6 hectare). Small size agricultural farms ranging from 0 to 5.0 hectare constitutes 66.76% of the total farms in the region, while several sources define small farms as those with less than 2.0 hectare of cultivated (World Bank, 2003; Hazell et al., 2007). Medium-sized farms vary between 5.0 and 20.0 hectare and the share of farms in total is 31.23%, while the number of farms of 20.0 hectare and above represents 2.00% and being the larger parcel of farms. Although the presence of small size farms in the region is proportionally high, cereals are generally grown in medium and large sized farm parcels in dry agricultural areas as dry farming. In addition, vegetables, fruits, corn and rice which are usually grown under irrigable conditions are mostly cultivated in small size parcels. Moreover, there has been an increase recently in legume cultivation, due to increasing livestock incentives by government, which is taken into crop rotation with cereals, especially in dry farming under rainfed conditions. On the other hand, 34.15% (~0.1 million hectare) of the total cultivated agricultural area in the region tend to be irrigable when 67.47% of these areas (76.4 thousand hectare) were recently irrigated by water supplied from irrigation dams (for example, Bayramic), ponds and groundwater wells. In all agricultural area of the region, field crops were grown in 41.5 thousand hectare (53.20%) under the irrigable conditions growing mostly rice, maize, alfalfa, beans, while vegetables (tomato, pepper, melon, cabbage and others) were cultivated in around 19.6 thousand hectares of the area, the remaining of 16.9 hectare were cultivated for horticulture (apple, cherry, peach, pear, plum, etc.).

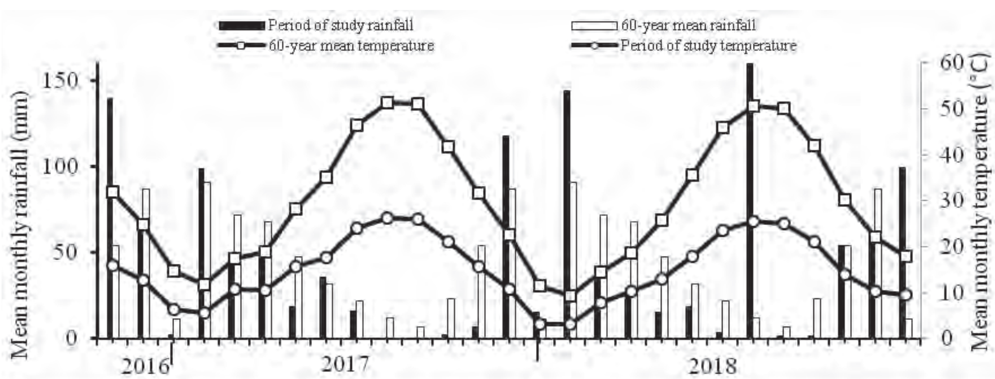
The potential of agricultural cultivation is popular in the study area when considering the geographical structure and climate characteristics, and also the soil structure, crop pattern, cultivation systems under both dry-farming (rainfed) and irrigable conditions. In recent years, with the being of water resources into dams and ponds, as well wells there has been an increase in the crop variety, especially under irrigable conditions, and there is also an effort to achieve higher efficiency from unit area. For higher crop yield from unit area, the agricultural mechanisation which accounts for almost 40% of the total investment of farms, especially tractor, is one of most important factors being effect on crop yield (Ruiyin et al., 1999) because tractor is one of the most important power sources in agriculture (Singh, 2006). For this reason, it is to determine the current mechanisation as tractor (brand, age, and other properties) and other social status and farm structure for the agricultural plains of Kumkale, Ezine and Bayramic which are in basin of Bayramic Dam, the part of which is also known as Karamenderes Basin. A questionnaire survey was conducted in the pre-determined agricultural farms by using the Farmer Registration System under Directorate of Agriculture and Forestry. The questionnaire was completed by interviewing face-to-face with farmers in the villages of the three-plain. The data obtained from the studied farms were evaluated in Excel spreadsheet to achieve the results of the mechanisation and farm characteristics.

Material and Method

Study Area

The study was conducted in Canakkale (*Dardanelles*) region

Fig. 2 Monthly rainfall and mean temperature from August 2016 to December 2018, and for long term.



(39°27'-40°45' N, 25°40'-27°30' E, altitude: 10 m a.s.l.). Canakkale (331633 hectare) has approximately 1.39% of agriculture area of the country (23,930,676 hectare). There are 48,747 agricultural farms in the province, 21,999 farms (45%) are only under Farmer Registration System. The region surrounds the southern edge of Ida mountain (1,774 m elevation) which is one of the most representative nature water source in the area. Therefore, it has a few agricultural plains due to land fragmentation in the foothill of the mountain in topological view. This region covers an area of 9,737 square kilometres, lying in South Marmara Region of west of Turkey which is surrounded by three sides by Mediterranean, Black and Aegean Seas (**Fig. 1**). In the study area, annual rainfall, average humidity, the lowest and highest temperature are 620 mm, 65%, 12 °C and 30 °C, respectively, on average years of 1958-2018 (average, National Meteorological Service) (**Fig. 2**). Many annual and perennial crops are growing under both irrigation and dry farming systems under specific agricultural locations having different local climatic conditions due to the hills and altitudes created by Ida Mountain. The water used in these agricultural locations is generally provided by the transformation of ground-wells, dams (Bayramic Dam) or ponds as surface water collecting by rivers from Ida mountain. Therefore, some of the most important agricultural plains are Bayramic-Ezine-Kumkale where different annual (e.g., tomatoes, pepper, corn) and perennial (apple, cherry, peach, walnut) crops are grown. Irrigable cultivation systems have recently increased by 98.20% the replacement of the dry farming due to increasing irrigation facilities such as dams or other water resources, especially in the agricultural area of 3-plain. The 70.41% of the total irrigable agricultural area are mostly irrigated by dams and groundwater wells in the region, but this is lower at the country level with 65.00%.

Sampling Method and Data Collection

During 2017-2018 growing season, the study was conducted in villages of 3-agricultural plain have already irrigated by Bayramic Dam, with a capacity of 96 m^3 and completed at the beginning of 2000 years. The size of required sample was determined using Neyman method in order to collect data from the studied area (Yamane, 1967).

$$n = \frac{N^2 \times s^2 \times t^2}{(N-1)\, d^2 + (s^2 \times t^2)} \quad (1)$$

where n is the required population (sample size), N is the number of farmers in the target population, s is the standard deviation, t is the t-value at 95% confidence limit (1.96), and d is the acceptable error. The permissible error in the sample size was defined to be 5% for 95% confidence. Based on this method of sampling, 401 farms were identified from the study area. 123 villages among 177 villages of three-plain in the Bayramic basin area were recorded, whose main occupation was agriculture. The questionnaire was conducted in only 30 of 123 these villages. Thus, the number of questionnaires were 11 out of 34-village in the Bayramic plain, 11 out of 39-village in Ezine and 8 out of 50-village in centre of region covering only Kumkale (**Table 1**). Researchers used the questionnaire to conduct personal interviews face to face with farmers or workers known to use machinery intensively. Questions concentrated especially on the farmer social statues, farm structure and the use of Mechanisation in the agricultural cultivation. Data was analysed to find out the required results of the study. All data obtained from the questionnaire were evaluated in Microsoft Excel 2016 spreadsheets.

Results and Discussion

Social Status of Farmers

The socio-economic characteristics of the farmers including age, family population, the role of family person in agriculture and educational status are outlined in the following paragraphs (**Tables 2**, **3**, **4**). The number of human labour has significant importance to maintain the quality of crops by doing physical labour of agricultural practices and operating an agricultural machinery. Age of farmer employed in each farm is a significant indicator for qualified and conscious cultivation. The age distribution of the farmers is ranging between 20 and 76 years on average three agricultural

Table 1 The number of villages and farms in the study area of three-agricultural plain

Plain	Village (nm)$^+$	Village in basin area		Questioned village		Total farms in districts of plain (nm)	Possible farms to be questionnaire of districts (nm)	Questioned farms of districts	
		(nm)$^{++}$	(%)	(nm)$^{+++}$	(%)			(nm)	(%)
Ezine	75	34	45.33	11	32.25	2,433	2,157	36	1.67
Kumkale	49	39	79.59	11	28.21	1,164	926	107	11.56
Bayramiç	53	50	94.34	8	16.00	4,535	4,090	258	6.31
General	177	123	69.49	30	24.39	8,132	7,173	401	5.59

$^+$the number of total villages of Bayramiç, Ezine and Kumkale distirtcs; $^{++}$the number of total villages only located in Bayramic Dam Basin area; $^{+++}$the number of questioned villages within each agricultural plain.

plains (**Table 2**). After interviewing farmers, data clearly indicate that the majority of the farmers are belonging to middle-age group (20-50 years) (**Table 4**). The average age of the farmers in the Ezine agicultural plain is 50.13 years, while it was 46.39 and 41.47 years in Kumakle and Bayramiç, respectively (**Table 2**). It was indicated that farmers occupied with agriculture in the plains of Kumkale and Bayramic are younger than in Ezine. The farmers covered a narrow of age groups with the least under 42 years in villages of Bayramic. In recent years, the agricultural incentives provided by goverment for agricultural cultivation have increased the interest and efforts of the young agricultural engineers in agriculture sector. On the other hand, the increase in the use of Mechanisation in agriculture and the use of various type machinery that require high technology knowledge which was known more by younger age farmer groups. In contrast, it was found that majority of the farmers were in the age of 41-50 years by 29.80%, while age under 30 years and over 60 years is comparable very low by 11.87% and 6.08%, respectively (**Table 4**). The average age of the farmers is 44.82 years, and it means that more middle-age group was occupied with agriculture activities in the studied area. This shows that the income of the young people is mainly from non-agricultural sources. At the same time, this can be considered as a sign that young people prefer to live in the city instead of living in the village. Similarly, there were few young farmers in European countries; only about one in ten European countries farmer (10.60%) were under the age of 40 years (EuroState, 2018). In another study carried out in the same area of this study by questionnaire for vineyard farmers (Aydın et al., 2017) found the highest labour rate in 41-50 years range by 31.20%, followed by 51-60 years by 30.90%. In addition, another study conducted in Europe, Asia, Africa where were observed similar results that the labour of age in agriculture was stated to be between 40 and 45 years (Matthews, 2008). Author found that 40-49 age were more popular in European countries when the least farmer age was under 40 years. On the other hand, it was reported that the major of farmers (57.90%) is older than 55 years in a study conducted in European countries, while only 6% are younger than 35 years (EuroState, 2018). It was concluded that younger farmers especially tend to manage the largest farms where many small farms are managed by older farmers, often beyond the normal retirement age.

Sometimes labour by manpower were used to perform the agricultural activities, for example, such as hand-hoeing, fruit harvesting, etc. (**Table 3**), but the intensity of use of human labour varies according to the working person in agriculture activities for each family. When considering all the studied farms, the farming systems remain a predominantly family activity and many farms are family-run with only family members providing help on the farm at different times of the year, and that there are seasonal peaks in labour in harvesting, particularly in the olive for the area. The number of people in the family are varied between 3 and 4 persons, and family size consists of 4 persons on the average of all families (**Table 3**), and three in every four family

Table 2 Age and number of the farmers in the farms of three-agricultural plain

Plain	Farms (nm)	Age-known farmers		Age ranges (year)		
		(nm)	(%)	Max.	Min.	Average
Ezine	107	93	86.92+	72	23	50.13 ±11.78 (23.50)+
Kumkale	258	187	72.48	76	23	46.39 ±10.92 (23.55)
Bayramiç	36	36	100.00	62	20	41.47 ±9.78 (23.59)
General	401	316	78.80	76	20	46.94 ±11.33 (24.14)

Table 3 Family size and gender status in the questioned farms

Plain	Total family person (nm)	Gender rate in family		Gender status in agriculture	
		Male (%)	Female (%)	Male (nm)	Female (nm)
Ezine	3.64 ±1.69 (46.51)+	58.12	41.88	1.39 ±0.87 (62.63)	1.34 ±0.85 (63.57)
Kumkale	4.17 ±1.59 (38.15)	61.75	38.25	1.55 ±0.78 (50.27)	0.96 ±0.80 (83.22)
Bayramiç	3.75 ±0.76 (20.12)	53.93	46.07	1.33 ±0.53 (40.09)	1.14 ±035 (30.80)
General	4.00 ±1.57 (39.36)	39.84	60.16	1.49 ±0.79 (52.81)	1.05 ±0.79 (75.19)

Table 4 General characteristics of farmers of the studied farms

Age range	Age		Education level (%)				
	(year)	(%)	No-formal	Primer	Secon-dary	High-school	Univer-sity
20-30	26.02 ±3.75	11.87	-	46.97	16.33	18.37	18.33
31-40	36.03 ±2.91	24.49	-	55.45	18.39	13.63	12.53
41-50	45.33 ±2.77	29.80	-	59.53	14.37	17.00	9.10
51-60	55.39 ±2.96	27.78	-	63.00	24.50	8.17	4.33
61-+	66.13 ±4.84	6.08	0.50	69.95	24.36	5.19	-
Ave./Tot.	44.82 ±11.38	100.00	0.50	58.98	19.59	12.47	8.86

members are working regularly in agriculture. Farmers are generally composed of middle-size families (3-4 person per family). In a similar study conducted by Aydın et al. (2017) in the same area for vineyard cultivation concluded that middle-size family is the highest as 44.2% in total while multi person type family is 21.3%.

According to the gender status of the existing family population and the status of working in agriculture, the number of male working per farm is approximately one and a half-person, this was recorded for female as one-person. Agricultural activities were female dominated profession with relatively few male farmers because of many input hand hoeing and hand harvesting practices doing by female in the studied farms (**Table 3**). 60.16% of the total person were females and 39.84% is males on average three-plain farm, there are results introduced by EuroState (2018) for Netherlands, Latvia and Lithuania where the only one in every twenty farmers was female, corresponding to the 44.90% of farmers. However, the farms manager, who are responsible the normal daily finical and cultivation routines of running a farm, are typically male and relatively old. Only one family male member per farm can be take responsibility as a farm manager who was majority male and 45 years of age and more (**Table 4**) while this was even lower among female farmers. In contrast, there was a relatively low rate of farmers of 40 years of age or less in many farms of study, and only about one in every twenty-five managers was a young farmer under the age of 40 years. In contrast, in European countries, 71.50% of farmers were male and they are relatively old in EU, 55 years of age or more (EuroState, 2018). As seen in **Table 2**, although the use of mechanical energy in agriculture is increasing, human labour is still an important resource. Harvesting and other similar practices were still carried out by human in the area the fact that the labour force in agriculture is needed.

In considering different levels of education in three-plain, most of the farmers have basic primary education by 58.98%, followed by seconder and high school by 19.59% and 12.47%, respectively (**Table 4**). The rate of farmers who graduated from university was found very low by 8.86% compared to other education levels, but this rate was higher than in national level with 6% (TUIK, 2018). In general, young farmers had higher levels of educational attainment in terms of full agricultural training, and they had followed up to date professional training courses including those on new or innovative farming practices. Only 0.50% farmers have no-education which was lower than in the education level of the national agriculture by 15.20% (TUIK, 2018). In similar, a study conducted for the different countries resulted that 83.82% of the farmers had different education levels while the rest of them had no-formal education (Matthews, 2008). In another study concluded by Aydın et al. (2017), they found that all farmers have different level of education when the proportion of the university graduation is very low by 0.60%. In other hand, they concluded that the farmers with primary and high school education were higher by 70.61% and 14.52%, respectively, but the proportion of

Table 5 Registration of agricultural organizations in the agricultural farms

Plain	NSF	FRS		FA		AD		COOPS		KOSGEB		AC	
	(nm)	(nm)	(%)+	(nm)	(%)+	(nm)	(%)+	(nm)	(%)	(nm)	(%)+	(nm)	(%)+
Ezine	107	67	62.62	41	38.32	8	7.48	4	3.74			20	18.69
Kumkale	258	180	69.77	152	58.91	4	1.55	12	4.65	11	4.26	104	40.31
Bayramiç	36	17	47.22	15	41.67	3	8.33			1	2.78	4	11.11
General	401	264	65.84	208	51.87	15	3.74	16	3.99	12	2.99	128	31.92

+Percentage in the number of studied farms. NSF, number of studied farms; FRS, farmer registration system; AD, agrochemical dealer; COOPS, agricultural cooperatives; AC, agriculture chamber; FA, farmer association; KOSGEB, small and medium-sized farm development organizations.

Table 6 Agriculture area in the farms based on ownership and rental status

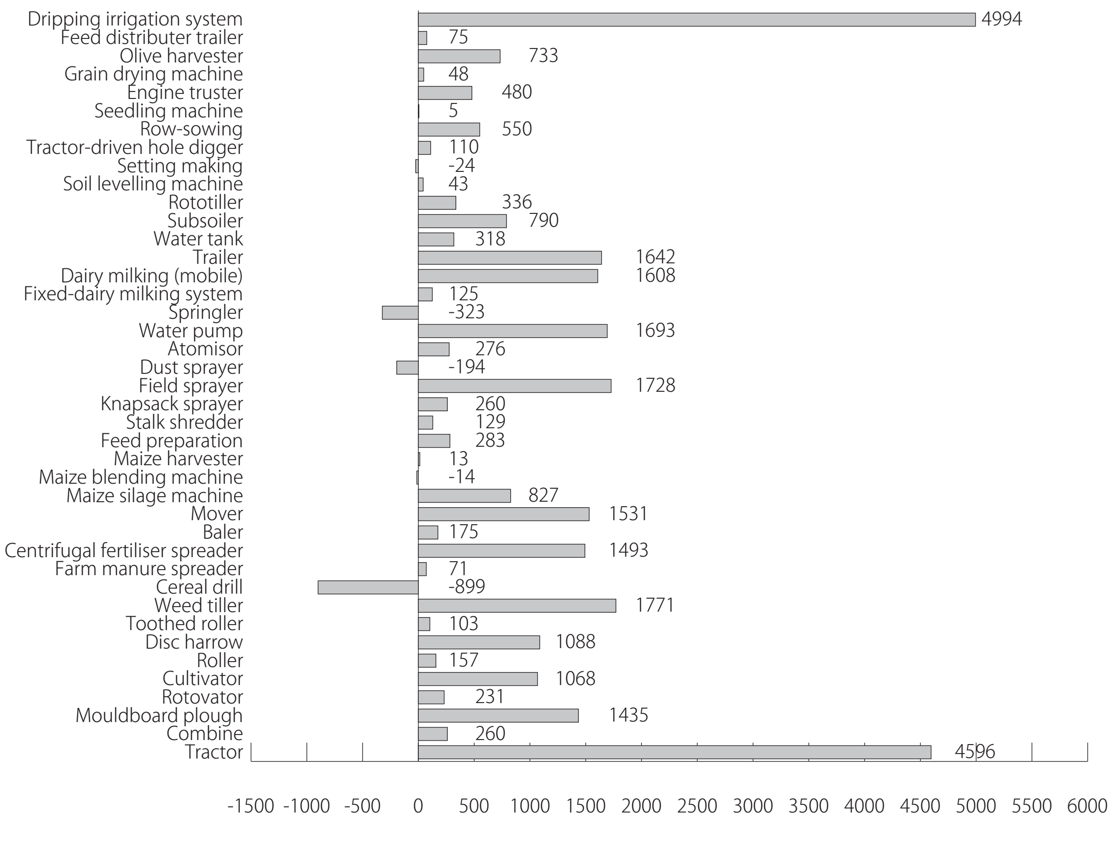
	Ezine (d+i) (hectare)			Kumkale (d+i) (hectare)			Bayramic (d+i) (hectare)			General (d+i) (hectare)		
	Own	Rent	Total	Own	Rent	Total	Own	Rent	Total	Own	Rent	Total
Total	923.9	119.3	1,043.2	3,546.9	710.3	4,257.2	384.0	-	384.0	3,930.9	710.3	4,641.2
%	88.56	11.44	100.00	81.61	18.39	100.00	100.00	-	100.00	84.70	15.30	100.00
Ave.	84.0	23.9	94.8	394.1	142.1	473.0	34.9	-	34.9	131.0	35.5	154.7
Max.	231.1	38.0	257.6	1073.7	277.0	1073.7	122.0	-	122.0	1073.7	277.0	1073.7
Min.	20.0	5.0	20.0	43.0	10.0	43.0	11.0	-	11.0	11.0		11.0
St	66.17	11.91	71.13	376.43	100.63	406.1	32.15	-	32.15	212.37	74.47	242.07

d, dry farming area in the studied farms; i, irrigable farming area in the studied farms; St, standard deviation (coefficient of variation).

the secondary school was lower by 13.23%.

Canakkale region has high potential of the agricultural cultivation for both crop and livestock by using mechanical energy in almost all agricultural activities with slightly human energy. Machinery per unit agricultural area of the farms are higher than national level (TUIK, 2018), usually using mechanical power, except in fruit harvest operations which were done by human, for example, apple, grape, and olive in some farms. Considering arable agricultural structure and water resources from the study area located in Karamenderes basin, machinery and other agricultural technology, for example; drip-irrigation, has been widely used (**Fig. 3**). Machinery was intensively used in all cultivation practices of the different agriculture branches, especially in Kumkale, followed by Bayramic and Ezine. In three-plain, agricultural cultivation is usually carried out in small size parcels which are irrigated by ground water or streams collected from Ida mountain to dams (e.g. Bayramic Dam) (**Table 7**). Wheat among the crop patterns was usually cultivated in more farms by 76.56% in regardless of dry or irrigation conditions, followed by pepper (46.13%), tomatoes (45.64%) and maize (33.42%). These were followed by the farms which are cultivated olive (26.68%), and rice, peach and barley by around 20%. The size of 73.13% of the farms is below 5.0 hectare among the studied farms due to the high level of land fragmentation. 6.18% of them have the agricultural area of less than 0.5 hectare, whereas only 3.55% are being in 15.0 hectare and above that are known as commercial farms increasing recently in the region despite small size farms. Crop pattern of the post-irrigation was increased compared to the pre-irrigation period by using Bayramic Dam (**Tables 8**, **9**). Considering crop pattern for pre-irrigation period (**Table 8**), it has been identified that there are a limited variety of crops, but agriculture area was found higher than the post-irrigation covering 1996-2018, due to the shift many agriculture areas to facilities such as housing, operation building and agriculture product processing units (e.g. cold storage, olive factory), especially in Kumkale plain decreasing by approximately 86.00%. In pre-irrigation, cereals are commonly grown, especially under dry farming, whereas crop growth under irrigation conditions is more restricted (**Table 8**). Although wheat is the most important crop among cereals in the area of the current basin for both periods, but its cultivation area is shifted to crops such as maize, rice, and others (cherry, peach, walnut) under irrigable agricultural areas. Although

Fig. 3 Increase and decrease in the number of agricultural machinery in post-irrigation period (the first quarter of 2018 compared to pre-irrigation period (1996)



the cultivation area of barley, rye, oats and some legumes, which are generally used to feed the animal, decreased compared to the pre-irrigation period since they continue to be grow in the post-irrigation period (**Tables 8**, **9**). However, some crops (e.g. silage maize, clover) that have been cultivated by using water of dams in period covered post-irrigation between 1996 and 2018 (**Table 9**), and their growing area are increased by using Bayramic Dam for the agricultural irrigation. For example, the growing of grain maize was increased by approximately 5.5 times in only Bayramic plan during the post-irrigation period compared with pre-irrigation when silage maize was grown approximately 1.7 thousand hectares in three-plain agriculture areas (**Table 9**). This was supported increasing the number of maize harvester and stalk shredder by 75.32% and 98.45%, respectively (**Fig. 3**). The growing of the clover or silage maize are usually under the drip irrigation which has been found to be increased by 77.15% and 100.00%, respectively (**Table 9**). The practices with irrigation is also increased the using of the water pump in the studied farms by 8.55% (**Fig. 3**). Pre-irrigation agricultural practices of the three-plain agriculture areas, the crops such as silage maize, sorghum, grass, canola, safflower and rice don't have almost growing areas, but they were grown with the irrigation applications (**Table 9**). By growing such as crops, it has encouraged to grow livestock (Özpınar, 2002), and it also caused to the opening of factories processed milk to produce cheese or other dairy products. It has been found that silage maize is commonly growing crop by 94.06% in the north of Ezine and Bayramic plains located in the central part of the Karamenderes basin (**Table 9**); therefore, livestock has become an important agricultural occupation in the same area. This was increased agricultural equipment in the machinery park, especially in number of silage maize harvester, stalk shredder, baler, mover, feed preparation and dairy milking machine and weed tiller (**Fig. 3**). By intensive agriculture system in the current study areas covering Bayramic-Ezine-Kumkale plains, there has also been an increase in surface tillage machinery such as rototiller (89.60%) and rotovator (35.48%) which were usually used in conservation soil tillage systems. Rice started to be grown by the using irrigation application, and it has begun to be cultivated widely in the east of the Ezine plain and partially in the south of Kumkale (**Table 9**), and this leads to increase the use of combine by 10.04%. On the other hand, there has been an increase in the number of tractor, especially in the last five years by 17.56% in regardless of

Table 7 Number and size of parcels according to crop pattern for both field and horticulture branch in the farms

Crop	< 0.5 hectare		0.5 − 4.9 hectare		5.0 − 14.9 hectare		≥ 15.0 hectare		Total < 0.5 − ≥ 15.0 hectare	
	(nm)	(%)	(nm)	(%)	(nm)	(%)	(nm)	(%)	(nm)	(%)
Wheat	0.5	1.63	17.9	58.31	9.8	31.92	2.5	8.14	30.7	76.56
Pepper	1.4	7.57	16.4	88.65	0.5	2.70	0.2	1.08	18.5	46.13
Tomatoes	2.4	13.11	14.1	77.05	1.7	9.29	0.1	0.55	18.3	45.64
Maize	0.1	0.75	10.9	81.34	1.9	14.18	0.5	3.73	13.4	33.42
Olive	0.6	5.61	7.0	65.42	2.9	27.10	0.2	1.87	10.7	26.68
Rice	-	-	2.9	35.37	3.7	45.12	1.6	19.51	8.2	20.45
Peach	0.2	2.44	6.6	80.49	1.4	17.07	-	-	8.2	20.45
Barley	-	-	5.7	69.51	2.3	28.05	0.2	2.44	8.2	20.45
Cherry	0.9	15.79	4.8	84.21	-	-	-	-	5.7	14.21
Oat	0.2	3.51	4.0	70.18	1.4	24.56	0.1	1.75	5.7	14.21
Apple	0.4	7.69	4.3	82.69	0.5	9.62	-	-	5.2	12.97
Bean	0.7	17.07	3.4	82.93	-	-	-	-	4.1	10.22
Sunflower	-	-	2.0	50.00	1.6	40.00	0.4	10.00	4.0	9.98
Melon	0.3	11.11	2.4	88.89	-	-	-	-	2.7	6.73
Plum	0.6	27.27	1.6	72.73	-	-	-	-	2.2	5.49
Vineyard	0.8	42.11	1.1	57.89	-	-	-	-	1.9	4.74
Vetch	-	-	1.7	100.00	-	-	-	-	1.7	4.24
Field bean	0.3	20.00	1.0	66.67	0.2	13.33	-	-	1.5	3.74
Watermelon	0.1	1.19	8.3	98.81	-	-	-	-	8.4	20.95
Strawberry	0.2	16.67	1.0	83.33	-	-	-	-	1.2	2.99
Apricot	0..4	36.36	0.7	63.64	-	-	-	-	1.1	2.74
Cotton	-	-	0.9	90.00	0.1	10.00	-	-	1.0	2.49
Trifolium	-	-	0.8	100.00	-	-	-	-	0.8	2.00
Total	10.1	6.18	119.5	73.13	28.0	17.14	5.8	3.55	163.4	100.00

Table 8. Crop pattern in the pre-irrigation period of the farms according to crop branches

Crop	Bayramic		Ezine		Kumkale		Total	
	(hectare)	(%)	(hectare)	(%)	(hectare)	(%)	(hectare)	(%)
Field crops	**(General 69.02%)**							
Wheat	6,915.2	28.40	6,439.0	26.44	10,998.4	45.16	24,352.6	42.87
Maize	31.0	40.90	18.5	24.41	26.3	34.70	75.8	0.13
Barley	3,758.4	42.31	3,187.0	35.88	1,937.0	21.81	8,882.4	15.64
Rye	79.8	75.57	11.5	10.89	14.3	13.54	105.6	0.19
Oat	1,738.4	83.92	936	4.52	239.6	11.57	2,071.6	3.65
Vetch	144.8	23.85	163.8	26.98	298.6	49.18	607.2	1.07
Potatoes	49.8	87.06	-	-	7.4	12.94	57.2	0.10
Broad bean	1,641.8	28.62	1,599.4	27.89	2,494.4	43.49	5,735.6	10.10
Chickpea	413.4	25.56	193.2	11.95	1,010.8	62.50	1,617.4	2.85
Cotton	-	-	3,421.3	37.58	5,683.6	62.42	9,104.9	16.03
Sunflower	24.6	2.44	45.8	4.54	939.4	93.03	1,009.8	1.78
Sesame	1,605.8	75.26	190.0	8.90	338.0	15.84	2,133.8	3.76
Peanut	14.2	60.17	9.4	39.83	-	-	23.6	0.04
Clover	69.0	17.92	232.0	60.26	84.0	21.82	385.0	0.68
Bean	104.6	24.31	191.3	44.46	134.4	31.23	430.3	0.76
Kidney bean	15.8	56.83	10.0	35.97	2.0	7.19	27.8	0.05
Animal bean	-	-	175.0	97.22	5.0	2.78	180.0	0.32
Total	16,606.6	29.24	15,805.8	27.83	24,208.2	42.62	56,800.6	100.00
Fruits	**(General 23.05%)**							
Apple	2,372.5	90.64	10.0	0.38	235.0	8.98	2,617.5	13.80
Peach	150.0	43.99	11.0	3.23	180.0	52.79	341.0	1.80
Strawberry	-	-	2.0	100.00	-	-	2.0	0.01
Pear	13.0	100.00	-	-	-	-	13.0	0.07
Cherry	6.0	100.00	-	-	-	-	6.0	0.03
Apricot	-	-	-	-	6.0	100.00	6.0	0.03
Grape	2,007.0	64.99	356.0	11.53	725.0	23.48	3,088.0	16.28
Olive	3,260.0	25.37	8,877.5	69.08	714.0	5.56	12,851.5	67.76
Almond	20.0	47.62	-	-	22.0	52.38	42.0	0.22
Total	7,828.5	41.27	9,256.5	48.80	1882.0	9.92	18,967.0	100.00
Vegetables	**(General 7.93%)**							
Onion	138.3	24.33	246.4	43.34	183.8	32.33	568.5	8.72
Garlic	11.2	21.21	25.2	47.73	16.4	31.06	52.8	0.81
Leek	5.0	9.11	23.4	42.62	26.5	48.27	54.9	0.84
Carrot	5.0	71.43	1.0	14.29	1.0	14.29	7.0	0.11
Radish	5.0	48.08	1.0	9.62	4.4	42.31	10.4	0.16
Cauliflower	1.4	8.67	10.0	61.92	47.5	29.41	161.5	0.25
Cabbage	16.3	14.78	50.5	45.78	43.5	39.44	110.3	1.69
Lettuce	10.8	39.56	2.0	7.33	14.5	53.11	27.3	0.42
Spinach	10.5	28.38	6.5	17.57	20.0	54.05	37.0	0.57
Purslane	-	-	-	-	1.0	100.00	1.0	0.02
Parsley	2.2	52.38	2.0	47.62	-	-	4.2	0.06
Rocket	1.0	100.00	-	-	-	-	1.0	0.02
Tomato	218.8	5.77	1,172.5	30.93	2,400.0	63.30	3,791.3	58.13
Cucumber	32.5	20.09	96.3	59.52	33.0	20.40	161.8	2.48
Pepper	24.3	18.74	22.8	17.58	82.6	63.69	129.7	1.99
Okra	11.0	24.28	25.3	55.85	9.0	19.87	45.3	0.69
Eggplant	20.0	11.03	56.3	31.05	105.0	57.92	181.3	2.78
Pumpkin	4.0	17.94	8.0	35.87	10.3	46.19	22.3	0.34
Pea	23.3	10.30	-	-	203.0	89.70	226.3	3.47
Melon	190.0	40.88	129.8	27.93	145.0	31.20	464.8	7.13
Watermelon	215.0	35.29	149.3	24.50	245.0	40.21	609.3	9.34
Total	945.6	14.50	2,028.3	31.10	3,548.8	54.41	6,522.7	100.00
General (total)	**25,380.7**	**30.84**	**27,090.6**	**32.92**	**29,639.0**	**36.02**	**82,290.3**	

Table 9 Crop pattern in the post-irrigation period of the farms according to crop branches

Crop	Bayramic		Ezine		Kumkale		Total	
	(hectare)	(%)	(hectare)	(%)	(hectare)	(%)	(hectare)	(%)
Field crops				**(General 53.54%)**				
Wheat	9,303.0	63.63	4,058.6	27.76	1,257.9	8.60	14,619.5	44.56
Maize	171.1	18.62	549.4	59.78	198.6	21.61	919.1	2.80
Barley	4,547.9	62.53	2,229.0	30.65	496.0	6.82	7272.9	22.17
Rye	12.5	55.80	6.0	26.79	3.9	17.41	22.4	0.07
Rice	-	-	622.1	86.44	97.6	13.56	719.7	2.19
Oat	1,870.0	67.14	745.0	26.75	170.1	6.11	2,785.1	8.49
Vetch	390.0	43.42	440.0	48.99	68.2	7.59	898.2	2.74
Broad bean	102.0	31.04	210.0	63.91	16.6	5.05	328.6	1.00
Chickpea	350.0	76.09	68.0	14.78	42.0	9.13	460.0	1.40
Cotton	0.0	0.00	10.0	87.72	1.4	12.28	11.4	0.03
Sunflower	36.0	5.26	299.2	43.69	349.6	51.05	684.8	2.09
Sesame	287.0	91.00	17.0	5.39	11.4	3.61	315.4	0.96
Clover	750.0	58.18	490.0	38.01	49.0	3.80	1,289.0	3.93
Bean	110.0	71.29	32.0	20.74	12.3	7.97	154.3	0.47
Animal bean	135.0	47.01	97.0	33.77	55.2	19.22	287.2	0.88
Maize (silage)	900.0	53.58	680.0	40.48	99.8	5.94	1,679.8	5.12
Sorghum	159.0	75.46	45.0	21.36	6.7	3.18	210.7	0.64
Grass	15.0	38.66	22.0	56.70	1.8	4.64	38.8	0.12
Canola	86.0	100.00	-	-	-	-	86.0	0.26
Safflower	5.0	100.00	-	-	-	-	5.0	0.02
Total	19,229.5	58.65	10,620.3	32.39	2,938.1	8.96	32,787.9	100.00
Fruits				**(General 39.70%)**				
Apple	2,992.5	96.62	32.8	1.06	72.0	2.32	3,097.3	12.74
Peach	676.0	67.10	66.0	6.55	265.5	26.35	10075	4.14
Strawberry	12.0	88.89	1.0	7.41	0.5	3.70	135	0.06
Pear	56.0	84.85	5.0	7.58	5.0	7.58	660	0.27
Cherry	494.0	90.23	26.5	4.84	27.0	4.93	547.5	2.25
Apricot	7.7	7.93	55.8	57.47	33.6	34.60	97.1	0.40
Grape	1,972.0	91.83	150.0	6.99	25.4	1.18	2,147.4	8.83
Olive	4,032.0	25.20	11,653.0	72.84	313.4	1.96	15,998.4	65.81
Almond	69.0	22.22	230.0	74.07	11.5	3.70	310.5	1.28
Date	4.2	47.73	2.0	22.73	2.6	29.55	8.8	0.04
Quince	26.0	44.22	31.0	52.72	1.8	3.06	58.8	0.24
Plum	42.5	55.19	22.5	29.22	12.0	15.58	77.0	0.32
Medlar	0.3	37.50	-	-	0.5	62.50	0.8	0.00
Pomegranate	2.0	4.30	42.0	90.32	2.5	5.38	46.5	0.19
Peanuts	2.6	50.98	1.8	35.29	0.7	13.73	5.1	0.02
Hazelnut	1.7	100.00	-	-	-	-	1.7	0.01
Chestnut	4.4	100.00	-	-	-	-	4.4	0.02
Walnut	355.0	43.28	430.0	52.43	35.2	4.29	820.2	3.37
Total	10,749.9	44.22	12,749.4	52.45	809.2	3.33	24,308.5	100.00
Vegetables				**(General 6.76%)**				
Onion	19.0	39.26	23.0	47.52	6.4	13.22	48.4	1.17
Garlic	13.5	85.99	1.2	7.64	1.0	6.37	15.7	0.38
Leek	2.5	31.25	4.0	50.00	1.5	18.75	8.0	0.19
Carrot	0.2	50.00	-	-	0.2	50.00	0.4	0.01
Radish	0.6	42.86	0.2	14.29	0.6	42.86	1.4	0.03
Cauliflower	8.5	18.85	35.0	77.61	1.6	3.55	45.1	1.09
Cabbage	9.0	31.58	16.0	56.14	3.5	12.28	28.5	0.69
Lettuce	17.7	44.25	15.1	37.75	7.2	18.00	40.0	0.97
Spinach	11.6	41.13	14.0	49.65	2.6	9.22	28.2	0.68
Parsley	2.0	62.50	0.2	6.25	1.0	31.25	3.2	0.08
Tomato	680.0	34.26	1,060.0	53.40	245.0	12.34	1,985.0	47.96
Cucumber	11.4	32.95	21.7	62.72	1.5	4.34	34.6	0.84
Pepper	518.0	49.68	487.9	46.79	36.8	3.53	1,042.7	25.19
Okra	2.5	29.41	5.5	64.71	0.5	5.88	8.5	0.21
Eggplant	4.2	23.60	10.0	56.18	3.6	20.22	17.8	0.43
Pumpkin	20.0	79.68	4.0	15.94	1.1	4.38	25.1	0.61
Pea	45.3	29.45	100.9	65.60	7.6	4.94	153.8	3.72
Melon	95.0	32.93	155.0	53.73	38.5	13.34	288.5	6.97
Watermelon	110.0	30.29	240.0	66.10	13.1	3.61	363.1	8.77
Total	1,571.0	37.96	2,193.7	53.01	373.3	9.02	4,138.0	100.00
General (total)	**31,550.4**	**51.52**	**25,563.4**	**41.75**	**4,120.6**	**6.73**	**61,234.4**	

the tractor power size and brand compared to pre-irrigation period, it means that each farmer has at least one tractor. Moreover, the use of drip irrigation systems instead of sprinkler, which can use water more economically, has become more widely used, especially in the cultivation of vegetables and fruits.

Agricultural Mechanisation and Its Indicators in the Farms

The Relationship Between Agricultural Area and Tractor

Most farms are family farms and only employ family labour and they are considerably smaller than those in the national, with the size of the average farm in country being 6.5 hectare. Small scale farming is important characteristic of the region agriculture. Region agriculture also suffers from inadequate farm management and technology such as farm tractors and machineries, water shortages and droughts, an inefficient rural credit system to produce the agriculture area, as well as high costs. The farmers for increasing agricultural production of the region, especially for the three-agricultural plain where the study was carried out, are expected to be further productivity growth with irrigation schemes supporting improvements such as Bayramic Dam, and with agriculture tractor and machinery. Tractor has traditionally been used on farms to mechanize several agricultural operations and accessed as Mechanisation level in terms of number per farm and unit area (Ozmerzi, 1998) (**Table 10**). A modern tractor is used for ploughing, tilling, planting, landscape maintenance, moving or spreading fertiliser and cleaning bushes. Tractor offers advantages on small farms as well as horticultural operations, and the various benefits of using tractors to mechanize farming. Effect of tractor power on agricultural cultivation is quite important and varying according to agricultural area. Therefore, tractor power may differ considerably in different area and productivity and it was positively correlated with potential unit farm power. The average agricultural area per tractor was 11.7 hectare on average three-plain, but this was found to be higher for Kumkale with 13.6 hectare per tractor which was higher than two other plains, 11.6 hectare per tractor for Bayramic and 8.3 hectare per tractor for Ezine. When compared with national level, agriculture area per tractor was higher and recorded as 22.0 hectare in 2004, but it was found lower by 17.8 hectare in 2012 (Akdemir, 2013) and 14.7 hectare in 2014 (Civelek, 2016) and 11.6 hectare in 2018 (Yücel, 2019). This means that the tractor number was increased by year. On the other hand, when the current tractors per farm was considered, the average of three plains was 0.99 tractor per farm. It can be say that there was less than one tractor per farm. The numbers of tractor per farm was determined as 1.17, 0.92 and 0.92 in Ezine, Kumkale and Bayramic, respectively. There are results concluded by Oğuz et al. (2017) who recorded higher tractor per farm for Konya as 1.57. They also concluded that tractor number per farm was higher (1.64) in large size parcels than in small size parcels (1.17). On average 3-plain, machinery per tractor was found as 7.67 which describes conventional farming systems are still dominant in the area because of us-

Fig. 4 Number of machinery per tractor in each farm depending on average farms of three agricultural plains

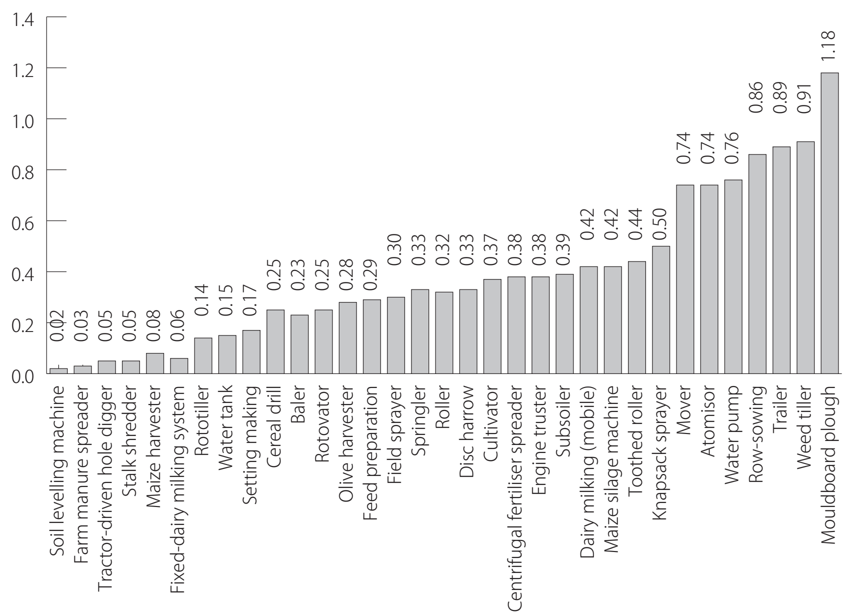


Table 10 Agriculture area (owned+rental), tractors and their indicators in the farms of three-plain

Plain	Agri. area (hectare)	Farm (nm)	Tractor (nm)	Machinery (nm)	(hectare per farm)	(hectare per tractor)	(tractor per farm)	(machinery per tractor)
Ezine	10,432	107	103	734	97	83	1.17	5.87
Kumkale	32,140	258	239	2,080	125	136	0.92	8.78
Bayramic	3,840	36	33	217	107	116	0.92	6.58
General	46,412	401	395	3,031	116	117	0.99	7.67

ing many equipment in tillage, seedbed preparation, protection and other cultural practices. It also means that conservation and direct cultivation systems are not much known or used by many local farmers. In **Fig. 4**, it is clearly shows that the machinery used in all studied farms are more suitable for traditional agriculture. This is especially confirmed by the fact that the number of mouldboard plough is one or more per tractor, while other machinery using for conservation or sustainable management systems were lower, for example rototiller, rotovator, etc. On the other hand, it was concluded that from studied farms during the questionnaire, although farmers are willing to buy more new tractors (**Table 17**), they are not very conscious of the replacement of existing machinery used in conventional agriculture. However, the largest farms such as commercial have managed to improve their technical equipment thanks to the funds from the national budge. However, in general, the majority of machinery are overworked and fully exploited in the studied farms. In general, the owners of small farms do not invest for the new machinery, but prolong the utilization life of the existing machinery even to 30 or 40 years. This increases the frequency and costs of repair. Machinery per tractor was resulted higher by 7.67 for studied farms than the national level by 7.26, but it was lower than some agricul-

Table 11 Number and rate of tractors by brands in all farms of three-plain

Brand	Ezine	Kumkale	Bayramic	General
MF	24 (19.20)$^{+}$	38 (16.03)	13 (39.39)	75 (18.99)
NH	35 (28.00)	89 (37.55)	3 (9.09)	127 (32.15)
FR	4 (3.20)	3 (1.27)	-	7 (1.77)
FI	26 (82.16)	10 (16.67)	-	36 (9.11)
SM	7 (5.60)	12 (5.06)	1 (3.03)	20 (5.06)
ER	1 (0.80)	1 (0.42)	-	2 (0.51)
B	1 (0.80)	3 (1.27)	1 (3.03)	5 (1.27)
CS	12 (9.60)	16 (6.75)	3 (9.09)	31 (7.85)
ST	2 (1.60)	10 (4.22)	2 (6.06)	14 (3.54)
TM	3 (2.40)	6 (2.53)	1 (3.03)	10 (2.53)
JD	4 (3.20)	23 (9.70)	5 (15.15)	32 (8.10)
DTZ	5 (4.00)	10 (4.22)	1 (3.03)	16 (4.05)
UN	-	4 (1.69)	1 (3.03)	5 (1.27)
KB	-	1 (0.42)	-	1 (0.25)
LN	-	3 (1.27)	-	3 (0.76)
VLT	-	7 (2.95)	2 (6.06)	9 (2.28)
HT	1 (0.80)	1 (0.42)	-	2 (0.51)
Total	125 (31.65)	237 (60.00)	33 (8.35)	395 (100.00)

+ Percentage of tractor brand within total tractors of three-plain. MF, Massey Ferguson; NH, New Holland; FR, Ford; HT, Hattat; FI, Fiat; SM, Same; ER, Erkunt; B, Basak; CS, Case IH; ST, Steyr; TM, Tumosan; JD, John Deere; DT, Deutz; UN, Universal; KB, Kubota; LN, Landini; VLT, Valtra.

Table 12 Number and rate of farms having one or more than one tractor brands in three-plain

Brand	Number of farms having one tractor				Brand	Number of farms having more than one tractor			
	Ezine	Kumkale	Bayramic	Total		Ezine	Kumkale	Bayramic	Total
MF	3 (2.80)$^{+}$	38 (14.73)	4 (11.11)	45 (11.22)	NH+NH	1 (0.93)	16 (6.20)	2 (5.56)	19 (4.74)
NH	9 (8.41)	86 (33.33)	12 (33.33)	107 (26.68)	NH+FI	1 (0.93)	-	-	1 (0.25)
FR	-	2 (0.78)	-	2 (0.50)	NH+MF	-	7 (2.71)	7 (19.44)	14 (3.49)
HT	1 (0.93)	1 (0.39)	-	2 (0.50)	NH+B	1 (0.93)	-	-	1 (0.25)
FI	12 (11.21)	10 (3.88)	-	22 (5.49)	NH+SM	1 (0.93)	3 (1.169)	-	4 (1.00)
SM	2 (1.87)	12 (4.65)	1 (2.78)	15 (3.74)	NH+JD	1 (0.93)	7 (2.719)	2 (5.56)	10 (2.50)
ER	1 (0.93)	1 (0.39)	-	2 (0.50)	NH+TM	-	5 (1.94)	-	5 (1.25)
B	-	3 (1.16)	1 (2.78)	4 (1.00)	NH+ER	-	3 (1.16)	1 (2.78)	4 (1.00)
CS	4 (3.74)	15 (5.81)	3 (8.33)	22 (5.49)	NH+CS	-	7 (2.71)	-	7 (1.75)
ST	1 (0.93)	9 (3.49)	2 (5.56)	12 (2.99)	MF+MF	-	1 (0.399)	1 (2.78)	2 (0.50)
TM	2 (1.87)	6 (2.33)	1 (2.78)	9 (2.24)	MF+FI	2 (1.87)	3 (1.16)	-	5 (1.25)
JD	2 (1.87)	23 (8.91)	5 (13.89)	30 (7.48)	MF+FR+DT	1 (0.93)	-	-	1 (0.25)
DT	-	10 (3.88)	1 (2.78)	11 (2.74)	JD+JD	-	-	1 (2.78)	1 (0.25)
UN	-	3 (1.16)	1 (2.78)	4 (1.00)	JD+KB	-	1 (0.39)	-	1 (0.25)
KB	-	1 (0.39)	-	1 (0.25)	TM+ST	-	1 (0.39)	1 (2.78)	2 (0.50)
LN	-	3 (1.16)	-	3 (0.75)	CS+CS	1 (0.93)	-	-	1 (0.25)
VLT	-	5 (1.94)	2 (5.56)	7 (1.75)					
Total	37 (34.58)	228 (88.37)	33 (91.67)	298 (74.31)	Total	9 (8.41)	54 (20.93)	15 (41.67)	78 (19.45)
FN	107	258	36	401	FN	107	258	36	401

$^{+}$The percentage of farms having tractor brand in each agricultural plain of farms. FN, total number of farms questioned for each agricultural plain.

tural areas which were located closer the study area, for example, Edirne (9.13), Kırklareli (8.81) and Tekirdag (9.67), and Thrace region (9.24) (Abdikoğlu, 2019).

Availability Tractors and Their Brands

In questioned agricultural farms, the tractor brands were determined to be more than half of the existing tractor in the country with 30 brands. Thus, 17 tractor brands were identified in the studied agricultural farms and it was determined that they consist of both foreign and domestic brands according to Turkish Association of Agricultural Machinery and Equipment Manufacturers (Tarmakbir, 2018). New Holland was the highest (32.15%) brand within all tractors, followed by Massey Ferguson (18.99%), and Fiat (9.11%), John Deere (8.10%), Case IH (7.85%), Same (5.06%), Deutz (4.05%), Steyr (3.54%), Valtra (2.28%), Tumosan (2.53%), Basak (1.27%), Universal (1.27%), Hattat (0.51%) and Kubota (0.25%), etc. The reason for the higher number of New Holland and Massey Ferguson is the existence of seller dealers and maintenance-repair service facilities in the region. The opportunity of the service and seller dealers for both brands were sometimes found to provide sales to some tractors such as Hattat, Kubota, Valtra and Deutz. It determined that some tractor brands, for example Same, Universal, Stery and Tumosan, were generally sold as second hand at the same seller dealers (**Table 11**). Similarly, according to the results concluded by Aybek and Sener (2009) for a local agricultural area which are under intensive agriculture, Massey Ferguson has been reported to be the most used

Table 13 Number and rates of tractors in the studied farms of three-plain according to the purchasing

Brand	Ezine			Kumkale			Bayramic			Total of three-plain		
	FH	SH	TT	FH	SH	TT	FH	SH	TT	FH	SH	TT
MF	11 (68.75)	5 (31.25)	16	35 (89.74)	4 (10.26)	39	1 (33.33)	2 (66.67)	3	47 (81.03)	11 (18.97)	58
NH	24 (75.00)	8 (25.00)	32	83 (96.51)	3 (3.49)	86	11 (100.00)	-	11	118 (91.47)	11 (8.53)	129
FR	-	1 (100.00)	1	2 (66.67)	1 (33.33)	3	-	-	-	2 (50.00)	2 (50.00)	4
FI	11 (73.33)	4 (26.67)	15	6 (60.00)	4 (40.00)	10	-	-	-	17 (68.00)	8 (32.00)	25
SM	6 (66.67)	3 (33.33)	9	5 (41.67)	7 (58.33)	12	1 (100.00)	-	1	12 (54.55)	10 (45.45)	22
ER	1 (100.00)	-	1	1 (100.00)	-	1	-	-	-	2 (100.00)	-	2
B	-	-	-	2 (66.67)	1 (33.33)	3	1 (100.00)	-	1	3 (75.00)	1 (25.00)	4
CS	4 (57.14)	3 (42.86)	7	10 (66.67)	5 (33.33)	15	2 (100.00)	-	2	16 (66.67)	8 (33.33)	24
ST	3 (23.08)	10 (76.92)	13	9 (69.23)	4 (30.77)	13	2 (100.00)	-	2	14 (50.00)	14 (50.00)	28
TM	4 (80.00)	1 (20.00)	5	6 (85.71)	1 (14.29)	7	1 (50.00)	1 (50.00)	2	11 (78.57)	3 (21.43)	14
JD	4 (100.0)	-	4	9 (42.86)	12 (57.14)	21	5 (100.00)	-	5	18 (60.00)	12 (40.00)	30
DTZ	-	1 (100.00)	1	8 (80.00)	2 (20.00)	10	1 (100.00)	-	1	9 (75.00)	3 (25.00)	12
UN	-	-	-	3 (100.00)	-	3	-	1 (100.00)	1	3 (75.00)	1 (25.00)	4
KB	-	-	-	1 (100.00)	-	1	-	-	-	1 (100.00)	-	1
LN	-	-	-	2 (66.67)	1 (33.33)	3	-	-	-	2 (66.67)	1 (33.33)	3
VLT	-	-	-	7 (100.00)	-	7	1 (100.00)	-	1	8 (100.00)	-	8
HT	1 (100.00)	-	1	1 (100.00)	-	1	-	-	-	2 (100.00)	-	2
Total	69 (65.71)	36 (34.29)	105	190 (80.85)	45 (19.15)	235	26 (86.67)	4 (13.33)	30	285 (77.03)	85 (22.97)	370

FH, first-hand (new) tractor; SH, second-hand (old) tractor; TT, total tractor (first and second hand) for each agricultural plain.

tractor brand with a rate of 36.30% in regardless of model and size. Others recorded that the most commonly used tractor at the national level was Massey Ferguson with a ratio of 32.69 (Civelek, 2016). The same researcher recorded that the other most commonly used tractor brands were Fiat and then New Holland sold by Turk Tractor Company. According to a study conducted in another local area of the country in the same period, it was concluded that the farms had more Tumosan by 30.00%, and then Massey Ferguson (18.18%), New Holland (15.46%) and John Deere (10.00%) (Keles et al., 2016). When considering these studies carried out under the different region conditions, it can be said that the use of different brands of tractor varies according to the region's climate, crop pattern and most importantly the income level of the farmers.

The status of having different tractor brands of the farms was determined on the basis of each agricultural plain and the results of the farms having one or more than one brands are given in **Table 12**. 19.45% of farms have more than one tractor brands, while 74.31% of farms have only one tractor brand. The single brand used in the farms are usually New Holland (26.68%), Massey Ferguson (11.22%), John Deere (7.48%), Case (5.49%) and Fiat (5.49%), followed by others such as Same, Steyr, Deutz. etc. (**Table 12**). It was determined that the farms having more than one tractor brands generally use dual tractor such as NH+NH (4.74%), NH+MF (3.49%), NH+JD (2.50%), NH+CS (1.75%) and NH+TM (1.25%), and others. In both cases. the New Holland can be used widely in the farms that it may be result of its service and seller dealers in the region. The largest proportion of the farms having more than one tractor brands was found in Bayramic with 41.67% of 36 farms, followed by Kumkale with 20.93% of 258 farms and Ezine with 8.41% of 107 farms (**Table 12**). The reason using of the more tractor brands in Bayramic plain may be attributed to the different agricultural branches such as field crops, horticulture as well as animal production. Aybek and Sener (2009) recorded that 89.30% of farms had one tractor, 7.80% had two, 0.50% had three and 2.40% had four tractors, regardless of brands in an area of intensive agriculture located in Çukurova region.

Effective Methods and Factors to Purchase the Tractors for Farms

The 395 tractors were recorded (**Table 11**) in the studied farms in regardless of the brand, size and age of them, but the purchase status of only 370 was determined (**Table 13**) while no-information was obtained about the purchasing of the remaining of 25 tractors. The first-hand purchasing as new one, and second-hand purchasing of tractors are identified in farms of all villages (**Table 13**), but they were recorded only one in some farms, and two type purchasing in others. When considering the results, it is concluded that one of the way to have the tractors in farms is to purchase new tractor which corresponds to 77.03% for 3-plain. On the other hand, it was determined that the rate of the tractor ownership in the second-hand was 22.97%. It was concluded that with the change in agricultural cultivation branches and crop pattern in the three agricultural plains of the post-irrigation period, the tractors requirements with the different characteristics has increased and it is appropriate to meet purchasing with second-hand tractors to continue without interruption of the farm operations. In addition, it is also say that the standard type tractors are sufficient for the completion of the work in animal production, especially for feeding operations. For this purpose, it is also emphasized that it is more economical to purchase the second-hand type of tractors without active working properties. Considering that the studied farms having tractors, agricultural cultivation branches have been identified as an important factor in combination with the availability of service facility, spare parts, while Özpınar and Çay (2018) concluded similar results for purchasing tractor for farms. They also reported that the tractor power was the more efficiently factor, followed by the service availability, PTO properties and others such as the bank loan, fuel saving, wheel and gear characteristics (**Table 14**).

The role of financial capital as a factor of agricultural cultivation is to facilitated economic growth and development. Credit is an important instrument that enables farmers to obtain requirements with consumption materials and also plays an important role in increasing agricultural productivity. The availability of credit enables farmers to purchase the required inputs and machinery to carry out farm operations on time (Marandi and Rashidpour, 2017). Agricultural cultivation in the studied area needs more agricultural credit availability because of certain structural characteristics, notably its small family farm. Most farms are small-scale family type, fragmented and scattered (Özpınar, 2002). So, agricultural credit has great precaution for their development and they

Table 14 Number and rate of farms in terms of methods of the purchasing tractors

Plain	Cash		Loan		Agricultural credit coop.		Total	
	(nm)	(%)	(nm)	(%)	(nm)	(%)	(nm)	(%)
Ezine	32	35.56	48	53.33	10	11.11	90	100.00
Kumkale	75	32.89	153	67.11	-	-	228	100.00
Bayramic	14	53.85	11	42.31	1	3.85	26	100.00
General	121	35.28	212	61.63	11	3.20	344	100.00

meet their credit requirements from formal funds for loans through public sector, alongside with informal sources. At the national level, however, Ziraat Bank and Agricultural Credit Cooperatives have been the principle supplier of loanable funds in the agriculture sector (Gunes and Movassaghi, 2017) as formal credit sources. They also concluded that Ziraat Bank, private banks (domestic and foreign-owned and operated), agricultural credit and sales cooperatives and other cooperatives (e.g. Pankobirlik) are the major formal suppliers of credit, but wealthy farmers and money lenders are among the informal credit sources which are generally provide short term loans, saddling borrowers with high interest rates. On the other hand, small-scale farms need in order to meet short term requirements such as purchasing fuel and long term purposes; for example, investment in agricultural area, irrigation facilities and machinery. When the financial methods used in the purchasing of tractors for farms were considered, it was found that the highest system was agricultural loan system with 61.63% by private or public (Ziraat) banks, whereas in cash purchasing was lower with 35.28% because loan system gives the farmers enough time opportunity to do their repayments step-by-step (**Table 14**). Meanwhile, farmers have more confidence in Ziraat Bank because of giving subsidized credit. It is determined that the loan system is generally pay with 5% cash in advance and the rest is repaid within next 20 or 60 months as long term. Additionally, the loan system is the most effective system to purchase the tractor for farms because it provides financial facilities for long-time period. In addition to this purchase method, agricultural credit system is not preferred by farmers due to its low advantage compared to the loan system due to higher interest rate. Moreover, it was also emphasized that the loan system facilitates provide to the farmers to purchase different type, varying power size, axle type, tractor brands, and improving the agricultural equipment and Mechanisation level increasing the yield and ensured food security, but this system is varying depending on bank loan system (Özpınar and Çay, 2018). On the other hand, two factors have been emerged to be important to purchase tractors for farms, one of which is the size of the agricultural area, and other is the appropriate or reasonable price of the tractor (**Table 15**). Therefore, when the **Table 15** is considered, it was said that the size of the area is more effective factor to purchase a tractor when the 67.15% of the farms have preferred this type method. On the other hand, the rest of the farms have encouraged the reasonable price in regardless of tractor brand, power size and axle number or type because they have emphasized that the reasonable price is sometimes the easy way system due to simple access way of tractors.

The Proficiency Level of the Current Tractors in Farms

Considering on average tractor number in three-agricultural plains, 64.62% of farms have been found to be sufficient tractors to carry out their agricultural operations (**Table 16**). However, it is stated that the current tractors are not sufficient to carry out agricultural operations in 35.38% of farms which were occupied more than one agricultural branches such as field, horticulture and as well as animal production. The common of animal production in the region together crop production has revealed the requirement for tractors with different power sizes and characteristics. On the other hand, in some villages of the Bayramic and Ezine agricultural plains, it was determined that the cultivation of the horticulture together with the field cultivation increased the requirement of the tractors in different power and brands. In addition, the absence of sharing farm machinery or tractor system in the region, it was determined that each farmer have to buy required tractors and machineries to carry out their agricultural operations on time. On the other hand, farmers borrow the machinery or tractors from neighbours that is traditionally sustainable system in the area.

Varying and Distribution of Age Statues of Owned Tractors by Farms Based on Brands

The age characteristics of the tractor brands in the studied farms have been observed in similar for the country farms (**Table 17**). Current tractors in the farms were classified according to their age on the basis of brand, and then they were divided

Table 15 Number and rate of farms according to effective factors of purchasing tractors

Plain	Area size		Reasonable price		Total	
	(nm)	(%)	(nm)	(%)	(nm)	(%)
Ezine	52	56.52	40	43.48	92	100.00
Kumkale	171	74.03	60	25.97	231	100.00
Bayramic	11	39.29	17	60.71	28	100.00
General	234	67.15	117	32.85	351	100.00

Table 16 Number and rate of farms in terms of the proficiency level of the tractors

Plain	Sufficient		Insufficient		Total	
	(nm)	(%)	(nm)	(%)	(nm)	(%)
Ezine	49	56.32	38	43.68	87	100.00
Kumkale	156	67.53	75	32.47	231	100.00
Bayramic	16	66.67	8	33.33	24	100.00
General	221	64.62	121	35.38	342	100.00

into two groups as young (0-20-year) and old (20-year and over) while it has been declared that the different economic life for tractor, for example, 20-24 years at the national level. The age grouping on the brand basis was done by selecting the youngest and oldest age tractors. When considered according to age groups; the age of tractors such as Massey Ferguson, Fiat and John Deere are quite high compared to others. For example, Massey Ferguson and John Deere were found to be in the age group of 44 years which is old age group category. However, although there were found to be very old tractors for both tractor brands, the youngest tractors were also recorded for the same brands because of the reason of its long term using in the agriculture area. The other reason may be the presence of Massey Ferguson brand in the region due to the availability of sale dealers, service facilities and spare-parts which were especially settled in Ezine district. On the other hand, some models of New Holland, Erkunt, Kubota and Valtra were found younger than Massey Ferguson and John Deere, for example, although New Holland brand was used in the country for long time, they were reasonability took place in young group range for the studied farms. It can be said that the availability of New Holland tractors in farms as well in the region are directly depending on the availability of the sale dealers, service facilities which provide an increase in the use of this brand. In the region, New Holland tractors have progressively increased in the use of the agriculture after the sales dealers and service facilities were served in the area from 2010-year. Therefore, New Holland has caused to be in the category of young age as well as in the study farms. Similarly, the same opportunities for young age brands have allowed to increase its sales and used widely in the area. Özpınar and Çay (2018) found similar results about tractors age in respect to brands. On the other hand, many tractor brands found within 15-year economic life age range (Tezer and Sabancı, 1997). In a similar study, it was found that the economic life of 45.71% of total tractors is over than 25-year old at the national level, regardless of brands and sizes (Civelek, 2016) who declared that 9.02% of remaining tractors are in range 20-25 years. 11.03% in 15-20 years, 13.11% in 10-15 years and 21.14% under the age of 10 years. In another intensive agriculture region, it was concluded that 20.8% of tractors were at the age of 16 or more while 79.25% of them were under 16 years (Aybek and Sener, 2009). They explained that 30% of young tractors have 0-5 years, while 36.3% of them are 6-10 years. 12.00% are 11-15 years. When economic life of a tractor is considered to be 20-year (Yılmaz and Sümer, 2018), it can be seen that 12.50% of tractors in the study area have already completed their economic life (**Table 17**) while 87.00% was in economic life although they have low working hours in year, 500-600 hours compared to developed countries with 1000 hours per year (TAGEM, 2019). Considering tractor age at the national level, 54.00% of tractors varied between 1-24 years, while 46% are over 25 years, 50.9%

Table 17 Age of tractors according to their brands in all farms

Brand	Age group (year)		Young		Old		Tot. Trac.
	Young	Old	(nm)	(%)	(nm)	(%)	(nm)
MF	7.29 ±4.61 (63.25)+	44.33 ±15.63 (35.25)	60	89.55	7	10.45	67
NH	4.88 ±3.52 (72.15)	6.75 ±4.92 (72.95)	120	94.49	7	5.51	127
FR	6.75 ±4.92 (72.95)	44.38 ±19.25 (43.38)	3	75.00	1	25.00	4
FI	13.50 ±16.26 (120.47)	27.50 ±15.31 (55.66)	21	84.00	4	16.00	25
SM	4.60 ±2.41 (52.35)	12.50 ±10.97 (87.73)	17	77.27	5	22.73	22
ER	5.00 ±1.00 (20.00)	6.00 ±2.00 (8.00)	1	100.00	-	-	1
B	5.00 ±3.83 (76.59)	17.67 ±4.73 (26.75)	2	40.00	3	60.00	5
CS	5.75 ±3.30 (57.46)	10.33 ±8.04 (77.82)	21	87.50	3	12.50	24
ST	18.20 ±12.85 (70.62)	24.00 ±3.46 (14.43)	20	80.00	5	20.00	25
TM	4.91 ±3.52 (71.59)	8.33 ±4.93 (59.19)	13	86.67	2	13.33	15
JD	4.00 ±4.24 (106.07)	8.33 ±7.07 (84.85)	24	80.00	6	20.00	30
DTZ	5.85 ±1.30 (22.23)	15.50 ±20.21 (130.37)	11	91.67	1	8.33	12
UN	15.50 ±20.21 (130.37)	35.75 ±6.88 (19.25)	3	75.00	1	25.00	4
KB	4.91 ±3.52 (71.59)	5.00 ±2.94 (58.88)	1	100.00	-	-	1
LN	3.00 ±1.00 (33.33)	6.75 ±4.92 (72.95)	3	100.00	-	-	3
VLT	5.00 ±3.35 (66.93)	7.17 ±2.47 (34.42)	8	100.00	-	-	8
HT	5.33 ±2.52 (47.19)	15.50 ±20.51 (132.30)	2	100.00	-	-	2
General			330	88.00	45	12.00	375

+Mean tractor age ± standard deviation (coefficient of variation); MF, Massey Ferguson; NH, New Holland; FR, Ford; HT, Hattat; FI, Fiat; SM, Same; ER, Erkunt; B, Basak; CS, Case IH, ST, Steyr; TM, Tumosan; JD, John Deere; DTZ, Deutz; UN, Universal; KB, Kubota; LN, Landini; VLT, Valtra.

of tractors over 25-years are over 40 years, and remaining take place 25-40 years. It also concluded that very old tractor usage reduces agricultural cultivation activity whereas increases fuel usage costs and greenhouse gas emissions due to old technology engines (Civelek, 2016). Therefore, it needs changing old tractors with new tractors which reduce engine emission levels and time loses on the field with benefits such as electrical control, GPS guidance and ISO-Bus systems. The reason the use of old tractors is due to the low annual working hours with 600-hour in the country compared to 12 thousand hours in development countries. Using of such as old tractors will result in high fuel usage, extend working hours, extra labour costs that means less production and profit.

Conclusion

The existence of the possibilities for the sustainability of agricultural cultivation have crucial importance. Sometimes the existence of these possibilities is not enough for sustainable agriculture, but also they have to be used correctly. Therefore, it is necessary to know agricultural possibilities in an agricultural area and to determine them for to be planned for next projections. For this purpose, a questionnaire is conducted to make the necessary determinations about agriculture activities which were performed by Mechanisation possibilities and human sources. The questionnaire survey was focused to determine the agriculture structure and Mechanisation for some villages of Bayramic-Ezine-Kumkale agricultural plains in Canakkale region. In studied farms, families generally have four persons on average, and the two male and one female person per family are working and occupying in the agriculture activities. Farmers have some organizations to keep their products right, for example; more popular was the farmer recording system followed by agriculture chamber, agrochemical dealers, and others. On the other hand, agricultural activities are performed according to traditional cultivation systems despite having enough tractors. Tractors of different brands have been recorded in the studied farms, they are Massey Ferguson, New Holland, Ford, Valtra, Tumosan, Deutz, Kubota, Erkunt, Hattat, Case. However, Massey Ferguson and New Holland were the highest because of existence of their service facilities in the region. Farms generally have more than one tractor brands due to existence of more than one agriculture occupation branches such as field, horticulture crops, and even animal production. The number of tractors per farm is acceptable level in studied farms with 0.99, but it was less than one tractor. Agricultural area per tractor was found higher by 11.7 hectare per tractor in the studied farms. The number of machinery per tractor is approximately 8 on average three-agricultural plain, more suitable for traditional cultivation systems. The agriculture area per farm was 11.6 hectare on average three plains, but it consists of many small parcels size which are small than 5.0 hectare. Farmers were preferred the ways that is to purchase the tractor for farms using terming system (loan), which is ranges between 20 and 60 months compared with cash and agricultural credit systems. 88% of tractors recorded in studied farms were included in young group varying 0 and 20 years, while 12.00% were old, 20 years and over, particularly including old series of Massey Ferguson, Ford, Fiat.

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News

Obiatuary

Dr. A. M. Michael

One of our Co-operating editors, Dr. A. M. Michael, left for heavenly adobe on November 12, 2021 at the age of 91, in India. He was associated with AMA for a long time. Formerly, in his roles as the Director of Indian Agriculture Research Institute (ICAR) and the Vice Chancellor of Kerala Agriculture University, he has greatly contributed to Indian agriculture research development while focusing irrigation systems on minimized water loss and introduction of agricultural informatics.

Optimizing the Working Parameters of a Pneumatic Precision Metering Unit by Using Response Surface Methodology

by

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Abstract

The aim of this research was to identify optimum values for working parameters of a pneumatic precision metering unit by using a Central Composite Design (CCD) of Response Surface Methodology (RSM). Sticky belt tests were carried out in the laboratory conditions. To define the performance criteria of seed spacing accuracy, quality of feed index, miss index and multiple index values were used. The optimum values of vacuum pressure, peripheral speed, number of holes and the diameter of holes for precision seeding of hybrid maize seeds (KWS 6565) were found 7.2 kPa, 0.225 m/s, 26 holes and 4.1 mm, respectively.

Keywords: crop production, planters, maize, modeling, assessment.

Introduction

Origin of maize including enough phytogenetic protein and being economically important for the world is America. Maize farming and production especially contribute to production of animal protein. In addition, polysaccharide, glucose and maize oil produced from icker are very important for trade as raw material. Seeding of maize is done by vacuum type precision planters. Thus, the adjustment of row spacing, intra-row and planting depth are possible and so the plant grows in smoothness of the habitat.

Determining the appropriate row spacing and forward speed, ensuring the proper vacuum pressure, using of appropriate hole diameter and hole number for the vacuum plate are important to take advantages of suitable habitat during vegetation. All of these parameters' impact on the success of seeding has been proven by many studies done (Aykas et al., 2016).

Bereket Barut and Ozmerzi (2003), examined the effect of different operating parameters on seed holding in a single seed metering unit. They found that the holes' shape, peripheral velocity, vacuum pressure, the hole area and thousand grain weight of seed had an effect on the seed holding ratio at a significance level of 1% ($P < 0.01$) and the most suitable shape of the holes in the seed plate was oblong for maize seeds. As a result of the study the seed holding ratio decreased when the peripheral velocity of the seed plate increased, whereas the seed holding ratio increased parallel to the increase in vacuum pressure. An increase in the thousand grain weight of seed necessitated a larger hole area for holding seeds on the plate holes.

Yazgi et al. (2010) developed mathematical equations and optimized the performance of a vacuum type precision planter for metering corn seeds in their study. The variables considered in the study were the seed hole diameter, peripheral speed of the vacuum plate and vacuum on vacuum plate. RSM was applied to optimize the performance of the planter and the experiments were conducted using Central Composite Design (CCD). The results obtained from the experiments based on CCD that use five different levels for each variable were used to develop a polynomial function in quadratic form for corn seeds The optimum level of the peripheral speed of the vacuum plate (0.068 m/s), hole diameter (3.77 mm) and vacuum pressure (76.75 mbar) were verified in the lab and under field conditions.

Onal et al. (2012) developed a nomogram using equations describing the technical characteristics of the planter used in this study and to describe the seed capture mechanism relying on basic principles of fluid mechanics and aerodynamic properties of seeds. The regression models developed using the data obtained via sticky band tests showed that 16 seeds/s was the upper limit of seed release frequency for cotton and maize seeds. The upper limit of vacuum plate peripheral speed was found to be 0.34 m/s. The forward speed of either 1.0 or 1.5 m/s was found to be acceptable for the seed spacing of 0.05 and 0.10 m, respectively.

Yazgi and Degirmencioglu (2014) determined the seed spacing uniformity performance of a precision metering unit when vacuum plates with different number of holes were used. Vacuum plates with hole diameter of 3.5 mm for cotton and 4.5 mm for corn seeds were used at 1.0, 1.5 and 2.0 m/s of forward speed and 6.3 kPa of vacuum pressure. For both, cotton and corn seeds, five different vacuum plates (20, 26, 36, 52, and 72 holes) were considered in the experiments. The highest performance was determined when 26 and 36 holes were used for cotton and corn, respectively.

Yazgi and Degirmencioglu (2015) optimized the seed spacing uniformity performance of a precision planter using spherical materials and RSM. The variables including vacuum on seed plate, the diameter of seed holes and peripheral speed of the seed plate were considered. Experiments based on CCD, one of the designs in RSM, were carried out with using plastic spherical materials in the laboratory.

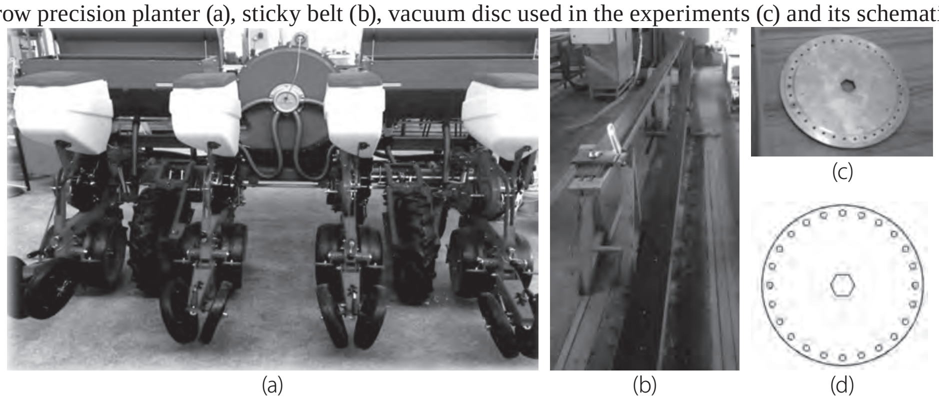
Only a few of the parameters known to affect the seeding performance were investigated on many studies. This is because study including lots of parameters conducts as full factorial design and so it needs to very long time, intensive labor and high cost. Instead of full factorial design, RSM being a very limited number of samples in the test of the agricultural machinery reduces number of experiment. Thus there is saving on time, cost and labor. The objective of this study was to find the optimum values of vacuum pressure, peripheral speed, the number of holes and the diameter of seed holes on the seed plate for maize seeds with using RSM.

Material and Methods

This study was conducted at laboratory of the Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Ege University, Izmir. Four-row precision planter having vacuum type metering units produced in Turkey was used in this research (**Fig. 1a**). According to the RSM design, vacuum plates having intended hole numbers and diameters were prepared for this study.

The Theoretical seed spacing was set to 20 cm for maize seed. In order to obtain the seed spacing of 20 cm, the necessary gear ratios were chosen for each vacuum disc with specific number of holes. The vacuum discs used in the experiments were produced in accordance with the specified hole numbers and hole diameters (**Fig. 1c**, **1d**). The diameter of the vacuum discs were 0.2 m. Sticky belt tests were performed in the laboratory conditions. The metering unit of the precision planter was simultaneously activated by a multi-speed drive arrangement, while vacuum pressure was provided by another electronic activating mechanism using shaft driven. Sticky belt (**Fig. 1b**) has length of 15 m and width of 0.15 m and was driven by electric motor having changeable rpm. In order to stick the seeds on the belt, grease was applied onto belt before every test. The distances between the seeds on the sticky belt were measured by software of

Fig. 1 Four-row precision planter (a), sticky belt (b), vacuum disc used in the experiments (c) and its schematic view (d)



computerized measurement system (CMS) developed in the same department where the study conducted (Onal and Onal, 2009). Fifty intra-row spacing measurement were made for each trial (10 meter). CMS hardware consists of a high precision optical mouse aided with laser pointer and a notebook computer. The software of the CMS stores coordinate data of the seeds with the precision of 0.1 mm using a simple user interface and sends to Microsoft Excel for further statistical analysis. Rotational speed of power take-off during the tests was set to remain constant at 540 rpm. Some physical characteristics of maize seeds used are shown on **Table 1**.

Multiple index, miss index and quality of feed index were used to determine seed spacing accuracies. The evaluation of the criteria used to determine the uniformity of seed spacing are given in **Table 2** and **Table 3**.

RSM composes of a group of mathematical and statistical techniques used in the progress of a sufficient functional relationship between a response of interest, y, and a number of associated control variables symbolized by $x_1, x_2,..., x_k$. (Khuri and Mukhopadhyay, 2010). The RSM designs are not primarily used for understanding the mechanism of the underlying system and assessing treatment main effects and interactions, but to determine, within some limits, the optimum operating conditions of a system (Myers, 1971). It is an efficient method for optimizing complicated processes. It decreases the number of experiments (Lee et al., 2006).

The response surface problem centers on response Y, which is a function of k independent variables $x_1, x_2,..., x_k$, that is,

$$Y = f(x_1, x_2,...,x_k) \quad (1)$$

and response function is characterized in the quadratic polynomial form as follows,

$$Y = \beta_0 + \sum_{i=1}^{n} B_i X_i + \sum_{i=1}^{n} B_{ii} X_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} X_i X_j + \epsilon_0 \quad (2)$$

Where, the response is Y; the intercept is β_0 the regression coefficients are; β_i, β_{ii}, β_{ij}; the coded variables are X_i X_j; and the error is ε_0. The independent variables coding into X_i are denoted by the following equation:

$$X_i = \frac{x_1 - x_0}{s_i} \quad (3)$$

Where, X_i is the actual value in original units; X_0 is the mean value (center point); and S_i is the step value (Box and Draper, 1987).

The process steps of RSM are choosing dependent and independent variables, generating the design of the experiment and coded-uncoded variables, conducting the experiments, developing the model equation, obtaining the optimum values of independent variables and conducting the verification experiments, respectively. The vacuum pressure, peripheral speed, the number of holes and the diameter of seed holes on the seed plate were the chosen variables for this study. CCD used and each independent variable had five levels. These levels were coded as -2, -1, 0, +1 and +2. The center value of vacuum pressure, peripheral speed, hole number of and hole diameter of vacuum disc were chosen 6.3 kPa, 0.45 m/s, holes of 48 and 3.8 mm, respectively and the step value of vacuum pressure, peripheral speed, hole number of and hole diameter of were chosen 1 kPa, 0.15 m/s, 12 of holes, 0.2 mm, respectively. Coded and uncoded values of independent variables were given at **Table 4** in addition the experiment design creating according to CCD were shown at **Table 5**. The center point and step values of the independent variables were chosen based on the physical properties of the maize seeds and the operating range of the planter and the sticky belt and also previous research (Yazgi et al., 2010; Onal et al., 2012; Yazgi and Degirmencioglu , 2014, 2015).

All tests were conducted triplicate and then the quality feed indexes were evaluated as dependent variables. To generate the polynomial equations and for optimization, JMP

Table 1 Some physical characteristics of maize seeds

Length (a; mm)	Width (b; mm)	Thickness (c; mm)	Sphericity (%)	One thousand seeds mass (g/1000 seeds)
11.46 (±2.08)	7.36 (±0.83)	4.39 (±0.89)	64.0 (±1.9)	289.22 (±4.42)

Table 2 Definition of the seed/plant spacing distribution indexes (Onal I., 2017)

Seed Spacing	Definition
$< 0.5\ Z_s$	Multiple index (I_{mult})
$(0.5 – 1.5)\ Z_s$	Quality of feed index (I_{qf})
$> 1.5\ Z_s$	Miss index (I_{miss})

Table 3 The classification of seed distribution for precision seeding (Onal I., 2017)

Quality of feed index (I_{qf}, %)	Multiple index (I_{mult}, %)	Miss index (I_{miss}, %)	Classification
> 98.6	< 0.7	< 0.7	Very good
> 90.4 – ≤ 98.6	≥ 0.7 – < 4.8	≥ 0.7 – < 4.8	Good
≥ 82.3 – ≤ 90.4	≥ 4.8 – ≤ 7.7	≥ 4.8 – ≤ 10	Moderate

Table 4 Coded and uncoded values of independent variables

Independent variables		Coded levels				
		-2	-1	0	1	2
Vacuum pressure (kPa)	X_1	4.3	5.3	6.3	7.3	8.3
Peripheral speed of vacuum disc (m/s)	X_2	0.15	0.3	0.45	0.6	0.75
Hole number of vacuum disc (pieces)	X_3	24	36	48	60	72
Hole diameter of vacuum disc (mm)	X_4	3.4	3.6	3.8	4	4.2

(statistical discovery software from SAS) was used.

Results and Discussion

The results of the experiments conducted according to CCD were given at **Table 5**. The model equation was generated using JMP software. The quality of feed index model has significance level of 1% ($P < 0.01$).

Quality of feed index model:

$$Y = 96,06 - 8,28X_2 + 3,63X_1 - 0,07X_3 + 2X_4 - 5,17X_2^2 + 2,71X_2X_1 - 4,85X_1^2 - 1,90X_2X_3 - 0,18X_2X_4 - 3,58X_2^2X_3 - 1,62X_2^2X_4 \quad (4)$$

Stepwise regression analysis results for the quality of feed index model were given at **Table 6**. As understanding from the **Table 6**, X_2 (peripheral speed of vacuum disc) is the first independent variable which enter into the model. The effect of the peripheral speed of vacuum disc on quality of feed index is 41%. X_1 (vacuum pressure) is the second independent variable which enter into the model.

The model is valid for the conditions given at the **Table 4**. After the analysis made with JMP software, the optimum coded values of the independent variables were obtained, which are 0.9, -1.5, -1.83 and 1.5 for X_1, X_2, X_3 and X_4, respectively. And then the coded values converted into un-coded values.

$$0.9 = \frac{x_1 - 6.3}{1} \quad (5)$$

$$-1.5 = \frac{x_2 - 0.45}{0.15} \quad (6)$$

$$-1.83 = \frac{x_3 - 48}{12} \quad (7)$$

$$-1.5 = \frac{x_4 - 3.8}{0.2} \quad (8)$$

The un-coded values are 7.2 kPa, 0.225 m/s, 26 and 4.1 mm for X_1, X_2, X_3 and X_4, respectively. Verification tests were carried out as triplicate with optimum values in the laboratory. The verification tests performed at a peripheral speed of 0.225 m/s, vacuum pressure of 7.2 kPa, 26 of hole number on vacuum disc and 4.1 mm of hole diameter. Therefore, an average value of quality of feed index of 99.25% was obtained.

The vacuum pressure level was based on the physical properties of the maize seeds and the optimum value of this variable (7.2 kPa) supports the other studies have been done by other researchers such as Yazgi et al. (2010) with the optimum vacuum pressure level of 77 mbar (7.7 kPa).

The optimum peripheral speed level of vacuum disc was obtained as 0.225 m/s. This speed match up to forward speed of 0.96 m/s and this speed is low for field capacity but this is the speed obtained for maximum performance of the planting machine.

Twenty-six hole number on vacuum disc was obtained for optimum level and Onal et al. (2010) and Yazgi and Degirmencioglu (2014) were achieved the same result in their

Table 5 The experiment design created according to CCD and the experimental data

No	Independent variables*				Dependent variable
	Vacuum pressure (kPa)	Peripheral speed of vacuum disc (m/s)	Hole number of vacuum disc (pieces)	Hole diameter of vacuum disc (mm)	Quality of feed index (%)
	X_1	X_2	X_3	X_4	Y_{qf}
1	-1 (5.3)	1 (0.6)	1 (60)	1 (4)	75.00
2	1 (7.3)	-1 (0.3)	1 (60)	-1 (3.6)	91.67
3	-1 (5.3)	-1 (0.3)	-1 (36)	1 (4)	96.97
4	1 (7.3)	1 (0.6)	-1 (36)	-1 (3.6)	97.06
5	0 (6.3)	2 (0.75)	0 (48)	0 (3.8)	56.52
6	2 (8.3)	0 (0.45)	0 (48)	0 (3.8)	83.87
7	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	96.97
8	-1 (5.3)	-1 (0.3)	1 (60)	-1 (3.6)	93.94
9	1 (7.3)	-1 (0.3)	-1 (36)	-1 (3.6)	97.88
10	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	96.97
11	-1 (5.3)	1 (0.6)	-1 (36)	-1 (3.6)	76.00
12	1 (7.3)	1 (0.6)	1 (60)	1 (4)	76.67
13	0 (6.3)	0 (0.45)	0 (48)	2 (4.2)	96.88
14	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	97.88
15	1 (7.3)	-1 (0.3)	1 (60)	1 (4)	90.32
16	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	96.55
17	1 (7.3)	1 (0.6)	1 (60)	-1 (3.6)	75.00
18	0 (6.3)	0 (0.45)	0 (48)	-2 (3.4)	88.89
19	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	97.06
20	-1 (5.3)	-1 (0.3)	1 (60)	1 (4)	90.63
21	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	96.77
22	0 (6.3)	-2 (0.15)	0 (48)	0 (3.8)	95.12
23	0 (6.3)	0 (0.45)	2 (72)	0 (3.8)	96.77
24	0 (6.3)	0 (0.45)	-2 (24)	0 (3.8)	97.06
25	-1 (5.3)	-1 (0.3)	-1 (36)	-1 (3.6)	87.88
26	1 (7.3)	1 (0.6)	-1 (36)	1 (4)	90.00
27	1 (7.3)	-1 (0.3)	-1 (36)	1 (4)	97.88
28	0 (6.3)	0 (0.45)	0 (48)	0 (3.8)	96.67
29	-1 (5.3)	1 (0.6)	1 (60)	-1 (3.6)	64.00
30	-2 (4.3)	0 (0.45)	0 (48)	0 (3.8)	70.37
31	-1 (5.3)	1 (0.6)	-1 (36)	1 (4)	72.00

* The values in the parenthesis are un-coded values

studies. Hole diameter of vacuum disc level was based on the physical properties of the maize seeds and 4.1 mm hole diameter was the optimum level for this study.

Conclusions

Instead of full factorial design, RSM requires a few number of samples in the test of agricultural machinery, and hence reduces number of experiment. Thus, there is saving on time, cost and labor. The experiment and analyses planned thorugh RSM helps to optimize the parameters. In this study, the optimum values of vacuum pressure, peripheral speed, hole number and hole diameter of vacuum disc were obtained from maize seeding with vacuum-type precision metering unit for the maximum performance of seeding. Peripheral speed of vacuum disc was the most important independent variable. The optimum peripheral speed of vacuum disc was 0.225 m/s, whereas, the velocity of the seeding machine is 0.96 m/s for intra-row of 20 cm and 26 of hole number on vacuum disc. Vacuum pressure is the second important independent variable and the optimum value of vacuum pressure was 7.2 kPa for adherence of seed on the vacuum disc. As a matter of course vacuum pressure, this value is under the influence of the physical parameters of maize seed and hole diameter of vacuum disc. Another important parameter under the influence of the physical parameters of maize seed is hole diameter of vacuum disc. Its optimum value was 4.1 mm.

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Table 6 Stepwise regression analysis results for the quality of feed index model

Step	Variable	Estimate	Standard Error	R^2	P
-	model constant	96.06	1.11	-	< 0.0001
1	X_2	-8.28	0.82	0.41	< 0.0001
2	X_1	3.63	0.82	0.49	0.0003
3	X_3	-0.07	1.41	0.52	0.9596
4	X_4	2.00	1.41	0.53	0.1735
5	X_2^2	-5.17	0.74	0.69	< 0.0001
6	X_2X_1	2.71	1.00	0.72	0,0137
7	X_1^2	-4.85	0.74	0.89	< 0.0001
8	X_2X_3	-1.90	1.00	0.90	0.0729
9	X_2X_4	-0.18	1.00	0.90	0.8618
10	$X_2^2X_3$	-3.58	1.73	0.92	0.0524
11	$X_2^2X_4$	-1.62	1.73	0.92	0.3609

Development of a Tractor-Operated Subsurface Drip Laying Machine

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Abstract

Modern cultivation of staple food grains through rice-wheat cropping pattern requires ample irrigation. While promoting sustainable agricultural productivity and ensuring food security, states like Punjab have overused and eventually depleted their good quality ground water resources. By utilizing water-saving technologies, the water usage may be reduced for irrigation purposes leading to prevention of severe ground water depletion. In Subsurface drip irrigation, water is applied to roots of plants directly through laterals, which are buried at a depth below the soil surface depending on root zone of crop to be grown and farming practices to be followed. Laying of drip laterals manually at subsurface requires lots of labour and time. To reduce the drudgery of labour and timeliness in operation subsurface drip laying machine was developed which was consists of two subsoilers and the injector units. The performance results of the machine and manual methods for cotton and paddy crop were studied. In both the crops the laterals were laid at a depth of 200 mm so that all secondary tillage operations can be carried out above this depth. The forward speed of the machine varied between 1.40 to 2.70 km/h for row to row spacing between 400 to 675 mm and the actual field capacity of the machine varied between 0.064 and 0.11 ha/h respectively. The average fuel consumption of the machine varied between 6.27 to 6.48 l/h. The cost of operation for subsurface drip laying machine varied between Rs. 7,218/ha (675 mm row to row spacing) to Rs. 12,580/ha (400 mm row to row spacing). At row to row spacing of 400 mm, the manual method of laying the laterals required approximately Rs. 32,143/ha. Overall operational cost for laying of laterals with machine was considerably lesser (61%) as compared to the manual method of laying the lateral. Saving in labour was 96% approximately. Due to mechanization, the area under subsurface drip irrigation would increase, which results in considerable water saving.

Keywords: Drip laterals, Irrigation, Subsurface irrigation, Subsoiler

Introduction

The Green Revolution in India was successful in combating a severe food crisis by bringing a paradigm shift in agricultural productivity (Rena, 2004). Modernized cultivation of staple food grains throughrice-wheat cropping patternwere mainly focused during this period, which required ample irrigation. Hence, utilization of groundwater resources was a major component of the Green revolution, and has played a key role in its success in India (Srivastava et al., 2015).

States of Northern India, including Punjab, Haryana, and western

Uttar Pradesh (UP) played vital role in the success of Green revolution (Pal et al., 1992). However, accommodating the expanding area under cultivation of wheat and rice and other modified crop patterns has vastly increased the water requirement for irrigation (Kaur et al., 2010). In fact, minor irrigation census 2011 revealed that the three states (Punjab, Haryana and UP) account for 55 percent of the tube wells in India (Pandey, 2014). In Punjab, the increasing dependence on groundwater resources has led to widespread decline in water (Baweja et al., 2017).

While promoting sustainable agricultural productivity and ensuring food security, states like Punjab have overused and depleted their good quality ground water resources. Despite being one of the smallest states in India (1.5% of total area), Punjab still accounts for 13-14% of total food grain production of the country (Grover et al., 2016). In compliance with the irrigation requirements, the number of tube-wells in Punjab was found to increase from 14.06 lakh in 2014-15 to 14.19 lakh in 2015-16 (Anon, 2016). An excessive consumption of groundwater in agricultural practices involving cultivation of wheat and rice has led to a severe deterioration of groundwater resources in Punjab (Srivastava et al., 2015). The extent of declining water table is worst in some of the major districts of Punjab, such as Ludhiana, Jalandhar, Moga, and Sangrur (Kaur et al., 2011). This data proclaims a dire need to implement a range of regulatory and technological interventions to address ground water management in Punjab.

By utilizing water-saving technologies, the water usage may be reduced for irrigation purposes leading to prevention of severe ground water depletion (Aggarwal et al., 2009). Drip irrigation is a very promising technique in comparison to alternate irrigation techniques with respect to crop production (Okunade et al., 2008). Drip irrigation is further of two types, viz; Surface Drip irrigation and Subsurface Drip irrigation. In Subsurface drip irrigation, water is applied to roots of plants directly through laterals, which are buried at a depth below the soil surface depending on root zone of crop to be grown and farming practices to be followed (Payero et al., 2005). By delivering water and nutrients directly to the root zone as per requirement of the plant leads to significantly greater yield and reduced losses. (Lamm, 2002). Subsurface drip irrigation has main advantage over the surface drip irrigation is that it has lesser system cost associated with regular repair and replacement, subjected to condition subsurface drip irrigation system lasts longer enough to overcome the high initial set-up cost. Another advantage that subsurface drip irrigation holds over surface drip irrigation is that in this technique various cultural operations can be performed on the surface of the soil as laterals under the surface remain undisturbed (Devasirvatham, 2009).

Laying of drip laterals manually at subsurface requires lots of labour and time. In manual method the labour first digs the soil with the help of pickaxe followed by laying of laterals and then covering of soil manually. In manual method, man hour requirement for laying laterals in one hectare area is 795 hours which is almost equal to 100 days. All this steps requires lot of labour and time. To reduce the drudgery of labour and timeliness in operation, a subsurface drip laying machine was developed in the Department of Farm Machinery & Power Engineering, Punjab Agricultural University, Ludhiana.

Material and Methods

Development of Tractor Operated Subsurface Drip Laying Machine

To install drip laterals at subsurface a two row subsurface drip laying machine consists of two subsoilers and the injector units was designed. The total width of the machine is 1,250 mm. The injector unit consists of a roll and a shank (curved pipe). The subsoilers loosen and break the soil surface, roll holds the lateral tape and the shank buries the tape in the loosen soil at desired depth. As the subsoiler opens

Fig. 1 Stationery view of subsurface drip laying machine

Table 1 Technical specifications of subsurface drip laying machine

S. No.	Parameter	Specification
1	Overall dimensions, L × W × H, mm	850 × 1250 × 800
2	Approximate weight, kg	425
3	Type & Hitching	Tractor mounted with 3 Point Linkage
4	Number of rows	02
5	Row to row spacing, mm	400 – 750 (adjustable)
6	Diameter of rollers for laterals,mm	800
7	Diameter of shanks, mm	50 (outer)
		32 (inner)
8	Blade, L × W × T, mm	300 × 67 × 15.5
9	Depth of operation, mm	150 – 300
10	Angle of blade from horizontal, degree	40

the soil, the lateral from the roll is guided into the soil through a shank mounted behind the subsoiler. Two tapered (in front) blades having length, width and thickness of 300, 67and 15.5 mm are mounted on the subsoilers. The blade is mounted on the subsoiler at an angle of 40o with the horizontal. The diameter of the roll is 800 mm. The inner diameter of the shank is 32 mm. Two ground wheels are attached at the sides to control the depth of the machine. The machine can be operated at a depth of 150–300mm. The height of the machine from the ground is 800 mm. During operation, high draft has to be observed, since the subsoiler has to work inside the soil so a tractor of 45 hp and above is required. Stationary view of the machine is shown in **Fig. 1**, its isometric and side view is shown in **Fig. 2** and **Fig. 3** respectively. The brief specifications of machine are given in **Table 1**.

Fig. 2 Isometric view of subsurface drip laying machine

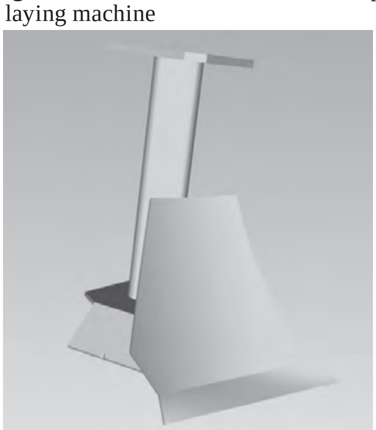


Fig. 4 A view of subsurface drip laying machine in operation

Evaluation Procedure

Field trial were conducted to access the performance of the machine for the cotton and paddy crop at different locations viz. Faridkot (Location 1), Abohar (Location 2) and Agronomy Farm, PAU, Ludhiana (Location 3) during 2018 and 2019 against manual method of laying drip laterals. A view of the machine laying laterals in the soil is shown in **Fig. 4**. The performance of the tractor operated subsurface drip laying machine was evaluated in the terms of field capacity, fuel consumption, row to row spacing and depth of lateral laying. Field capacity was measured as total area in which laterals are laid by the machine per unit time. Fuel consumption was measured for 50 m run using fuel flow meter installed in the fuel line of the tractor having least count of 1 ml. In case of cotton-wheat rotation the row to row spacing was kept at 675 mm and direct seeded rice-wheat rotation it was 400 mm. Drip laterals of 200 mm spacing were used during the evaluation. The procedure was replicated for 5 times.

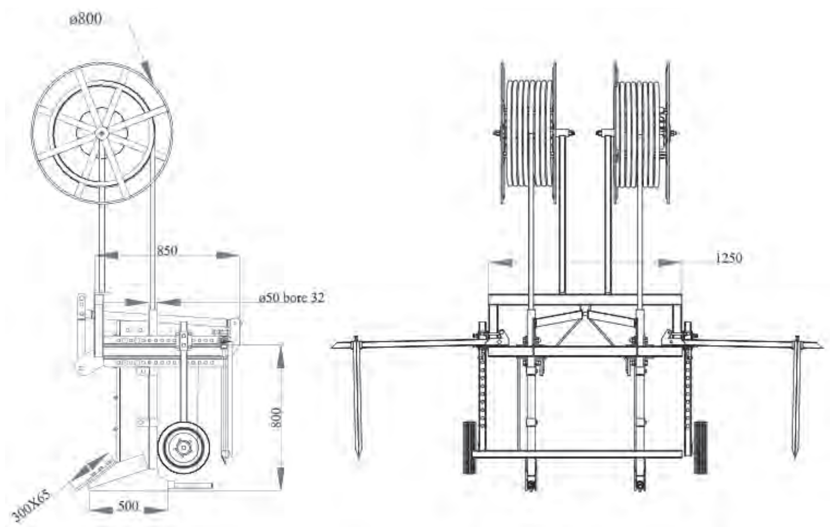
Economic Analysis

Human labour used for laying drip laterals were recorded separately for each treatment. Time (h) required to complete operation for each treatment was expressed as person-day/ha (8 h equal 1 person/day). Similarly, time and diesel required by tractor to lay the laterals for (h/ha and l/h, respectively) were also noted. The cost of operation was calculated using straight line method based on the cost of machine, life of machine, average annual usage, rate of interest, field capacity, human labour, tractor, other fixed and variable cost. Cost of operation was compared with the manual method for laying of drip laterals.

Results and Discussion

The performance results of the machine and manual methods for cotton and paddy crop are shown in Table 2. In both the crops the laterals are laid at a depth of 200 mm so that all secondary tillage operations can be carried out above this depth. The forward speed of the machine varies between 1.40 to 2.70 km/h for row to row spacing between 400 to 675 mm and the actual field capacity of the machine varies between 0.064 to 0.11 ha/h respectively. The average fuel consumption of the machine varies between 6.27 to 6.48 l/h. One labour along with tractor operator is required for the operation of the machine as the laterals

Fig. 3 Side and rear view of subsurface drip laying machine



has to be hold and cut on both the ends of the plot and the bundles of the laterals has to be refilled after its completion. The low field capacity of the machine is also due to the reason that whenever one bundle of drip lateral exhausts, it takes almost 10 minutes to refill the roller with new bundle of drip laterals.

In manual method, the total area covered by 3 person is 907.2 m^2 in 4 days by working 6 hours a day approximately. Depth of laying laterals is same as that of laying by machine (200 mm) and row to row spacing is 400 mm. The labour requirement comes out to be 794 man-h/ha (**Table 2**).

The cost of operation was calculated using straight line method based on the cost of machine (Rs. 75,000), life of machine (10 years), average annual usage (600 h), rate of interest (11%), human labour (Rs. 40/h), tractor (Rs. 225/h), field capacity and other fixed, variable cost. The cost of operation for subsurface drip laying machine comes out to be Rs. 7,300.83/ha and Rs. 7,218.49/ha at location 1 and location 2 where the row to row spacing is 675 mm (**Table 2**).

At location 3, where the row to row spacing was 400 mm the manual method of laying the laterals requires approximately Rs. 32,143/ha whereas cost of operation with the machine was Rs. 12,580/ha. Overall operational cost for laying of laterals with machine is considerably lesser (61%) as compared to the manual method of laying the lateral. Saving in labour comes out to be 96% approximately (**Table 2**).

Conclusions

Based on this study the following conclusions are drawn:

1. Tractor operated subsurface drip laying machine can be used for laying of drip laterals at required depths up to 30 cm with adjustable row to row spacing up to 75 cm.
2. The cost of operation for subsurface drip laying machine varies between Rs. 7,218/ha (675 mm row to row spacing) to Rs. 12,580/ha (400 mm row to row spacing).
3. At row to row spacing of 400 mm, the manual method of laying the laterals requires approximately Rs. 32,143/ha.
4. Overall operational cost for laying of laterals with machine is considerably lesser (61%) as compared to the manual method of laying the lateral at 400 mm row to row spacing.
5. Saving in labour comes out to be 96% approximately resulting more income of the farmers with lesser drudgery.
6. Due to mechanization, the area under subsurface drip irrigation will increase which results in considerable water saving.

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Table 2 Technical specifications of subsurface drip laying machine

S. No.	Attribute	Observation			
		Machine			Manual
1	Location of trial	Location 1	Location 2	Location 3	Location 3
2	Crop rotation	Cotton-Wheat	Cotton-Wheat	DSR – Wheat	DSR – Wheat
3	Area covered, ha	0.10	0.10	0.20	0.09
4	Forward speed, km/h	2.70	2.64	1.42	-
5	Depth of lateral laying, mm	198	200	233	200
6	Row to row spacing, mm	675	675	400	400
7	Drip to drip spacing, mm	200	200	200	200
8	Field capacity, ha/h	0.108	0.11	0.064	-
9	Fuel consumption, l/h	6.27	6.34	6.48	-
10	Labour required, man-h/ha	9.25 + 9.25*	9.09 + 9.09*	15.62 + 15.62*	793.65
11	Cost of operation, Rs/ha	7,300.83	7,218.49	12,580.02	32,142.83
12	Saving in operational cost, %	-	-	61	-
13	Labour saving, %	-	-	96	-

* Hours of operator for operating the tractor

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News

Kishida International Award Winner in 2022

Dr. Hongwei Xin

Hongwei Xin, ASABE Fellow, is the recipient of the 2022 Kishida International award for outstanding accomplishments in esearch and education on sustainable animal production systems and techniques benefitting livestock and allied agricultural enterprises worldwide.

Xin is dean and director of UT AgResearch at the Institute of Agriculture at the University of Tennessee (UT) in Knoxville. He is responsible for the research programs of approximately 145 faculty and over 400 professional staff in agricultural and natural resources across eight academic departments. He also oversees the management of ten research and education centers in strategic locations across Tennessee, where field research, demonstrations, and education programs are conducted. In 2020, Xin spearheaded the launch of the UT One Health Initiative, an interdisciplinary program seeking to protect and promote health for all life on Earth.

Mathematical Modelling and Optimization of the Distribution Uniformity of Twin-Disc Centrifugal Spreader

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Abstract

The objective of this study was to obtain the mathematical models and to optimize the distribution uniformity in the twin-disc granular broadcast spreader. This study aims to optimize the variables considered in the study to minimize the coefficient of variation (CV, %) for three different fertilizers. A domestic twin-disc granular broadcast spreader was used along with three different granular fertilizers, namely urea, compound fertilizer of 15-15-15, and compound fertilizer of 20-20-0. The variables considered in the study were the height of vanes (H), vane angle (α), fertilizer flow rate (Q), and disc peripheral speed (V). Not only the main effects on the distribution uniformity of each of these variables but also interactions of these variables are the subject matter of this study. Therefore, the models formed in polynomial form, including the interactions of variables, were used to express the performance of distribution uniformity in mathematical form. To achieve the objectives, Response Surface Methodology (RSM) was used. The study builds on RSM, which helped to develop mathematical functions in the form of polynomial models, thus making it possible to find the optimum level of the variables from these models, and finally, to verify the optimums. According to the results of the verification tests, the twin-disc granular broadcast spreader provided "good" range of distribution uniformity, which was 6.775% for urea fertilizer, 8.135% for compound fertilizer of 15-15-15, and 8.11% for compound fertilizer of 20-20-0, while CV of distribution from the original spreader was 19.29%.

Keywords: Fertilizer, broadcaster, coefficient of variation, distribution pattern, response surface methodology, polynomial models.

Introduction

Disc type fertilizer broadcasters are very common because of their advantages including low cost, high field work rate, ease of use, and manufacturing. Several factors may affect the distribution uniformity of these machines. While some of the factors are related to physico-mechanical properties of the material, others are related to shape and size of the disc, peripheral disc speed, size and profile of the vanes, number and angles of blades, shape and position of the feeding hole, and flow rate of the fertilizer.

Parish (2002) reported that reducing the rotational speed of the disc gave a worse distribution uniformity. Besides, Yildirim and Ozturk (2007) expressed that feeding radius and flow rate of the fertilizer had significant effect on the distribution uniformity.

A useful result from fertilization depends not only on the quality and the norm of fertilizer but also on the distribution uniformity provided by the machine used for this purpose (Prummel & Datema, 1962). The distribution uniformity of the fertilizer has significant effects on the yield. Coefficient of Variation (CV) is used to determine distribution uniformity of the centrifugal broadcaster, and the upper limit of the acceptable distribution uniformity is 20%. In other words, the lower CV is a more uniform distribution.

Fig. 1 Physical properties of the fertilizers

Many variables and their interactions may affect the distribution uniformity of centrifugal broadcaster. That's why large numbers of variables should be tested in order to obtain the best results. However, because of the required high labor and time demand of full factorial design, it seems complicated to conduct these experiments. On the other hand, it is possible to reduce the time and labor needed for these tests by using Response Surface Methodology (RSM) (Degirmencioglu & Yazgi, 2006). Although RSM is used widely in several research areas, there is limited research into the agricultural engineering area.

Much independent research has been conducted on the distribution pattern and distribution uniformity of granular broadcasters. However, none of them includes the optimization of the variables discussed in this study. The objective of this study was to obtain the mathematical models and optimize the distribution uniformity in the twin-disc granular broadcaster. The goal expected from this study was to optimize the variables considered in the study to minimize CV for three different fertilizers. Besides, the study was expected to help to make the amount of fertilizer on both sides in the longitudinal direction within the allowed limits.

Fig. 2 Marking the vane angles on the spreader disc

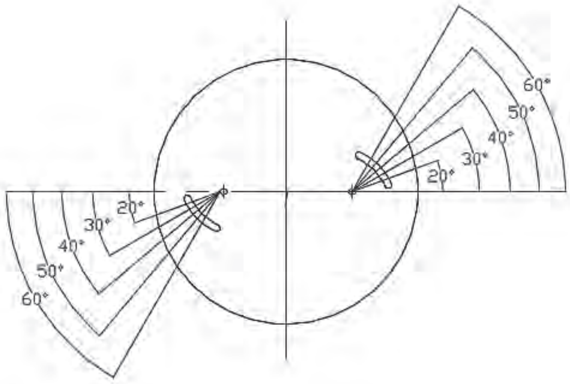

Table 1 Physical properties of the fertilizers

Physical Properties	Urea	15-15-15 compound	20-20-0 compound
Bulk Density (kg m^{-3})	724.86 [1.35]	903.95 [1.15]	901.45 [1.60]
Angle of Repose (°)	28.79 [1.08]	33.84 [0.48]	39.31 [0.36]
Moisture Content (%)	0.38 [0.02]	0.66 [0.02]	0.33 [0.03]
Sieve Analysis (%fertilizer)			
> 4 mm	0.00	0.00	0.00
3.35 mm < ... < 4 mm	0.29 [0.04]	12.57 [0.96]	11.21 [0.80]
2 mm < ... < 3.35 mm	91.54 [1.26]	82.98 [1.36]	81.66 [0.88]
1 mm < ... < 2 mm	7.92 [1.37]	4.12 [0.63]	6.82 [0.42]
... < 1 mm	0.24 [0.10]	0.32 [0.17]	0.32 [0.06]
Mass median diameter (mm)	2.58	2.75	2.7

*Values in brackets are the standard deviations

Table 2 Coded and un-coded values of independent variables

Independent variables		Coded Levels				
		-2	-1	0	1	2
Height of vanes (H)	X_1	20	35	50	65	80
Vane angle (α)	X_2	20	30	40	50	60
Fertilizer flow rate (Q)	X_3	10	25	40	55	70
Disc peripheral speed (V)	X_4	11.7	14.1	16.5	18.9	21.3

Material and Methods

A twin-disc centrifugal spreader (**Fig. 1)** was used to conduct experiments in the outdoor area on a level smooth surface. Physical properties of the fertilizers used in experiments are given in **Table 1**.

The design used in this study was a Central Composite Design (CCD) of RSM. RSM composes a group of mathematical and statistical techniques used in the progress of a sufficient functional relationship between a response of interest, y, and several associated control variables symbolized by x_1, x_2,..., x_k (Khuri & Mukhopadhyay, 2010). It is less laborious and time-consuming than other approaches and is a useful technique for optimizing complex processes since it reduces the number of experiments needed to evaluate multiple parameters and their interactions (Yazgi, Degirmencioglu, Onal, & Bayram, 2010). There are seven steps for RSM, namely choosing the independent variables, making the experimental design, development of the coded and un-coded values, carrying out the experiments, development of the model, obtaining the optimum values of independent variables, and testing the optimum values in the field.

The independent variables were coded into x_i (codded or standardized value) denoted by Equation 1:

$$X_i = \frac{x_1 - x_0}{S_i} \quad (1)$$

where, the current region of interest is x_1 in original units; the center of the region is x_0; and the step value is S_i (Box & Draper, 1987). The variables of this study were the height of vanes (H), vane angle (α), fertilizer flow rate (Q), and disc peripheral speed (V). CCD requires five levels for each independent variable, and these levels were coded as -2, -1, 0, +1 and +2. The center values of H, α, Q and V were chosen as 50 mm, 40º, 40 kg/min and 16.5 m/s, respectively. Coded and un-coded values of independent variables are given in **Table 2**.

The twin-disc fertilizer broadcaster had two spreader discs with a diameter of 357 mm. There were two oblong holes on the discs to provide the vane angles from 20º to 60º (**Fig. 2**). The vanes were manufactured according to these heights, and the vane angles were marked on the spreader discs for five levels. Experiments were carried out for the five levels of fertilizer flow rate, and suitable positions of adjusting handle were determined with these experiments. The equivalent power take-off (PTO) revolutions were calculated to adjust discs peripheral speed since peripheral speed is a function of PTO linearly. Hence, to provide peripheral speeds 11.7, 14.1, 16.5, 18.9 and 21.3 m/s, PTO was rotated at 383.7, 462.4, 540, 619.8 and 698.5 rpm respectively. Disc speed of 16.5 m/s corresponds to PTO rotation of 540 rpm, which is the middle point for this variable.

All tests were replicated three times, and then, CV in each test was calculated and they were evaluated as dependent variables to generate the polynomial equations. The experimental design for the CCD of RSM is given in **Table 3**.

Collection trays used on the field tests followed the ASAE S341.4 standard. Cardboard separators in 50 mm height were placed in collection trays to prevent the fertilizer bounce. Collecting trays are aligned as a two-dimensional matrix on the field according to ASAE S341.4 and related researcher's suggestion. In the experiments, 53 collection trays were placed adjacently on the lateral row for each replication, and three rows of collection trays in 2 m intervals were used to provide three replications in one pass (**Fig. 3**). Tractor tire tracks were kept clean for tractor passing.

Wind speeds and directions were measured instantly during the field tests at a height of 1.5 m above the ground (ASAE S341.4). All experiments were conducted when the wind speed was less than 8 km/h, and when there was wind, travel direction was selected as a parallel to the wind direction. The wind

Fig. 3 Schematic view of the collection trays on the field

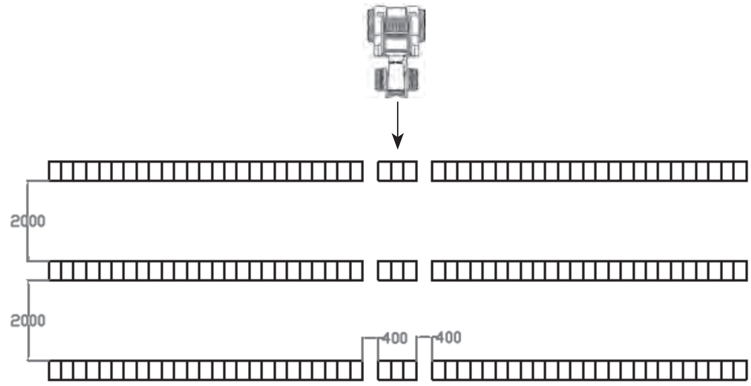

Table 3 The experimental design for CCD of RSM

No.	Height of vanes (H) (mm)	Vane angle (α) (º)	Fertilizer flow rate (Q) (kg/min)	Disc peripheral speed (V) (m/s)
	X_1	X_2	X_3	X_4
1	-1 [35]	1 [50]	1 [55]	1 [18.9]
2	1 [65]	-1 [30]	1 [55]	-1 [14.1]
3	-1 [35]	-1 [30]	-1 [25]	1 [18.9]
4	1 [65]	1 [50]	-1 [25]	-1 [14.1]
5	0 [50]	2 [60]	0 [40]	0 [16.5]
6	2 [80]	0 [40]	0 [40]	0 [16.5]
7	0 [50]	0 [40]	0 [40]	0 [16.5]
8	-1 [35]	-1 [30]	1 [55]	-1 [14.1]
9	1 [65]	-1 [30]	-1 [25]	-1 [14.1]
10	0 [50]	0 [40]	0 [40]	0 [16.5]
11	-1 [35]	1 [50]	-1 [25]	-1 [14.1]
12	1 [65]	1 [50]	1 [55]	1 [18.9]
13	0 [50]	0 [40]	0 [40]	2 [21.3]
14	0 [50]	0 [40]	0 [40]	0 [16.5]
15	1 [65]	-1 [30]	1 [55]	1 [18.9]
16	0 [50]	0 [40]	0 [40]	0 [16.5]
17	1 [65]	1 [50]	1 [55]	-1 [14.1]
18	0 [50]	0 [40]	0 [40]	-2 [11.7]
19	0 [50]	0 [40]	0 [40]	0 [16.5]
20	-1 [35]	-1 [30]	1 [55]	1 [18.9]
21	0 [50]	0 [40]	0 [40]	0 [16.5]
22	0 [50]	-2 [20]	0 [40]	0 [16.5]
23	0 [50]	0 [40]	2 [70]	0 [16.5]
24	0 [50]	0 [40]	-2 [10]	0 [16.5]
25	-1 [35]	-1 [30]	-1 [25]	-1 [14.1]
26	1 [65]	1 [50]	-1 [25]	1 [18.9]
27	1 [65]	-1 [30]	-1 [25]	1 [18.9]
28	0 [50]	0 [40]	0 [40]	0 [16.5]
29	-1 [35]	1 [50]	1 [55]	-1 [14.1]
30	-2 [20]	0 [40]	0 [40]	0 [16.5]
31	-1 [35]	1 [50]	-1 [25]	1 [18.9]

* The values in the parenthesis are un-coded values

speed was measured to be between 0-6.48 km/h during the field tests. The height of the disc surface was 70 cm above the top of the collecting trays, and it was kept as parallel to the ground in the tests. The forward speed of the tractor was constant as 8 km/h during all experiments. After each pass, fertilizers collected in the trays were transferred into the plastic cups. The samples were weighed with the electronic scale having the maximum measurement capacity of 3100 g with an accuracy of 0.01 g. The measured values were entered to the MS Excel in order to calculate left\right distribution ratio and CV (%) of overlapped distribution. Regression and variance analysis was applied to the data. The desired CV (%) value that belongs to distribution uniformity of the broadcaster must be under 20%, and the difference of fertilizer amounts between left and right sides of the tractor should be within 4%. The evaluation of the distribution qualities according to CV (%) is given in **Table 4**.

Table 4 Definition of the CV (%) values (Onal, 2011)

CV (%)	Evaluation
< 5	Very Good
6-10	Good
11-20	Acceptable
>20	Inappropriate

Results and Discussion

The results of the experiments conducted according to CCD for urea, 15-15-15, and 20-20-0 compound fertilizers were given in **Table 5.** The model equations were generated using JMP software (Cary, NC 27513-2414, USA). The distribution uniformity (CV) models are significant at the 99% probability level. The CV is the coefficient to show distribution uniformity whereas X_1, X_2, X_3, and X_4 are the height of vanes (H), vane angle (α), fertilizer flow rate (Q) and disc peripheral speed (V), respectively. Stepwise regression analysis results for the distribution uniformity models are given in **Tables 6, 7,** and **8** for urea, 15-15-15, and 20-20-0 fertilizers, respectively.

Table 5 Experimental data of the tests for urea, 15-15-15 compound and 20-20-0 compound fertilizer

No.	Urea Fertilizer		15-15-15 Compound Fertilizer		20-20-0 Compound Fertilizer	
	CV (%)	Right/Left Ratio	CV (%)	Right/Left Ratio	CV (%)	Right/Left Ratio
1	12.82	1.04	18.651	1.06	13.982	1.05
2	12.59	0.99	24.256	0.93	18.387	0.98
3	11.00	1.02	19.136	0.91	12.311	0.90
4	29.48	0.99	25.158	1.08	20.597	1.07
5	40.65	0.83	20.445	1.03	11.220	1.07
6	18.64	1.03	14.494	0.89	14.813	0.91
7	12.17	1.01	10.252	0.93	11.095	0.91
8	12.41	1.00	19.679	0.92	8.846	0.91
9	12.67	1.02	30.823	1.16	23.953	0.93
10	11.10	0.99	13.106	0.89	10.488	0.93
11	30.58	0.98	23.442	0.99	16.028	1.02
12	13.00	1.03	12.323	1.04	11.044	1.13
13	20.92	0.92	14.365	0.89	11.972	0.92
14	10.41	1.03	8.309	0.98	10.382	0.92
15	7.70	0.96	12.452	1.00	12.294	0.98
16	12.14	1.02	9.154	0.96	9.742	0.96
17	12.73	1.05	19.748	1.06	18.462	1.14
18	11.63	0.98	17.876	0.84	11.584	0.91
19	11.70	1.00	10.021	0.92	8.478	0.95
20	8.35	0.92	10.076	0.93	14.075	0.93
21	12.85	1.04	8.115	0.95	10.045	0.97
22	65.64	1.17	10.053	1.08	11.034	1.05
23	15.17	0.93	12.849	0.9	8.829	0.97
24	5.22	0.96	17.179	0.86	15.817	0.87
25	13.1	1.04	26.950	0.87	15.720	0.85
26	15.98	1.02	18.998	1.08	17.345	1.10
27	10.70	1.00	13.133	0.88	21.366	0.94
28	12.56	0.99	9.156	0.94	10.906	0.89
29	14.13	1.09	16.773	0.99	10.880	1.06
30	12.08	1.05	16.846	0.79	11.660	0.97
31	16.18	1.01	24.130	0.99	8.916	0.99

Distribution Uniformity (CV) Model for Urea Fertilizer

$$y_{CV}\,(\%) = 11.85 - 4.66x_3 + 2.32x_4 + 1.64x_1 - 6.25x_2 - 12.62x_3^2 + 1.37x_3x_4 + 1.11x_4^2 + 0.88x_1^2 - 2.07x_2x_3 - 0.99x_2x_4 + 10.32x_2^2 + 1.79x_3^3 - 4.95x_3^2x_4 - 1.87x_1x_3^2 + 9.77x_2x_3^2 + 1.98x_2x_3x_4 + 3.05x_3^4 \quad (2)$$

Distribution Uniformity (CV) Model for 15-15-15 Compound Fertilizer

$$y_{CV}\,(\%) = 9.73 - 4.53x_4 - 1.08x_3 + 7.22x_4^2 + 1.32x_3^2 + 2.24x_2x_4 + 1.38x_2^2 - 1.76x_1x_4 + 1.48x_1^2 + 0.91x_4^3 - 1.91x_3x_4^2 + 0.17x_2x_4^2 - 1.4x_4^4 \quad (3)$$

Distribution uniformity (CV) model for 20-20-0 compound fer-tilizer

$$y_{CV}\,(\%) = 11.85 - 4.66x_3 + 2.32x_4 - 12.62x_3^2 + 1.37x_3x_4 + 1.1x_4^2 + 0.88x_1^2 - 2.07x_2x_3 - 0.99x_2x_4 + 10.32x_2^2 + 1.79x_3^2 - 4.94x_3^2x_4 - 0.23x_1x_3^2 + 3.52x_2x_3^2 + 1.98x_2x_3x_4 + 3.05x_3^4 \quad (4)$$

The models are valid for the following constraints;

$$20\ \text{mm} > X_1 > 80\ \text{mm} \quad (5)$$

$$20º > X_2 > 60º \quad (6)$$

$$10\ \text{kg/min} > X_3 > 70\ \text{kg/min} \quad (7)$$

$$11.7\ \text{m/s} > X_4 > 21.3\ \text{m/s} \quad (8)$$

Upon analyzing the data by JMP software, the optimum coded values of the independent variables were obtained. Afterwards, the coded values were converted into un-coded values by Equation 1. The optimum coded, un-coded values, and the estimated CV values are given in **Table 9**.

The verification tests were conducted with the optimum values for each fertilizer. The results of the verification tests are given in **Table 10**. Obtained CV (%) values from verification tests were between 6-10%, which is accepted to be in “good” range of distribution uniformity according to **Table 4**, while estimated values took place in "very good" range. The confidence level of the models and existence of many factors which may affect distribution quality in the field conditions such as vibration, wind speed, and directions were thought as the main reason for this difference.

There are many factors to be aware of when working with the centrifugal broadcasters. The wind velocity, for example, in the region, has a significant effect on fertilizer distribution uniformity. Wind velocities even lower than 8 km/h may cause unwanted effects, especially on smaller particles. Wind velocities above 8 km/h affect the distribution quality negatively, so it is necessary to provide all broadcasting job at the wind velocities lower than the indicated upper limit. Furthermore, during the broadcasting job, disc height and forward speed should be constant, and discs should be kept parallel to the soil surface.

The standard PTO revolution for granular broadcasters is 540 rpm. Parish (2002) reported that fertilizer distribution uniformity had a detrimental effect as the PTO revolution decreased below 540 rpm. Nowadays, widely used disc type granular broadcasters have single stage transmission systems. The optimum disc peripheral speed values obtained from the model equations

Table 6 Stepwise regression analysis results for the distribution uniformity (CV) model of urea fertilizer

Step	Variable	Estimate	Standard Error	R^2
-	model constant	11.85	0.25	-
1	x_3	-4.66	0.23	0.007
2	x_4	2.32	0.23	0.013
3	x_1	1.64	0.23	0.014
4	x_2	-6.25	0.23	0.014
5	x_3^2	-12.62	0.35	0.064
6	x_3x_4	1.37	0.16	0.072
7	x_4^2	1.11	0.13	0.082
8	x_1^2	0.88	0.13	0.100
9	x_2x_3	-2.07	0.16	0.117
10	x_2x_4	-1.00	0.16	0.121
11	x_2^2	10.32	0.13	0.671
12	x_3^3	1.79	0.09	0.709
13	$x_3^2x_4$	-4.95	0.28	0.741
14	$x_1x_3^2$	-1.87	0.28	0.746
15	$x_2x_3^2$	9.77	0.28	0.872
16	$x_2x_3x_4$	1.98	0.16	0.888
17	x_3^4	3.05	0.09	0.999

Table 7 Stepwise regression analysis results for the distribution uniformity (CV) model of 15-15-15 compound fertilizer

Step	Variable	Estimate	Standard Error	R^2
-	model constant	9.73	0.91	-
1	x_4	-4.53	0.85	0.159
2	x_3	-1.08	0.85	0.280
3	x_4^2	7.22	1.3	0.362
4	x_3^2	1.32	1.48	0.431
5	x_2x_4	2.24	0.6	0.525
6	x_2^2	1.38	0.48	0.615
7	x_1x_4	-1.76	0.6	0.662
8	x_1^2	1.48	0.48	0.787
9	x_4^3	0.91	0.34	0.823
10	$x_3x_4^2$	-1.91	1.04	0.842
11	$x_2x_4^2$	0.17	0.6	0.870
12	x_4^4	-1.4	0.34	0.957

Table 8 Stepwise regression analysis results for the distribution uniformity (CV) model of 20-20-0 compound fertilizer

Step	Variable	Estimate	Standard Error	R^2
-	model constant	11.84	1.8	-
1	x_3	-4.66	1.68	0.007
2	x_4	2.32	1.68	0.013
3	x_3^2	-12.62	2.56	0.063
4	x_3x_4	1.37	1.19	0.070
5	x_4^2	1.1	0.95	0.081
6	x_1^2	0.88	0.95	0.099
7	x_2x_3	-2.07	1.19	0.117
8	x_2x_4	-0.99	1.19	0.121
9	x_2^2	10.32	0.95	0.671
10	x_3^2	1.79	0.69	0.708
11	$x_3^2x_4$	-4.94	2.06	0.741
12	$x_1x_3^2$	-0.23	1.19	0.745
13	$x_2x_3^2$	3.52	1.19	0.872
14	$x_2x_3x_4$	1.98	1.19	0.887
15	x_3^4	3.05	0.69	0.998

were corresponding to 620, 604, and 540 rpm for Urea, 15-15-15, and 20-20-0 fertilizers respectively. In other words, different fertilizers have different optimum values for peripheral disc speed. These results suggest that disc type granular broadcasters should be able to provide continuous adjustment of the transmission ratio between the tractor PTO and the fertilizer broadcaster disc.

Onal & Tozan (1984) reported that the physico-mechanical properties of fertilizers were effective on distribution uniformity. This result accounts for the difference in the optimum disc peripheral speed values for urea, 15-15-15, and 20-20-0 fertilizers. The median mass diameter values are 2.58 mm for urea, 2.75 mm for 15-15-15, and 2.7 mm for 20-20-0. As a result of experiments, while the effective working width for urea was 13.21 m, it was 14.46 m for 15-15-15 and 20-20-0 compound fertilizers. In other words, the increase in particle size increased the effective working width.

Although Parish (2003) obtained the lowest CV (%) value at -50° in studying the effects of different vane angles on fertilizer distribution, the optimum values of the "vane angle" in this study were 40° for urea and 15-15-15, while it was 45.6° for 20-20-0. It is thought that the location of the feed point on the distributor discs and the physico-mechanical properties of the fertilizers affect the optimum vane angle value. For this reason, the manufacturers are strongly advised to make adjustable vane angles to enable broadcasters to work with different fertilizers.

Yildirim & Kara (2003) obtained the lowest CV (%) value at the vane height of 35 mm for TSP and CAN fertilizers in their study. But, in this study, while optimum vane heights were 50 mm for urea and 15-15-15, it was 65 mm for 20-20-0. One reason for this difference is also the physico-mechanical properties of the fertilizers. It follows that it is appropriate to use the different height of vanes for different fertilizer types.

The flow rates of the fertilizer are an effective parameter on both fertilizer distribution uniformity and fertilizer application rate. The nutrients should be given to the soil at the desired proportions. Application rate and flow rate of the fertilizer can be adjusted by using the adjusting lever. Optimum values for the fertilizer flow rate were 25 kg/min for urea fertilizer, 61 kg/min for 15-15-15 compound fertilizer and 47.2 kg/min for 20-20-0 compound fertilizer corresponds to the application rate of fertilizer. However, to be able to respond to different needs, farmers are working in different application rates. In this case, it may be advised to change the forward speed or the working width to adjust the application rate without changing fertilizer distribution uniformity.

Conclusions

A conventional twin disc broadcaster was selected and optimized for variables which have significant effects on distribution uniformity of the machine.

As a result of the application of RSM, mathematical models were obtained, and variables were optimized to predict the lowest CV value and to provide the best distribution quality for various fertilizers. Subsequently, verification tests were conducted to check the success of the optimized values. Although predicted CV values were lower than 3% for all three fertilizers, this low CV values could not be achieved at the verification tests. Together with uncontrollable field conditions like wind speed, wind direction, and vibration of the machine, having R^2 values less than one were thought to be one reason for this difference. On the other hand, CV values obtained

Table 10 The results of the verification tests for each fertilizer

Fertilizers	Estimated CV (%)	Obtained CV (%) and working width (m)	Right/Left Ratio
Urea Fertilizer	1.72	6.775 (13.21 m)	0.99
		7.887 (13.21 m)	0.98
		7.956 (13.21 m)	1.01
15-15-15 Compound Fertilizer	2.83	9.060 (14.46 m)	0.92
		9.483 (14.46 m)	0.93
		8.135 (14.46 m)	0.93
20-20-0 Compound Fertilizer	2.26	8.301 (14.46 m)	1.09
		8.110 (14.46 m)	0.99
		9.216 (14.46 m)	1.02

Table 9 Optimum coded and un-coded values of independent variables

Independent variables	Urea Fertilizer		15-15-15 Compound Fertilizer		20-20-0 Compound Fertilizer	
	Coded Values	Un-coded Values	Coded Values	Un-coded Values	Coded Values	Un-coded Values
Height of vanes (H) X_1	0	50 mm	0	50 mm	1	65 mm
Vane angle (α) X_2	0	40°	0	40°	0.56	45.6°
Fertilizer flow rate (Q) X_3	-1	25 kg/min	1.4	61 kg/min	0.48	47.2 kg/min
Disc peripheral speed (V) X_4	1	18.9 m/s	0.8	18.42 m/s	0	16.5 m/s
Estimated CV (%)	1.72		2.83		2.26	

from verification tests were lower than 10%. Therefore, this study showed that it could be possible to reduce CV values into "good range" by applying the optimized values (Komekci, 2017).

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An Innovative Optical Instrument for Meat Quality Inspection based on Artificial Intelligence Techniques

by

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Abstract

The protein and pH contents of meat are important references in assessing the quality and freshness of meat. This paper presents a developed a model-based reflex intelligent agent for non-destructive meat quality analysis, which is easily deployable in meat packaging plants. ATmega328 microcontroller was used for data acquisition of spectral data streaming from color sensor of TCS3200. The acquired spectral data and images captured by CCD camera were sent to a laptop for further processing by MATLAB R2013a. The experiments were carried out at the laboratories of Food Technology Department, Faculty of Agriculture, Kafrelsheikh University. Forty reflection spectrums were collected from the samples within ten days, the absorbance spectra and Kubelka-Munk spectra were estimated by spectra of reflection. Besides spectral variables, Computer Vision (CV) was used for protein and pH values predictions to give a more reliable instrument. Four different machine learning models were developed according to data types at the input (computer vision data, and reflection spectra) and the variable required to predict (protein and pH values). Back-Propagation Artificial Neural Network (BP-ANN) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) modelling algorithms were used for building these supervised machine learning models. The Fuzzy Logic Algorithm (FLA) was used to indicate the overall estimation of meat sample allowable for human consumption as a quality percentage. The results show that a reflection spectrum was the most suitable spectral variable for protein prediction that has a linear relationship with protein values by BP-ANN-based model (Root mean square of errors and coefficient of determination for calibration set, RMSEC and R_C^2, were 0.125mg/g protein and 0.966, respectively). The optimum machine learning model for optical meat quality inspection of protein and pH values was based on CV (image texture features) (RMSEC was 0.089 mg protein/g meat and 0.299 pH) that is created by BP-ANN-based machine learning algorithm. ANFIS-based machine learning models show the capacity to connect CV data with that of reflection spectra data. This property allows the intelligent agent to investigate whether the input data are reasonable or not and shows the spectral properties of meat sample. For achieved overall results, BP-ANN machine learning models were more adequate than ANFIS machine learning models for optical meat quality inspection. The novelty of

this optical instrument is its ability to give chemical and physical analyses together with quality degree of the meat sample.

Keywords: Supervised machine learning models, model-based reflex intelligent non-destructive on-site inspection device, meat processing plants.

Introduction

Meat is very important diet for humans. Eating 100 g of meat gives 50% of the daily needs of the human protein, 10% of the energy, 35% of the iron and 30-60% of the vitamin B group, niacin, riboflavin, and iron. Meat produced consists of large amounts of fat, energy, and organic elements, and low amounts of water and protein (Forrest et al., 1975). Spoilt meat causes many carcinogenic and serious diseases in humans. During meat storage, the decay of meat is produced by numerous synthetic and enzymatic reactions.

The fundamental components like, protein, carbohydrates and fat are decayed by microorganisms and enzymes, creating numerous Volatile Organic Compounds (VOCs); the carbohydrates are converted into ketones, hydrocarbons, aldehydes, alcohols, and carboxylic acid gases, the protein is deteriorated into, hydrogen sulfide, ethyl mercaptan, ammonia, etc.; the fat can be analyzed into aldehydes and aldehyde acids (Kong and Ma, 2003).

At the same time, the change in color is also a sign of meat deterioration, which occurs when microorganisms produce oxidizing substances such as hydrogen sulfide, hydrogen peroxide and nitrite. Some bacteria like (Pseudomonas, Micrococci, and Sarcinae) work directly on the dye.

As a result, the color of meat changes to the brown pigment (meta-myoglobin), which can combine with hydrogen sulfide and be a green pigment (sulf-myoglobin). The growth of some microorganisms on meat and meat products gives different colors, such as meat is stained with pink pigment as a result of bacteria (Pseudomonas), then a bluish green dye due to bacteria (Micrococci, and Sarcinae), and black pigment due to bacteria (Pseudomonas).

Meat quality problems on the production line are: shape, color, size and surface texture (Du and Sun, 2006; Zheng et al., 2006; Fathi et al., 2009 and Yang et al., 2009). Kjeldahl method as analytical method is generally used to evaluate protein content in food (Jung et al., 2003). The pH is also an important factor in the effect on meat spoilage because it controls the type of organisms that cause spoilage (mold, bacteria, and yeasts), which is estimated by pH meter (Prevolnik et al., 2009). The spectra of reflection (Ma et al., 2015), absorption (Martens et al., 2003; Xia et al., 2007 and Wang and li, 2013) and diffuse reflection (Lapaeva and Rogatkin, 2007) are produced as a result of the interaction between the samples and the light. The classification and forecasting of food quality is the most complex process that takes time for most food processing plants. But with the help of advanced technologies such as artificial intelligence using cameras, near infrared (NIR) spectrum, x-rays, hyperspectral, and lasers (Osborne et al., 1993; Prieto et al., 2009 and Zhao et al., 2012). It has got easier to measure and analyze every aspect of food as it moves. While the previous automatic sorting systems concentrated only on categorizing the bad from the good.

Artificial intelligence and machine learning made the facility to classify the foods for their optimal custom (Du and Sun, 2006). Predictive algorithms and machine learning can be utilized by food processing companies to model purchaser flavor preferences and anticipate how well they respond to new tastes.

The artificial neural network is a simulation of the biological nervous system of a human. The neural network is used as an artificial intelligence system used in prediction and classification analysis. The neuron is used to transmit signals through different cells. The artificial neural network uses data in a linear classification, which is the simplest type of classification, or a non-linear classification, which is a classification curve (Gardner and Dorling, 1998 and Fathi et al., 2009).

There are several types of artificial neural networks are Back Propagation - Artificial Neural Network (BP-ANN), Radial Basis Function – Neural Network (RBF-NN), and Self Organizing - Neural Network (SO-NN). Adaptive Neuro-Fuzzy Inference System (ANFIS) links the structures of the neural network and fuzzy logic, the aim of these systems is to take advantage of the properties of the neural network and fuzzy systems. ANFIS algorithm allowed us to calibrate membership functions of the fuzzy inference training the artificial neural network (Rizal and Efendi, 2020; Dotto and Salau, 2018; Wu et al., 2015 and Arikat, 2012). To accomplish the training, the description of the input parameters matrix, a single output value and the number of whiles (numbers of interpolating the training matrix) was needed. However, ANFIS models acquire information from data using the classic neural networks algorithms but illustrate it using fuzzy rules. These types of neural networks are principally designed on five different levels which independently produce systems of fuzzy rules that escort the process of building of the outputs, beginning from correlated inputs and outputs.

The main aim of the current investigation is to develop an optical intelligent instrument for meat quality measures achieved by the following specific objectives:

1. Manufacture a suitable data acquisition system for spectral and computer vision measurements acquisition,
2. Image texture features extraction and inference analysis of compound colors using color space model by MATLAB software,
3. Create the suitable predictive model using different machine learning algorithms for protein and pH values of meat samples, and
4. Build meat quality scaling model using fuzzy logic algorithm according to the predicted values of protein and pH of meat sample.

Materials and Methods

2.1 Sample Preparation

Beef meat samples were purchased from a local market after 4-hours slaughter process and were placed on a sterile surface and divided into 40 samples 20 × 20 × 0.5mm (length, width, and thickness). Mass of each sample was 2.4 ±0.48 g. The samples were divided manually into two groups, 24 calibration samples, 6 samples per analysis per day, and 16 validation samples, 4 samples per analysis per day. All samples were placed in sterile plastic bags and placed in the 4 °C refrigerator. All samples were tested on four different days (1 Sunday, 4 Wednesday, 7 Saturday, and 10 Tuesday).

2.2 Chemical Analysis

The Chemical analysis of hydrogen number and protein values was carried out at the laboratories of Food Technology Department, Faculty of Agriculture, Kafrelsheikh University, Egypt in January, 2020. The protein ratio was estimated using the Kjeldahl method, which passes through the following steps, 2 grams of meat sample is ground, then the sample is held in a filter paper free of nitrogen, then the filter paper is placed in the digestive flask. 15 of sodium sulfate was added with 0.45 of copper sulfate inside the digestive flask. 25 ml of concentrated sulfuric acid was added (98%) using a completely dry pipette. The digestion flask was inserted into the digestion unit and the digestion process continued until the color in the sample was removed entirely. The samples were transferred after the fumes had disappeared using water of the distillation flask. 25 ml of boric acid, two point of methyl red guide, and two drops of guide green bromo were added. 37.5 were added to the sample flask, then heated, and began receiving ammonia in boric acid. The process continues until the exit of the ammonia stops completely (McGill, 1981). Planck is done for the procedure in the same previous stages, but without adding samples and the burial reading is recorded (Lynch and Barbano, 1999). Protein ratio was calculated through the following series of equations (DPMKM, 2017) as:

Hydrochloric volume × hydrochloric standard = [nitrogen weight × 1000] / [molecular weight (14.007)] (1)

% of nitrogen = (volume of hydrochloric × standard hydrochloric standard × 14.007 × 100) / (1000 × weight samples) (2)

So,

% of protein in meat = % of nitrogen × (16 / 100) (3)

2.3 Spectral Perception System

The optical percept tools for meat quality inspection environment were spectral and computer vision systems. **Fig. 1** shows the spectral system which consists of a light source 5W with, CdS Photoresistor (LDR) 20mm, Arduino Uno Board (ATmega328 microcontroller, China Clone) and Red, Green, and Blue (RGB) color sensor (TCS3200). The incident light is converted by the color sensor to an electrical current, and then this current is converted to frequencies through bilateral valves made of silicon during a 50% duty cycle using the CMOS circuit. The resulting three frequencies are varied according to the color intensity that falls on Red, Green, and Blue sensors. The sensor is affected by the surrounding light and the prox-

Fig. 1 Computer vision and spectrum system

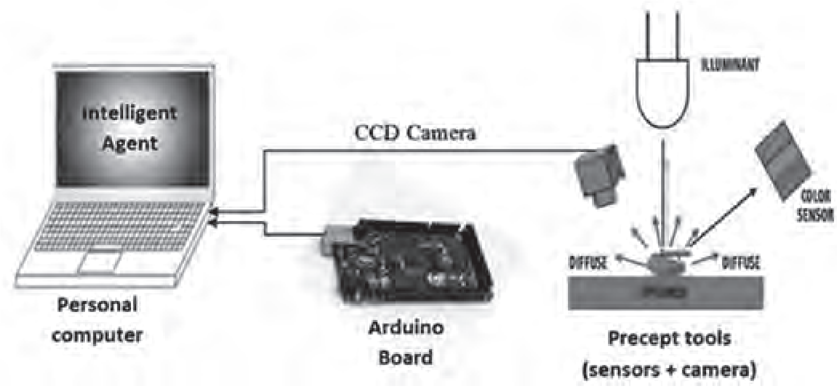
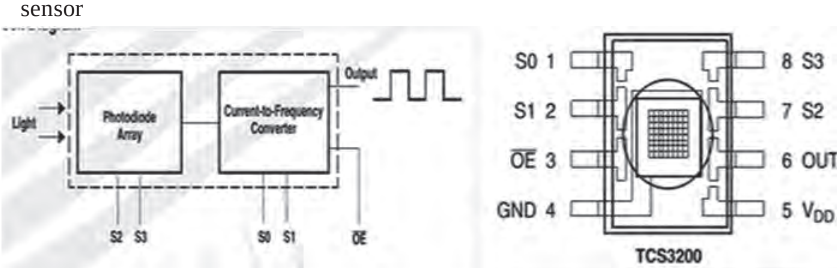


Fig. 2 The functional block diagram and package 8-lead soic (top view) of the color sensor



imity of the color of the sample.

The light is converted to a frequency through a group of photodiodes with the same 110 µm × 110 µm, which are located in the centers 134 µm. **Fig. 2** shows the following pins of S0, S1, S2, S3, which are located in the sensor that connected to the Arduino board to determine the frequencies of the following colors (red, green, blue, and transparent). In order to obtain the previous three colors, 16 color filters were used for filters for each color.

In order to compare the performance factors of the three different spectral measurement, the Reflection Spectra (RS) of the samples were converted to the absorbance spectra and diffusion reflectance spectra through the following equations (Liu et al., 2014; Quansheng, 2009; Lapaeva and Rogatkin 2007; Wang and Li 2013) as:

$$A = -\log_{10}(R) \quad (4)$$

$$K\text{-}M = \frac{(1-R)^2}{2R} \quad (5)$$

Where A is absorbance, R is reflectance and K-M is Kubelka-Munk.

2.4 Imaging Perception System

A Charge coupled device (CCD) camera (Kodak EasyShare M530). 12.2 Megapixels CCD, 3x (36-108 mm) Optical Zoom Lens, 2.7" LCD, ISO up to 1600, Blur Reduction. Video Recording with Audio was used to capture the image of the samples. In order to calibrate the images, white reference pictures were taken, the reflection ratio was 99% and black reference images ratio was 0%. The following equation was used (Ma et al., 2019):

$$M = \frac{I_S - I_D}{I_W - I_D} \times 100\% \quad (6)$$

Where M is the calibrated image, I_S is the raw image, I_D is the mean dark reference image, and I_W is the mean white reference image.

The images were taken and were sized (3264 × 2446) pixels. To calculate statistical variables of the image texture, images are converted from RGB scale image to gray scale image; to remove noise the unsharp filter was used. The mask of the Region of Interest (ROI) was selected, which is a binary image is the same size as the image you want to process with pixels that define the ROI set to 1 and all other pixels set to zero (Lui et al., 2014). The size (ROI) for the image become (211 × 259) pixels was done through creating a binary mask. The selected region of the image has been filtered through the low path filter smoothing (median filter). The tissue analysis results was represented by the following statistical variables are the mean (m) which represents average intensity of pixels, the standard deviation (σ) is normally utilized to discover how each pixel differs from the neighboring pixel (or center pixel) and is utilized in classifying into diverse regions that represents the amount of difference between pixels. Entropy (e) measures the quality of images by measuring the extent of information in the image, smoothness (R) used to remove noise from the image, and uniformity (U) represents uniformity of the histogram of the image (Li et al., 2015). P (zi) is the probability density function of pixels intensity distribution in the region, where L is the number of possible intensity levels. The statistical variables tissue analysis of images was calculated using the following equations:

$$m = \sum_{i=0}^{L-1} Z_i p(Z_i) \quad (7)$$

$$\sigma = \sqrt{\sum_{i=0}^{L-1} p(Z_i) \log_2 p(Zi)} \quad (8)$$

$$e = -\sum_{i=0}^{L-1} p(Z_i) \log_2 p(Zi) \quad (9)$$

$$R = 1 - (1 / 1 + \sigma^2) \quad (10)$$

$$U = -\sum_{i=0}^{L-1} p^2(Zi) \quad (11)$$

2.5 Building Machine Learning Model Steps

Machine learning is a frame of artificial intelligence that allows a system to learn from data instead of through express programming. However, machine learning is not an easy method. Machine learning employs different algorithms that iteratively learn from data to progress, define data, and predict outputs (FAMLP, 2018). **Fig. 3** shows the steps for building machine learning algorithms. As the algorithms digest training data, it is then conceivable to deliver more accurate models based on that data. Machine learning model is the output created when you train your machine learning algorithm with data.

2.6 BP-ANN-Based Machine Learning Model Algorithm

Back-Propagation artificial neural network (BP-ANN) consists of a group of nerves, an input layer, a hidden layer and an output layer, (**Fig. 4**). Equations from 12 to 16 are expressing the BP-ANN-based model (Dong et al., 2018 and Xiang et al., 2017). Weights represent the

Fig. 4 Architecture of BP-ANN

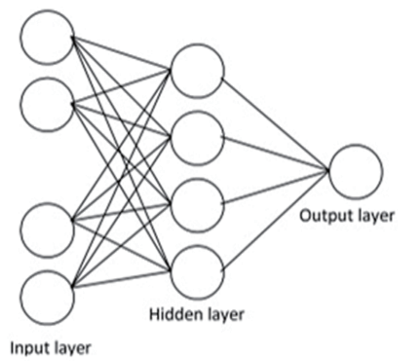
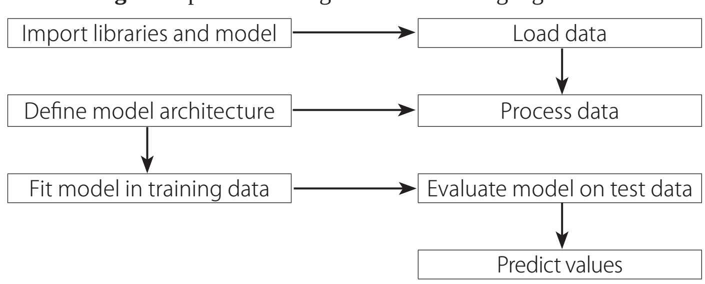


FIg. 3 Steps for building machine learning algorithms



strength of connection between units. The weights bring down the importance of the input value. New input (Bias) is a constant that aids the model in a method that it can fit best for the specified data. The control of the speed of the neural network is through learning rate and the value of which ranges from 0 to1. The learning ratio was 0.1, number of neurons in hidden layer and output layer was 3 and 1 respectively. Epochs were of 1000. The output consists of two components are sum of product and activation function, **Fig. 5.** The types of activation functions in the hidden layer and output layer were logsig and purelin, equations 12 and 13, respectively, **Fig. 5**.

$$n = \sum_{i=1}^{N} w_i x_i \quad (12)$$

$$z = f(y) = \text{logsig}(y) = 1 / (1 + \exp(y)) \quad (13)$$

Where n is purelin function, b is bias, N is number of inputs. x_i is weights, x_i is inputs, and y is applied to the activation function $f(y)$ to produce the output z.

The neural network was trained through the equations 14, 15 and 16 of sum of product, prediction error, and adaptive of weights respectively.

$$m = \sum_{1}^{m}(x_i w_i) + \text{Bias} \quad (14)$$

$$E = 1 / 2\,(d - o)^2 \quad (15)$$

Where, S is sum of product, m is number of inputs, x_i is inputs, and w_i is weight.

Where, E is prediction error, d is desired output, and o is predicted output.

$$w_{i\,new} = w_{i\,old} - \eta * (\partial E / \partial w_i) \quad (16)$$

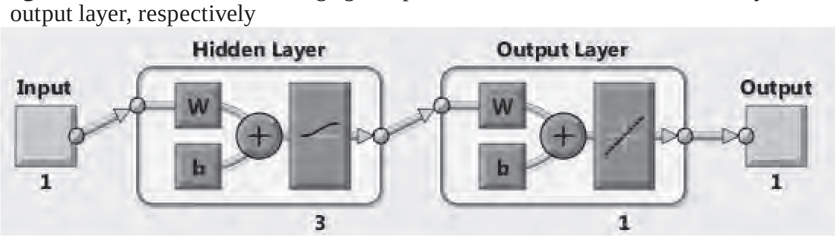
Where $w_{i\,old}$ is old weights, $w_{i\,new}$ is new weights, ∂E is derivation of error, ∂w_i is dervative weight, η is learing rate.

2.7 BP-ANN-Based Neural Network Training

The neural network is one of the best methods for deep learning in artificial intelligence in the process of prediction and classification data. The neural network is trained through the following steps, **Fig. 6**.

The weights matrices are achieved after training process of each BP-ANN-based model, **Table 1**. The first and second models were according to image features as inputs and to predict protein and pH values. However, the weight matrices of the third and fourth models were relaying on image features and reflection spectra & pH, respectively and to predict reflection spectra and protein values, respectively.

Fig. 5 Activation functions of logsig and purelin that is used for the hidden layer and output layer, respectively



2.8 Ordinary Least Squares Regression

Ordinary Least Squares regression (OLS) is used in the regression analysis, and also it used for reducing the sum of the residual squares, through reducing the sum of the vertical squared areas between the responses observed in the data set and the responses expected from linear approximation. In the current study OLS was used to find the best spectrum of the three spectra for protein prediction (Stone and Brooks, 1990). The equation of the OLS regression model writes (OLS, 2020a & b) as:

$$y_i = \beta_0 + \sum_{j=1\text{-}p} \beta_j x_j + \varepsilon \quad (17)$$

Where y_i is the dependent variable, β_0, is the intercept of the model, x_j corresponds to the jth explanatory variable of the model (j = 1 to p), and ε is the random error with expectation zero and variance σ^2.

2.9 Adaptive Neuro-Fuzzy Inference System (ANFIS) Algorithm

Fig. 7 shows the structure of the Adaptive Neuro-Fuzzy Inference System (ANFIS), which consists of five layers explained by equations from 18 to 28 (Sugeno and Kang, 1988; Mancini *et al.*, 2012 and Şahin and Erol, 2017).

Layer 1: The first layer is called the "fuzzification layer" this layer contains the inputs and the type of

FIg. 6 Neural network training steps

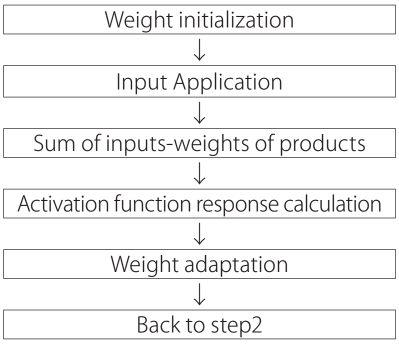
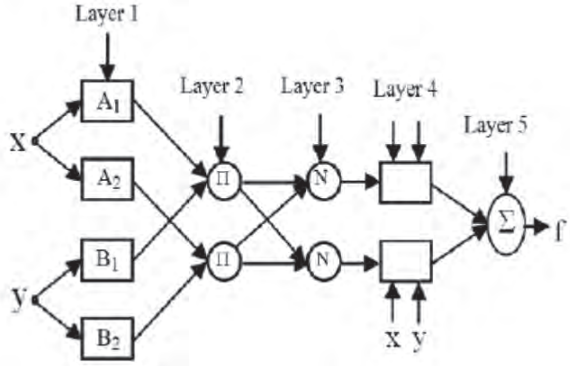


Fig. 7 Architecture of hybrid neuro fuzzy network



membership function. Membership function of trimf (triangular function) for each input of reflection spectrum and pH (i.e., x and y, respectively), equations 21 and 22, respectively. However, gauss2mf membership function was used for all image features (i.e., z_1. z_2. z_3 and z_4), equation 23. The output ofach node can be calculated through the following formulas, equation 18, 19 and 20 as follows:

$O_j^1 = \mu_{Aj}(x)$, for j = 1, 2 & 3 for linguistic labels number of x (18)

And/or

$O_k^1 = \mu_{\beta k}(y)$, for k = 1, 2 & 3 for linguistic labels number of y (19)

And/or

$O_{mn}^1 = \mu_{fmn}(z_n)$, for m = 1, 2 & 3 for linguistic labels number of z and n = 1, 2, 3 & 4 for image features number (20)

Where the membership functions are as follows:

$$\mu_{Aj}(x) = \max\left(\min\left(\frac{x - a_j}{b_j - a_j}, 1, \frac{c_j - x}{c_j - b_j}\right), 0\right) \quad (21)$$

$$\mu_{Bk}(y) = \max\left(\min\left(\frac{y - a_k}{b_k - a_k}, 1, \frac{c_k - y}{c_k - b_k}\right), 0\right) \quad (22)$$

$$\mu_{fmn}(Zn) = e^{\frac{-(Z_n - C_{mn})^2}{2\sigma_n}} \quad (23)$$

Where $\{a_j,b_j,c_j\}$, $\{a_k,b_k,c_k\}$ and $\{c_{mn}, \sigma_n^2\}$ are the parameter sets of μ_{Ai} (x), $\mu_{\beta k}$ (y) and $\mu_{fmn}(z_n)$, respectively. These parameters are called premise parameters. x, y and z are the inputs to the nodes, and A_j, β_k and f_{mn} are the linguistic labels.

Layer 2: This layer is called "rule layer". It is responsible for finding the strengths between the rules, and this layer (O_i^2) is calculated through the following formula.

$O_i^2 = w_i = \mu_{Aj}(x).\mu_{\beta k}$ (y), for j = 1, 2, 3 and k = 1, 2, 3 (24)

where

i = j × k = 9 rules = 1, 2, 3,..., 9.

i = number of rules which is the product of number of states of inputs x and y.

w_i is the node output which represents the firing strength of a rule.

In neuro fuzzy system the rules for the orders Sugeno fuzzy model can be expressed as follows:

Rule i: If x is A_j and y is β_k, then

$f_i = p_i x + q_i y + r_i$, (25)

Where A_j and β_k are the fuzzy sets, f_i is the output, and p_i, q_i, and r_i are the design parameters that are determined during the training process.

Layer 3: Is called "defuzzification layer". The main function is to normalize the computed firing strengths, this layer is calculated through the following formula:

$O_i^3 = \overline{w}_i = w_i / (w_1 + w_2 +...+ w_9)$
for i = 1, 2,..., 9 (26)

Layer 4: This layer is called "normalization layer". It takes the values that were distorted to the last layer through the following equation:

Table 1 Weight matrices after training the four BP-ANN-based machine learning models

Model No.	Variables			Weight matrices
	Inputs		Outputs	
1	Image features	Mean Variance Entropy Standard deviation	Protein	1.5854 -0.45271 2.0824 2.6588 -1.1158 2.0202 2.3419 1.4914 2.7228 2.2977 0.88811 0.86075 0.31457 2.3986 -2.2974 1.3438 -1.6067 1.8345 -1.7336 -2.9149 1.9707 1.1221 2.027 -0.67662 0.91433 0.31096 -0.029249 -0.65763 0.60056 0.41209
2	Image features	Mean Variance Entropy Standard deviation	pH	-1.3494 1.5531 1.9566 1.3331 2.7234 -2.8263 -0.71645 -1.184 -2.2947 3.026 0.9851 1.8428 -2.3539 -0.019437 1.3425 1.0131 -2.7728 -1.2281 -1.2589 -1.85 -0.42161 2.5209 2.0318 -1.5144 -0.62625 0.50253 -0.020471 -0.48981 -0.10883 0.011914
3	Image features	Mean Variance Entropy Standard deviation	Reflection spectra	0.91216 -1.3218 -2.1587 1.589 -2.5021 -2.0573 1.3516 2.2527 -0.27193 2.3475 -3.0012 0.21776 0.25349 -0.32555 -2.1057 -2.8134 -2.6509 -1.6575 1.5983 2.3656 -1.8159 -1.8755 0.83681 1.3108 0.37843 0.63461 0.4963 0.73739 -0.098917 -0.83113
4	Reflection spectra pH	Reflection spectra pH	Protein	-2.4481 1.834 4.1865 4.1865 3.3275 -4.4717 -3.5281 -1.8772 -1.3524 4.8463 -4.6574 0.18189 -0.70892 -0.19638 -0.72786 -0.84807 0.73858 -0.52017

$$O_i^4 = \overline{w}_i * f_i = \overline{w}_i / (p_i x + q_i y + r_i) \quad (27)$$

Where the $\overline{w}_i$ output of layer 3, and the parameter set is $\{p_i, q_i, r_i\}$

Layer 5: This layer is called "output layer". In this layer the final output is obtained through the following equation:

$$O_i^5 = \textstyle\sum_i \overline{w}_i * f_i = \frac{\sum_i \overline{w}_i * f_i}{w_i * f_i} \quad (28)$$

2.10 Performance Analysis Measure of ANFIS-Based Models

The ANFIS-based model is hybrid machine learning algorithm that incorporates the learning ability of the neural network with fuzzy inference system to approximate non-linear functions. The control of fuzzy nervous system transactions is through the influence range that measures the extent of the influence of nodes within the graph, the squash factor is a positive constant that is used to reduce the density of cluster members, the acceptance ratio determines whether or not the group members can accept, the rejection rate that determines the number of rejected shares, the lower the refusal rate, the higher the efficiency (Rizal and Efendi, 2020).

In order to calculate R^2 of ANFIS-based machine learning model, subtractive clustering was used and the following parameters were set for this model as follows: influence radius was 0.3, maximum number of epochs was 200, error goal was 0, initial step size was 0.01, step size decrease rate was 0.9, and step size increase rate was 1.1. To reduce the Root Mean Square Error (RMSE), neural fuzzy system parameters were set as follows, error tolerance was 0.005. Epochs was 100, range of influence was 0.5, squash factor was 1.25, accept ratio 0.5, and reject ratio was 0.15. RMSE was determined by Eqn 29 (Xiang et al., 2017):

$$\text{RMSE} = \sqrt{\frac{1}{2}\textstyle\sum_{s=1}^{n}(y_j - \hat{y}_j)^2} \quad (29)$$

Where n is number of value, s the absolute value of the residual, y_j is the original value, $\hat{y}_j$ is predicted value of y.

Fig. 9 Membership functions of input variables for the linguistic values

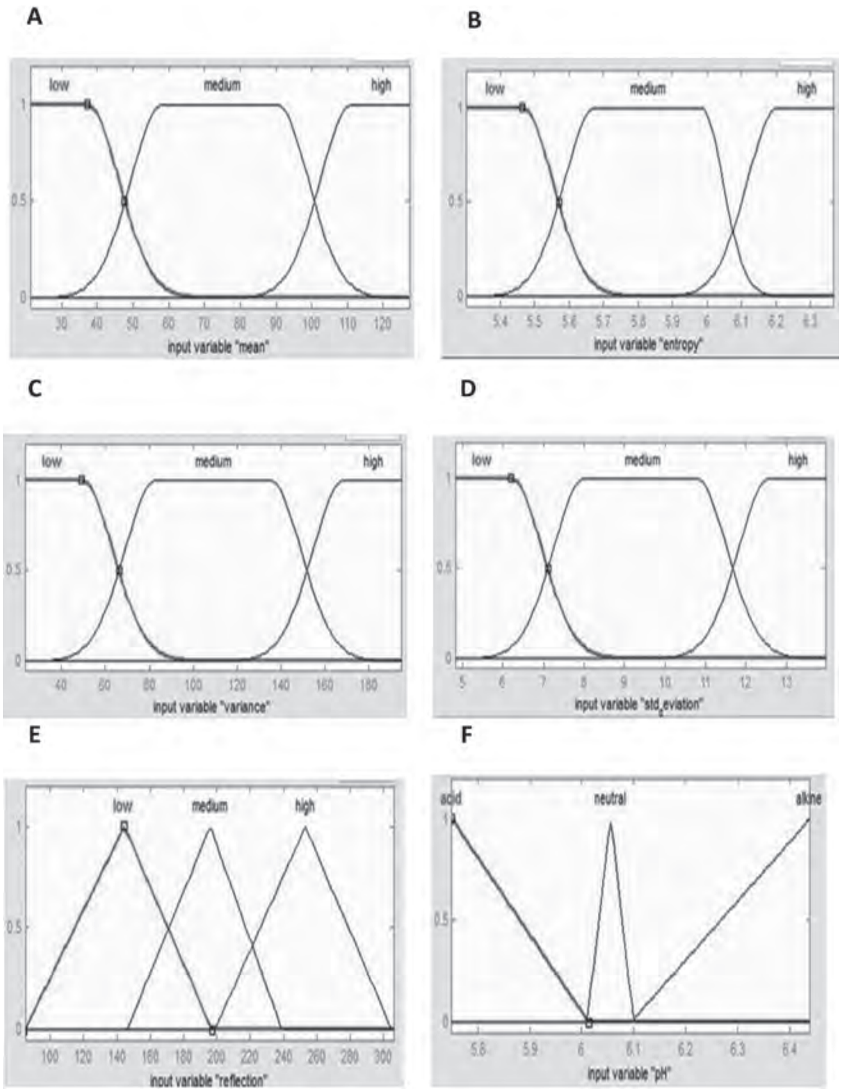
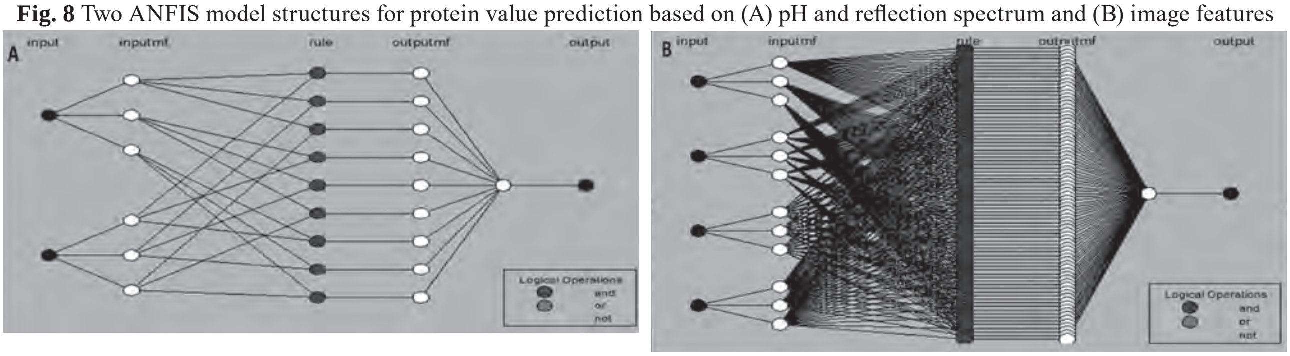


Fig. 8 Two ANFIS model structures for protein value prediction based on (A) pH and reflection spectrum and (B) image features



2.11 Building of Machine Learning Model by ANFIS Algorithm

The fuzzy inference process of ANFIS algorithm includes three important concepts: logical operations, membership functions, and IF–THEN rules (Gutiérrez-Estrada *et al*., 2005; Ocampo-Duque et al., 2006 and Zadeh, 1965). In ANFIS model, Takagi-Sugeno inference model (Sugeno and Kang, 1988) was used to get the desired results. **Fig. 8** shows two different ANFIS structures each one consists of five layers (Shoorehdeli et al., 2006). The first layer is the layer that deals directly with the inputs and determines the type of membership function for each input. The first ANFIS structure, **Fig. 8A** has two inputs owed to pH and Reflection Spectrum (RS).

The applied membership function was *trimf* function, **Figs. 9E** & **F**. Both of RS and pH inputs have 3 linguistic labels of (low, medium, and high) and (acid, neutral and alkaline), respectively, as shown in **Figs. 9E** & **F**. Meanwhile, the second ANFIS architecture, **Fig. 8B** has four inputs of the image features of mean, variance, entropy and standard deviation. The type of used membership function was gauss 2 mf. Each input has three linguistic values of (low, medium, and high), **Figs. 9A-D**. The second layer explains the rules that were grouped between the inputs and through which a specific base ratio is calculated according to the other rules. The number of IF-Then rules can be calculated by multiplying the number of inputs by the number of applied linguistic labels. The first and second structure of ANFIS has 9 and 81 IF-THEN rules, respectively, as shown in **Fig. 10**. The third layer contains 9 and 81 nodes which are the same number of IF-THEN rules for the first and second structure of ANFIS, respectively, **Figs. 8** and **10** that defuzzify the received fuzzy logic values after applying the suitable logic operations. The fourth layer is the normalization layer, and the fifth layer has the output value. The first structure of ANFIS is appropriate for the model that has inputs of reflection spectra (RS) and pH values and one output of protein value. As a result, there are 9 rules, **Fig. 10C**. However, the second structure of ANFIS algorithm is suitable for models that have the inputs of the four features of the analyzed image and one output of protein value, **Fig. 10A**, pH **Fig. 10B**, or RS **Fig. 10D**. As a result, the second structure has 81 rules.

2.11. Fuzzy Logic Inference Algorithm

Fuzzy logic algorithm was used to classify the achieved data about meat analysis that cannot belong to the class and its opposite at the same

Fig. 10 IF-THEN rules viewer for 81 rules, A, B, D and 9 rules C

time, meaning the element is true or false. As for the philosophy of fuzzy logic, it depends on whether the element can belong to a certain category, but to a certain degree (Mancini, 2012 and lee, 1990). **Fig. 11** shows the steps of data processing to achieve the appropriate name for each class. The fuzzy Logic system consists of several layers, called the membership function, ruler editor, viewer of ruler, and surface of viewer. Membership functions of trimf and trapmf were used for fuzzification of the input variables (Mancini, 2012).

$$f(x.a.b.c.) = \max\left(\min\left(\frac{x-a}{b_j-a}, 1, \frac{c-x}{c-b}\right), 0\right) \quad (30)$$

$$f(x.a.b.c.d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (31)$$

Whereas, the trapezoidal one be determined by four scalar parameters (a, b, c and d).

2.12. Software Packages

The reflection spectrum data of RGB color sensor were acquired by Arduino software 1.8.12 (IDE). Machine learning models of BP-ANN-based and ANFIS-based were built by MATLAB R2013a. Ordinary Least Square Regression (OLS) was implemented by Excel 2013.

Results and Discussion

3.1. Reference Measurement of Protein and pH

The change in protein content and acidity number was measured for 12 samples during a 10-day period. The results of the protein and acidity number were obtained through the chemical analysis of Kjeldahl, and pH meter respectively. Carbohydrates are the energy source for most microorganisms, and since meat is poor in carbohydrates, the microorganisms (bacteria, mold, and yeasts) feed on protein to obtain energy, and they also feed on nitrogen from amino acids. The following **Table 2** shows the change in protein content and acidity number with the significant differences between the averages, were calculated by comparing the Least Significant Difference (LSD) for the differences between the averages at the level of significance 0.05. The change in protein content and acidity number after the 4-day increased with a significant level ($p < 0.05$) due to a decrease in protein content (Huang et al., 2014). To consume psychrophiles bacteria for the protein found in meat in order to obtain energy that grows at a level close to the neutral pH.

3.2. Image Features Extraction by image Texture Analysis

Texture analysis of the image is used to identify the spatial distribution of light in each image, according to the spatial resolution that represents the number of pixel in the image. When the spatial resolution is high, the pixel number increases, and more distinct information can be obtained about the image. As a result of the meat chemical changes during the stages of deterioration, a change in tissue analysis occurs during the storage period. The following **Table 3** shows that with an increase in the storage period, mean, variance, standard deviation and entropy decreases after 4-day due to the samples have become dark in color, which indicates an increase in the absorption of a large amount of light, the pixel intensity and in the pixel approach, which reduces mean, entropy, variance, and standard deviation. The image is called in this case low contrast. **Fig. 12** shows the histogram of the digital images that represents the value of the color degrees that express the number of pixels present in the image (Li et al., 2016). The histogram of the digital image consists of two axes, the first axis is the horizontal axis that represents the color degree, and the horizontal axis is divided into three regions, the left side that represents the dark areas, the middle side that represents the gray areas, and the right side that represents

FIg. 11 Flowchart of the developed Fuzzy logic inference system

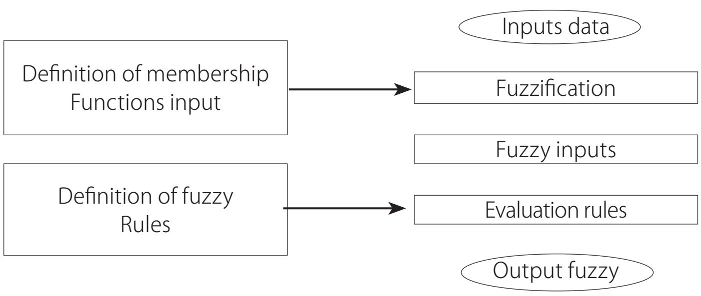


Table 2 Change in protein content and acidity number during storage days

	Storage period			
	1-day	4-day	7-day	10-day
Protein	27.33 ±0.87	25.86 ±0.75[a]	24.03 ±0.36[b]	23.34 ±0.35[c]
pH	6.44 ±0.02	6.24 ±0.01[a]	6.03 ±0.02[b]	5.79 ±0.04[c]

Table 3 Changes in texture analysis of the optimum image during storage days

Storage days	Mean (m)	Entropy (e)	Variance (σ^2)	Standard deviation (σ)
1	81.6189	6.1803	81.2511	9.0139
4	41.5948	5.9530	31.7230	5.6323
7	34.5465	5.7602	24.6521	5.7602
10	21.2410	5.3032	23.2171	4.8184

the light areas. The second axis is the vertical one axis that represents the number of pixels in each region, which represents size of pixels in each region.

3.3. Visualization of Meat Validity by RGB Color Space Model

Fig. 13 shows jet-type color-map that is interpolating the three main colors, Red, Green, and Blue (RGB) of all the possible color compounds that are presented in meat sample images. It contains three columns array (VSCC, 2020). The color grades range from 0 to 1, each row defines a specific color. The color-bar shows the changes in the color of meat samples through the stages of deterioration in beef meat from red to bluish-green, and ultimately to black which is represented by a value from 1 (fully fresh) to zero (fully deteriorated).

3.4. Spectra Features

Fig. 14 shows the change in spectra measurements of the three different spectra types, (reflection, absorbance, and diffuse reflection) during the meat storage period of 10 days. The magnitudes of reflection spectra on the first storage day were at higher level than other storage days due to the freshness of meat sample that absorbs a small amount of light (Ma et al., 2019). As meat storage age advances, the sample color changes into dark color due to some bacteria convert the pink pigment of the meat into a brown pigment (meta-myoglobin), then a bluish green dye is formed (sulf-myoglobin) and finally to the black dye. So it can be inferred that the reflection values decrease through the storage period due to color changes.

3.5. Superlative Analysis Among the Three Different Spectra

The Back Propagation of Artificial Neural Network (BP-ANN) and the Ordinary Least Square Regression (OLS) models were preliminarily used, in order to choose one represented spectrum to reduce the number of inputs for further application by either ANFIS or BP-ANN, through comparing the spectra of reflection, absorption and diffuse reflection to achieve the best spectrum for linear fitting with protein ratio of beef meat. The following **Table 4** shows that Reflection Spectrum (RS) was the best determinant variable for protein ratio predictions by both neural network model and ordinary least square regression. On the other hand, BP-ANN model can predict meat protein ratio more potential than OLS model. Calibration set of BP-ANN model gives coefficient of determination (R_C^2) of 0.966 and Root Mean Square Error (RMSEC) of 0.125. Coefficient of determination (R_v^2) and Root Mean Square Error of Validation set of the BP-ANN model was of 0.983 and 0.054, respectively, **Table 4**.

3.6. Machine Learning Model BP-ANN-Based for Meat Inspection

The first two models can be applied for a model-based reflex intelligent non-destructive measuring device. These two models were built using the image features analysis data as inputs, and the protein and pH values as outputs, respectively. The best coefficient of determina-

Fig. 12 Digital image histograms for beef samples during different storage days

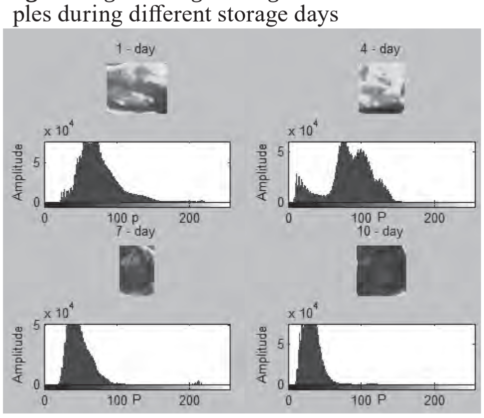


Fig. 13 RGB color-map of beef images during storage days

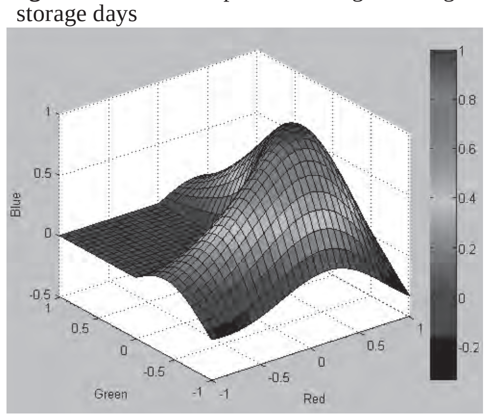
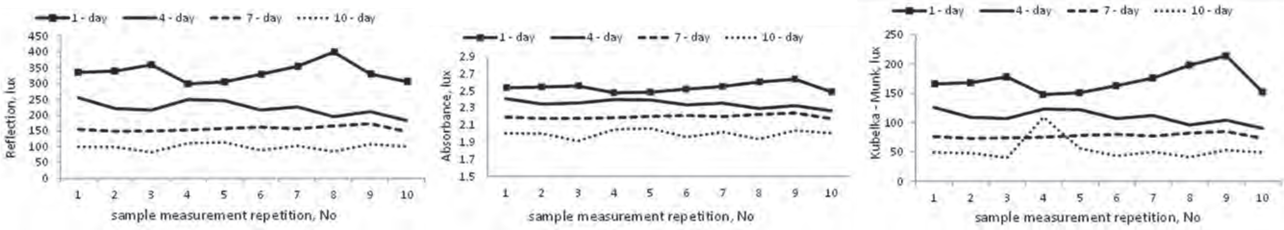


Fig. 14 Experimental spectra features of meat stored at different storage periods, (A) Reflection, (B) Absorbance, (C) Diffuse reflection



tion value of R_C^2 and R_V^2 and the Root Mean Square of Errors of calibration (RMSEC) and validation (RMSEV) were achieved at epoch 3 and 3 respectively, for the first model. However, the second model was at epoch 3 and 6 respectively. The third and fourth models were built for describing how the world evolves and updating the historical data with the current data of inputs and outputs. The third model utilizes the image features analysis data as inputs, and Reflection Spectra (RS) as outputs. Meanwhile, the fourth model is setting a chemical scale of pH along with the physical measures (RS) to predict the protein values, and model also can be implemented for non-destructive measuring devices for laboratory specific gauging devices with the highest R_C^2 and R_V^2 and RMSEC and RMSEV as listed in **Table 5**.

3.7. Machine Learning Model ANFIS-Based for Meat Inspection

Table 6 demonstrates Root Mean Square Error (RMSE) and the coefficient of determination in the calibration and validation set in Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS is based on Takagi-Sugeno inference model (Sugeno and Kang, 1988). When comparing the results of meat quality prediction for BP-ANN-based models, **Table 5**, and ANFIS-based models, **Table 6**, it was found that the prediction results of BP-ANN-based models are better than the ANFIS-based models. But the third ANFIS-based machine learning model, which has one of its surface viewers, **Fig. 15C** shows the capacity to connect computer vision data with that of reflection spectra data. Third ANFIS-based model can be also used to compare and update the data achieved by computer vision to those obtained by reflection spectra. In general, **Fig. 15** shows samples of surface viewers for different models of ANFIS-based.

From **Table 6**, it was observed that the ANFIS-based models have very small values of RMSEC and RMSEV which indicates that the predicted values are very close to the real values. Meanwhile their coefficient of determination is small too, which means that the changes or differences in outputs cannot be totally explained by a difference in inputs. In this situations the models are under fitting, where there are too many degrees of freedom available to residual space and too few to the regressor space.

3.8. Meat Quality Classes Scaling model

As the previous machine learning models that are able to predict protein and pH values of the processed meat. However, there is still a need to show meat quality degree in a way that suits the worker mind inside meat plants through specific Human Machine Interface (HMI). Fuzzy logic algorithm was used to create a deterministic express as a percentage of meat quality with three linguistic classes of acceptation (low, acceptable and high) was built based

Table 4 Performance coefficients for the three spectra are reflection, absorption, and diffuse reflection of two prediction models (BP-NN) and (OLS)

Model	Spectra	Calibration set		Validation set	
		R_c^2	RMSEC (mg/g)	R_v^2	RMSEC (mg/g)
BP-NN	Reflection	0.966	0.125	0.983	0.054
	Absorbance	0.964	0.044	0.908	0.697
	K-M	0.832	0.021	0.960	0.028
OLS	Reflection	0.953	0.352	0.978	0.286
	Absorbance	0.867	0.595	0.897	0.618
	K-M	0.805	0.721	0.948	0.441

Table 5 Different BP-ANN-based structures of machine learning models

Model No.	Variables			Number of samples	Calibration set		Validation set	
	Inputs		Outputs		RMSEC	R_c^2	RMSEV	R_v^2
1	Image features	Mean	Protein	20	0.089	0.929	0.044	0.902
		Variance						
		Entropy						
		Standard deviation						
2	Image features	Mean	pH	20	0.089	0.929	0.044	0.902
		Variance						
		Entropy						
		Standard deviation						
3	Image features	Mean	Reflection spectra	20	0.089	0.929	0.044	0.902
		Variance						
		Entropy						
		Standard deviation						
4	Reflection spectra	Reflection spectra	Protein	12	0.077	0.941	0.032	0.993
	pH	pH						

on three inputs of pH, protein and reflection spectra. Mamdani system was used to control the fuzzy set (lancuLancu, 2012). The membership functions were trimf and trapmf. **Fig. 17**, element values vary for the pH component of the following functions trimf and trapmf is between 0 to14 (datum). **Fig. 16** and **Table 7** show IF-THEN rules used for meat quality scaling process. When the meat is acidic, pH value is lower than 5.5, then meat quality is high, when the pH increases from 5.5 to 5.8, meat quality starts to decrease to be at acceptable level. If pH rises to be more than 6 (the meat becomes an alkaline), then the meat color turns into green color, the meat becomes inappropriate for human consumption and the quality of meat is poor (EpHFQ, 2009). Overall protein values were from 19 to 31 mg protein/g (datum), if the protein value is less than 19 mg protein/g, the quality of meat decreases (low), when it exceeds 19 to 25 mg protein/g, the quality of meat increases (acceptable), and as the protein value raises more than 25 mg protein/g, the quality of meat is (high). The light reflection for the samples in this experiment ranges from 50 to 500 lux, when the reflection decreases to 100 lux; this indicates the dark color of the sample and the low quality of the meat. Reflection spectrum from 100 to 250 lux shows the quality of meat increases (acceptable), and when the light reflection increases further more than 250 lux the quality of the meat is high. For each beef quality scale has a specific 3D surface viewer, for instance the 3D surface viewer of the scaling model at acceptable level of beef quality was shown at **Fig. 18**. There are two different input patterns for beef quality scaling. The first and second input patterns were based on pH and reflection spectrum, and pH and protein values, **Figs. 18A** and **B**, respectively.

Fig. 15 Surface viewer of the ANFIS-based models

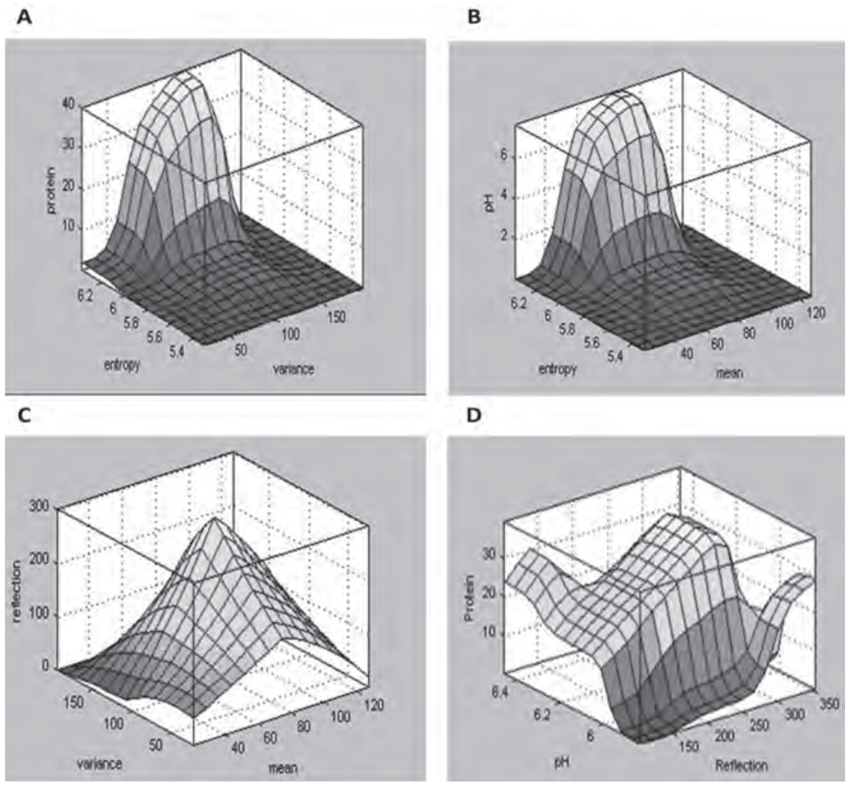


Table 6 Different ANFIS-based structures of machine learning models

Model No.	Variables: Inputs		Outputs	Number of samples	Calibration set: RMSEC	R_c^2	Validation set: RMSEV	R_v^2
1	Image features	Mean	Protein	20	0.000229	0.592	0.000232	0.627
		Variance						
		Entropy						
		Standard deviation						
2	Image features	Mean	pH	20	0.00005049	0.623	0.00004555	0.394
		Variance						
		Entropy						
		Standard deviation						
3	Image features	Mean	Reflection spectra	20	0.000683	0.833	0.000832	0.913
		Variance						
		Entropy						
		Standard deviation						
4	Reflection spectra	Reflection spectra	Protein	12	0.000132	0.713	0.000564	0.584
	pH	pH						

Conclusions

The results indicate that meat spoilage and low protein content can be predicted through the use of the effect of light spectra reactions with samples and also through the use of color changes in image processing, which is considered one of the non-destructive methods to detect deterioration and quality degree. A color map was used that indicates a change in the color of the samples during the spoilage stages. Through comparing the spectra of reflection, absorption and diffuse reflection to achieve the best spectrum for linear fitting with protein ratio of beef reflection spectrum was the best determinant variable for protein ratio predictions. Machine learning models created by back -propagation of artificial neural network -based modelling algorithm can predict the protein content ratio and pH values more accurately than others created by adaptive neuro-fuzzy inference system -based modelling algorithm. Those machine learning models were built using the image features analysis data as inputs. The coefficient of determination value for calibration and validation sets of R_C^2 and R_V^2 is 0.929 & 0.902 and 0.792 & 0.802 for protein and pH values, respectively. Those of two machine learning models are recommended for model-based reflex intelligent non-destructive optical on-site device for meat quality inspection inside meat processing plants. The root mean square errors of calibration and validation sets are 0.089 & 0.044 mg protein/g meat and 0.299 & 0.258 pH values, respectively. The other two (third and fourth) models are built for describing how does the world evolve? And update the historical data with the current data of inputs and outputs. The third machine learning model constructed by adaptive neuro-fuzzy inference system -based modelling algorithm is better than formed by back -propagation of artificial neural network -based modelling algorithm which utilizes the image features analysis data as inputs, and reflection spectra as outputs. The coefficient of determination value for calibration

Table 7 If-Then rules

No.	Rules
1	IF ‘pH’ IS ‘acid’ AND ‘protein’ IS ‘high’ AND ‘reflection’ IS ‘high’ THEN ‘quality’ IS ‘high’.
2	IF ‘pH’ IS ‘neutral’ AND‘Protein’ IS ‘medium’ AND‘ reflection’ is ‘medium’ THEN ‘quality’ IS ‘ acceptable’.
3	IF ‘pH’ IS ‘alkine’ AND ‘Protein’ IS ‘low’ AND ‘reflection’ IS ‘low’ THEN ‘quality’ IS ‘low’.

Fig. 16 IF-THEN rules viewer

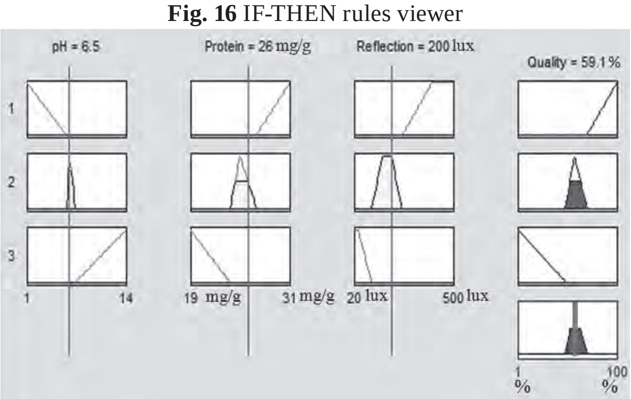


Fig. 18 3D surface viewer of the acceptable quality level of beef

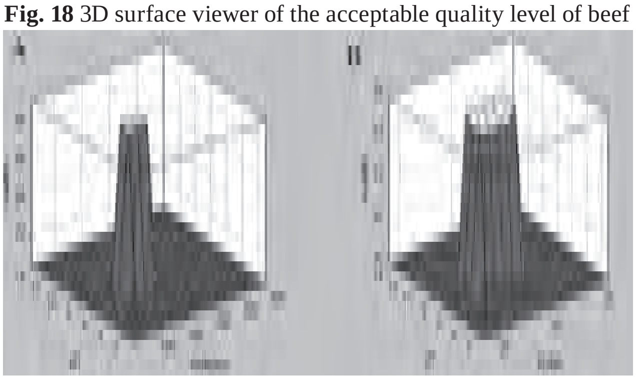
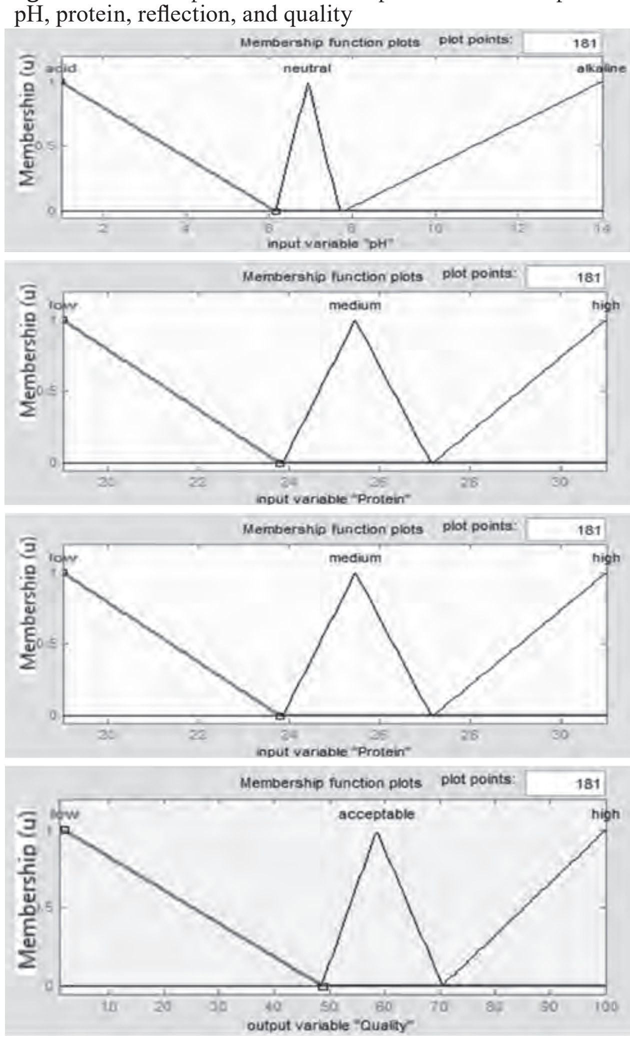


Fig. 17 Membership function of the input values and output: pH, protein, reflection, and quality



and validation sets of R_C^2 and R_V^2 are 0.833 and 0.913, respectively. The root mean square errors of calibration and validation sets are 0.000683 and 0.000832 lux, respectively. The fourth back -propagation of artificial neural network -based machine learning model is the most precise model at all which is setting a chemical scale of pH along with the physical measures of reflection spectrum to predict the protein values for referencing purposes, this model can be implemented for partially non-destructive measuring devices for laboratory-specific gauging devices with the highest R_C^2 and R_V^2 and The root mean square errors of calibration and validation sets are 0.941 & 0.993 and 0.077 & 0.032 mg protein/g meat, respectively. Fuzzy logic inference-based machine learning model can categorize the physical and chemical inspections of beef meat into its suitable class of low, acceptable and high quality with its percentage value of human consumption availability.

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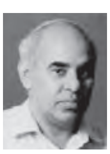
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