International Journal of Statistics and Applied Mathematics

**ISSN:** 2456-1452
Maths 2023; SP-8(4): 391-398

https://www.mathsjournal.com
Received: 01-04-2023
Accepted: 03-05-2023

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# Modelling studies on energy use pattern in agriculture: A mini review

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**DOI:** https://doi.org/10.22271/maths.2023.v8.i4Sf.1093

**Abstract**
To meet out the demand of food production on decreasing arable land energy use of the crop is more important to attain self-sufficient in agriculture. Energy use efficiency and energy productivity for cereals, millet, fodder, oilseeds, commercial crop, sugar crop, plantation, vegetable and fruit shows energy utilized by crops at various stages differ by crop cultivation practice. Evolution of mathematical model to machine learning is rapidly increases over the decades. In machine learning, evolution of neural network algorithm is rapid than any other models. Mostly for energy auditing supervised machine learning models were used. Artificial Neural Network is most accurate predicted model and Data Envelopment Analysis (DEA) is most used model for energy auditing. Model performance is also measured by coefficient of determination, root mean square error. Even though DEA is used frequently for energy auditing it as its own drawbacks. At future prediction of data machine learning will get lead than mathematical\econometrical models.

**Keywords:** Energy auditing, energy productivity, machine learning models, Data Envelopment Analysis (DEA)

## 1. Introduction

The agricultural sector plays an important role in Indian economy. In India 55% of population relies on agriculture and its allied activities. Hence, GDP contribution in agricultural sector, industrial sector and service sector is 20.19%, 25.92% and 53.89% respectively in 2021. Over the years GDP contribution of agricultural sector decreases in compare to industrial and service sector [1]. India's total arable land area is 159.7 million hectare. As growth of population increases energy consumption increases. But availability of arable land decreases [2]. To overcome demand of food production and to attain self-sufficiency in agriculture energy use is becoming more intensive in form of mechanized activities using machineries for field operation, consumption of more electricity for irrigation, more labour involvement for fertilizer application, pesticide and chemical spraying activities [3]. Intensive energy use in agriculture often entangles economic problems to farmers in addition to environmental issues.

Efficient energy use is important requirement for sustainable agriculture. Energy input-output utilization differs from crop to crop. Most energy utilization in agricultural sector is classified as direct energy (Animal, Human, Water, Fuel), indirect energy (Manures, Seed, Fertilizers, Machinery, Chemicals) and renewable energy (Seeds, Water, Animal, Manures, Human), non-renewable energy (Machinery, Fuels, Fertilizers, Chemicals). Energy modelling requires to reduce the activities of excess amount of input energy used in certain stages and to pertain the loss of energy resources [4]. In agriculture it is quite difficult to measure crop production due to involvement of biological process and number of factors which affects the crop yield in various stages [5].

Hence, the efficient use of energy at right time will reduce the loss in input consumption of energy which directly related to benefit of crop yield as output energy [6]. Researcher's shows very low amount of interest in analysing energy use pattern due to data shortage and very poor interdisciplinary activities at lower level [7]. The objective of the study is to compare the energy utilization by crops using energy indices and accuracy on model findings.

## 2. Models useful for energy auditing

To improve the crop management practices energy utilized by the crop as input and consumed energy delivered as output analysis is important [8].These analysis can be done through various mathematical and statistical models. Through which we can know the contribution of various energy utilized by the crops at various stages. Energy use pattern and its accuracy measurement of the models of various agricultural crops are mentioned in table1.

**Table 1:** Energy use pattern of various crops and models used and its accuracy

| S. No | Crop Name | Energy use Efficiency (Energy ratio) | Energy Productivity (Kg $MJ^{-1}$) | Models worked on | Karl Pearson coefficient (r) | $R^2$ value | RMSE (Root Mean Squared Error) | Durbin-Watson | Reference |
|---|---|---|---|---|---|---|---|---|---|
| **Cereal crops** | | | | | | | | | |
| 1. | Rice | 1.51-2.69 | 0.11-0.19 | Cobb-Douglas | 0.89 | 0.80 | - | 1.52 | [9-13] |
| | | | | Data envelopment analysis (DEA) | 0.98 | 0.96 | - | - | |
| | | | | Artificial Neural Network (ANN) | 0.94 | 0.90 | 42.38 | - | |
| 2. | Wheat | 2.5-2.8 | 0.16-0.19 | Cobb-Douglas | 0.53 | 0.29 | - | 1.21 | [14] |
| | | | | Artificial neural network (ANN) | 0.99 | 0.99 | 0.105 | - | [7] |
| | | | | Support Vector Regression (SVR) | 0.40 | 0.16 | 22.43 | - | [2] |
| | | | | Multiple linear regression (MLR) | 0.87 | 0.77 | 4963 | - | [15] [8, 16] |
| 3. | Maize | 8.63-10.26 | 0.59-0.70 | Cobb-Douglas | 0.99 | 0.99 | - | 2.17 | [17, 19] |
| 4. | Barely | 2.86 | 0.19 | - | 0.98 | 0.98 | - | 1.16 | [6] |
| **Millet crop** | | | | | | | | | |
| 5. | Pearl millet | 3.4-5.8 | 0.13 | Data envelopment analysis (DEA) | - | - | - | - | [20] |
| **Fodder crop** | | | | | | | | | |
| 6. | Alfalfa | 1.88 | 0.12 | Cobb-Douglas | - | - | - | - | [21] |
| | | | | Ordinary least square (OLS) | - | - | - | - | |
| | | | | Data envelopment analysis (DEA | - | - | - | - | |
| **Oilseed crops** | | | | | | | | | |
| 7. | Soya bean | 4.62 | 0.16 | Cobb -Douglas | 0.99 | 0.99 | - | 2.15 | [22] |
| | | | | Data envelopment analysis (DEA) | - | - | - | - | [23] |
| 8. | Canola (rapeseed) | 4.68 | 0.17 | - | - | - | - | - | [1] |
| 9. | Sesame | 1.5 | 0.06 | Cobb-Douglas | - | - | - | - | [24, 25] |
| **Commercial crop** | | | | | | | | | |
| 10. | Cotton | 1.85 | 0.11 | Data envelopment analysis (DEA) | 0.93 | 0.88 | - | 2.12 | [26-28] |
| **Sugar crops** | | | | | | | | | |
| 11. | Sugarcane | 5.6 | 1.15 | Cobb-Douglas | 0.99 | 0.99 | - | 1.75 | [29] |
| | | | | Artificial Neural Network (ANN) | 0.97 | 0.96 | 0.352 | - | [30] [5] |
| 12. | Sugar beet | 25.75 | 1.53 | Data envelopment analysis (DEA) | - | - | - | - | [31] |
| **Plantation crop** | | | | | | | | | |
| 13. | Arecanut | 1.4 | 0.1 | Data envelopment analysis (DEA) | - | - | - | - | [32] |
| **Vegetable crops** | | | | | | | | | |
| 14. | Potato | 1.71 | 0.47 | Cobb-Douglas | 0.94 | 0.90 | - | 2.18 | [33] |
| | | | | Linear programming | - | - | - | - | [74] |
| | | | | Data envelopment analysis (DEA) | - | - | - | - | [4] |
| 15. | Tomato | 1.53-1.78 | 0.45-0.74 | - | 0.84 | 0.72 | - | - | [35-37 |
| | | | | Data envelopment analysis (DEA) | - | - | - | - | [18] |
| 16. | Cucumber | 0.64 | 0.51 | Cobb-Douglas | - | - | - | - | [38] |
| 17. | Garlic | 0.66 | 0.41 | Cobb-Douglas | - | - | - | - | [39] |
| | | | | Ordinary least square (OLS) | - | - | - | - | |
| **Fruit crops** | | | | | | | | | |
| 18. | Apple | 1.16 | 0.49 | Cobb-Douglas | 0.97 | 0.96 | - | 2.11 | [3] |
| 19. | Orange | 0.99-1.25 | 0.52 | Cobb-Douglas | - | - | - | - | [40-42] |
| | | | | Data envelopment analysis (DEA) | - | | - | - | |
| 20. | Grapes | 2.99-5.10 | 0.25 | Cobb -Douglas | 0.95 | 0.91 | - | 2.03 | [43-45] |
| | | | | Data Envelopment Analysis (DEA) | 0.91 | 0.84 | - | - | |
| | | | | Artificial neural network (ANN) | - | - | - | - | |
| 21. | Kiwi | 1.16 | 0.61 | Cobb-Douglas | - | - | - | - | [46] |
| | | | | Artificial neural network (ANN) | 0.98 | 0.98 | 0.054 | - | |
| 22. | Watermelon | 1.29-2.0 | 0.68-1.15 | Cobb -Douglas | 0.92 | 0.86 | - | 1.89 | [47] [48] |
| 23. | Mandarin | 0.77-1.17 | 0.41 | - | - | - | - | - | [40] [41] |
| 24. | Lemon | 1.06 | 0.65 | - | - | - | - | - | [40] |
| 25. | Melon | 1.9 | 1.02 | - | - | - | - | - | [24] |
| 26. | Strawberry | 0.32 | 0.17 | Data envelopment analysis (DEA) | - | - | - | - | [49] [50] |

## 3. Genesis of models evolved

Complex mathematical problems were solved at high speed by the invention of computers at initially. Later many programs were developed for user interface including hardware and software. Further memory were introduced to store the data of the users and years later many models and algorithms were developed based on function activities of neurons in human brains after this evolution of models from mathematical to machine learning. At present machine learning evolved rapidly in decades and used for prediction in various fields of work. Models evolution from mathematical to machine learning is mentioned in table 2.

**Table 2:** Models evolved from mathematical to machine learning.

| Models evolved | Inventors | year | Remarks | Reference |
|---|---|---|---|---|
| Ordinary Least Square | Carl Friedrich Gauss | 1795 | Considered one of the earliest known general prediction methods. | [51] |
| Cobb-Douglas | Charles Cobb and Paul Douglas | 1928 | Mathematical model | [52] |
| Learning neural networks | Donald Hebb | 1940's | Based on activities of neurons in human brain | [53] |
| Machine learning | Arthur Samuel | 1952 | He coined the term and he developed an alpha-beta pruning which helps to find a scoring function. | [54] |
| Perceptron | Frank Rosenblatt | 1957 | Combined activities of Donald Hebb and Arthur Samuel created perceptron | [53] |
| ADALINE and MADALINE | Bernard Widrow and Marcian | 1959 | MADALINE was the first neural network developed and applied to a real world | [55] |
| Multilayer perceptron | Frank Rosenblatt | 1960's | This multilayer led to develop feed forward neural networks and back propagation. | [56] |
| Generalized Portrait Algorithm | Vapnik and Lerner | 1963 | - | [57] |
| Nearest neighbor algorithm | Marcello pelillo | 1967 | Which help to find the efficient way by using nearest neighbor rule | [58] |
| Back propagation | Seppo Linnainmaa | 1974 | It used to create and adjust hidden layers of neurons also errors are distributed backwards. | [59] |
| Data Envelopment Analysis | Charnes, Cooper and Rhodes | 1978 | It is a mathematical modelling. | [60] |
| Multilayered artificial neural network | Kunihiko Fukushima | 1979 | - | [53] |
| Artificial intelligence and machine learning | - | 1980's | Both gets separated | [61] |
| Boosting algorithms | Robert Schapire | 1990 | Recently used boosting algorithm is AdaBoost, BrownBoost, LPBoost, MadaBoost, TotalBoost, xgboost, and LogitBoost. | [62] |
| Support Vector Machine | Boser, Guyon and Vapnik. | 1992 | - | [63] |
| Convolutional Neural Networks | Yan LeCun | 1998 | - | [64] |

## 4. Different types of machine learning algorithm

**Supervised learning:** This algorithm is a part of machine learning. Here algorithms are trained with relevant input and output data. And predict desired outputs. (Learn with data)

**Unsupervised learning:** Here machine learning need of relevant input data to predict output without the need of human assistance. (Learn without data teaching)

**Semi-supervised learning:** It includes both supervised and unsupervised learning methods.

**Reinforcement learning:** Algorithm interacts with a dynamic environment, and it must perform a certain goal without assistance. Algorithm uses software to automatically optimize and evaluate on its own to improve its efficiency and lower its risk. (Learn by environment).

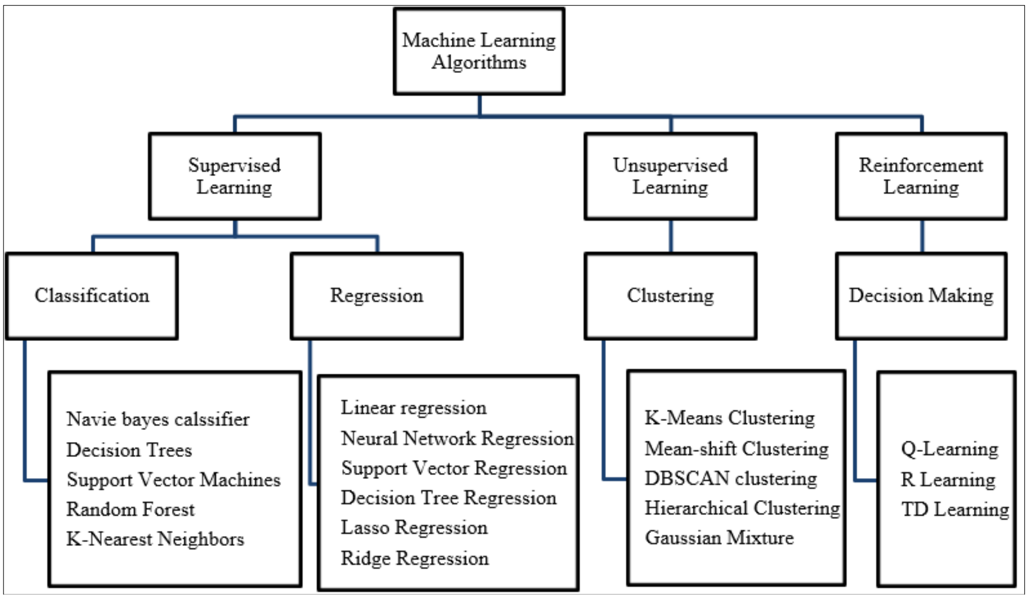


**Fig 1:** Machine Learning Algorithms category

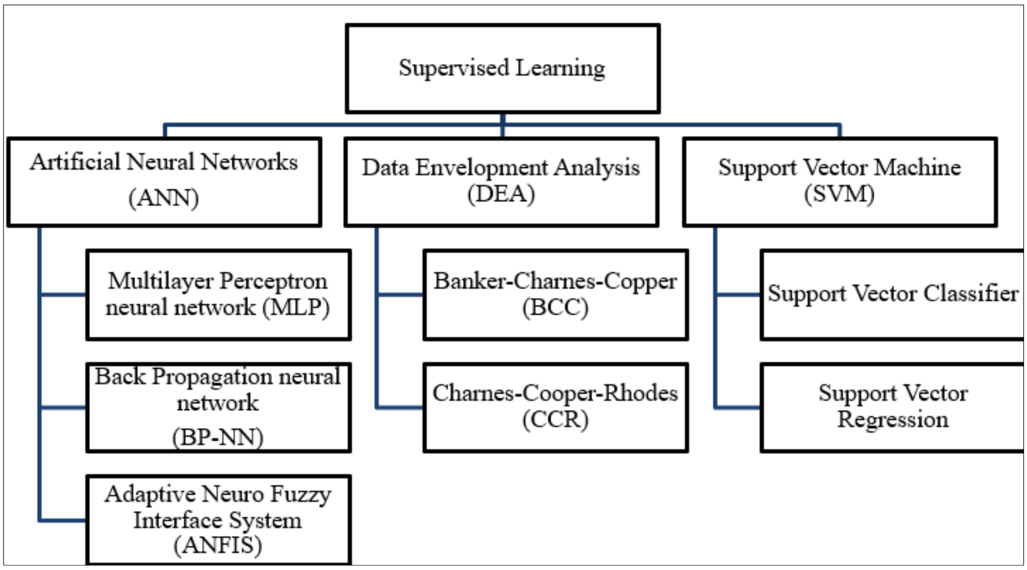


**Fig 2:** Supervised Learning models used for energy analysis

## 5. Models useful in energy auditing

The coefficient of determination ($R^2$) for various models was calculated to see whether the variable is correlated with each other. Various correlation functions like linear, exponential, log-linear, reciprocal, quadratic, Robb's parabolic, Nedlor's curve, and wood's curve were used to analysis the coefficient of determination ($R^2$) for various input energies with respect to yield. Among various correlations function Robb's parabolic gives higher correlation of coefficient ($R^2$) [65]. Value of Root Mean Square Error (RMSE) is useful in determining the errors of the data.

In energy use pattern analysis for various crops different models like Cobb-Douglas production function, Artificial Neural Network (ANN), Data Envelopment Analysis (DEA), Ordinary Least Square (OLS), Support Vector Machine (SVM), and Multiple Linear Regression (MLR) were used.

$$RMSE = \sqrt{1/n \sum_{i=1}^{n}(Y_{predicted} - Y_{actual})^2} \quad \ldots\ldots\ldots\ldots\ldots (1)$$

$$R^2 = \frac{\sum_{i=1}^{n}(Y_{predicted} - Y_{actual})^2}{\sum_{i=1}^{n}(Y_{predicted} - Y_{mean})^2} \quad \ldots\ldots\ldots\ldots \quad (2)$$

In, Cobb-Douglas modeling sensitive analysis is carried out by calculating Marginal Physical Product (MPP) i.e. one unit change in energy of inputs will determine the change in output energy. Where, $GM(Y)$is geometric mean of the yield, $GM(x_j)$ is the geometric mean of the j[th] Energy input. $\alpha_j$ Is regression coefficient of j[th] input [Singh *et al.*, 2004].

$$MPP_j = \frac{GM(Y)}{GM(x_j)}\alpha_j \quad \ldots\ldots\ldots\ldots\ldots \quad (3)$$

And Durbin Watson test is used to determine the autocorrelation between the variables. If the values lies between 1.5-2.5 it is said to be no autocorrelation between the variables. Both MPP and Durbin Watson is important factor in validating Cobb-Douglas model.

Here, ANN uses Multilayer Perceptron network (MLP) and hence ANN gives better prediction than Cobb-Douglas because its coefficient of determination ($R^2$) and root mean square error (RMSE) is 0.99 and 1.93 kg ha$^{-1}$ respectively which higher than Cobb-Douglas model. So, ANN prediction is more accurate [11].

In Data Envelopment Analysis (DEA) model it uses various efficiency to calculate the input-output energy. Efficiency like Technical efficiency (TE), Pure Technical Efficiency (PTE), Scale Efficiency (SE) is calculated. Where, TE and PTE is always lies between zero to one and TE should always lesser than PTE. This efficiency is used to determine whether Decision Making Unit (DMU) is efficient or inefficient. If DMU is equal to one it is efficient and DMU is less than one it is said to be inefficient.

DEA uses tool like benchmarking ranking method which helps in elucidating the efficient and inefficient DMU's. Mean and standard deviation for each efficiency like TE, PTE, SE is calculated and we can find the reasons of inefficiency in energy inputs with the help of DMU's [50].

ANN's have minimized training error where SVM's have minimized structural risk. ANN's solve high risk non-linear problem easier. ANN's will have lesser error and prediction is faster than SVM. Support Vector Machine (SVM) uses both classifier and regression. In classifier it used different types of kernel functions based on linear and non-linear. In non-linear Gaussian radial basis function, homogeneous polynomials are some kernel. SVM builds a hyper plane to separate the classifiers [66]. SVM which transfers lower dimensional inputs to a higher dimensional feature space in indirect way. ANN's uses a hidden layer which implies some weights to predict an accurate result.

Hence, Data is separated into training data and test data. And using training data we train the model for better prediction. But in training data set which model has higher $R^2$ and lower RMSE is said to be higher/accurate predicted model. Based on these values of performance the model is determined. ANN model which gives accurate result than any other models.

## 6. Models advantages and drawbacks

Models will have both positives and negatives but author should select the model based on our work and criteria. Memory consumption, hardware dependency, prediction performance, data handling, time durability, processing capabilities and simultaneous work capability these are some criteria which differ for models. Advantages and drawbacks of models mentioned in table 3 these are the model most frequently used in energy analysis.

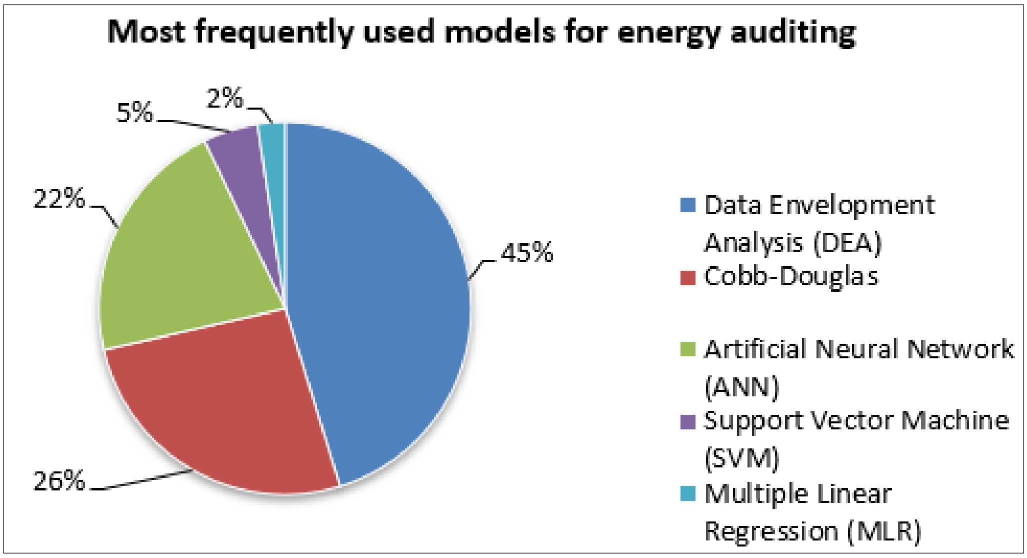


**Fig 3:** Most frequently used models for energy auditing.

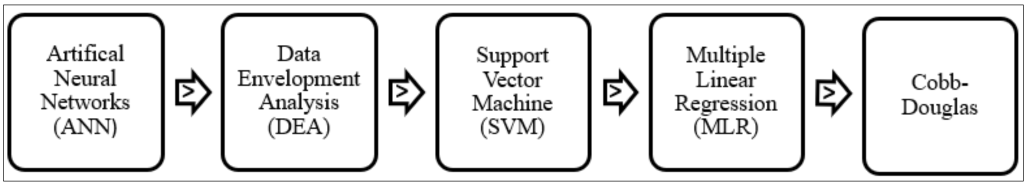


**Fig 4:** Most accurate predicted models in energy use patterns.

**Table 3:** Models advantages and drawbacks

| Models | Advantage | Drawbacks | Reference |
|---|---|---|---|
| Cobb-Douglas | It shows a relationship between the variables which is contributing to cost and its effort. | Parameters should be converted to linear form if in non-linear form. | [67] |
| | It use return scale like increasing, decreasing and constant to measure relation between predictor and predicted variables. | It couldn't able to find the collinearity on models of time series. | [68] |
| Artificial Neural Networks (ANN) | It able to work with even missing data if model is trained with training data. | It works under dependency of hardware and it is critical to interpret and understand the formation of network and its structures. | [69] |
| | It is able to store entire data in memory and can capable of parallel processing of given works. | It reduces errors after training data and results which it's generated are not optimum. | |
| Data Envelopment Analysis (DEA) | Analysis of input variable efficiency and output variable efficiency on same time. | Will neglect the exogenous variables. | [70] [71] |
| | Comparison of relative efficiency using decision making units (DMU) for each observation. | It won't show the way to improve the efficiency. | |
| | No need of cost of production as to include as variable. | It is tedious to test statistical methods as it ignores errors on it. | |
| Support Vector Machine (SVM) | SVM use efficient method to solve problem by convex optimization. | SVM processing is slow while running data and it is more | [72] |
| | SVM works well in higher dimensional datasets. | expensive. Support vectors increases in numbers sparsity decreases and classification delays. | |
| | During classification margin separation over categories is more accuracy. | The performance ability of the algorithm decreases timely when target variables have more noisy data or overlapped data. | |
| Multiple Linear Regression (MLR) | In MLR it's possible to incorporate predictor variable and can know its strength or contribution of predictor variable. | Future prediction of data is very poor. | [73] |
| | Easy to identify outliers present in data. | Covariance matrix is not always applicable in every situation. | |

## 7. Conclusion

Energy equivalents for various crops including total input and output energies was calculated. The results show that different amount of energy was consumed for different crops due to different field operations /management were followed [4]. Energy consumption will be higher in smaller size farm than larger size farm [46] Field operations/management at optimum level was sufficient. Required amount of input energy were enough to meet out the yield of crop. Addition input energy doesn't give higher amount of yield [9]. Crops like Pearl millet, Cucumber, Garlic, Strawberry shows net energy value as negative. Were due to higher amount of field operations/management as carried out consumption energy for crop production is higher [38]. Data Envelopment Analysis (DEA), Cobb-Douglas, and Artificial Neural Networks (ANN) models are the mostly used energy analysing modeling. In general $R^2$, RMSE, Durbin Watson test were used to evaluate the performance of the different models used for energy use analysis.

Hence, Cobb-Douglas production function used for calculating benefit cost ratio, whereas Data Envelopment Analysis (DEA) used for calculating carbon emission and life cycle assessment of crops including energy analysis. Based on our research topic application of models for energy use pattern may differ. Most used model was Data Envelopment Analysis (DEA) and most least used model was Multiple Linear Regression (MLR) in energy input-output analysis [4] And most accurate and faster forecasting model is Artificial Neural Networks (ANN's). Than econometric/mathematical models machine learning models gives better results in future prediction.

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