International Journal of Electrical and Electronics Research ISSN 2348-6988 (online)
Vol. 5, Issue 2, pp: (48-54), Month: April - June 2017, Available at: www.researchpublish.com

Energy Audit of Sugar Mill Using Neural Networks

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Abstract: **Energy audit is an important commercial tool to save energy and to improve financial state of an organization. Almost all the large scaled and many small scaled organizations like industries as well as non-industrial sectors are conducting energy audit to save energy and to minimize the electricity cost.. There is a good scope of energy conservation in various sectors, via domestic, industry and agriculture. In the proceeding sections energy audit is briefly discussed. The energy conservation is cost effective with a short payback period and modest investment**

Keywords: **Energy Efficiency, Audit, Figures, Tables, Results.**

I. INTRODUCTION

It has been observed that practically in today's world Sugar manufacturing plant's electricity consumption is increasing every year, due to prolonged use of the equipments in inefficient operating parameters and also due to increase in production. Sugar manufacturing process comes with a large design safety factor, which has to be optimized after process stabilization for optimum power consumption. The energy cost to production cost is around 15 to 20% and this comes second to raw material. So, in Sugar industry focus area is energy consumption at load end and optimizing the energy usage of Sugar manufacturing machines.

Sugar is a broad term applied to a large number of carbohydrates present in many plants and characterized by a more or less sweet taste. The primary sugar, glucose, is a product of photosynthesis and occurs in all green plants. In most plants, the sugars occur as a mixture that cannot readily be separated into the components. In the sap of some plants, the sugar mixtures are condensed into syrup. Juices of sugarcane and sugar beet are rich in pure sucrose, although beet sugar is generally much less sweet than cane sugar. These two sugar crops are the main sources of commercial sucrose.

The sugarcane is a thick, tall, perennial grass that flourishes in tropical or subtropical regions. Sugar synthesized in the leaves is used as a source of energy for growth or is sent to the stalks for storage. It is the sweet sap in the stalks that is the source of sugar as we know it. The reed accumulates sugar to about 15 percent of its weight. Sugarcane yields about 2,600,000 tons of sugar per year.

A. Types of energy audit:

The term energy audit is commonly used to describe a broad spectrum of energy studies ranging from a quick walk-through a facility to identify major areas of comprehensive analysis of the implications of alternative energy efficiency measures sufficient to satisfy the financial criteria of sophisticated investors. Numerous audit procedures have been developed for non residential (tertiary) buildings audit is to identify the most efficient and cost-effective Energy Conservation Opportunities (ECOs) or Measures (ECMs). Energy Conservation Opportunities (or Measures) can consist in more efficient use or of partial or global replacement of the existing installation.

II. INTRODUCTION TO NEURAL NETWORKS

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. . This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

III. DATA ANALYSIS AND RECOMMENDATIONS

There can be three types of parameters for the analysis done on Rewound Induction Motor to conserve energy these are explained as:

- Rated parameters
- Measured parameters
- Calculated parameters

A. Rated parameters: -

These are printed on the name plate and given in the manual by manufacturer.

B. Measured parameters:-

These are measured using different instruments under different conditions, like no-load, partial-load and full-load.

One or more of the following measurements may be involved:

- Speed measured by tachometer.
- Currents measured by clamp-on transducer.
- Voltages measurement.
- Input power measurement.
- Stator winding resistance reading.
- Winding temperature data.

C. Calculated parameters:

That are determined (or computed) from rated and measured parameters using standard formulae’s.

D. Standard formulas’ for calculated parameters synchronous speed:

It can be calculated as:

Synchronous Speed = 120f/p

Here f = supply frequency

P = No. of poles

Stator resistance:

It can be calculated as:

Stator resistance of N.L and F.L motor = $R_2/R_1 = (235+T_2)/(235+T_1)$

Here R_2 = unknown resistance at temp. T_2

R_1 = resistance at temp. T_1

F.L = Full Load

N.L = No Load

Stator Copper loss:

It can be calculated as:

Stator Cu. loss at N.L and F.L = I^2R

Here, I = N.L/F.L current

R= N.L/F.L resistance

Iron and friction and windage losses:

It can be calculated as:

Iron and friction and windage losses = P_{in} - stator Cu. loss at N.L

Here P_{in} = input power

Full load rotor losses:

It can be calculated as:

F.L rotor losses = I^2R

Here I = Current at Full Load

R = rotor resistance

Stray losses:

It can be calculated as:

Stray losses = 1.5% of F.L input power for 1-125 HP motor

1.3% of F.L input power for 126-500 HP motor

1.2% of F.L input power for 501-2499 HP motor

0.9% of F.L input power for 2500 and above HPM

Full load output power:

It can be calculated as:

F.L Output Power = P_{in} (F.L) - Stator Copper Loss at F.L - F&W Losses - Rotor Copper Loss - Stray Losses

Percentage loading:

It can be calculated as:

Percentage loading = (F.L. output power/rated power) × 100

Efficiency:

It can be calculated as:

Actual efficiency = (actual output power/actual input power) ×100

Rated efficiency = (rated output power/rated input power) ×100

Net saving:

It can be calculated as:

Net saving = benefits - (running cost + electrical expenses)

IV. ENERGY AUDITING BY PAYBACK PERIOD CALCULATIONS

This chapter aims to analyze the efficiencies of the in-house rewound induction motors in the Sugar manufacturing plant under study and to minimize (or conserve) energy usage by improving the efficiencies of these motors. The electrical energy audit process in rewound induction motors is evaluated in process stages. The choice of stages is due to the nature of the process and as well, the details of rewound induction motors in the Sugar manufacturing plant. As far as possible the same structure will be used for all the different rated motors to facilitate comparison between the rewound induction motor and new motor.

A. Methodology:

The methodologies adopted for conducting the detailed energy audit are:

- List of electrical motors of different horse power and operating parameters.
- Measurement of operating parameters of various equipments under different conditions, to estimate their operating efficiency.
- Analysis of data collected to develop specific energy saving proposals.

B. Problem formulation:

In this study the subject of investigation (or say under study) is a major Sugar manufacturing plant Naraingarh Sugar industry This plant includes a 22KV substation and 1 MW diesel plant. The installed capacity is 16,425Tons Per Annum (TPA).

- In the method, energy auditing is done by calculating the rated and actual efficiency, total capital cost and net savings of different rewound motors. With the help of these parameters, the payback period can be calculated and on the basis of payback period calculations, energy auditing can be done.

Neural network will be used for data validation of calculated parameters of Sugar mill. Once a neural network has been trained it must be evaluated to see if it is ready for actual use. This final step is important so that it can be determined if additional training is required. To correctly validate a neural network, validation data must be set aside that is completely separate from the training data. In my work rewound motors parameters are data to be validated and rest motors parameters are training data.

C. Analysis on rewound motor:

With the help of tables different parameter of rewound motor are explained, it is compared with new motor. Following results are found.

Table 4.1 Rated Parameters of 20 HP Rewound Motors

MOTOR IDENTITY	MOTOR MODEL	MOTOR TYPE	NO. OF PHASES	NO. OF POLES	RATED POWER (W)	RATED POWER (HP)	RATED VOLTAGE (V)	RATED CURRENT (A)	F.L. RATED SPEED (RPM)	SUPPLY FREQ. (Hz)	RATED O/P POWER (W)
New	New	20hp	3	4	15000	20	415	27	1460	50	13800
R.M.1	Old		3	4	15000	20	415	27	1460	50	13800
R.M.2			3	4	15000	20	415	27	1460	50	13800
R.M.3			3	4	15000	20	415	27	1460	50	13800

Table 4.2(A) Measured Parameters of 20 HP Rewound Motors

MOTOR IDENTITY	N.L. VOLT(V)	N.L. CURRENT (A)	N.L.I/P POWER (W)	N.L.SPEED (RPM)	TEMP.OF STILL MOTOR(°C)	RESIS.OF R.M
New	415	11	615	1490	20	0.25
R.M.1	410	10	660	1490	24	1.2
R.M.2	410	10	660	1490	23.5	0.91
R.M.3	410	10.5	680	1490	30	0.77

Table 4.2(B) Measured Parameters of 20 HP Rewound Motors

MOTOR IDENTITY	TEMP.OF N.L MOTOR(°C)	TEMP.OF LOADED MOTOR(°C)	F.L.VOLT(V)	F.L.CURRENT (A)	F.L. I/P POWER (W)	F.L. SPEED (RPM)	ROTOR RESISTANCE
New	39	137	410	30	17000	1475	0.298
R.M.1	41	141	410	31	17300	1475	0.262
R.M.2	40	131	410	34.5	17200	1475	0.211
R.M.3	47	150	415	33	18000	1475	0.248

Table 4.2(C) Measured Parameters of 20 HP Rewound Motors

MOTOR IDENTITY	Capital Cost (Rs.)	Installation Cost (Rs.)	Running Cost (Rs.)	Running Time (Hrs.)	Electrical Expenses (Rs.)	Benefit (Rs.)
New	50040	5000	180	20	1679.6	36372.1
R.M.1	10600	5000	185	20	1709.24	28202.57
R.M.2	10100	5000	180	20	1699.36	27346.03
R.M.3	9700	5000	190	20	1778.4	14376.73

Table 4.3(a) Calculated Parameters of 20 HP Rewound Motors

Motor identity	Sync Speed (RPM)	Stator Resistance at no load (Ω)	Stator cu Loss (W)	F& W Loss (W)	F.L. rotor loss (W)	Stray Loss (W)	F.L o/p Power (W)
New	1080	0.7366	0.1128	614.8872	268.2	255	1.59E+04
R.M.1	1080	0.734	0.4766	659.5234	251.782	259.5	1.61E+04
R.M.2	1080	0.7514	0.3623	659.6377	251.1427	258	1.60E+04
R.M.3	1080	0.7325	0.3143	679.6857	270.072	270	1.68E+04

Table 4.3 (b) Calculated Parameters of 20 HP Rewound Motors

MOTOR IDENTITY	% Loading	Actual Efficiency	Rated Efficiency (%)	Total Capital Cost (Rs.)	Net Saving (Rs.)	Payback Period (yr.)
New	114.9406	93.3047	92	55040	3.4513e+04	1.5948
R.M.1	116.8748	93.2296	92	15600	2.6308e+04	0.5930
R.M.2	116.1656	93.2027	92	15100	2.5467e+04	0.5929
R.M.3	121.5937	93.2218	92	14700	1.2408e+04	1.1847

V. RESULTS & DISCUSSION

The above explained work is carried out using MATLAB as a tool. A graphical user interface is developed which facilitated the selection and analysis of all types of motors used in Sugar mill. A backward propagation neural network approach is used for training the calculated parameters of new rewound motor with other motors. Parameters of new motors are our desired parameters.

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Neural networks can also be trained to solve problems that are difficult for conventional computers or human beings. The toolbox emphasizes the use of neural network paradigms that build up to--or are themselves used in--engineering, financial, and other practical applications.

Backpropagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

Standard backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods. The Neural Network Toolbox™ software implements a number of these variations. This chapter explains how to use each of these routines and discusses the advantages and disadvantages of each.

Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs. There are two features of Neural Network Toolbox software that are designed to improve network generalization: regularization and early stopping.

In our dissertation no of epochs and learning rate is set to 700 and 0.3 for neural network training. A gui figure for 15 hp motor is shown in figure 5.1.

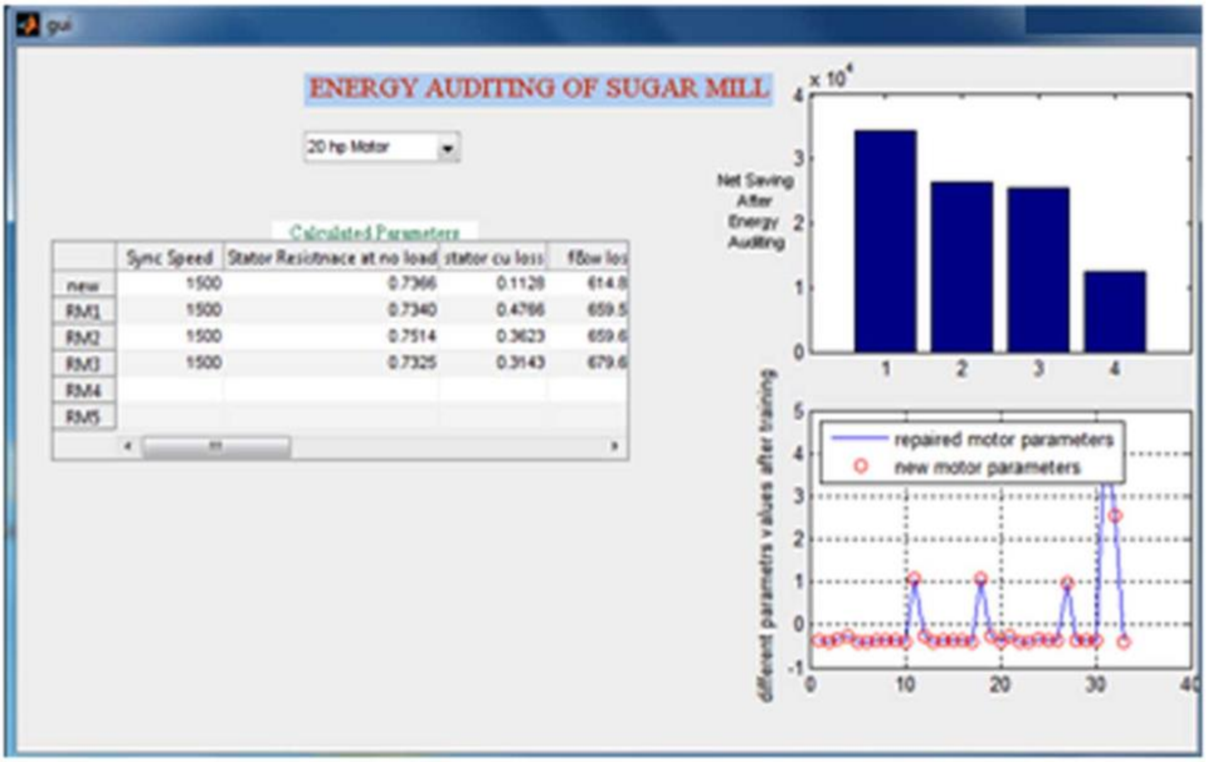

Figure 5.1: GUI for 20 hp motor

VI. CONCLUSION

Electrical energy is the most flexible type of energy since it can be converted to any form and can be transferred with equal ease. With every passing year the demand of electrical energy rises much higher than its supply and therefore the only way to plug this gap is to identify the place where it can be conserved. The preliminary study of Sugar plant has explored the possible energy saving areas such as induction motor, power factor improvement and optimized parallel loading of transformer. Analysis of some has been done to save energy. It has been seen in this study that a huge chunk of energy can be saved by replacing in- house rewound induction motor by new motor. After doing a thorough analysis on the rewound induction motor for its efficiency, it is found that rewound motor, if replaced by new ones, have a payback period in the range of 2 years to as less as 6 months. It is therefore recommended that the rewound motor should be analyzed for its efficiency and if the efficiency has found inadequate, these could be replaced by the new motors. In second method, energy auditing also has been done after power factor improvement by installing capacitor bank to the different motors for energy saving purpose. After doing this analysis, it is found that the total capital cost and benefits increased but the payback period is decreased as compared to first analysis. It is also noticed that the efficiency improves.

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