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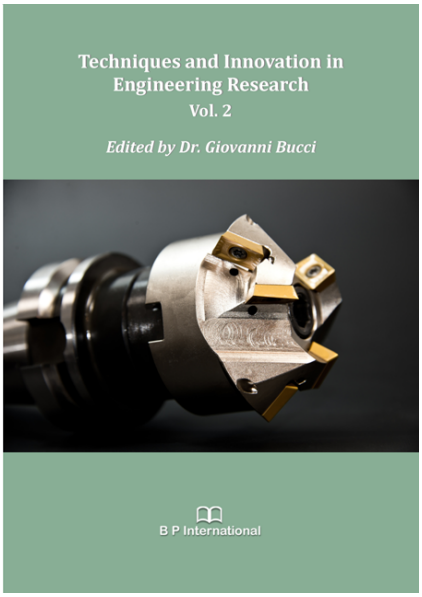

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Industrial Automation of Gas Tunnel Kiln Using Relay Logics, PLC and VFD's

K. Mahesh ; S. Inbasakaran ; J. Lithesh ; S. Praveen

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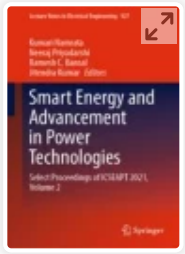
Abstract

Automation is one of the most pressing issues in any sector today. Automation is affecting almost every aspect of life, from agriculture to space technology. Plant automation is a must-have for the manufacturing business in today's internationally competitive market. It refers to the system's ability to function without human involvement at all times. We are designing a control circuit for the automation of the Gas Tunnel Kiln (GTK) using relay logics and Variable Frequency Drives (VFD's) in this paper because the current doors and movement of the transfer car in and out of the kiln are being operated manually and the temperature of the kiln is very high, making manual operation unsafe. The GTK has a vestibule on the front and the rear side. The charging and discharging of the green Insulators is being automated as a whole. The first stage is to create ladder diagrams that can be realised with hardware components and then simulate them using LADSIM - PLC Simulator.

Keywords: Automation; gas tunnel kiln; relay logics; PLC; VFD’s



Smart Energy and Advancement in Power Technologies pp 421–435

Simulation of Modular Fly-Back Current-Fed Push–Pull DC-DC Converter for High Voltage Low Current Applications

D. Beula ✉, M. S. Indira & N. Balaji

Conference paper | First Online: 22 October 2022

Part of the Lecture Notes in Electrical Engineering book series (LNEE,volume 927)

Abstract

A DC-DC converter has been proposed using Fly-back Current-fed Push–Pull topology with multiple secondary windings for high voltage low current applications. The converter is modular at the output which gives the flexibility to cater to specific output voltage levels. The High Voltage Transformer (HVT)

with multiple secondary windings and rectifier with voltage doublers result in a smaller turns ratio for higher voltage conversion. The rectifier components on the high voltage side are subjected to lower voltages that reduce the voltage stress on the rectifier component, compared to HVT with the single secondary winding. The converter is operated in complete energy transfer mode (Discontinuous conduction mode) for effective utilization of stored energy in the fly-back inductor as it is fed-back to the source. The discontinuous current-fed scheme provides an instantaneous current limiting facility for short circuits at the load side. Zero current turn-on of switches due to the discontinuous mode of operation reduces switching losses and the non-overlapping mode of power switches minimizes conduction loss. The operation of the converter is analyzed under steady-state conditions. A design procedure is established and the converter is designed for a typical load of 5 kV, 500 W at a switching frequency of 20 kHz. The performance of the converter is verified by simulation.

Keywords

Current-fed **DC-DC converter** **Modular**

Energy feedback **High voltage application**

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Author information

Authors and Affiliations

Department of Electrical and Electronics Engineering, Sir M Visvesvaraya Institute of Technology, Bangalore, Karnataka, India

D. Beula

M.S. Ramaiah University of Applied Sciences, Bangalore, Karnataka, India

M. S. Indira

Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India

N. Balaji

Corresponding author

Correspondence to D. Beula .

Editor information

Editors and Affiliations

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

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Ramesh C. Bansal

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

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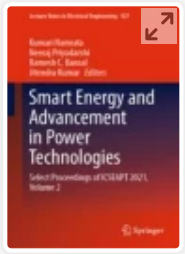

Smart Energy and Advancement in Power Technologies pp 331–341

Identification and Validation of Prominent Features for Predicting Mortality in Heart Patients with Left Ventricular Dysfunction Using Machine Learning

R. Subha ✉, Rekha Radhakrishnan, P. Sumalatha & B. R. Nayana

Conference paper | First Online: 22 October 2022

439 Accesses

Part of the Lecture Notes in Electrical Engineering book series (LNEE,volume 927)

Abstract

Machine Learning (ML) is a strong tool for medical prognosis, and it has the potential to give this branch of medicine a huge boost by allowing doctors to make accurate predictions about a patient's future

health using various forms of medical data. ML algorithms have proven to be reliable and effective in decision making with good classification accuracy. They can model nonlinear relationships, which are frequent in medical data, and apply them to predictive tasks such as forecasting a future event. In this paper, an attempt has been made to predict the mortality of heart patients with left ventricular dysfunction. Feature selection methods have been used to rank the input features in the dataset and identify four prominent features. Different combinations of these prominent features have been applied to five ML algorithms namely, Decision Tree, Gradient Boost, Random Forest, Support Vector Machine and k Nearest Neighbors to find the best performing combinations using F1-Score and AUC ROC. Considering additional performance parameters, further analysis is carried out to identify the best feature combination and the most effective ML algorithm for predicting mortality and the results are provided for the same.

Keywords

Cardiovascular disorder **Classification**

Decision trees **Machine learning**

Medical prognosis

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Author information

Authors and Affiliations

Department of Electrical and Electronics Engineering, M S Ramaiah Institute of Technology, Bangalore, India

R. Subha

Department of Electrical and Electronics Engineering, Sir M Visvesvaraya Institute of Technology, Bangalore, Karnataka, India

Rekha Radhakrishnan, P. Sumalatha & B. R. Nayana

Corresponding author

Correspondence to R. Subha .

Editor information

Editors and Affiliations

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

Kumari Namrata

Department of Energy Technology, Aalborg University, Esbjerg, Denmark

Neeraj Priyadarshi

Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates

Ramesh C. Bansal

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

Jitendra Kumar

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Review of State of Health Monitoring Techniques inBattery Management System

R Sivapriyan, Sushmitha S V, C V Mohan, S Lavanraj
Department of EEE, Sir MVIT, Karnataka, India. sivapriyan@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. sushmithasv390@gmail.com Department of EEE, Sir MVIT, Karnataka, India. eeecvm@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. lavanraj.s@gmai.com

Abstract.

As in recent trends, the Electric Vehicles are tremendously growing and major research works are found in Battery Management System. This paper comprehensively analysis about the State Of Health (SOH) and its methodologies in applications of Battery Management System (BMS). Various algorithms along with the flowchart have been briefly discussed. The comparative analyses along with the various methodologies are included in the table for reference. The SOH monitoring and controlling applications in lithium-ion batteries and fuel cells are considered and discussed as regarding main topics. The model-based methods along with the real time applications with input and output features has briefed in general with a comparison. The algorithms with real time application in Machine Learning and AI techniques has given a highlight and its applications in real time examples are briefed. Thus, this paper briefs about BMS and discharge methods of the battery of the SOH techniques and highlights upon various algorithms which is used as model-based methods in Battery management system as well as SOH techniques.

Keywords. Battery Management System, State of Health, Experimental Method Analysis, Machine Learning, Model Based Methods.

1. INTRODUCTION

Nowadays, Electric vehicles are a trending technology in various applications, and one of its applications is used in Battery Management Systems (BMS). BMS monitors and protects the battery by considering its safe operation area such as Overvoltage/under voltage, Overpressure, over temperature/under temperature [1]. Also, to prevent the current leakage where battery cell is charged by an intelligent battery pack and makes use of rechargeable battery which has to be managed in an electronic or power storage system by considering available data for calculating and monitoring it in the environment and is efficiently used in the EV applications [2]. BMS consists of many cells stacked together within a smart battery pack to release the cell's energy to meet the load demand. Stability plays a significant role in the whole Battery Management System, where users can monitor each cell individually by authenticating and reporting the data [3]. There are many IC's available in BMS. It includes some functional blocks to keep track of all voltage balance,

monitor temperature and the energy recovery in electric vehicle systems, and sometimes the state of the battery can also be monitored by considering the state of the machine for simplicity purposes as shown in Fig.1.1. By considering standard parameters like SOC (State Of Charge) [4][5], SOH (state of health) [6], SOP (state of power), and SOS (state of safety), BMS computation can be determined [7].

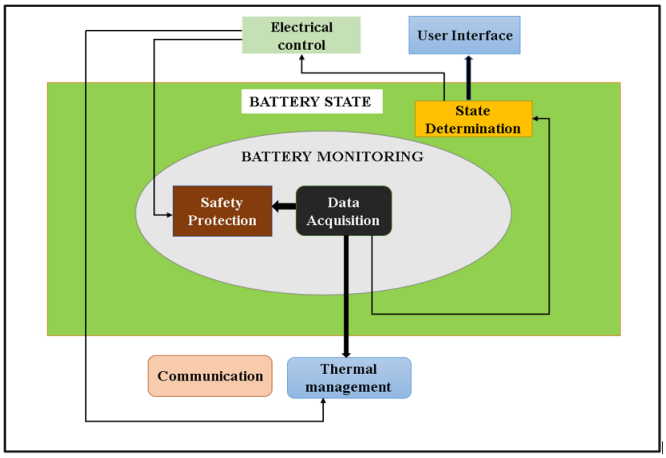

Figure 1.1 Battery Management System[8]

It can track the total number of cycles and energy consumed per kWh for the total operating time [9]. BMS also uses wireless kWh for the total operating time [9]. BMS also uses wireless communications for communicating with the hardware when it comes to internal purposes at the basic level of the cell.

When it comes to the external purpose, the hardware level will be high, making use of PCs, laptops, etc. For internal communication, BMS restricts with bulk number of cells [9]. When it comes to modular architecture with an increasing number of nodes, hardware combination cannot be used as it is limited, and cost plays a major role as cell price comes into existence which is comparable.

The protection of BMS is also important, so we can include a relay that acts as a protective switch by detecting faults when the battery's SOA crosses its limit. The balancing part of the BMS is handled by the balancers where energy is shuffled and also by passive regulators by connecting charged cells of an increasing number to the load side, and the major task is to maintain voltage at the same level for cells where the battery is composed, to prevent overcharging thus the battery's capacity can be maximized. Thus, BMS (Battery management system) plays a major role in electric and hybrid vehicles such as electric cars and lithium-ion batteries [10].

In electric train traction batteries, BMS is used to manage the high power and large battery packs. Some BMS applications are also found in Garbage compressors, Industrial machines, Hoists, Cranes, Robots, Forklifts, etc.

2. STATE OF HEALTH

SOH stands for the State of Health, and it is a battery condition to estimate the charge in smart battery packs by considering some of the Safe Operating Area (SOA) and aging limitations at the same time for monitoring the battery conditions for electric vehicle applications [11] as shown in Figure 2.1.

By considering ideal parameters, when manufacturing SOH's battery condition is 100 percent and due to some aging process, the battery's performance will decrease [12]. It is calculated by considering the ratio of capacitance, impedance to its initial rating.

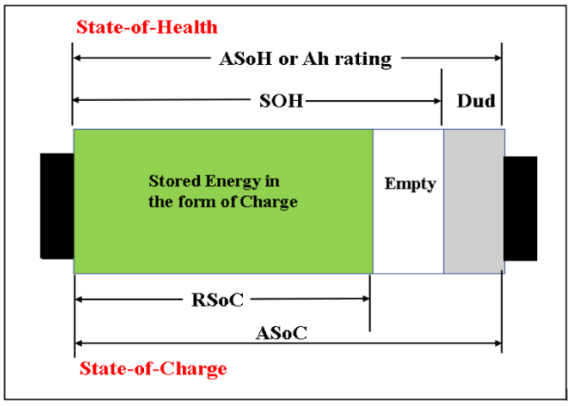

Figure 2.1 State of Health[13]

Nowadays, Lithium-ion batteries are used in SOH's battery for reliability purposes. A detailed analysis has been carried out to check for safety measures in power storage or energy storage requirements.

Currently, the study has been carried out in self-discharge rate, Number of operating cycles, power capability to ensure battery monitoring system by considering internal impedance, resistance, and capacitance aspects.

Some of the health features (HFs) for SOH battery estimation are the physical parameters to characterize the battery capacity, Electrochemical models with some degradation mechanisms.

The factors affecting the behaviour of the battery in SOH's batteries are dealt with by some of the algorithms and Artificial Neural Networks (ANNs) techniques by considering the capacity loss in the cycling behaviour of the power periodically [14]. The response of the voltage will be varied by considering the rate of current at different SOH parameters.

The battery parameters like SOC and SOH are the approaches used in various battery system methods such as Kalman Filter, Enhanced Coulomb Counting, and voltage methods in applications of Electric and Hybrid vehicles, HVDC, and photovoltaic applications systems [15].

3. SOH TECHNIQUES

As the Electric Vehicle Technology is tremendously growing in past few years, the Battery Management System (BMS) acts as a central coordinating system or main control system so as to provide reliability, efficiency, stability and safe use of battery by considering some standard parameters like State of Charge (SOC), State of Health (SOH), State of Power (SOP)[16][17].

SOC is used to collect the energy being consumed by battery and storage specifications of the battery. SOP is used for determining the power required for the battery and the flowchart of SOH Monitoring is shown in Figure 3.1.

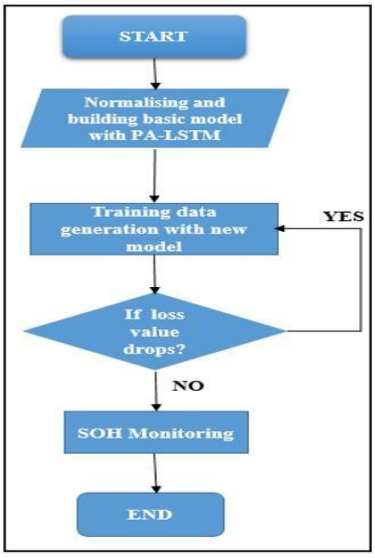

Figure 3.1. Flow Chart of SOH Monitoring[18]

SOH is a battery condition to estimate the charge and to detect degradation level of the battery in real-time automotive applications.

The Battery performance can be analyzed by SOH in HEV and AI applications [19] and discusses about the distribution of energy and how to improve their self-discharge rate, consumption of energy during their lifetime. So, some of the standard methods/techniques are used for SOH's battery estimation by considering internal resistance of the battery, battery's impedance, state of machine, state of discharge [20] and its capacity [21].

The SOH Battery estimation methods can be divided into 3 methods which include Experimental methods, Model-Based methods and Machine Learning methods. From the standard methods, machine learning technology can be implemented and it includes some of the techniques such as Support Vector Regression, Neural Network, Fuzzy logic and other standard algorithms.

In Experimental methods, some techniques include Impedance measurement, ICA/DVA, Internal resistance measurement, Capacity level etc. and these methods are usually conducted in laboratories.

Some Model Based methods include Adaptive filtering such as Kalman Filters, EKF, UKF, RLS, MAFFRLS, Electrochemical models and Enhanced Coulomb counting methods etc. SOH's battery uses PA-LSTM algorithm for monitoring accuracy of battery and also by updating the learning mechanism where data obtained from the experimental results are close to real time data model dynamically and can further be used in approach of Lithium-ion batteries.

4. VARIOUS METHODS OF SOH TECHNIQUES

In SOH Battery estimation, there are 3 types of methods namely Experimental technique, Machine learning methods and Model Based methods as shown in Figure 4.1.

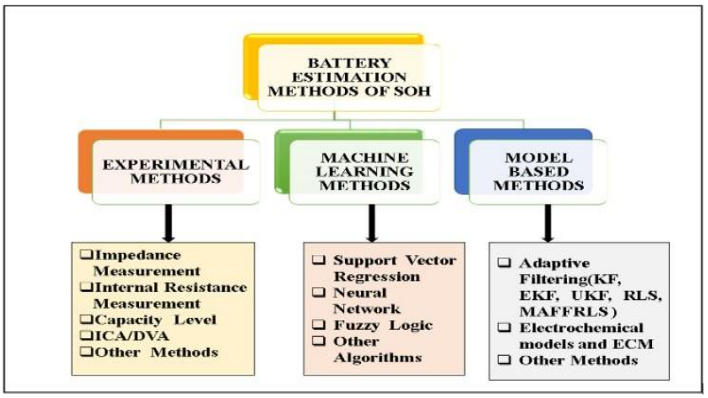

Figure 4.1 Battery SOH Estimation Methods[22]

5. EXPERIMENTAL METHOD ANALYSIS OF BATTERY SOH ESTIMATION

Usually, these Experimental methods are often time consuming and preferable equipment's have to be used in specific to meet the criteria or requirements, so these methods are usually performed in laboratories. The aging behaviour of the battery can be determined using these methods by collecting raw data measurements and understanding the behaviour of these collected data. Some of the techniques used in Experimental methods are discussed below:

• Impedance Measurement of the Battery:

The major technique which is used frequently to measure the impedance of the battery is Electrochemical Impedance Spectroscopy (EIS) which dealt with energy storage and conversion and it acts as a SOH indicator of battery. This technique is conducted as a function of frequency as a sinusoidal AC current is applied and output voltage response is calculated. Meanwhile, it is a non-destructive method and it is found that impedance of the battery is directly proportional to the aging phenomena.

The EIS method discusses about the super capacitor, cycling effect and energy storage in real-time applications of EV and major advantage is the accuracy which can be calculated efficiently in the aging phenomenon of the battery [23].

• Internal Resistance Measurement of the Battery:

In this technique, by applying AC sinusoidal current the voltage drops and current pulse is the most frequently used method to deter- mine the Internal Resistance which is based on the principle of Ohm's Law and acts as a SOH indicator.

By considering the parameters like aging and degradation whose impact decreases the resistance values with SOH battery conditions. With the help of Joule's law, loss of energy in Battery is evaluated by considering the impacting parameters. The main advantage of this method is the accuracy in domains of evaluating battery's internal resistance in different environmental working conditions and widely used in laboratories but is often a time-consuming process.

• Capacity Level:

In this technique, battery charging capacity is evaluated and energy stored in a battery is evaluated by a capacitor and it is inversely proportional to the aging phenomenon of the battery [24]. Here, time is the major factor to decide number of charging/discharging cycles based on the output voltage under different working conditions of the temperature for different levels of degradation by experimentally evaluating the capacity fading level in Lithium-ion battery applications [25].

• ICA/DVA and Other Methods:

ICA and DVA stands for Incremental Capacity Analysis and Differential Voltage Analysis respectively. These methods have to be done experimentally by testing battery SOH which is time consuming and these parameters vary with aging of the battery. By using some of the destructive methods such as X-ray Diffraction, state of the battery and machine can be determined from inside and estimation can be changed feasibly with modification of specific working conditions [26].

6. MACHINE LEARNING METHOD ANALYSIS

This method is basically a combination of both standard methods which include Experimental and Model Based methods. To estimate battery SOH some data has to be gathered using machine learning algorithms in process of learning to setup the standard algorithms [27].

• Support Vector Regression (SVR):

In this technique, training data is to be evaluated which requires a controller of high performance to manage the energy and taking into consideration real time data and experimentally to determine the online SOH indicator using Electrochemical Impedance Spectroscopy (EIS) technique. This SVR algorithm is also used to estimate RUL (Remaining Useful Life) of the battery and its applications in Fuel cells, e-Bikes, Hybrid Electric vehicles etc.

• Fuzzy Logic:

This technique is used for nonlinear systems and is the most commonly used machine learning method along with EIS technique to evaluate the training data to be accurate

which often uses Gaussian Algorithm process [28] to estimate the battery SOH in Lithium-ion batteries along with WLTC profiles [29].

• Neural Networks:

It is the most frequently used machine learning algorithm and it takes less data for computational analysis combining with EIS measurements and results are found to be more accurate with ample amount of data received than the Fuzzy Logic.

The main disadvantage of this method is difficulties faced in complex as well as nonlinear systems and also it requires a controller of high performance.

• Other Methods:

Some algorithms such as Gaussian algorithm makes use of training data to track accuracy of SOH battery in Lead Acid Batteries as well as Lithium-ion batteries.

Back Propagation Neural Network (BPNN) is the algorithm to trace the battery parameters like Internal Impedance, Resistance and to track the energy level and tolerance was found to be less.

Particle-filter based algorithm is used extensively for different vehicle applications and its accuracy on estimation of battery SOH and requirement of training data is found to be less for computational purpose in machine learning process.

RLS (Recursive Least Square) algorithm and LSTM-NN (Long Short-Term Memory Neural Network) are also used which are trending research topics and has to be tested experimentally for better accuracy of the SOH battery indicator.

7. MODEL BASED SOH BATTERY ESTIMATION ANALYSIS

In the research for evaluating the Battery SOH and real time feasibility, model-based methods have come into existence with filtering and standard indicators to determine battery capacity, impedance, energy level [30] etc. Some of the techniques are:

• Kalman Filters:

In order to evaluate the SOH battery parameters, an adaptive filtering algorithm is used in real time to consider the ECM (Equivalent Circuit Models). The advantage of these filters are some nonlinear systems as well as complex system battery state and parameters can be evaluated using Kalman Filters (KF), Extended Kalman Filters (EKF), Unscented Kalman Filter (UKF), Dual Kalman Filters etc.

• Electrochemical methods:

Differential equations of nonlinear systems as well as complex systems can be evaluated accurately and these models are found to be complex in tracing the battery's parameters and behaviour. It uses recursive parameter [31] for identification purpose and to predict online SOH indicator and capacity effects in SOC battery. For accurate results the battery behaviour can be predicted using ECM techniques where they have less complexity equations.

The main drawback of this method is the difficulty level of the equations and complexity of the algorithm to trace behaviour of SOH battery parameters like internal resistance and diffusion time of the battery.

• Other Methods:

Observers are also used in Model Based SOH estimation methods due to its robustness against error margin and diffusion time parameter for variations in temperature [32]. Least Square Based Filters is widely used one of the algorithms for testing the battery states in the OCV (Open Circuit Voltage) along with RLS algorithm for testing the high performance of a battery model.

MAFFRLS (Multi Adaptive Forgetting Factors RLS) is also used along with PSO (Particle Swam Optimization) algorithms for better efficiency and accurate results in temperature and time variations of dataset in Battery models.

8. COMPARATIVE ANALYSIS

In Support Vector Regression (SVR) method, the quality and quantity are entirely based upon the data used in the training and uses a controller when there is a need of high performance to control the training data. Compared to the other methods, the results obtained in the SVR is of accurate and applicable for any systems. The main advantage of SVR is as the system results obtained are of accurate and hence the system is stable and efficient. It can also be used to solve the regression problems. The main disadvantage of using SVR algorithm is that it is difficult for humans to understand the code and it takes long training time. In Feed Forward Neural Network (FNN) Algorithm, mathematical relationships are used for the algorithm with some input features to dynamics of battery such that SOH Estimation can be done in an accurate manner and rule used in FNN is of back propagation learning. The equations used in FNN are of mapping function where some function can be almost approximated to other functions. The main advantages of using FNN are the computation required to analyze the mathematical relations is less, so this type of algorithm is beneficial.

As large equations are being used, overfitting problem exists as to store the data of large number of parameters. In Recurrent Neural Network (RNN) Algorithm, the main input to be considered are current, temperature, voltage and output used to determine the application of SOH in functions of temperature in BMS applications [33]. The main advantage of using RNN Algorithm is information can also be easily stored in functions of time which is easy task and memory requirement is less. The pixel quality is effective and time series can be easily predicted. The disadvantage of this RNN algorithm is to train the RNN task and sometimes long sequences such as tanh function cannot be processed easily and gradient problems usually occur for this type of algorithm. In case of Particle Swarm Optimization (PSO) Algorithm the principle is based on the latest technology and its applications are still being in research for Electric Vehicles and Plug-in hybrid Electric vehicles. It makes use of Swarm Intelligence where parameters control can be done using simple concept and efficiency of computation compared to other algorithms is found to be extremely good and effective. This PSO algorithm can be easily implemented for different and various systems so that the over fitting problem can be overcome by this algorithm.

The main disadvantage of this algorithm is that it provides solution of some techniques which is of low quality and each time when the program is updated, memory updating has to be done which is time consuming and tedious process or task.

Table 1 COMPARISON OF EXPERIMENTAL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Internal Resistance measurements [34]	• Simple to implement and direct method to under-stand. • Less complexity and high level of accuracy.	• Estimation through online cannot be made. • Time consuming and tedious task.
Internal Impedance Measurements	• High accuracy and simplicity. • Reliable and degradation of the battery methods can be easily understood.	• Battery degradation and discharges is difficult to analyze.
ICA/DVA and Capacity Level [35]	• This technique is much faster than other methods. • It is fast to analyze and provides high level of accuracy.	• Sometimes this method is not reliable and feasible. • Operating conditions of the battery is difficult to analyze when fully charged.

Table 2 COMPARISON OF MODEL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Kalman FilterBased (KF) methods	• Simple to understand and accurate to interpret theoutput • It is bounded to errors	• For advanced systems and versions system is complex. • A controller of high performance is required and not valid for nonlinear systems [39].
Electrochemical models	• High accuracy and reliable • The battery degradation phenomenon can be understood and predicted easily.	• The computational level of high-performance con- troller is required [40]. • Structure of the battery is difficult to analyze.
Least Square Based methods	• This Technique is much precise and robust than other techniques. • The structure is easy to analyze.	• The model is mostly concentrated on accuracy and high-level performance controller is required [41].

Table 3 COMPARISON OF MACHINE LEARNING BASED METHODS [36].

Parameters	**Support Vector Regression Algorithm**	**Feed Forward Neural Network Algorithm**	**Recurrent neural network (RNN) Algorithm**	**Particle Swarm Optimization (PSO) Algorithm [37]**
INPUT	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), T(t), SOC(t), R/C(t)	I(t), V(t), T(t)
OUTPUT	SOH(t)	SOH(t)	SOH(t)	SOH(t)
FUNCTION	Regression and Classification Hyperplane Equation	Supervised Learning, Sigmoid function, Mapping of function to approximate value	Non-Linear, Auto-Regressive Network, Time Series Based Function	Swarm Intelligence, Randomized, Population Based Optimization Method
EQUATION	y=wx+b(Hyperplane) Condition: $-a > y-wx+b < a$	f(x)=yf(x) for all (x,y)	Current state equation: $h_t=f(h_{t-1}, x_t)$ Output equation: $y_t=W_{hy}h_t$ Activation Function: $h_t=\tanh(W_{hh}h_{t-1}+W_{xh}x_t)$	$x_i^{k+1}= x_i^{k}+ v_i^{k+1}$
ADVANTAGES	• Overfitting can be prevented as it has good regularization capabilities. • Using Kernel function, it handles non-linear data efficiently • Stable and Efficient. • Can be used to solve both classification and regression.	• Easy to setup. • Less computation. • Complex and Non- linear systems can be analyzed.	• Easy information is stored accordingly with time. • It is good for effective pixel extension. • Helps in prediction of time series.	• Simple concept. • Easy implementation. • Robustness to control parameters • High computational Efficiency.

LIMITATIONS	• The difficult task is to choose an appropriate Kernel function. • For large datasets, it takes long training time [38]. • It is difficult to understand the algorithm or models of SVR for humans.	• There exists Vanishing and Exploding Gradient problem. • Large model size. • There exists Overfitting of large number of parameters.	• Gradient Vanishing and problems are exploding. • It is difficult to train an RNN task. • As tanh function is used for activation function, it cannot process long sequences.	• Low convergence rate in iterative process. • Memory updating required and falls under local search. • Low quality solution.

Table 4 COMPARISON OF SOH ESTIMATION METHODS.

Methods	Advantages	Disadvantages
Experimental Based methods	• Simple to understand and accuracy is more. • Computational level is low	• Time consuming. • The measurements and the equipment to be used should be specific [42].
Machine Learning methods	• High accuracy and reliable compared to other two methods. • Easy to implement and process can be carried out easily.	• The computational level is difficult to understand and depends more on the training data [43]. • Sometimes the algorithms are difficult to under- stand for humans.
Model Basedmethods	• A simple structure is required to analyze the training data and easy to implement. • Accuracy level is high and robust estimation of battery parameters can be done.	• The model is mostly concentrated on accuracy levels of training data and pre-experimental setup is required. • The development process of the battery is time consuming and rely more on computational time.

9. CONCLUSION

As Electric vehicles are tremendously growing in recent technologies, BMS (Battery Management System) plays an important role in monitoring and controlling the various applications of Battery. This paper briefs about the different computational efficiency and the current technologies used in BMS. With respect to SOH, various techniques have been implemented for better performance. The objective, uncertainties, accuracy and efficiency has been discussed in this paper. Regarding SOH techniques, various algorithms have been used along with recent technologies of Machine Learning. It discusses about different algorithm advantages, limitations, standard equations along with the technology being implemented with a comparison structure. In brief, BMS and its applications, SOH with its techniques, Intelligent Algorithms have been highlighted in terms of input and output features. This paper has highlighted the real time applications with respect to EV and HEV with Lithium-ion batteries, Fuel cells, Lead acid batteries etc. Some model-based methods using different algorithms and techniques for the SOH estimation methods are key concerns. Overall, battery parameters with respect to EV model accuracy, adaptability, compatibility with best estimation methods for real time identifications and their applications summarized in a brief manner.

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Intelligent Surveillance System with Mask Detection and Temperature Monitoring

Publisher: IEEE

R Sivapriyan ; N Pavan Kumar ; CV Mohan ; N Sakshi **All Authors**

Abstract: An efficient and adroit surveillance system is im-perative in the fast-paced digital world, with a monumental rise in video-based surveillance systems for security and mo... **View more**

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Abstract:

An efficient and adroit surveillance system is im-perative in the fast-paced digital world, with a monumental rise in video-based surveillance systems for security and monitoring. The pandemic has created the need for effective surveillance and made it more relevant than ever before. The AI-based surveillance system proposed in this paper is capable of performing the traditional functions of a surveillance system and checking if a person is wearing a mask and if his temperature is below a certain threshold. The proposed surveillance system is a video-based surveillance system capable of logging people who are not wearing a mask or whose temperature is not below a specified value. This system is implemented with Raspberry Pi as the central hub for processing, extracting, and analyzing the video stream from a camera. The proposed system aims to identify the mask on people by using a cascade classifier generated by Machine learning techniques, thus mulling down the effects of external factors (lighting condition, position, etc.) that affect the performance of a traditional video surveillance system.

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I. Introduction

Surveillance involves monitoring and gathering information to capture the behavior of an object or person. Surveillance today involves capturing and monitoring online web traffic to video feed from a camera running around the clock. Video surveillance is the most-real form of monitoring and information gathering, which is deployed everywhere due to its sheer reliability and the watered-down cost of surveillance cameras due to the reduction in the fabrication cost of the camera sensors. Surveillance is mostly done to apprehend or prevent any malicious activity performed by a person. Surveillance can also be used to profile and aggregate the behavior of an object or person, which can further be used to analyze and apprehend any suspicious activities in the future, this is mainly made possible by the transparency of the social networking platforms and the advancements in data mining and pattern recognition can reveal unmask unnoticed connections in data collected unanimously. Surveillance systems are not just limited to monitoring the behavior of objects or persons it can be used to predict behavior based on past and present events. Surveillance has become customary in this digital age, as it ensures safety and transparency at all times [1].

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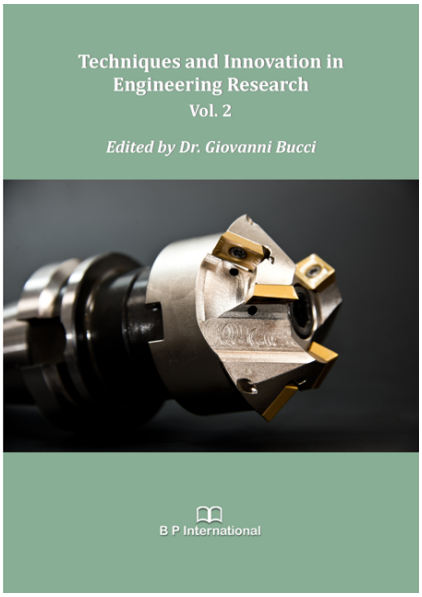

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Industrial Automation of Gas Tunnel Kiln Using Relay Logics, PLC and VFD's

K. Mahesh ; S. Inbasakaran ; J. Lithesh ; S. Praveen

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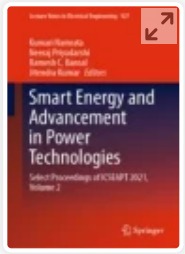
Abstract

Automation is one of the most pressing issues in any sector today. Automation is affecting almost every aspect of life, from agriculture to space technology. Plant automation is a must-have for the manufacturing business in today's internationally competitive market. It refers to the system's ability to function without human involvement at all times. We are designing a control circuit for the automation of the Gas Tunnel Kiln (GTK) using relay logics and Variable Frequency Drives (VFD's) in this paper because the current doors and movement of the transfer car in and out of the kiln are being operated manually and the temperature of the kiln is very high, making manual operation unsafe. The GTK has a vestibule on the front and the rear side. The charging and discharging of the green Insulators is being automated as a whole. The first stage is to create ladder diagrams that can be realised with hardware components and then simulate them using LADSIM - PLC Simulator.

Keywords: Automation; gas tunnel kiln; relay logics; PLC; VFD’s



Smart Energy and Advancement in Power Technologies pp 421–435

Simulation of Modular Fly-Back Current-Fed Push–Pull DC-DC Converter for High Voltage Low Current Applications

D. Beula ✉, M. S. Indira & N. Balaji

Conference paper | First Online: 22 October 2022

Part of the Lecture Notes in Electrical Engineering book series (LNEE,volume 927)

Abstract

A DC-DC converter has been proposed using Fly-back Current-fed Push–Pull topology with multiple secondary windings for high voltage low current applications. The converter is modular at the output which gives the flexibility to cater to specific output voltage levels. The High Voltage Transformer (HVT)

with multiple secondary windings and rectifier with voltage doublers result in a smaller turns ratio for higher voltage conversion. The rectifier components on the high voltage side are subjected to lower voltages that reduce the voltage stress on the rectifier component, compared to HVT with the single secondary winding. The converter is operated in complete energy transfer mode (Discontinuous conduction mode) for effective utilization of stored energy in the fly-back inductor as it is fed-back to the source. The discontinuous current-fed scheme provides an instantaneous current limiting facility for short circuits at the load side. Zero current turn-on of switches due to the discontinuous mode of operation reduces switching losses and the non-overlapping mode of power switches minimizes conduction loss. The operation of the converter is analyzed under steady-state conditions. A design procedure is established and the converter is designed for a typical load of 5 kV, 500 W at a switching frequency of 20 kHz. The performance of the converter is verified by simulation.

Keywords

Current-fed **DC-DC converter** **Modular**

Energy feedback **High voltage application**

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Author information

Authors and Affiliations

Department of Electrical and Electronics Engineering, Sir M Visvesvaraya Institute of Technology, Bangalore, Karnataka, India

D. Beula

M.S. Ramaiah University of Applied Sciences, Bangalore, Karnataka, India

M. S. Indira

Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India

N. Balaji

Corresponding author

Correspondence to D. Beula .

Editor information

Editors and Affiliations

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

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Neeraj Priyadarshi

Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates

Ramesh C. Bansal

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

Jitendra Kumar

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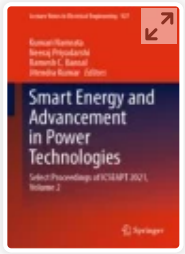

Smart Energy and Advancement in Power Technologies pp 331–341

Identification and Validation of Prominent Features for Predicting Mortality in Heart Patients with Left Ventricular Dysfunction Using Machine Learning

R. Subha ✉, Rekha Radhakrishnan, P. Sumalatha & B. R. Nayana

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Abstract

Machine Learning (ML) is a strong tool for medical prognosis, and it has the potential to give this branch of medicine a huge boost by allowing doctors to make accurate predictions about a patient's future

health using various forms of medical data. ML algorithms have proven to be reliable and effective in decision making with good classification accuracy. They can model nonlinear relationships, which are frequent in medical data, and apply them to predictive tasks such as forecasting a future event. In this paper, an attempt has been made to predict the mortality of heart patients with left ventricular dysfunction. Feature selection methods have been used to rank the input features in the dataset and identify four prominent features. Different combinations of these prominent features have been applied to five ML algorithms namely, Decision Tree, Gradient Boost, Random Forest, Support Vector Machine and k Nearest Neighbors to find the best performing combinations using F1-Score and AUC ROC. Considering additional performance parameters, further analysis is carried out to identify the best feature combination and the most effective ML algorithm for predicting mortality and the results are provided for the same.

Keywords

Cardiovascular disorder **Classification**

Decision trees **Machine learning**

Medical prognosis

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Author information

Authors and Affiliations

Department of Electrical and Electronics Engineering, M S Ramaiah Institute of Technology, Bangalore, India

R. Subha

Department of Electrical and Electronics Engineering, Sir M Visvesvaraya Institute of Technology, Bangalore, Karnataka, India

Rekha Radhakrishnan, P. Sumalatha & B. R. Nayana

Corresponding author

Correspondence to R. Subha .

Editor information

Editors and Affiliations

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

Kumari Namrata

Department of Energy Technology, Aalborg University, Esbjerg, Denmark

Neeraj Priyadarshi

Department of Electrical Engineering, University of Sharjah, Sharjah, United Arab Emirates

Ramesh C. Bansal

Department of Electrical Engineering, National Institute of Technology Jamshedpur, Jamshedpur, Jharkhand, India

Jitendra Kumar

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Review of State of Health Monitoring Techniques inBattery Management System

R Sivapriyan, Sushmitha S V, C V Mohan, S Lavanraj
Department of EEE, Sir MVIT, Karnataka, India. sivapriyan@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. sushmithasv390@gmail.com Department of EEE, Sir MVIT, Karnataka, India. eeecvm@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. lavanraj.s@gmai.com

Abstract.

As in recent trends, the Electric Vehicles are tremendously growing and major research works are found in Battery Management System. This paper comprehensively analysis about the State Of Health (SOH) and its methodologies in applications of Battery Management System (BMS). Various algorithms along with the flowchart have been briefly discussed. The comparative analyses along with the various methodologies are included in the table for reference. The SOH monitoring and controlling applications in lithium-ion batteries and fuel cells are considered and discussed as regarding main topics. The model-based methods along with the real time applications with input and output features has briefed in general with a comparison. The algorithms with real time application in Machine Learning and AI techniques has given a highlight and its applications in real time examples are briefed. Thus, this paper briefs about BMS and discharge methods of the battery of the SOH techniques and highlights upon various algorithms which is used as model-based methods in Battery management system as well as SOH techniques.

Keywords. Battery Management System, State of Health, Experimental Method Analysis, Machine Learning, Model Based Methods.

1. INTRODUCTION

Nowadays, Electric vehicles are a trending technology in various applications, and one of its applications is used in Battery Management Systems (BMS). BMS monitors and protects the battery by considering its safe operation area such as Overvoltage/under voltage, Overpressure, over temperature/under temperature [1]. Also, to prevent the current leakage where battery cell is charged by an intelligent battery pack and makes use of rechargeable battery which has to be managed in an electronic or power storage system by considering available data for calculating and monitoring it in the environment and is efficiently used in the EV applications [2]. BMS consists of many cells stacked together within a smart battery pack to release the cell's energy to meet the load demand. Stability plays a significant role in the whole Battery Management System, where users can monitor each cell individually by authenticating and reporting the data [3]. There are many IC's available in BMS. It includes some functional blocks to keep track of all voltage balance,

monitor temperature and the energy recovery in electric vehicle systems, and sometimes the state of the battery can also be monitored by considering the state of the machine for simplicity purposes as shown in Fig.1.1. By considering standard parameters like SOC (State Of Charge) [4][5], SOH (state of health) [6], SOP (state of power), and SOS (state of safety), BMS computation can be determined [7].

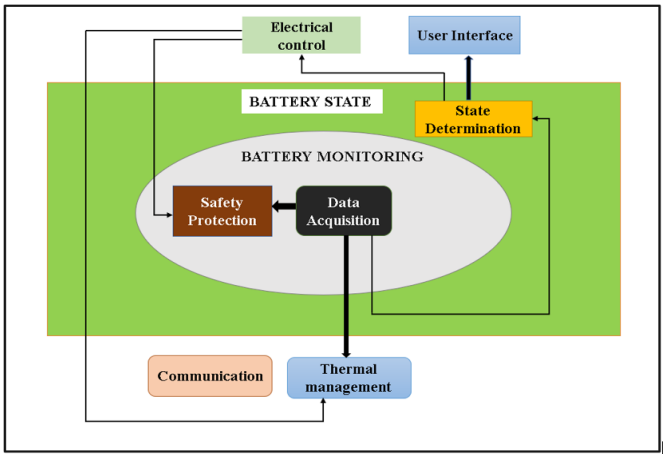

Figure 1.1 Battery Management System[8]

It can track the total number of cycles and energy consumed per kWh for the total operating time [9]. BMS also uses wireless kWh for the total operating time [9]. BMS also uses wireless communications for communicating with the hardware when it comes to internal purposes at the basic level of the cell.

When it comes to the external purpose, the hardware level will be high, making use of PCs, laptops, etc. For internal communication, BMS restricts with bulk number of cells [9]. When it comes to modular architecture with an increasing number of nodes, hardware combination cannot be used as it is limited, and cost plays a major role as cell price comes into existence which is comparable.

The protection of BMS is also important, so we can include a relay that acts as a protective switch by detecting faults when the battery's SOA crosses its limit. The balancing part of the BMS is handled by the balancers where energy is shuffled and also by passive regulators by connecting charged cells of an increasing number to the load side, and the major task is to maintain voltage at the same level for cells where the battery is composed, to prevent overcharging thus the battery's capacity can be maximized. Thus, BMS (Battery management system) plays a major role in electric and hybrid vehicles such as electric cars and lithium-ion batteries [10].

In electric train traction batteries, BMS is used to manage the high power and large battery packs. Some BMS applications are also found in Garbage compressors, Industrial machines, Hoists, Cranes, Robots, Forklifts, etc.

2. STATE OF HEALTH

SOH stands for the State of Health, and it is a battery condition to estimate the charge in smart battery packs by considering some of the Safe Operating Area (SOA) and aging limitations at the same time for monitoring the battery conditions for electric vehicle applications [11] as shown in Figure 2.1.

By considering ideal parameters, when manufacturing SOH's battery condition is 100 percent and due to some aging process, the battery's performance will decrease [12]. It is calculated by considering the ratio of capacitance, impedance to its initial rating.

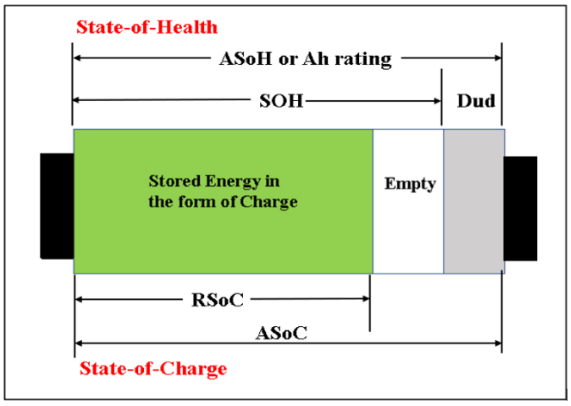

Figure 2.1 State of Health[13]

Nowadays, Lithium-ion batteries are used in SOH's battery for reliability purposes. A detailed analysis has been carried out to check for safety measures in power storage or energy storage requirements.

Currently, the study has been carried out in self-discharge rate, Number of operating cycles, power capability to ensure battery monitoring system by considering internal impedance, resistance, and capacitance aspects.

Some of the health features (HFs) for SOH battery estimation are the physical parameters to characterize the battery capacity, Electrochemical models with some degradation mechanisms.

The factors affecting the behaviour of the battery in SOH's batteries are dealt with by some of the algorithms and Artificial Neural Networks (ANNs) techniques by considering the capacity loss in the cycling behaviour of the power periodically [14]. The response of the voltage will be varied by considering the rate of current at different SOH parameters.

The battery parameters like SOC and SOH are the approaches used in various battery system methods such as Kalman Filter, Enhanced Coulomb Counting, and voltage methods in applications of Electric and Hybrid vehicles, HVDC, and photovoltaic applications systems [15].

3. SOH TECHNIQUES

As the Electric Vehicle Technology is tremendously growing in past few years, the Battery Management System (BMS) acts as a central coordinating system or main control system so as to provide reliability, efficiency, stability and safe use of battery by considering some standard parameters like State of Charge (SOC), State of Health (SOH), State of Power (SOP)[16][17].

SOC is used to collect the energy being consumed by battery and storage specifications of the battery. SOP is used for determining the power required for the battery and the flowchart of SOH Monitoring is shown in Figure 3.1.

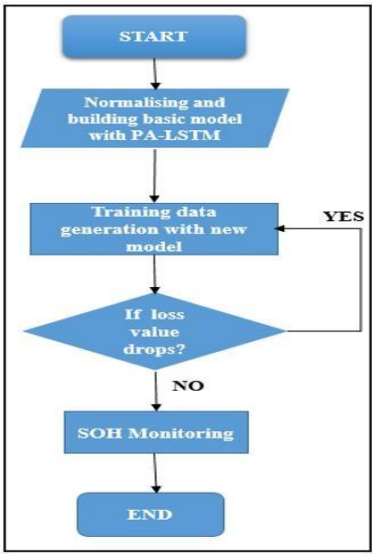

Figure 3.1. Flow Chart of SOH Monitoring[18]

SOH is a battery condition to estimate the charge and to detect degradation level of the battery in real-time automotive applications.

The Battery performance can be analyzed by SOH in HEV and AI applications [19] and discusses about the distribution of energy and how to improve their self-discharge rate, consumption of energy during their lifetime. So, some of the standard methods/techniques are used for SOH's battery estimation by considering internal resistance of the battery, battery's impedance, state of machine, state of discharge [20] and its capacity [21].

The SOH Battery estimation methods can be divided into 3 methods which include Experimental methods, Model-Based methods and Machine Learning methods. From the standard methods, machine learning technology can be implemented and it includes some of the techniques such as Support Vector Regression, Neural Network, Fuzzy logic and other standard algorithms.

In Experimental methods, some techniques include Impedance measurement, ICA/DVA, Internal resistance measurement, Capacity level etc. and these methods are usually conducted in laboratories.

Some Model Based methods include Adaptive filtering such as Kalman Filters, EKF, UKF, RLS, MAFFRLS, Electrochemical models and Enhanced Coulomb counting methods etc. SOH's battery uses PA-LSTM algorithm for monitoring accuracy of battery and also by updating the learning mechanism where data obtained from the experimental results are close to real time data model dynamically and can further be used in approach of Lithium-ion batteries.

4. VARIOUS METHODS OF SOH TECHNIQUES

In SOH Battery estimation, there are 3 types of methods namely Experimental technique, Machine learning methods and Model Based methods as shown in Figure 4.1.

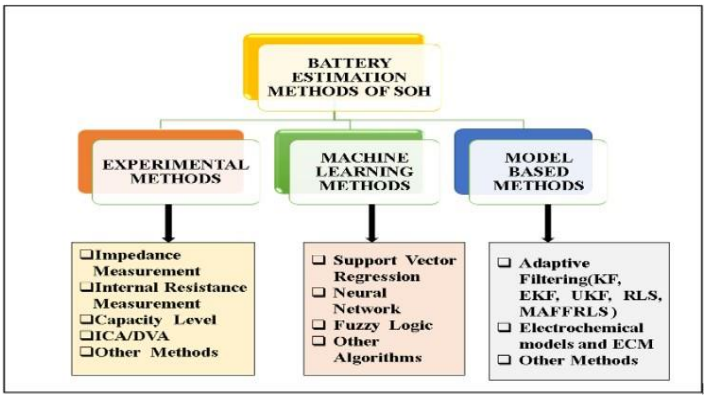

Figure 4.1 Battery SOH Estimation Methods[22]

5. EXPERIMENTAL METHOD ANALYSIS OF BATTERY SOH ESTIMATION

Usually, these Experimental methods are often time consuming and preferable equipment's have to be used in specific to meet the criteria or requirements, so these methods are usually performed in laboratories. The aging behaviour of the battery can be determined using these methods by collecting raw data measurements and understanding the behaviour of these collected data. Some of the techniques used in Experimental methods are discussed below:

• Impedance Measurement of the Battery:

The major technique which is used frequently to measure the impedance of the battery is Electrochemical Impedance Spectroscopy (EIS) which dealt with energy storage and conversion and it acts as a SOH indicator of battery. This technique is conducted as a function of frequency as a sinusoidal AC current is applied and output voltage response is calculated. Meanwhile, it is a non-destructive method and it is found that impedance of the battery is directly proportional to the aging phenomena.

The EIS method discusses about the super capacitor, cycling effect and energy storage in real-time applications of EV and major advantage is the accuracy which can be calculated efficiently in the aging phenomenon of the battery [23].

• Internal Resistance Measurement of the Battery:

In this technique, by applying AC sinusoidal current the voltage drops and current pulse is the most frequently used method to deter- mine the Internal Resistance which is based on the principle of Ohm's Law and acts as a SOH indicator.

By considering the parameters like aging and degradation whose impact decreases the resistance values with SOH battery conditions. With the help of Joule's law, loss of energy in Battery is evaluated by considering the impacting parameters. The main advantage of this method is the accuracy in domains of evaluating battery's internal resistance in different environmental working conditions and widely used in laboratories but is often a time-consuming process.

• Capacity Level:

In this technique, battery charging capacity is evaluated and energy stored in a battery is evaluated by a capacitor and it is inversely proportional to the aging phenomenon of the battery [24]. Here, time is the major factor to decide number of charging/discharging cycles based on the output voltage under different working conditions of the temperature for different levels of degradation by experimentally evaluating the capacity fading level in Lithium-ion battery applications [25].

• ICA/DVA and Other Methods:

ICA and DVA stands for Incremental Capacity Analysis and Differential Voltage Analysis respectively. These methods have to be done experimentally by testing battery SOH which is time consuming and these parameters vary with aging of the battery. By using some of the destructive methods such as X-ray Diffraction, state of the battery and machine can be determined from inside and estimation can be changed feasibly with modification of specific working conditions [26].

6. MACHINE LEARNING METHOD ANALYSIS

This method is basically a combination of both standard methods which include Experimental and Model Based methods. To estimate battery SOH some data has to be gathered using machine learning algorithms in process of learning to setup the standard algorithms [27].

• Support Vector Regression (SVR):

In this technique, training data is to be evaluated which requires a controller of high performance to manage the energy and taking into consideration real time data and experimentally to determine the online SOH indicator using Electrochemical Impedance Spectroscopy (EIS) technique. This SVR algorithm is also used to estimate RUL (Remaining Useful Life) of the battery and its applications in Fuel cells, e-Bikes, Hybrid Electric vehicles etc.

• Fuzzy Logic:

This technique is used for nonlinear systems and is the most commonly used machine learning method along with EIS technique to evaluate the training data to be accurate

which often uses Gaussian Algorithm process [28] to estimate the battery SOH in Lithium-ion batteries along with WLTC profiles [29].

• Neural Networks:

It is the most frequently used machine learning algorithm and it takes less data for computational analysis combining with EIS measurements and results are found to be more accurate with ample amount of data received than the Fuzzy Logic.

The main disadvantage of this method is difficulties faced in complex as well as nonlinear systems and also it requires a controller of high performance.

• Other Methods:

Some algorithms such as Gaussian algorithm makes use of training data to track accuracy of SOH battery in Lead Acid Batteries as well as Lithium-ion batteries.

Back Propagation Neural Network (BPNN) is the algorithm to trace the battery parameters like Internal Impedance, Resistance and to track the energy level and tolerance was found to be less.

Particle-filter based algorithm is used extensively for different vehicle applications and its accuracy on estimation of battery SOH and requirement of training data is found to be less for computational purpose in machine learning process.

RLS (Recursive Least Square) algorithm and LSTM-NN (Long Short-Term Memory Neural Network) are also used which are trending research topics and has to be tested experimentally for better accuracy of the SOH battery indicator.

7. MODEL BASED SOH BATTERY ESTIMATION ANALYSIS

In the research for evaluating the Battery SOH and real time feasibility, model-based methods have come into existence with filtering and standard indicators to determine battery capacity, impedance, energy level [30] etc. Some of the techniques are:

• Kalman Filters:

In order to evaluate the SOH battery parameters, an adaptive filtering algorithm is used in real time to consider the ECM (Equivalent Circuit Models). The advantage of these filters are some nonlinear systems as well as complex system battery state and parameters can be evaluated using Kalman Filters (KF), Extended Kalman Filters (EKF), Unscented Kalman Filter (UKF), Dual Kalman Filters etc.

• Electrochemical methods:

Differential equations of nonlinear systems as well as complex systems can be evaluated accurately and these models are found to be complex in tracing the battery's parameters and behaviour. It uses recursive parameter [31] for identification purpose and to predict online SOH indicator and capacity effects in SOC battery. For accurate results the battery behaviour can be predicted using ECM techniques where they have less complexity equations.

The main drawback of this method is the difficulty level of the equations and complexity of the algorithm to trace behaviour of SOH battery parameters like internal resistance and diffusion time of the battery.

• Other Methods:

Observers are also used in Model Based SOH estimation methods due to its robustness against error margin and diffusion time parameter for variations in temperature [32]. Least Square Based Filters is widely used one of the algorithms for testing the battery states in the OCV (Open Circuit Voltage) along with RLS algorithm for testing the high performance of a battery model.

MAFFRLS (Multi Adaptive Forgetting Factors RLS) is also used along with PSO (Particle Swam Optimization) algorithms for better efficiency and accurate results in temperature and time variations of dataset in Battery models.

8. COMPARATIVE ANALYSIS

In Support Vector Regression (SVR) method, the quality and quantity are entirely based upon the data used in the training and uses a controller when there is a need of high performance to control the training data. Compared to the other methods, the results obtained in the SVR is of accurate and applicable for any systems. The main advantage of SVR is as the system results obtained are of accurate and hence the system is stable and efficient. It can also be used to solve the regression problems. The main disadvantage of using SVR algorithm is that it is difficult for humans to understand the code and it takes long training time. In Feed Forward Neural Network (FNN) Algorithm, mathematical relationships are used for the algorithm with some input features to dynamics of battery such that SOH Estimation can be done in an accurate manner and rule used in FNN is of back propagation learning. The equations used in FNN are of mapping function where some function can be almost approximated to other functions. The main advantages of using FNN are the computation required to analyze the mathematical relations is less, so this type of algorithm is beneficial.

As large equations are being used, overfitting problem exists as to store the data of large number of parameters. In Recurrent Neural Network (RNN) Algorithm, the main input to be considered are current, temperature, voltage and output used to determine the application of SOH in functions of temperature in BMS applications [33]. The main advantage of using RNN Algorithm is information can also be easily stored in functions of time which is easy task and memory requirement is less. The pixel quality is effective and time series can be easily predicted. The disadvantage of this RNN algorithm is to train the RNN task and sometimes long sequences such as tanh function cannot be processed easily and gradient problems usually occur for this type of algorithm. In case of Particle Swarm Optimization (PSO) Algorithm the principle is based on the latest technology and its applications are still being in research for Electric Vehicles and Plug-in hybrid Electric vehicles. It makes use of Swarm Intelligence where parameters control can be done using simple concept and efficiency of computation compared to other algorithms is found to be extremely good and effective. This PSO algorithm can be easily implemented for different and various systems so that the over fitting problem can be overcome by this algorithm.

The main disadvantage of this algorithm is that it provides solution of some techniques which is of low quality and each time when the program is updated, memory updating has to be done which is time consuming and tedious process or task.

Table 1 COMPARISON OF EXPERIMENTAL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Internal Resistance measurements [34]	• Simple to implement and direct method to under-stand. • Less complexity and high level of accuracy.	• Estimation through online cannot be made. • Time consuming and tedious task.
Internal Impedance Measurements	• High accuracy and simplicity. • Reliable and degradation of the battery methods can be easily understood.	• Battery degradation and discharges is difficult to analyze.
ICA/DVA and Capacity Level [35]	• This technique is much faster than other methods. • It is fast to analyze and provides high level of accuracy.	• Sometimes this method is not reliable and feasible. • Operating conditions of the battery is difficult to analyze when fully charged.

Table 2 COMPARISON OF MODEL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Kalman FilterBased (KF) methods	• Simple to understand and accurate to interpret theoutput • It is bounded to errors	• For advanced systems and versions system is complex. • A controller of high performance is required and not valid for nonlinear systems [39].
Electrochemical models	• High accuracy and reliable • The battery degradation phenomenon can be understood and predicted easily.	• The computational level of high-performance con- troller is required [40]. • Structure of the battery is difficult to analyze.
Least Square Based methods	• This Technique is much precise and robust than other techniques. • The structure is easy to analyze.	• The model is mostly concentrated on accuracy and high-level performance controller is required [41].

Table 3 COMPARISON OF MACHINE LEARNING BASED METHODS [36].

Parameters	**Support Vector Regression Algorithm**	**Feed Forward Neural Network Algorithm**	**Recurrent neural network (RNN) Algorithm**	**Particle Swarm Optimization (PSO) Algorithm [37]**
INPUT	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), T(t), SOC(t), R/C(t)	I(t), V(t), T(t)
OUTPUT	SOH(t)	SOH(t)	SOH(t)	SOH(t)
FUNCTION	Regression and Classification Hyperplane Equation	Supervised Learning, Sigmoid function, Mapping of function to approximate value	Non-Linear, Auto-Regressive Network, Time Series Based Function	Swarm Intelligence, Randomized, Population Based Optimization Method
EQUATION	y=wx+b(Hyperplane) Condition: $-a > y-wx+b < a$	f(x)=yf(x) for all (x,y)	Current state equation: $h_t=f(h_{t-1}, x_t)$ Output equation: $y_t=W_{hy}h_t$ Activation Function: $h_t=\tanh(W_{hh}h_{t-1}+W_{xh}x_t)$	$x_i^{k+1}= x_i^{k}+ v_i^{k+1}$
ADVANTAGES	• Overfitting can be prevented as it has good regularization capabilities. • Using Kernel function, it handles non-linear data efficiently • Stable and Efficient. • Can be used to solve both classification and regression.	• Easy to setup. • Less computation. • Complex and Non- linear systems can be analyzed.	• Easy information is stored accordingly with time. • It is good for effective pixel extension. • Helps in prediction of time series.	• Simple concept. • Easy implementation. • Robustness to control parameters • High computational Efficiency.

LIMITATIONS	• The difficult task is to choose an appropriate Kernel function. • For large datasets, it takes long training time [38]. • It is difficult to understand the algorithm or models of SVR for humans.	• There exists Vanishing and Exploding Gradient problem. • Large model size. • There exists Overfitting of large number of parameters.	• Gradient Vanishing and problems are exploding. • It is difficult to train an RNN task. • As tanh function is used for activation function, it cannot process long sequences.	• Low convergence rate in iterative process. • Memory updating required and falls under local search. • Low quality solution.

Table 4 COMPARISON OF SOH ESTIMATION METHODS.

Methods	Advantages	Disadvantages
Experimental Based methods	• Simple to understand and accuracy is more. • Computational level is low	• Time consuming. • The measurements and the equipment to be used should be specific [42].
Machine Learning methods	• High accuracy and reliable compared to other two methods. • Easy to implement and process can be carried out easily.	• The computational level is difficult to understand and depends more on the training data [43]. • Sometimes the algorithms are difficult to under- stand for humans.
Model Basedmethods	• A simple structure is required to analyze the training data and easy to implement. • Accuracy level is high and robust estimation of battery parameters can be done.	• The model is mostly concentrated on accuracy levels of training data and pre-experimental setup is required. • The development process of the battery is time consuming and rely more on computational time.

9. CONCLUSION

As Electric vehicles are tremendously growing in recent technologies, BMS (Battery Management System) plays an important role in monitoring and controlling the various applications of Battery. This paper briefs about the different computational efficiency and the current technologies used in BMS. With respect to SOH, various techniques have been implemented for better performance. The objective, uncertainties, accuracy and efficiency has been discussed in this paper. Regarding SOH techniques, various algorithms have been used along with recent technologies of Machine Learning. It discusses about different algorithm advantages, limitations, standard equations along with the technology being implemented with a comparison structure. In brief, BMS and its applications, SOH with its techniques, Intelligent Algorithms have been highlighted in terms of input and output features. This paper has highlighted the real time applications with respect to EV and HEV with Lithium-ion batteries, Fuel cells, Lead acid batteries etc. Some model-based methods using different algorithms and techniques for the SOH estimation methods are key concerns. Overall, battery parameters with respect to EV model accuracy, adaptability, compatibility with best estimation methods for real time identifications and their applications summarized in a brief manner.

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Intelligent Surveillance System with Mask Detection and Temperature Monitoring

Publisher: IEEE

R Sivapriyan ; N Pavan Kumar ; CV Mohan ; N Sakshi **All Authors**

Abstract: An efficient and adroit surveillance system is im-perative in the fast-paced digital world, with a monumental rise in video-based surveillance systems for security and mo... **View more**

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Abstract:

An efficient and adroit surveillance system is im-perative in the fast-paced digital world, with a monumental rise in video-based surveillance systems for security and monitoring. The pandemic has created the need for effective surveillance and made it more relevant than ever before. The AI-based surveillance system proposed in this paper is capable of performing the traditional functions of a surveillance system and checking if a person is wearing a mask and if his temperature is below a certain threshold. The proposed surveillance system is a video-based surveillance system capable of logging people who are not wearing a mask or whose temperature is not below a specified value. This system is implemented with Raspberry Pi as the central hub for processing, extracting, and analyzing the video stream from a camera. The proposed system aims to identify the mask on people by using a cascade classifier generated by Machine learning techniques, thus mulling down the effects of external factors (lighting condition, position, etc.) that affect the performance of a traditional video surveillance system.

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Contents

I. Introduction

Surveillance involves monitoring and gathering information to capture the behavior of an object or person. Surveillance today involves capturing and monitoring online web traffic to video feed from a camera running around the clock. Video surveillance is the most-real form of monitoring and information gathering, which is deployed everywhere due to its sheer reliability and the watered-down cost of surveillance cameras due to the reduction in the fabrication cost of the camera sensors. Surveillance is mostly done to apprehend or prevent any malicious activity performed by a person. Surveillance can also be used to profile and aggregate the behavior of an object or person, which can further be used to analyze and apprehend any suspicious activities in the future, this is mainly made possible by the transparency of the social networking platforms and the advancements in data mining and pattern recognition can reveal unmask unnoticed connections in data collected unanimously. Surveillance systems are not just limited to monitoring the behavior of objects or persons it can be used to predict behavior based on past and present events. Surveillance has become customary in this digital age, as it ensures safety and transparency at all times [1].

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Antipodal Vivaldi Antennas Arranged in Circular Array for RADAR

Sasmita Mohapatra

Chapter | First Online: 03 February 2022

Part of the EAI/Springer Innovations in Communication and Computing book series (EAISICC)

Abstract

RADAR section usually requires antenna, which can be used as ultra-wideband antenna at a higher microwave frequency range, and at the same time, the antenna should be robust to withstand the adverse climatic effects. In this present work, an array antenna has been proposed, which consists of antipodal Vivaldi antennas. The Vivaldi antennas are arranged in a spherical fashion where each row of the antenna array can be used alternatively for transmitting and receiving signals also. The designed individual antipodal Vivaldi antenna has very high directivity and stable VSWR over the frequency range of 2–20 GHz. The designed array of antipodal Vivaldi antenna can work for a wideband ratio of 10:1. However, if the antennas are arranged with little gap, the wideband structure is a little disturbed as individual antenna tries to resonate at a particular frequency. But this also leads to an advantage that when the individual Vivaldi antenna is arranged in an array, the azimuth and elevation coverage of the antenna array increases as a result of the combination of individual antenna beam area. To make the antenna structure mechanically reliable and electrically stable, a new dielectric material Astra® MT77 has been used, which has very low dissipation factor with stable dielectric constant and impedance throughout the antenna structure. For weather protection, the complete antenna structure is shielded by a radome with proper dielectric constant.

Keywords

Antipodal Vivaldi antenna | Array of antenna | RADAR | Radome | Coverage | VSWR

Design and Analysis of Algorithm is very important for designing algorithm to solve different types of problems in the branch of computer science and information technology.
Designing algorithm is necessary before writing the program code as the algorithm explains the logic even before the code is developed.
The code can be written in any programming language but the algorithm is written in a common language.
For solution of any problem there may exist many versions of the same program written by same or different programmers. By just reading the source code the efficiency of the code cannot be judged.
So we design algorithms and analyse them for Time complexity, Space complexity, efficiency etc.

Dr. Suma Swamy is currently working as Professor, Department of CSE, Sir M. Visvesvaraya Institute of Technology, Bengaluru. She is guiding 6 research scholars under VTU and one research scholar is awarded Ph.D degree.She has 32 years of experience in teaching.She has published 2 patents.She is BOE member of CS/IS Board, VTU Belagavi.

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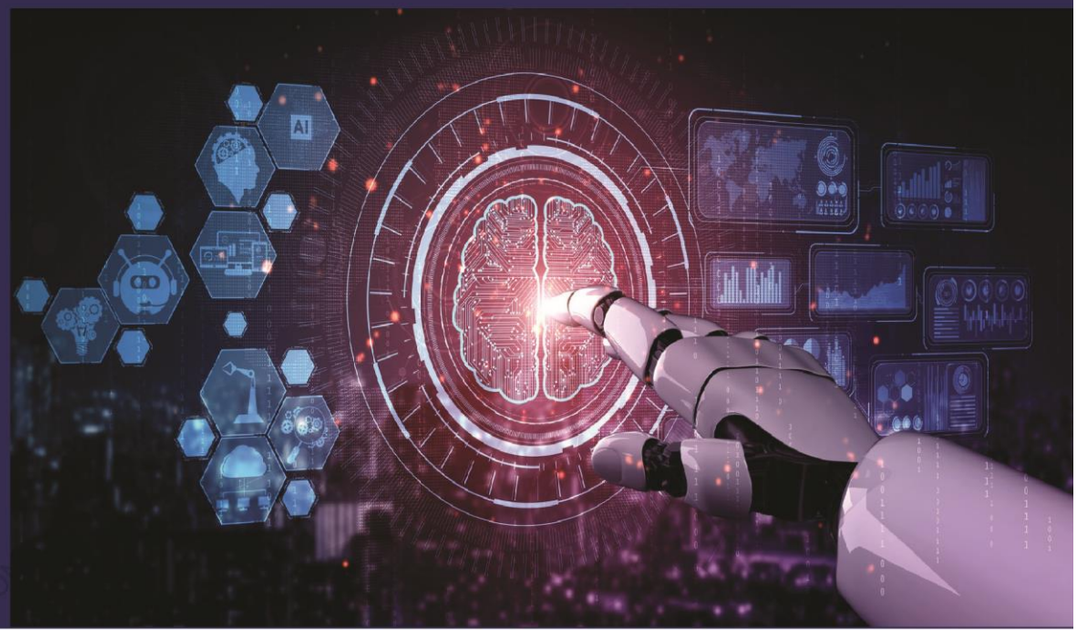

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Intelligent Surveillance System with Mask Detection and Temperature Monitoring

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An efficient and adroit surveillance system is im-perative in the fast-paced digital world, with a monumental rise in video-based surveillance systems for security and monitoring. The pandemic has created the need for effective surveillance and made it more relevant than ever before. The AI-based surveillance system proposed in this paper is capable of performing the traditional functions of a surveillance system and checking if a person is wearing a mask and if his temperature is below a certain threshold. The proposed surveillance system is a video-based surveillance system capable of logging people who are not wearing a mask or whose temperature is not below a specified value. This system is implemented with Raspberry Pi as the central hub for processing, extracting, and analyzing the video stream from a camera. The proposed system aims to identify the mask on people by using a cascade classifier generated by Machine learning techniques, thus mulling down the effects of external factors (lighting condition, position, etc.) that affect the performance of a traditional video surveillance system.

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Review of State of Health Monitoring Techniques inBattery Management System

R Sivapriyan, Sushmitha S V, C V Mohan, S Lavanraj
Department of EEE, Sir MVIT, Karnataka, India. sivapriyan@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. sushmithasv390@gmail.com Department of EEE, Sir MVIT, Karnataka, India. eeecvm@gmail.com PRTI (OPC) Pvt. Ltd, Karnataka, India. lavanraj.s@gmai.com

Abstract.

As in recent trends, the Electric Vehicles are tremendously growing and major research works are found in Battery Management System. This paper comprehensively analysis about the State Of Health (SOH) and its methodologies in applications of Battery Management System (BMS). Various algorithms along with the flowchart have been briefly discussed. The comparative analyses along with the various methodologies are included in the table for reference. The SOH monitoring and controlling applications in lithium-ion batteries and fuel cells are considered and discussed as regarding main topics. The model-based methods along with the real time applications with input and output features has briefed in general with a comparison. The algorithms with real time application in Machine Learning and AI techniques has given a highlight and its applications in real time examples are briefed. Thus, this paper briefs about BMS and discharge methods of the battery of the SOH techniques and highlights upon various algorithms which is used as model-based methods in Battery management system as well as SOH techniques.

Keywords. Battery Management System, State of Health, Experimental Method Analysis, Machine Learning, Model Based Methods.

1. INTRODUCTION

Nowadays, Electric vehicles are a trending technology in various applications, and one of its applications is used in Battery Management Systems (BMS). BMS monitors and protects the battery by considering its safe operation area such as Overvoltage/under voltage, Overpressure, over temperature/under temperature [1]. Also, to prevent the current leakage where battery cell is charged by an intelligent battery pack and makes use of rechargeable battery which has to be managed in an electronic or power storage system by considering available data for calculating and monitoring it in the environment and is efficiently used in the EV applications [2]. BMS consists of many cells stacked together within a smart battery pack to release the cell's energy to meet the load demand. Stability plays a significant role in the whole Battery Management System, where users can monitor each cell individually by authenticating and reporting the data [3]. There are many IC's available in BMS. It includes some functional blocks to keep track of all voltage balance,

monitor temperature and the energy recovery in electric vehicle systems, and sometimes the state of the battery can also be monitored by considering the state of the machine for simplicity purposes as shown in Fig.1.1. By considering standard parameters like SOC (State Of Charge) [4][5], SOH (state of health) [6], SOP (state of power), and SOS (state of safety), BMS computation can be determined [7].

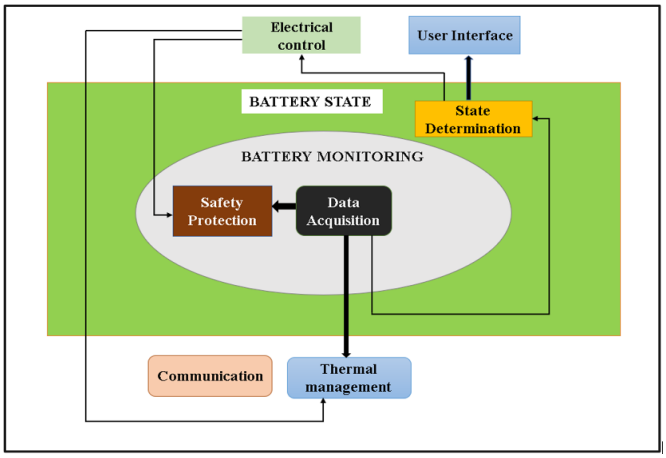

Figure 1.1 Battery Management System[8]

It can track the total number of cycles and energy consumed per kWh for the total operating time [9]. BMS also uses wireless kWh for the total operating time [9]. BMS also uses wireless communications for communicating with the hardware when it comes to internal purposes at the basic level of the cell.

When it comes to the external purpose, the hardware level will be high, making use of PCs, laptops, etc. For internal communication, BMS restricts with bulk number of cells [9]. When it comes to modular architecture with an increasing number of nodes, hardware combination cannot be used as it is limited, and cost plays a major role as cell price comes into existence which is comparable.

The protection of BMS is also important, so we can include a relay that acts as a protective switch by detecting faults when the battery's SOA crosses its limit. The balancing part of the BMS is handled by the balancers where energy is shuffled and also by passive regulators by connecting charged cells of an increasing number to the load side, and the major task is to maintain voltage at the same level for cells where the battery is composed, to prevent overcharging thus the battery's capacity can be maximized. Thus, BMS (Battery management system) plays a major role in electric and hybrid vehicles such as electric cars and lithium-ion batteries [10].

In electric train traction batteries, BMS is used to manage the high power and large battery packs. Some BMS applications are also found in Garbage compressors, Industrial machines, Hoists, Cranes, Robots, Forklifts, etc.

2. STATE OF HEALTH

SOH stands for the State of Health, and it is a battery condition to estimate the charge in smart battery packs by considering some of the Safe Operating Area (SOA) and aging limitations at the same time for monitoring the battery conditions for electric vehicle applications [11] as shown in Figure 2.1.

By considering ideal parameters, when manufacturing SOH's battery condition is 100 percent and due to some aging process, the battery's performance will decrease [12]. It is calculated by considering the ratio of capacitance, impedance to its initial rating.

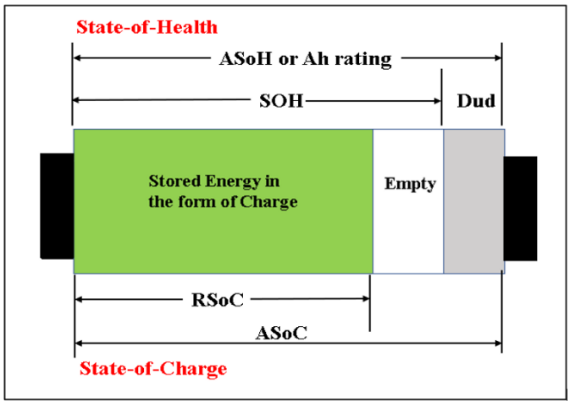

Figure 2.1 State of Health[13]

Nowadays, Lithium-ion batteries are used in SOH's battery for reliability purposes. A detailed analysis has been carried out to check for safety measures in power storage or energy storage requirements.

Currently, the study has been carried out in self-discharge rate, Number of operating cycles, power capability to ensure battery monitoring system by considering internal impedance, resistance, and capacitance aspects.

Some of the health features (HFs) for SOH battery estimation are the physical parameters to characterize the battery capacity, Electrochemical models with some degradation mechanisms.

The factors affecting the behaviour of the battery in SOH's batteries are dealt with by some of the algorithms and Artificial Neural Networks (ANNs) techniques by considering the capacity loss in the cycling behaviour of the power periodically [14]. The response of the voltage will be varied by considering the rate of current at different SOH parameters.

The battery parameters like SOC and SOH are the approaches used in various battery system methods such as Kalman Filter, Enhanced Coulomb Counting, and voltage methods in applications of Electric and Hybrid vehicles, HVDC, and photovoltaic applications systems [15].

3. SOH TECHNIQUES

As the Electric Vehicle Technology is tremendously growing in past few years, the Battery Management System (BMS) acts as a central coordinating system or main control system so as to provide reliability, efficiency, stability and safe use of battery by considering some standard parameters like State of Charge (SOC), State of Health (SOH), State of Power (SOP)[16][17].

SOC is used to collect the energy being consumed by battery and storage specifications of the battery. SOP is used for determining the power required for the battery and the flowchart of SOH Monitoring is shown in Figure 3.1.

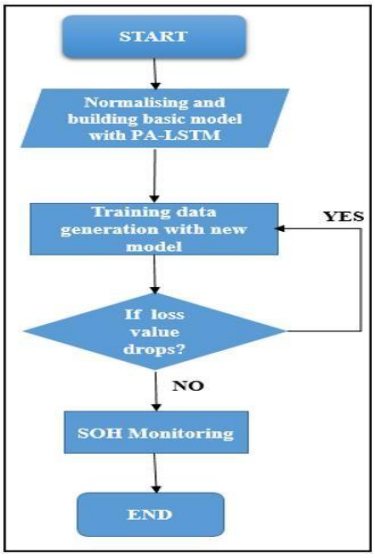

Figure 3.1. Flow Chart of SOH Monitoring[18]

SOH is a battery condition to estimate the charge and to detect degradation level of the battery in real-time automotive applications.

The Battery performance can be analyzed by SOH in HEV and AI applications [19] and discusses about the distribution of energy and how to improve their self-discharge rate, consumption of energy during their lifetime. So, some of the standard methods/techniques are used for SOH's battery estimation by considering internal resistance of the battery, battery's impedance, state of machine, state of discharge [20] and its capacity [21].

The SOH Battery estimation methods can be divided into 3 methods which include Experimental methods, Model-Based methods and Machine Learning methods. From the standard methods, machine learning technology can be implemented and it includes some of the techniques such as Support Vector Regression, Neural Network, Fuzzy logic and other standard algorithms.

In Experimental methods, some techniques include Impedance measurement, ICA/DVA, Internal resistance measurement, Capacity level etc. and these methods are usually conducted in laboratories.

Some Model Based methods include Adaptive filtering such as Kalman Filters, EKF, UKF, RLS, MAFFRLS, Electrochemical models and Enhanced Coulomb counting methods etc. SOH's battery uses PA-LSTM algorithm for monitoring accuracy of battery and also by updating the learning mechanism where data obtained from the experimental results are close to real time data model dynamically and can further be used in approach of Lithium-ion batteries.

4. VARIOUS METHODS OF SOH TECHNIQUES

In SOH Battery estimation, there are 3 types of methods namely Experimental technique, Machine learning methods and Model Based methods as shown in Figure 4.1.

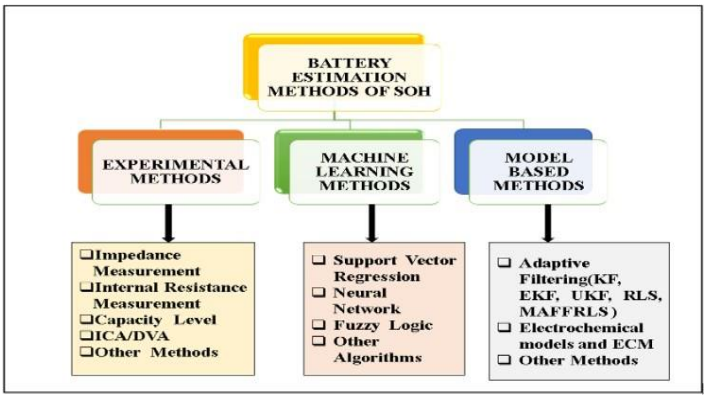

Figure 4.1 Battery SOH Estimation Methods[22]

5. EXPERIMENTAL METHOD ANALYSIS OF BATTERY SOH ESTIMATION

Usually, these Experimental methods are often time consuming and preferable equipment's have to be used in specific to meet the criteria or requirements, so these methods are usually performed in laboratories. The aging behaviour of the battery can be determined using these methods by collecting raw data measurements and understanding the behaviour of these collected data. Some of the techniques used in Experimental methods are discussed below:

• Impedance Measurement of the Battery:

The major technique which is used frequently to measure the impedance of the battery is Electrochemical Impedance Spectroscopy (EIS) which dealt with energy storage and conversion and it acts as a SOH indicator of battery. This technique is conducted as a function of frequency as a sinusoidal AC current is applied and output voltage response is calculated. Meanwhile, it is a non-destructive method and it is found that impedance of the battery is directly proportional to the aging phenomena.

The EIS method discusses about the super capacitor, cycling effect and energy storage in real-time applications of EV and major advantage is the accuracy which can be calculated efficiently in the aging phenomenon of the battery [23].

• Internal Resistance Measurement of the Battery:

In this technique, by applying AC sinusoidal current the voltage drops and current pulse is the most frequently used method to deter- mine the Internal Resistance which is based on the principle of Ohm's Law and acts as a SOH indicator.

By considering the parameters like aging and degradation whose impact decreases the resistance values with SOH battery conditions. With the help of Joule's law, loss of energy in Battery is evaluated by considering the impacting parameters. The main advantage of this method is the accuracy in domains of evaluating battery's internal resistance in different environmental working conditions and widely used in laboratories but is often a time-consuming process.

• Capacity Level:

In this technique, battery charging capacity is evaluated and energy stored in a battery is evaluated by a capacitor and it is inversely proportional to the aging phenomenon of the battery [24]. Here, time is the major factor to decide number of charging/discharging cycles based on the output voltage under different working conditions of the temperature for different levels of degradation by experimentally evaluating the capacity fading level in Lithium-ion battery applications [25].

• ICA/DVA and Other Methods:

ICA and DVA stands for Incremental Capacity Analysis and Differential Voltage Analysis respectively. These methods have to be done experimentally by testing battery SOH which is time consuming and these parameters vary with aging of the battery. By using some of the destructive methods such as X-ray Diffraction, state of the battery and machine can be determined from inside and estimation can be changed feasibly with modification of specific working conditions [26].

6. MACHINE LEARNING METHOD ANALYSIS

This method is basically a combination of both standard methods which include Experimental and Model Based methods. To estimate battery SOH some data has to be gathered using machine learning algorithms in process of learning to setup the standard algorithms [27].

• Support Vector Regression (SVR):

In this technique, training data is to be evaluated which requires a controller of high performance to manage the energy and taking into consideration real time data and experimentally to determine the online SOH indicator using Electrochemical Impedance Spectroscopy (EIS) technique. This SVR algorithm is also used to estimate RUL (Remaining Useful Life) of the battery and its applications in Fuel cells, e-Bikes, Hybrid Electric vehicles etc.

• Fuzzy Logic:

This technique is used for nonlinear systems and is the most commonly used machine learning method along with EIS technique to evaluate the training data to be accurate

which often uses Gaussian Algorithm process [28] to estimate the battery SOH in Lithium-ion batteries along with WLTC profiles [29].

• Neural Networks:

It is the most frequently used machine learning algorithm and it takes less data for computational analysis combining with EIS measurements and results are found to be more accurate with ample amount of data received than the Fuzzy Logic.

The main disadvantage of this method is difficulties faced in complex as well as nonlinear systems and also it requires a controller of high performance.

• Other Methods:

Some algorithms such as Gaussian algorithm makes use of training data to track accuracy of SOH battery in Lead Acid Batteries as well as Lithium-ion batteries.

Back Propagation Neural Network (BPNN) is the algorithm to trace the battery parameters like Internal Impedance, Resistance and to track the energy level and tolerance was found to be less.

Particle-filter based algorithm is used extensively for different vehicle applications and its accuracy on estimation of battery SOH and requirement of training data is found to be less for computational purpose in machine learning process.

RLS (Recursive Least Square) algorithm and LSTM-NN (Long Short-Term Memory Neural Network) are also used which are trending research topics and has to be tested experimentally for better accuracy of the SOH battery indicator.

7. MODEL BASED SOH BATTERY ESTIMATION ANALYSIS

In the research for evaluating the Battery SOH and real time feasibility, model-based methods have come into existence with filtering and standard indicators to determine battery capacity, impedance, energy level [30] etc. Some of the techniques are:

• Kalman Filters:

In order to evaluate the SOH battery parameters, an adaptive filtering algorithm is used in real time to consider the ECM (Equivalent Circuit Models). The advantage of these filters are some nonlinear systems as well as complex system battery state and parameters can be evaluated using Kalman Filters (KF), Extended Kalman Filters (EKF), Unscented Kalman Filter (UKF), Dual Kalman Filters etc.

• Electrochemical methods:

Differential equations of nonlinear systems as well as complex systems can be evaluated accurately and these models are found to be complex in tracing the battery's parameters and behaviour. It uses recursive parameter [31] for identification purpose and to predict online SOH indicator and capacity effects in SOC battery. For accurate results the battery behaviour can be predicted using ECM techniques where they have less complexity equations.

The main drawback of this method is the difficulty level of the equations and complexity of the algorithm to trace behaviour of SOH battery parameters like internal resistance and diffusion time of the battery.

• Other Methods:

Observers are also used in Model Based SOH estimation methods due to its robustness against error margin and diffusion time parameter for variations in temperature [32]. Least Square Based Filters is widely used one of the algorithms for testing the battery states in the OCV (Open Circuit Voltage) along with RLS algorithm for testing the high performance of a battery model.

MAFFRLS (Multi Adaptive Forgetting Factors RLS) is also used along with PSO (Particle Swam Optimization) algorithms for better efficiency and accurate results in temperature and time variations of dataset in Battery models.

8. COMPARATIVE ANALYSIS

In Support Vector Regression (SVR) method, the quality and quantity are entirely based upon the data used in the training and uses a controller when there is a need of high performance to control the training data. Compared to the other methods, the results obtained in the SVR is of accurate and applicable for any systems. The main advantage of SVR is as the system results obtained are of accurate and hence the system is stable and efficient. It can also be used to solve the regression problems. The main disadvantage of using SVR algorithm is that it is difficult for humans to understand the code and it takes long training time. In Feed Forward Neural Network (FNN) Algorithm, mathematical relationships are used for the algorithm with some input features to dynamics of battery such that SOH Estimation can be done in an accurate manner and rule used in FNN is of back propagation learning. The equations used in FNN are of mapping function where some function can be almost approximated to other functions. The main advantages of using FNN are the computation required to analyze the mathematical relations is less, so this type of algorithm is beneficial.

As large equations are being used, overfitting problem exists as to store the data of large number of parameters. In Recurrent Neural Network (RNN) Algorithm, the main input to be considered are current, temperature, voltage and output used to determine the application of SOH in functions of temperature in BMS applications [33]. The main advantage of using RNN Algorithm is information can also be easily stored in functions of time which is easy task and memory requirement is less. The pixel quality is effective and time series can be easily predicted. The disadvantage of this RNN algorithm is to train the RNN task and sometimes long sequences such as tanh function cannot be processed easily and gradient problems usually occur for this type of algorithm. In case of Particle Swarm Optimization (PSO) Algorithm the principle is based on the latest technology and its applications are still being in research for Electric Vehicles and Plug-in hybrid Electric vehicles. It makes use of Swarm Intelligence where parameters control can be done using simple concept and efficiency of computation compared to other algorithms is found to be extremely good and effective. This PSO algorithm can be easily implemented for different and various systems so that the over fitting problem can be overcome by this algorithm.

The main disadvantage of this algorithm is that it provides solution of some techniques which is of low quality and each time when the program is updated, memory updating has to be done which is time consuming and tedious process or task.

Table 1 COMPARISON OF EXPERIMENTAL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Internal Resistance measurements [34]	• Simple to implement and direct method to under-stand. • Less complexity and high level of accuracy.	• Estimation through online cannot be made. • Time consuming and tedious task.
Internal Impedance Measurements	• High accuracy and simplicity. • Reliable and degradation of the battery methods can be easily understood.	• Battery degradation and discharges is difficult to analyze.
ICA/DVA and Capacity Level [35]	• This technique is much faster than other methods. • It is fast to analyze and provides high level of accuracy.	• Sometimes this method is not reliable and feasible. • Operating conditions of the battery is difficult to analyze when fully charged.

Table 2 COMPARISON OF MODEL BASED METHODS.

Methods	**Advantages**	**Disadvantages**
Kalman FilterBased (KF) methods	• Simple to understand and accurate to interpret theoutput • It is bounded to errors	• For advanced systems and versions system is complex. • A controller of high performance is required and not valid for nonlinear systems [39].
Electrochemical models	• High accuracy and reliable • The battery degradation phenomenon can be understood and predicted easily.	• The computational level of high-performance con- troller is required [40]. • Structure of the battery is difficult to analyze.
Least Square Based methods	• This Technique is much precise and robust than other techniques. • The structure is easy to analyze.	• The model is mostly concentrated on accuracy and high-level performance controller is required [41].

Table 3 COMPARISON OF MACHINE LEARNING BASED METHODS [36].

Parameters	**Support Vector Regression Algorithm**	**Feed Forward Neural Network Algorithm**	**Recurrent neural network (RNN) Algorithm**	**Particle Swarm Optimization (PSO) Algorithm [37]**
INPUT	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), T(t), SOC(t), R/C(t)	I(t), V(t), T(t)
OUTPUT	SOH(t)	SOH(t)	SOH(t)	SOH(t)
FUNCTION	Regression and Classification Hyperplane Equation	Supervised Learning, Sigmoid function, Mapping of function to approximate value	Non-Linear, Auto-Regressive Network, Time Series Based Function	Swarm Intelligence, Randomized, Population Based Optimization Method
EQUATION	y=wx+b(Hyperplane) Condition: $-a > y-wx+b < a$	f(x)=yf(x) for all (x,y)	Current state equation: $h_t=f(h_{t-1}, x_t)$ Output equation: $y_t=W_{hy}h_t$ Activation Function: $h_t=\tanh(W_{hh}h_{t-1}+W_{xh}x_t)$	$x_i^{k+1}= x_i^{k}+ v_i^{k+1}$
ADVANTAGES	• Overfitting can be prevented as it has good regularization capabilities. • Using Kernel function, it handles non-linear data efficiently • Stable and Efficient. • Can be used to solve both classification and regression.	• Easy to setup. • Less computation. • Complex and Non- linear systems can be analyzed.	• Easy information is stored accordingly with time. • It is good for effective pixel extension. • Helps in prediction of time series.	• Simple concept. • Easy implementation. • Robustness to control parameters • High computational Efficiency.

LIMITATIONS	• The difficult task is to choose an appropriate Kernel function. • For large datasets, it takes long training time [38]. • It is difficult to understand the algorithm or models of SVR for humans.	• There exists Vanishing and Exploding Gradient problem. • Large model size. • There exists Overfitting of large number of parameters.	• Gradient Vanishing and problems are exploding. • It is difficult to train an RNN task. • As tanh function is used for activation function, it cannot process long sequences.	• Low convergence rate in iterative process. • Memory updating required and falls under local search. • Low quality solution.

Table 4 COMPARISON OF SOH ESTIMATION METHODS.

Methods	Advantages	Disadvantages
Experimental Based methods	• Simple to understand and accuracy is more. • Computational level is low	• Time consuming. • The measurements and the equipment to be used should be specific [42].
Machine Learning methods	• High accuracy and reliable compared to other two methods. • Easy to implement and process can be carried out easily.	• The computational level is difficult to understand and depends more on the training data [43]. • Sometimes the algorithms are difficult to under- stand for humans.
Model Basedmethods	• A simple structure is required to analyze the training data and easy to implement. • Accuracy level is high and robust estimation of battery parameters can be done.	• The model is mostly concentrated on accuracy levels of training data and pre-experimental setup is required. • The development process of the battery is time consuming and rely more on computational time.

9. CONCLUSION

As Electric vehicles are tremendously growing in recent technologies, BMS (Battery Management System) plays an important role in monitoring and controlling the various applications of Battery. This paper briefs about the different computational efficiency and the current technologies used in BMS. With respect to SOH, various techniques have been implemented for better performance. The objective, uncertainties, accuracy and efficiency has been discussed in this paper. Regarding SOH techniques, various algorithms have been used along with recent technologies of Machine Learning. It discusses about different algorithm advantages, limitations, standard equations along with the technology being implemented with a comparison structure. In brief, BMS and its applications, SOH with its techniques, Intelligent Algorithms have been highlighted in terms of input and output features. This paper has highlighted the real time applications with respect to EV and HEV with Lithium-ion batteries, Fuel cells, Lead acid batteries etc. Some model-based methods using different algorithms and techniques for the SOH estimation methods are key concerns. Overall, battery parameters with respect to EV model accuracy, adaptability, compatibility with best estimation methods for real time identifications and their applications summarized in a brief manner.

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An Energy-Competent Enhanced Memetic Artificial Bee Colony-Based Optimization in WSN

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An Energy-Competent Enhanced Memetic Artificial Bee Colony-Based Optimization in WSN

S. Sowndeswari and E. Kavitha

Abstract Wireless sensor networks (WSNs) are a significant technology for the twenty-first century because of its wide range of applications in various fields. Energy consumption and network security are the major challenges among other challenges in WSN because of existence of various hard problems in wireless sensor networks. Those hard problems cause the reduction of energy in each node of the network and also cause security threat which in turn decreases the packet delivery ratio and lifetime of the entire network. Some of the hard problems include routing, clustering, localization of the nodes, etc. These hard problems cannot be best solved using deterministic methods. Optimization methods are the best alternate to deterministic methods to address the hard problems in WSN. Mostly, the research involves multiple objectives which can be achieved by metaheuristic algorithms. Population-based metaheuristic algorithm is preferred than single solution-based metaheuristic algorithm because of its wide exploration to find the new good solution. In this research work, an energy-competent clustering and secure routing algorithm is proposed using artificial bee colony (ABC) metaheuristics with memetic technique which achieves the desired performance, and the results can be simulated using NS2/MATLAB.

Keywords Wireless sensor networks · Energy consumption · Hard problems · Optimization · Metaheuristics · Memetic · Secure routing · ABC algorithm

Introduction

A wireless sensor network (WSN) is an infrastructure less network does not possess static topology because of random movement of sensor nodes. Unpredictability in topology is caused by a simple change in node position. These sensor nodes can

S. Sowndeswari
Department of ECE, Sambhram Institute of Technology, Sir M VIT, Bengaluru, India

E. Kavitha (✉)
Department of Electronics and Telecommunication Engineering, Sir M Visveswaraya Institute of Technology, Bengaluru, India

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detect, process, and transfer data to the next node until the sink node is reached. The WSN sensor nodes are considerably cheap compared to MANET networks and require much less maintenance once they are deployed as a network in a big geographic area. In case of failure of single node, the entire network will not be functional.

Maintaining energy consumption by the nodes is a biggest challenge and ongoing global research problem in wireless sensor nodes due to limitations in memory, computation, processing, and power [1]. As wireless sensor network is used for wide range of applications mainly for continuous monitoring, controlling the energy usage is a herculean task. Different techniques involved in controlling energy consumption include keeping the radio transceiver in sleep mode in the absence of data, using structure-based hierarchical routing protocol because of good scalability, proper routing, efficient communication etc., Hierarchical routing protocols use a two-layer approach, with one layer used for sensing and the other for efficient routing. Because of its high scalability and efficient communication with low energy consumption, the cluster-based hierarchical routing protocol is preferred over the grid-based approach [2] (Fig. 1).

Wireless sensor network consists of several nodes ranging from few to several millions of nodes, and clustering of such millions of nodes and identifying the best path between the nodes or route is a toughest task. Clustering and identifying best available path for data transfer are the major requirements in wireless sensor network to decrease the energy consumption and increase the packet delivery ratio. Thus, the overall network lifetime is improved, and suspicious nodes can be avoided in data transfer. Compared to conventional clustering algorithms, an improved clustering based on population-based optimization technique is required to achieve the enhanced performance of the wireless sensor network. One such technique is an enhanced memetic artificial bee colony optimization technique which is a population-based metaheuristic approach for obtaining optimization in wireless sensor networks.

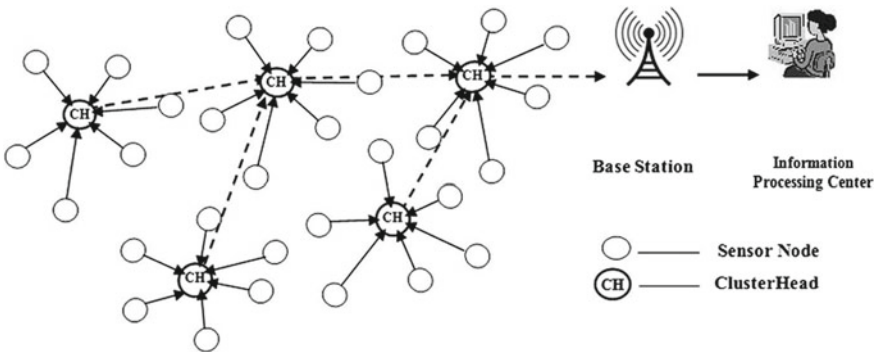

Fig. 1 Clustering in wireless sensor network

Related Works

Ant colony optimization (ACO) is swarm intelligence-based routing algorithm based on behavior of foraging behavior of ant colonies to solve the hard problems in wireless sensor networks [3]. Pareto multi-objective optimization strategy is included in conventional ACO to solve the security issues and issues related to limited resources. In multi-objective ACO algorithm, only two objectives are considered, and constraints such as maximizing network reliability and reducing failure rate of the network are not considered [4]. ACO uses pheromone concentration for finding the shortest feasible path in wireless sensor networks for the fastest packet transmission. This optimization provides reliable packet transmission and faster convergence but fails to consider the energy optimization.

Particle swarm optimization (PCO) [4] uses particle position and velocity for finding the optimal path which helps in faster packet transmission and convergence. This optimization considers the energy parameter of each sensor node, thus provides better energy optimization compared to ACO. In PCO, the number of hops is larger which causes network overhead. PCO works well when combined with other techniques.

Artificial bee colony (ABC) algorithm [4, 5] uses nectar amount to find the shortest path for packet transmission in wireless sensor networks by considering the energy parameter of the sensor nodes. The ABC algorithm achieves energy optimization but fails to meet the faster convergence rate [6]. ABC algorithm can be used to solve the complex problems in day-to-day life. But ABC algorithm attempts premature convergence and achieves slow convergence rate in wireless sensor networks. In order to overcome this, limitation of conventional ABC algorithm, memetic search is used with conventional ABC algorithm to explore the large search space. Thus, the premature convergence is reduced and faster convergence is achieved by using memetic search process.

Background

Memetic Algorithm

It is a problem-specific local search evolutionary algorithm that balances algorithm exploration and exploitation to improve quality. To limit the likelihood of premature convergence, the algorithm employs a local search approach [7]. In a memetic algorithm (MA), the fitness function is a function that takes a potential solution to the problem as an input and outputs how fit the answer is to the problem. To reach better milestone in finding solutions, memetic computation (MC) is evolved from memetic algorithms. Memetic computation uses a combination of memes which indicates group of information encrypted in complex structures which further interacts with each other for solving the problem.

Artificial Bee Colony Algorithm

In artificial bee colony (ABC) approach, each food source indicates viable path between the source node and sink node. Location of food sources are altered by artificial bees from colonies. Each colony is proficient of flourishing an intelligence which can be used for seeking the food. The food seeking operation [8] is divided into three major parts: employed food seekers for creating new food sources, onlooker food seekers for renewing the food sources depending on the nectar quantity, and scout food seekers for locating the new food sources in place of rejected food sources. In ABC, stair size is a combination of arbitrary number φ_{ij}, present solution and arbitrarily selected solution. The stair size decides the quality of the upgraded solution. If stair size is too big, the upgraded solution transcends the true solution, and if stair size is too small, then convergence rate of ABC may decrease significantly. Therefore, incorporating the memetic computation into standard ABC averts the situation of transcending the true solution while simultaneously maintaining the convergence speed.

Proposed Enhanced Memetic Artificial Bee Colony (EMABC) Algorithm

In enhanced memetic artificial bee colony (EMABC) algorithm, a safe cluster-based routing is developed for improving the performances of the WSN. This research comprises three stages such as clustering, secure cluster head (CH) selection, and secure routing path generation. Initially, the K-means clustering algorithm is used to divide the network into clusters. Subsequently, the near optimal secure CH is selected by using the enhanced memetic artificial bee colony (EMABC) algorithm. The originality in EMABC algorithm is considering all the four different fitness values such as trust value of the nodes, residual energy, distance, and node degree. The trust value contemplation in the EMABC is used to avert the black hole attacks during the CH selection. The black hole assault is contemplated as one of the wide active attacks which devalues the performance and reliability of the network as a result of dropping all incoming packets by the malevolent node. Moreover, this EMABC algorithm is used to generate the secure routing path between the source and destination nodes. Similar to the ad-hoc on-demand distance vector (AODV), the EMABC routing uses the route request and route reply messages to generate the routing path. In the route discovery process, the source node telecasts the route request messages to the neighbor nodes. Then, the node which has better fitness transmits the route reply message to the source node. Likewise, the secure data transmission path is generated amid the source and destination nodes. After identifying the transmission path, the data packets are sent to the destination node. This research considers all

the four optimal fitness values, and performance is achieved using EMABC algorithm. Hence, the performance of enhanced memetic artificial bee colony (EMABC) algorithm is better than any other population-based heuristic algorithms.

Steps of Enhanced Memetic Artificial Bee Colony Algorithm

The original artificial bee colony algorithm works in three different stages such as employed food seekers, onlooker food seekers, and scout food seekers. Food availability is found out by only one employed food seekers. Using this information, onlooker food seekers makes a decision that which food source to visit. When availability of food is drained, then the unused food seekers become scout food seekers. In this working protocol, every food source represents one of the N feasible paths between each pair of nodes in wireless sensor networks. The location of a food source indicates possible solution for routing, and the nectar quantity of a food source is comparable to the strength of correlated solution measured by a fitness function. And each node stores two information in the neighbor table, first one is total time required for a packet to reach the next node, and second one is unused node energy. In order to get the accurate path in the search process, a local search space should be improved which is lagging in original ABC algorithm. Thus, by incorporating memetic computation [9] into original ABC algorithm, local search space is improvised which is done by adding one extra step to original ABC algorithm.

EMABC is population-based algorithm of size N where the candidate solutions a_i are vectors of M design variables within a decision space S. The initial population is generated randomly as follows:

$$a_{i,j} = \text{rand}(0, 1).(u_b - l_b) + l_b \text{ for } \quad j = 1, 2 \ldots M \tag{1}$$

where rand(0,1) generates a random value between 0 and 1, l_b, u_b represents lower and upper bounds of candidate solution a_i.

The exploration tasks in EMABC is given as follows:

1. Stochastic long distance type (comparable to employed food seekers in ABC)
2. Stochastic moderate distance type (comparable to onlooker food seekers in ABC)
3. Deterministic long distance type
4. Random long distance type (comparable to scout food seekers in ABC).

A. Stochastic long distance type

To get a trial solution, three operations such as mutation, crossover, and selection are performed on each of the candidate solution a_i. Mutation operation is performed as the first step to produce the trial solutions which can be calculated using the Eq. (2)

$$u_i^{(t)} = a_{r_1}^{(t)} + \left(a_{r_2}^{(t)} - a_{r_3}^{(t)}\right) \tag{2}$$

where $a_{r_1}^{(t)}$, $a_{r_2}^{(t)}$, $a_{r_3}^{(t)}$ are randomly picked candidate solutions, t is iteration number.

The number of modifications permitted to the trial solution is calculated using Eq. (3) which comes under crossover operation.

$$v_{i,j}^{(t)} = \left\{ \begin{array}{l} u_{i,j}^{(t)} \text{ if}\big(\text{rand}_j(0,1) \leq CR || j == j_{r4}\big), \\ a_{i,j}^{(t)} \text{ otherwise} \end{array} \right\} \tag{3}$$

where CR is crossover probability and j_{r4} is random dimension in trial solution.

The supreme solution between candidate and trial solution is calculated using Eq. (4)

$$a_i^{(t+1)'} = \left\{ \begin{array}{l} v_i^{(t)} \text{ if f}(v_i^{(t)}) \leq f(a_i^{(t)}) \\ a_{i,j}^{(t)} \text{ otherwise} \end{array} \right\} \tag{4}$$

where f represents the fitness function.

As this exploration is similar to employed food seekers in conventional ABC, a supreme solution is obtained using the fitness function. After the entire employed bee finishes the search process, they share that information to onlooker food seekers.

B. Stochastic moderate distance type

This exploration is similar to onlooker food seekers in conventional ABC, and the operations in obtaining the trial solution involve mutation, crossover, and selection which is similar to stochastic long distance type using Eq. (5)

$$u_i^{(t)} = a_i^{(t)} + \left(a_{\text{sup}}^{(t)} - a_i^{(t)}\right) + \left(a_{r_1}^{(t)} - a_{r_2}^{(t)}\right) \tag{5}$$

where $a_{\text{sup}}^{(t)}$ represents the supreme solution.

The crossover and selection operations are performed using Eq. (3) & (4)

At the end of this stage, best food path is obtained based on the quality of the nectar amount calculated by the onlooker food seekers.

III. Deterministic short distance type

This exploration tries to bring the candidate solution into local optima which are mainly concerned for maintaining the diversity and averting the situation of transcending the true solution. The success of any optimization algorithm depends on maintaining the diversity. The fitness on diversity can be expressed as

$$\varphi = 1 - \left| \frac{f_{\text{avg}} - f_{\text{bst}}}{f_{\text{wrst}} - f_{\text{bst}}} \right| \tag{6}$$

where f_{avg}, f_{bst}, and f_{wrst} are the average, best, and worst fitness values of food paths in the population.

IV. Random long distance type

When the food source is depleted, the food seekers become scouts, and the search process is repeated as described above in three different exploration tasks.

EMABC Algorithm

Step 1: Initial population is randomly created using Eq. (1)
Step 2: For each employed food seeker, the supreme solution is obtained using three operations such as crossover, mutation, and selection.
Step 3: Each onlooker food seeker updates the solution using the same three operations mentioned in step 2, and best solution is obtained using the nectar amount.
Step 4: Local search space is obtained by maintaining the diversity based on fitness function using the Eq. (6).
Step 5: In place of abandoned food sources, scout food seekers discovers the new food sources using the step 2, and best solution is obtained using step 3.
Step 6: The best solution or best food source so far found is memorized.

Experimentation and Result Analysis

The simulations are accomplished in ns 2.34 platform and organized in a square area of 1200 m × 1200 m with 100 sensor nodes which are deployed randomly. The simulation is executed to show the energy expenditure of the nodes using EMABC algorithm by changing the number of black hole nodes in each simulation step. The proposed algorithm EMABC achieves good performance than other population-based heuristic algorithms in terms of reduced energy consumption (Fig. 2 and Table 1).

The below figure shows the xgraph of black hole nodes versus the energy consumption. The energy consumption of the nodes is less in the proposed algorithm compared to the conventional population-based algorithms. The simulation is repeated by changing the number of black hole nodes while keeping the number of deployed nodes constant (Fig. 3).

The below figure shows the xgraph of black hole nodes versus routing load. The routing load is considerably less in the proposed algorithm compared to the conventional population-based algorithms. The simulation is repeated by changing the number of black hole nodes while keeping the number of deployed nodes constant (Table 2).

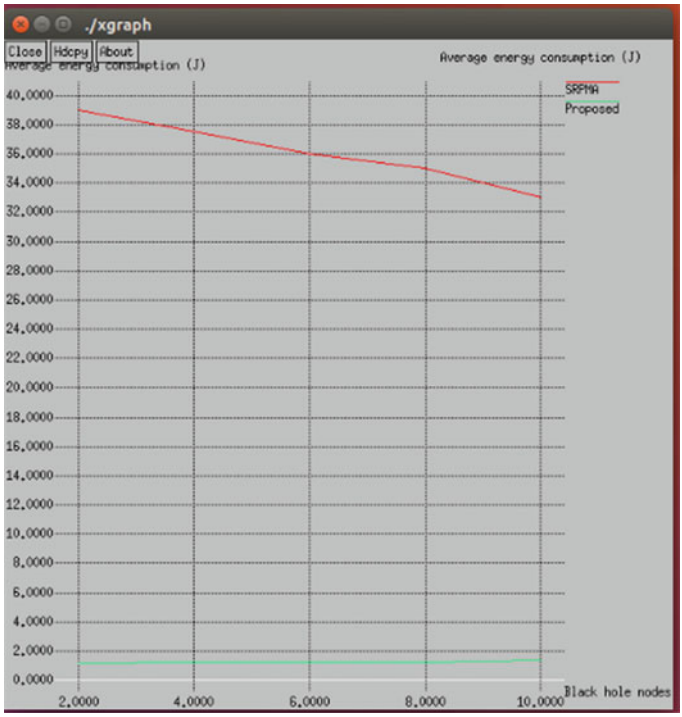

Fig. 2 Energy expenditure versus black hole nodes

Table 1 Simulation settings and parameters

Parameters	Values
Wireless propagation model	Two ray ground
MAC protocol	Mac/802.11
Network interface	WirelessPhy
Antenna	OmniAntenna
Queue	DropTail/PriQueue
Routing	AODV
Topography	1200 m x 1200 m
Initial energy	50 J
Number of nodes	100
Interface queue length	100
Simulation time	100 s

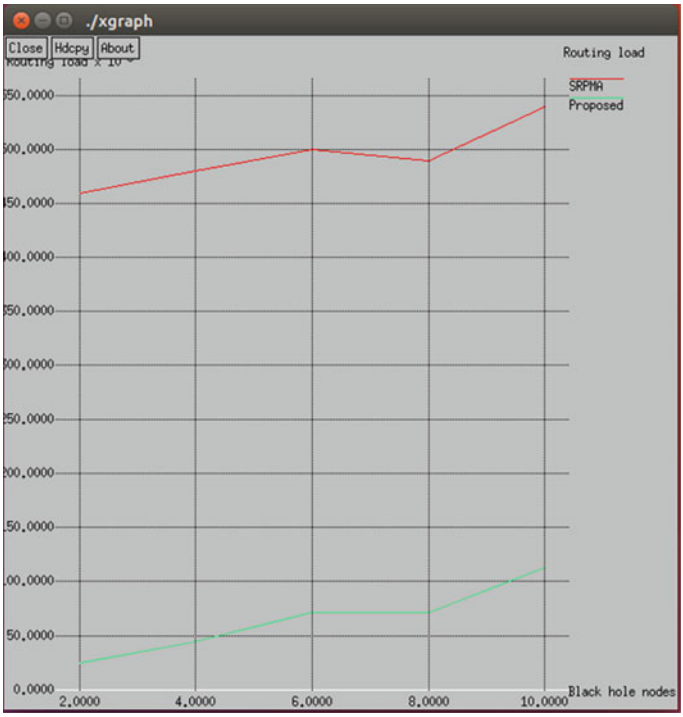

Fig. 3 Routing load versus black hole nodes

Table 2 Routing load, total energy consumption, and number of packets sent and received in the presence of different number of black hole nodes

Black hole nodes	No. of packets sent	No. of packets received	Total energy consumption	Routing load
2	392	388	1.1359	0.0242784
4	392	386	1.23102	0.0447927
6	392	384	1.19998	0.07125
8	392	384	1.19998	0.07125
10	392	377	1.35849	0.112626

Number of nodes deployed = 100

Conclusion

This research work uses memetic computation with existing artificial bee colony algorithm to give the solution to energy constraints in WSN. The proposed algorithm EMABC explores large search space by using memetic search to reduce premature convergence and improves the faster convergence rate. Thus, the algorithm proves

better performance in view of achieving one of the fitness functions in this research such as reduced energy consumption than the other popular population-based algorithms. Future work includes the achievement of other fitness functions such as trust value, distance, and node degree.

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Linkdb-TCP: A Congestion Control Technique For MANET Based On Link Layer Measurements.

Dr Sreenivasa B.C
Associate Professor
Department of Computer Science and Engineering
Sir M Visvesvaraya Institute of Technology,
Bangalore, INDIA
Email: srinivasa_cs@sirmvit.edu

Dr.G. C. Bhanu Prakash
Professor and Head
Department of Computer Science and Engineering,
Sir M Visvesvaraya Institute of Technology,
Bangalore, INDIA
Email: banuprakash_cs@sirmvit.edu

***Abstract*—Detection and control of congestion in Mobile ad-hoc networks (MANET) is a challenging task. Congestion hurts performance and reduces the throughput of the system. Thus it is imperative to avoid or control congestion in the network. Congestion control algorithms provided by the Transmission Control Protocol (TCP) is specially designed for wired communication and performs poorly in the case of ad-hoc networks. This paper presents a Link-Layer Congestion control algorithm for MANETs, which detects congestion in the network by carrying out an end-to-end analysis. The congestion window is appropriately modified if congestion persists in the system. The new congestion window is communicated to the sender, and its behavior is altered accordingly. The algorithm can be seamlessly incorporated into TCP for practical use**

***Keywords*—** *Congestion, TCP, Ad-hoc*

I. INTRODUCTION

Mobile ad-hoc networks (MANETs) consist of devices that can communicate without a fixed infrastructure. Devices in MANETs are mobile and each act as routers to forward packets from the sender to the receiver. Ad-hoc networks use the IEEE 802.11 MAC standard. MANETs generally find applications in sensor networks, wireless mesh networks, security systems, etc.

An unreliable shared multi-hop channel and node mobility reduces the effectiveness of TCP congestion control in ad-hoc networks. Packets are delivered slowly and are often lost due to the unreliability of the channel of communication. TCP often misreads these packet losses as congestion and reacts erroneously. Congestion in wired networks is usually concentrated at the routers in the system. However, in MANETs, the congestion clogs the coverage area and doesn't necessarily affect the mobile nodes. The network conditions result in varying Transmission and Round Trip times, making it tough to detect packet losses. The nodes compete for the use of the shared medium in an ad-hoc network.

The devices in a MANET compete for the occupation of the shared medium. Routers receive a large number of packets and fail to process all of them, which results in packet loss and retransmission further clogging up the network resources. To avoid such a scenario, the source nodes of the network must modify their transmission rate to accommodate the overloaded routers.

In this paper, we present a technique that predicts the existence of congestion in the network by carrying out end-to-end analysis. Special packets containing node-wise data are sent through the network if there is a sustained period of congestion. The special packet data is used to modify sender behaviour to reduce congestion in the network. The system follows TCP protocol in the absence of congestion. Organization of this paper: Section 2 outlines previous contributions to congestion control algorithms. Section 3 explains the proposed algorithm; Section 4 describes the Results of the experiment. Section 5 discusses the algorithm in depth while Section 6 and 7 conclude the paper with Conclusion and Acknowledgement.

II. RELATED WORK

Congestion control detection and mitigation in MANETs is considerably more difficult when compared to wired networks. Congestion related issues like reduction of throughput and flow fairness also present a significant challenge. Solutions to these challenges are discussed at length in [2][3][4][5][6][7][8][9][10].

The IEEE 802.11 MAC protocol provides single-hop reliability. The Link Layer drops received packets only if the connection is lost or the packets collide. A wireless communication medium has a higher probability of dropping random packets when compared to a wired medium. The packet losses affect TCP functioning and can wrongly interpret the losses as congestion. This section describes the various solutions proposed to reduce congestion in the network.

III. LINK-LAYER DELAY BANDWIDTH (LINKDB) TECHNIQUE

Due to the widespread success of TCP as the transport protocol in wired Internet, it is used as a standard for other communication networks running on the Internet. However, as previously discussed, it is not suited for ad-hoc networks. In this section, we will be presenting an efficient algorithm for congestion control.

A. Concept

The LINKDB technique presented in this paper predicts the occurrence of congestion. This prediction triggers the collection of link capacity measurements, like delay, round-trip time, and bandwidth at the Link Layer. With the information gathered, we can accurately triangulate the node which bottlenecks the network. Appropriate changes made at the sender's side can reduce the congestion and deliver a stable network throughput. The prediction of congestion involves the following four steps:

- Analysis by Receiver
- Prediction of Congestion
- SRTT Calculation
- Modification of congestion window
- Analysis by Receiver

Usually, the bandwidth of client's internal network is less than its connectivity with the external network. Thus the traffic that comes from the Internet to the client may consume the entire bandwidth of the client's network. In communication, one of the roles of the receiver is providing

useful feedback. This role of the receiver is one of the primary motivations to entrust the burden of congestion prediction and analysis to the receiver. The sink of the network (i.e., the receiver) obtains information such as send-time from the packets sent by the sender. This information is then used to find out the delay in the network and make appropriate predictions.

One of the characteristics of congestion in a network is the delayed receiving of packets and reduced throughput. These properties are used as the barometer to predict congestion in this paper. The receiver must also be able to predict when the network has returned to normalcy, i.e., when the congestion is no longer present. If and when the congestion is detected, the receiver must inform the sender to send a LINKDB packet which contains the delay and throughput parameters of each intermediate node to carry out further analysis.

Acknowledgment packets (ACK) in a communication network inform the sender about the receipt of a message. The ACK can be used to send other useful information by piggy-backing the data onto the packet. In this system, the receiver communicates details to the sender by attaching data to the ACK. Information such as when to start and stop analysis, smoothened Round-Trip time, previous network throughput etc. are communicated by the receiver.

B. Prediction of Congestion

One of the fundamental challenges in real-time networks is to predict the existence of congestion. Once the network achieves equilibrium, it maintains the same level of throughput until connections are taken down. The introduction of congestion to this system reduces the throughput, thereby increasing the time it takes for the packet to reach the receiver. This delay is used to predict the existence of congestion in a real-time situation.

The receiver collects a delay history of ten consecutive packets and uses it to calculate the average delay over this interval. The average delay is taken after the arrival of every 10th packet and is compared with the previous ten packet delay. The difference in the average delays helps predict the congestion in the network. If a spike in average delay persists for at least 20 packets, the system is said to have congestion, and the receiver instructs the sender to send the LINKDB packet to carry out further analysis.

When congestion is no longer present in the network, the receiver must inform the sender to stop sending the LINKDB packet. The delay at the start of congestion is noted as a reference to check the existence of congestion. If the current average ten packet delay is approximately equal to the reference value, then the congestion is said to be no longer present. The degree of approximation depends upon the maximum capacity of the system.

When congestion is no longer present in the network, the receiver must inform the sender to stop sending the LINKDB packet. The delay at the start of congestion is noted as a reference to check the existence of congestion. If the current average ten packet delay is approximately equal to the reference value, then the congestion is said to be no longer present. The degree of approximation depends upon the maximum capacity of the system. The degree of approximation determines how slowly or quickly the system responds to change in average delays. A best-fit curve was used to get the relationship between the maximum capacity of the network and the approximation factor. The algorithm for predicting congestion is as given below:

Algorithm 1 Congestion Prediction

```
1:  if seq_no%10 = 0 then
2:      current_average = average delay of prev 10 packets
3:      difference = current_average - previous_average
4:      if delay_start ≠ 0 then
5:          check_diff = current_difference - delay_start
6:          if check_diff > threshold then
7:              flag = true
8:              start analysis
9:          end if
10:     end if
11:     if difference > threshold then
12:         delay_start = previous_average;
13:     end if
14:     if current_average ≈ delay_start and flag then
15:         flag = false
16:         delay_start = 0
17:         stop analysis
18:     end if
19: end if
```

In Algorithm 1, seq_no is the sequence number of the packet. Lines 11-13 signifies the start of congestion. Delay_start holds the average delay at the beginning of congestion. This value is initially set to 0 and only changes when the receiver speculates that there is a bottleneck in the network. Lines 4-9 confirm the existence of congestion in the system and communicate the same to the sender via a flag sent with the ACK. Lines 14-18 check if the network has no more congestion. If true, then the same is communicated to the sender via ACK.

C. SRTT Calculation

In communication, Round-Trip Time (RTT) is the amount of time between sending the packet and receiving an acknowledgment for the same packet. RTT can be used as an indicator of congestion in the network and control transmission parameters. During congestion, the variation in values of RTT is too high to be considered as a control parameter. Hence, this paper proposes the use of a ten packet RTT history to calculate a smoothed RTT that can be used to regulate transmission rates.

Smoothened RTT (SRTT) is an estimate of how RTT varied during the use of the ad-hoc network. A moving ten packet RTT history is used to estimate the SRTT value for the network. This value is updated for every packet considering the RTT values of the previous ten packets. This provides a rough idea of how the network was behaving in the time interval of transmission of ten packets. The significant variations in RTT during congestion is reduced and is reasonably stable. The algorithm used to calculate SRTT is as given below:

Table I: Definitions

Parameter	*Definition*
srtt_estimaten	**SRTT estimate for the nth packet**
RTTn	**RTT for the nth packet**

For the first ten packets, Algorithm 2 considers SRTT to be the RTT of those packets. The SRTT calculation begins when the acknowledgment for the 10th packet is received.

Subsequently, the SRTT calculations can be done by considering the SRTT value of the previous packet and RTT value of 10 packets ago, as shown in Line 4 of Algorithm 2.

Algorithm 2 SRTT calculation

1: **if** $seq\_no = 10$ **then**
2: $srtt\_estimate_{10}$ = average of RTT for previous 10 packets
3: **else**
4: $srtt\_estimate_n = srtt\_estimate_{n-1} + (RTT_n - RTT_{n-10})/10$
5: **end if**

D. Modification of Congestion Window

Congestion window (cwnd) is a state variable that limits the amount of data that can flow through the network. Naturally, the congestion window affects the network throughput. After the system reaches a steady state, the congestion window remains constant. Keeping the congestion window fixed during congestion can cause packet drops and retransmission, reducing network throughput. Hence, the congestion window must react to congestion in the network. The sender does the modification of cwnd. With this modification, the sender regulates the throughput of the system.

In this paper, cwnd modification is governed by SRTT value, packet size, transmission rate, and the value of cwnd for the previous packet. The congestion window modification is done if the receiver detects congestion in the network. If there is no congestion, the TCP protocol for modifying the congestion window is used. SRTT is used instead of RTT to reduce the variation caused in the congestion window sizes. This reduces the overall variation in throughput, and results in the steady functioning of the network under congestion.

IV. Results and Analysis

A. Simulation Parameters:

The experiments for the algorithm are carried out in the NS2 simulator. The network is composed of 5 nodes in string topology. The nodes are present in a 500m x 500m square grid, with two auxiliary nodes to introduce traffic. The IEEE 802.11 MAC is the standard used by all the nodes in the network. Default conditions according to the MAC protocol. The maximum bit rate between any two nodes is 2Mbps, and the maximum transmission range is 250m. The nodes are mobile with a maximum speed of 4 m/s. Dynamic Source Routing (DSR) is used as the routing protocol. Nodes 6 and 7 are used to introduce a 1Mbps Constant Bit Rate (CBR) traffic. Node 1 is the source of the network with Node 5 as the destination. The simulation is run for 50s.

B. Throughput Analysis

Fig 1 presents the results of the simulation. After the warmup phase, the network attains a stable throughput of 32Kbps. Due to the CBR cross traffic introduced at 15s, the performance drops to 20Kbps and remains within 5Kbps of this value during the congestion. The throughput picks up after the congestion subsides at 30s and returns to 32Kbps. After congestion is re-introduced at 35s, the throughput drops and remains so till 45s. The network recovers from the congestion and performance returns to 32Kbps.

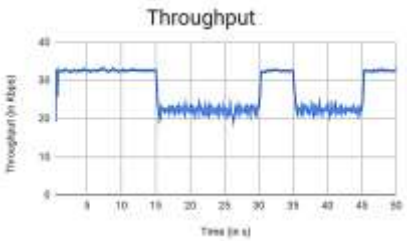

Fig. 1 Throughput Analysis

C. Congestion Window Analysis.

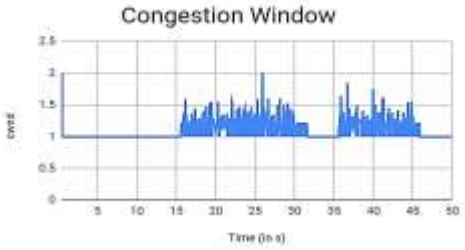

Fig. 2 Congestion window

Fig 2 depicts the variation of the congestion window during the simulation. Initially, the window size is set to 2, and almost immediately, the value drops to 1 and stagnates due to the low capacity of mobile ad-hoc networks. The link capacity is usually only a few Mbps and hence a high window size is not desirable. The window responds to congestion slightly after 15s. This time is spent by the receiver to confirm the congestion in the network. Similarly, the window's delayed response after congestion is removed can be attributed to the receiver confirming the same. Similar behavior is observed when the delay is re-introduced at 35s and removed at 45s.

D. RTT Analysis

Fig 3 shows the analysis of RTT for every packet sent by the sender. The RTT values show a small variation during the steady state of the network. When congestion is introduced the RTT value increases from 0.026ms to 0.06ms. For the duration of congestion, the RTT value shows a significant variation, which, as mentioned in this paper, cannot be used as a control parameter for cwnd. The RTT returns to 0.026ms after the congestion is removed. Similar results are observed when congestion restarts at 35s.

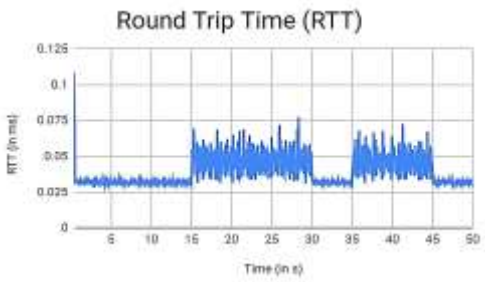

Fig. 3 RTT Analysis

E. Smoothened RTT Analysis

Fig 4 shows the SRTT values for all the packets sent. The SRTT values are stable at 0.026ms during the steady-state functioning of the network. At 15s, the SRTT value increases

to about 0.05ms, owing to the introduction of congestion. The following SRTT values show little variance, making it an ideal control parameter. The SRTT resets to 0.026ms after 30s. Similar trends are seen between 35s and 45s.

Fig. 4 Analysis of SRTT

F. Analysis at node N1

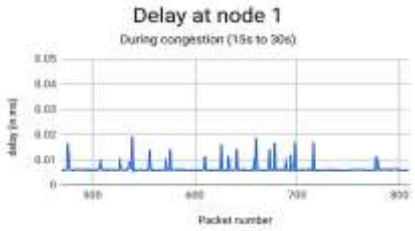

Fig. 5 Delay at node N1

Fig 5 and Fig 6 represent the analysis of packets at Node 1 during the first occurrence of congestion, i.e., between 15s to 30s. The spikes observed in delay measurements for LINKDB packets during this period is due to the CBR cross traffic. The spikes are negligible for this node and thus don't contribute to the bottleneck caused by the congestion. The variation in delay results in a corresponding variation in throughput. Similar graphs are obtained during the second occurrence of congestion between 35s and 45s.

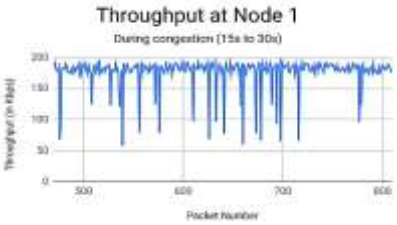

Fig. 6 Throughput at Node N1

G. Analysis at node N2

Fig 7 and Fig 8 denote the delay and throughput measurement for LINKDB packets between 15s to 30s. The delay measurements show a lot of variations with significant spikes. These measurements suggest that Node 2 is the cause of congestion in the network.

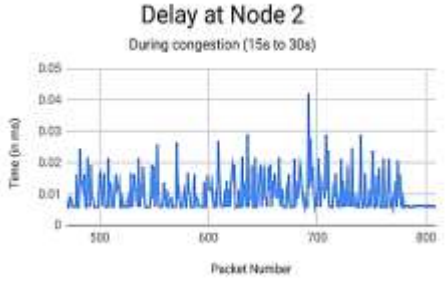

Fig.7 Delay at Node N2

The throughput measurements also suggest the same. The throughput drops below 50Kbps from a value of 200Kbps. Similar graphs are obtained between 35s and 45s during the second occurrence of congestion.

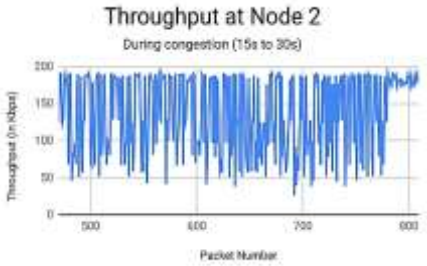

Fig. 8 Throughput at Node N2

H. Analysis at node N3

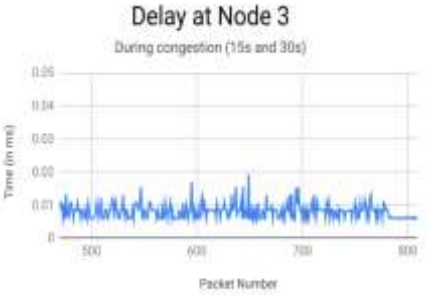

Fig. 9 Delay at Node N3

Fig.9 represents the delay experienced by the packets at node 3. The delay variation in node 3 is high due to the presence of large cross-traffic when compared to node 1. Fig. 10 depicts the bandwidth per packet at node 3 and bandwidth decrease when compared to node 1 due to the presence of large cross-traffic. Similar trends are obtained during 35s to 45s.

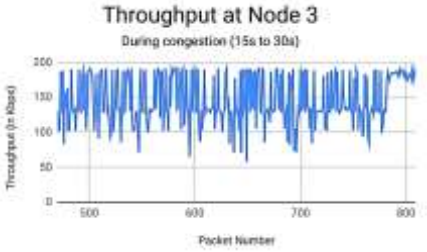

Fig. 10 Throughput at Node N3

I. Analysis at node N4

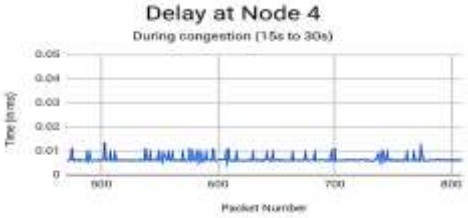

Fig. 11 Delay at Node N4

The plots of delay and throughput at node 4 resemble closely to that of Node 1, suggesting that the effect of cross-traffic is minimal. Fig 11 and Fig 12 present the readings for the duration between 15s to 30s. The variations in delay cause

relatively small spikes and do not affect the functioning of the network in a significant manner. Thus it can be concluded that Node 4 does not cause congestion. Similar plots are obtained between 35s to 45s.

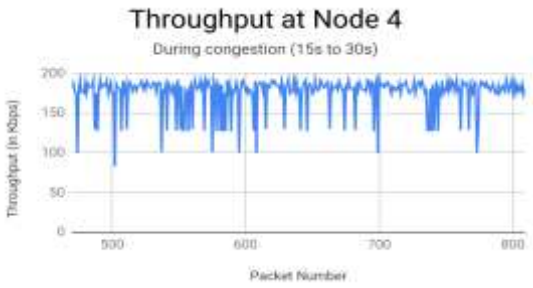

Fig. 12 Bandwidth at Node N4

V. Discussion and Conclusion

This paper, presented an efficient method to triangulate nodes that cause congestion in a network. The algorithm presented in this paper predicts the existence of congestion in the network by carrying out an analysis at every 10th packet. Once congestion is discovered by the receiver, an acknowledgment to send LINKDB packets to collect link parameters such as bandwidth and delay at each node. The energy expended to obtain this information is spent only if the receiver is sure about the existence of congestion. The system functions exactly like a TCP network in the absence of congestion. By sending LINKDB packets, useful data (i.e., the data needed to be transmitted) communicated reduces. The protocol works around this inconvenience by using LINKDB packets only during congestion. This feature ensures that the information will be delivered faster than a network with just LINKDB packets. This reduces the number of packets transmitted for a fixed size of data. The protocol is energy efficient with respect to the transmission of fixed size data through the link.

The algorithm also predicts the existence of congestion with a high degree of accuracy and timeliness. It is imperative for the receiver to detect and predict congestion in the network accurately and quickly. Delayed predictions cause packet losses due to large transmission rates while inaccurate predictions can waste network resources. To this effect, the receiver predicts that there is congestion in the network within 0.5s. This time can be reduced by taking a shorter history (say 5 or 8 packets). Sophisticated methods that involve machine learning can be used to predict far quickly, but it requires more substantial computational capabilities from the devices of the network. Mobile ad-hoc networks usually consist of low computation ability sensor nodes and thus, a machine learning approach is not suitable. Therefore a trade-off is made between timeliness and computation abilities. The algorithm also accurately predicts when the congestion has subsided in the network. The receiver recognizes the absence of congestion within 0.8s after the cross traffic has been removed. This prediction resets the network, and it returns to the steady state without incurring energy losses due to the transmission of extra LINKDB packets.

By varying parameters such as maximum bandwidth, initial congestion window sizes, congestion durations etc., the protocol is rigorously tested for real-time applications.

To conclude this technique is a method of efficient congestion control for MANETs is presented in this paper with rigorous experiments carried out in the NS2 simulator. The algorithm uses RTT history to predict congestion in the network and communicates the existence of congestion through the ACK packet. The sender then sends LINKDB packets to carry out in-depth analysis to calculate the optimal congestion window size for maximum throughput. The algorithm accurately and timely predicts the absence of congestion in the network to restore the normal function of TCP. The system adapts well to congestion and provides consistent throughput throughout its service.

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"STUDY OF BEHAVIOUR OF FLEXURAL AND SHEAR STRENGTH OF RC BEAM USING WELDED WIRE MESH"

Keshav G Yadav
UG student, Dept. of civil engineering
Sir. M Visvesvaraya Institute of Technology
Bengaluru, India
keshavyadav5204@gmail.com

Kiran Gowda G
UG student, Dept. of civil engineering
Sir. M Visvesvaraya Institute of Technology
Bengaluru,India
kirangowdag10@gmail.com

Harsha S
UG student, Dept. of civil engineering
Sir. M Visvesvaraya Institute of Technology
Bengaluru, India
harshasuresh342001@gmail.com

Madakasira Chinmaya Vikas
UG student, Dept. of civil engineering
Sir. M Visvesvaraya Institute of Technology
Bengaluru, India
mchinmayavikas@gmail.com

Dr. Ravi Kumar H
Assoc. Professor,
Dept. of civil engineering
Sir. M Visvesvaraya Institute of Technology
Bengaluru, India
ravikumar_cvl@sirmvit.edu

Abstract— **An alternative reinforcement system, Welded mesh is planned to achieve the purpose of stirrups in Reinforced Concrete Beams. Welded mesh reinforcement eliminates some of the detailing problems inherent in traditional rebar in the Reinforced Concrete Construction resulting in easier and faster construction, and better economy and quality control. The effects of welded wire mesh (WWM) used as shear reinforcement on the structural behaviour of reinforced concrete (RC) beams were experimentally investigate and to examine the flexural behaviour and crack pattern of RC beam. Totally five variations of beam were casted and number of mesh layers with percentage are varied in each specimen. The main test variables were spacings of longitudinal and transverse wires, two types of wire diameters and shear span to effective depth ratios. The tests showed that the degrees of improvement in the shear performance of the beams, such as shear strength and spacing of cracks, brought on by WWM were similar to those caused by vertical stirrups. It is obtained that the beam with continuous welded wire mesh and longitudinal bar given the maximum load carrying capacity and it is found that there is improvement in strength characteristics while using mesh layer when compared with control specimen.**

Keywords: Welded wire mesh, Flexural behaviour, Crack pattern, Maximum load carrying capacity

I. Introduction-

The development of reinforcement concrete structures was been largely employed under different methods and various situation based upon the conditions in engineering practice. Reinforcement concrete was been used in every place to withstand high strength to the building structures. As, renowned firms are involved in manufacturing and supplying a wide assortment of welded mesh, industrial wire products, welded wire products and other wire products. Our assortment includes welded wire mesh, mild steel wire, chain link fencing, barbed wire and galvanized wire. The use of welded wire mesh as the shear reinforcement in the flexural and shear behaviour. The welded wire mesh has a better characteristic strength and excellent bonding capacity it is formed from stainless steel that has extraordinary strength and reliability. The corrosion resistance meshed wire is long lasting. Because of its economy, ease and faster of construction as well as better quality control. Welded mesh has been widely used in bulldings that wired mesh can be a good substitute for the conventional reinforcement and yielded excellent results both in strength and ductility.

In the context of shear reinforcement, welded wire mesh is primarily used to resist the diagonal tension forces that occur in structural elements such as beams and slabs. These forces can cause the concrete to crack and potentially fail, compromising the structural integrity of the element. By incorporating welded wire mesh as shear reinforcement, the concrete's ability to resist these forces is significantly improved. The welds have strong mechanical anchorage behaviour at each the intersections are further responsible in imparting and immense deal of homogeneity to the R.C.C section as a whole. Welded wire mesh used for shear reinforcement typically has a square or rectangular grid pattern with evenly spaced wires. The wire diameter, spacing, and dimensions of the mesh are selected based on the design requirements and the specific structural application. The mesh is usually manufactured from high-strength steel wires, providing the necessary strength and durability to withstand the applied forces. Inadequate shear reinforcement causes shear failure. If the shear stress rides over the shear carrying capacity, the structures are possible to fail in brittle manner.

To overcome all above problems, Welded wire mesh is used as shear reinforcement. If we use closely spacing interlocks, the reinforced concrete member provides good ductility and bearing capacity.

II. LITERATURE REVIEW-

A. *EXPERIMENTAL AND ANALYTICAL INVESTIGATION OF RC BEAM WITH WELDED WIRE MESH AS SHEAR REINFORCEMENT-((05- May 2018) S GAYATRI, T Kirthiga)*

Experimental and analytical investigation of reinforced concrete beam with welded wire mesh as shear reinforcement in flexural and shear behaviour with different parameters.
Properties of fine aggregate, coarse aggregate and cement.
Compressive and tensile strength of concrete is found.
Deflection of the beams were measured.
Deflection of all the specimens capable of cracking and crushing by using ANSYS 16.0 Software. Solid 65 elements were used to model of concrete. LINK 180 elements were used to model of Steel.

B. FLEXURAL BEHAVIOUR OF RC BEAM WITH WELDED MESH AS SHEAR REINFORCEMENT (IJESRT) - (Ajin. M, H. Gokul Ram (March 2015))

It is obtained that the beam with continuous weld mesh gives the maximum load carrying capacity. Properties of fine aggregate, coarse aggregate and cement. After 7 and 28 days of curing compressive and tensile strength of concrete is found.

Load Deflection Behaviour: Load Vs deflection plot has been drawn for all test specimens from the experimental data. The behaviour of test specimens is compared.

C. STUDY ON SELF COMPACTING BEAM WITH WELDED WIRE MESH AS SHEAR REINFORCEMENT(IJCRT) - (Anila P.A., Anima P. (08-August))

This presents a study of shear behaviour of concrete beams using welded wire mesh.
Compressive Strength of Cube and Split Tensile strength of cylinder.
Load Deflection Behaviour:
Load Vs deflection plot has been drawn for all test specimens from the experimental data.
The rate of increase in the ductility index of a beam increases with increase in number of layers provided.

D. Behaviour of Reinforced concrete beams with wire mesh as shear reinforcement (IJITEE) - (Elavarasi D, Sumathi A (12-October))

This presents a study of shear behaviour of reinforced concrete beams. It is evident from the result that the use of wire mesh enhanced improved shear performance and bearing capacity in the examined beams.
Compressive and split tensile strength of concrete is found.
Load Deflection Behaviour:
The load vs displacement graph was drawn from the readings obtained from the testing of specimens.

E. Shear Strengthening of Reinforced Concrete Beam using Wire Mesh-Epoxy composite (C.E.J)- (Mustafa Al-Bazoon, Abdulkhaliq Jaffer, Haidar, Abbas Dawood (30 July 2022))

Load–deflection relationship, shear ductility index, beams' stiffness, energy absorption, were studied for all specimens and compared with those of the control beams to measure the improvement from WMEC addition.
After 7 and 28 days of curing compressive and tensile strength of concrete is found.
Load Deflection Behaviour:
Load Vs deflection plot has been drawn for all test specimens from the experimental data.
The behaviour of test specimens is compared.

III. METHODOLOGY-

Cement:
Ordinary Portland cement of grade 53 confirming to IS 12269-1987 will be used for the all the mixes.

Fine Aggregate:
M sand: Manufactured sand is a substitute of river sand for construction purposes.
- Sand produced from hard granite stone by crushing.
- The size of manufactured sand is less than 4.75mm.

Coarse Aggregate:
Locally available crushed granite aggregate, 12.5mm and down size will be used for all the mixes of SCC. The aggregates used for confirming to IS 383-1970.

Water:
Portable water fit for drinking will be used for making concrete.

Reinforcement:
(2-#10) in compression and (2-#12) in tension will be used.

Wire Mesh:
Stainless steel welded wire mesh of size 25mm*25mm of wire diameter of 3mm is used.
- These are available in steel, stainless steel and polymer varieties. It serves the same purpose as wire mesh; Enhancing concrete's flexural strength and preventing cracks.

Grade of concrete:
- M20 Grade concrete of 1:1.5:3 (Nominal mix) is used.

TESTS ON SPECIMENS-

6 Cubes of dimensions 150mmX150mmX150mm are casted for determining the compressive strength of concrete at 7 and 28 days.
6 Cylinders of dimension 150mm diameter and 300mm height for determining the indirect tensile strength at 7 and 28 days.
6 Beams of dimension 100mmX100mmX500mm for determining flexural strength by two-point loading at 7 and 28 days.

Different cases of beams-
- SP1- Fully conventional stirrups.
- SP2- Fully stirrup with weld mesh.
- SP3- From both the supports L/3 length of the specimen welded mesh and no stirrups for remaining length.
- SP4- From both the supports L/3 length of the specimen with double layer welded mesh and no stirrups for remaining length.

IV. TESTS ON CONSTITUENTS OF CONCRETE-

4.1 Tests on cement:

SPECIFIC GRAVITY OF CEMENT:

A 53 grade OPC from the local market is used and tested for the physical properties as per IS:4031-1988 conforming to specification as per IS:12269-1987.

Table 4.1.1. Specific Gravity Test on Cement

Sl. No	Description of mass	Results
1	Empty Bottle, W1	54 gms
2	W1+Water, W2	154.5 gms
3	W1+Kerosene, W3	134.5 gms
4	W3+Cement, W4	171 gms
5	Cement, W5	50 gms

Specific Gravity, S= W5 (W3-W1)/(W5+W3-W4) (W2-W1)
S= 50 (134.5-54)/(50+134.5-171) (154.5-54)
S= 3.15

NORMAL CONSISTENCY OF CEMENT:

Table 4.1.2. Normal Consistency of Cement

1	Percentage of Water	24%	28%	30%	32%	33%

2	Initial Reading	50	50	50	50	50
3	Final Reading	28	30	31	32	35
4	Height Penetrated (mm)	12	10	9	8	5

Normal Consistency of Cement = 33%

- FINENESS MODULUS OF CEMENT = 4 %
- INITIAL SETTING TIME OF CEMENT = 36 mins
- FINAL SETTING TIME OF CEMENT = 480 mins

4.2Tests on fine aggregate:

River Sand and Manufactured Sand are used as fine aggregates. The properties of F.A. like Specific Gravity, Fineness Modulus, Bulk Density are tested by using IS:2386-1963.

SPECIFIC GRAVITY OF FINE AGGREGATES:

Table 4.2.1. Specific Gravity of Fine Aggregates

	Description Of Mass	River sand (gms)	M-Sand (gms)
1	Weight of Empty Pycnometer, W1	442	442
2	W1 + 1/3rd Sand, W2	892	892
3	W2 + Water, W3	1528	1529
4	W1 + Water, W4	1248	1248

Specific Gravity, S= (W2-W1) / (W2-W1) - (W3-W4)
Specific Gravity of River Sand = (892-442) / (892-442) – (1528-1248)
Specific Gravity of River Sand = 2.65
Specific gravity of M-Sand = (892-442) / (892-442) – (1528-1248)
Specific Gravity of M-Sand = 2.66

4.3 Tests on coarse aggregate:

The size of the aggregate used was less than half an inch (12.5 mm). The tests are carried out as per the specifications of IS:2386-1963.

SPECIFIC GRAVITY OF COARSE AGGREGATES

Table 4.3.1. Specific Gravity of Coarse Aggregates

Sl. No.	Description of Mass	Values (gms)
1	Weight of Aggregates Suspended in Water with Basket, W1	2780.0
2	Weight of Basket in Water, W2	1488.5
3	Weight of Aggregates in Water (W1-W2) = Ws	1291.5
4	Weight of Surface Dry Aggregates in Air, W3	2001.5
5	Weight of Oven Dried Aggregates, W4	1988.0

Table 4.3.1. Specific Gravity of Coarse Aggregates

Specific Gravity of Coarse Aggregates = W4 / (W3-Ws)
Specific Gravity of Coarse Aggregates = 1988.0 / (2001.5-1291.5) = 2.8

Water Absorption = 100* (W3-W4)/W4 = 0.68 %

V. TESTS ON CONCRETE-

5.1 CALCULATION:

MATERIAL CALCULATION:

CONCRETE GRADE: M20 **MIX PROPTION: 1:1.5:3**
WATER CEMENT RATIO : 0.5

Compressive test (150*150*150mm)

Volume =3.375*10^-3 m^3
Cement =1/5.5*3.375*10^-3*2400*6 = 8.83 kg
Fine aggregate =1.5/5.5*3.375*10^-3*2400*6 = 13.25 kg
Coarse aggregate = 3/5.5*3.375*10^-3*2400*6 = 26.50 kg

Flexural test(500*100*100mm)

Volume =5*10^-3m^3
Cement =1/5.5*5*10^-3*2400 *6 = 13.09 kg
Fine aggregate =1.5/5.5*5*10^-3*2400 *6 = 19.63 kg
Coarse aggregate = 3/5.5*5*10^-3*2400 *6 = 39.27 kg

Split tensile test (Dia =150mm, L= 300mm)

Volume =5.30*10^-3m^3
Cement =1/5.5*5.30*10^-3*2400*6 =13.87 kg
Fine aggregate =1.5/5.5*5.30*10^-3*2400 *6 = 20.81 kg
Coarse aggregate = 3/5.5*5.30*10^-3*2400 *6 = 41.62 kg

Flexural test(700*150*150mm)

Volume =0.01575m^3
Cement =1/5.5*0.01575*2400 *6 = 41.23 kg
Fine aggregate =1.5/5.5*0.01575*2400 *6 = 61.85 kg
Coarse aggregate = 3/5.5*0.01575*2400 *6 = 123.70 kg

5.2 CASTING:

- After calculation of materials required for concrete 6 cubes, 6 cylinders, 6 beams are casted.
- Compressive strength, split tensile strength and flexural strength of concrete at 7 and 28 days are tested and the strength of concrete.

5.3 COMPRESSIVE, TENSILE, FLEXURAL STRENGTH:

- **Test done after 7 days of curing for specimens:**

Compressive strength of concrete = P/A
= (69*9.81*1000)/ (150*150)
=30.084 N/mm^2
Hence safe

Compressive strength of concrete = P/A
= (70*9.81*1000)/ (150*150)
=30.52 N/mm^2
Hence safe

Compressive strength of concrete = P/A
= (70*9.81*1000)/ (150*150)
=30.52 N/mm^2 Hence safe

- **Average Compressive strength**

= (30.084+30.52+30.52)/3= 30.37 N/mm^2

Tensile strength of concrete = (2*P)/(π*D*L)
= (2*22*1000*9.81)/(π*300*150)
=3.05 N/mm^2
Hence safe
Tensile strength of concrete = (2*P)/(π*D*L)
= (70*9.81*1000)/ (150*150)
=2.77 N/mm^2
Hence safe
Tensile strength of concrete = (2*P)/(π*D*L)
= (69*9.81*1000)/ (150*150)
=3.05 N/mm^2
Hence safe

- **Average tensile strength**

= (3.05+2.77+3.05)/3 =2.95 N/mm^2

Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (1.5*9.81*1000*500)/ (100*100^2)
= 7.35 N/mm^2
Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (1.6*9.81*1000*500)/ (100*100^2)
= 7.848 N/mm^2
Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (1.5*9.81*1000*500)/ (100*100^2)
= 7.35 N/mm^2

- **Average flexural strength**

= (7.35+7.848+7.35)/3 = 7.516 N/mm^2

Test done after 28 days of curing for specimens:

Compressive strength of concrete = P/A
= (104*9.81*1000)/(150*150)
=45.344 N/mm^2
Hence safe
Compressive strength of concrete = P/A
= (103*9.81*1000)/ (150*150)
=44.9 N/mm^2
Hence safe
Compressive strength of concrete = P/A
= (103*9.81*1000)/(150*150)
=44.9 N/mm^2
Hence safe

- **Average compressive strength**

= (45.344+44.9+44.9)/3= 45.048 N/mm^2

Tensile strength of concrete = (2*P)/(π*D*L)
= (2*29*1000*9.81)/(π*300*150)
=4.02 N/mm^2
Hence safe
Tensile strength of concrete = (2*P)/(π*D*L)
=(2*30*1000*9.81)/(π*300*150)
=4.16 N/mm^2
Hence safe
Tensile strength of concrete = (2*P)/(π*D*L)
=(2*30*1000*9.81)/(π*300*150)
=4.16 N/mm^2
Hence safe

- **Average tensile strength**

= (4.02+4.16+4.16)/3 =4.11 N/mm^2

Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (1.8*9.81*1000*500)/ (100*100^2)
= 8.829 N/mm^2
Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (1.9*9.81*1000*500)/ (100*100^2)
= 9.31 N/mm^2
Flexural strength of concrete = (P*L)/(B*D^2) (a>13.33cm)
= (2*9.81*1000*500)/ (100*100^2)
= 9.81 N/mm^2

Average flexural strength

= (8.829+9.31+9.81)/3 =9.31N/mm^2

VI. TESTS ON DIFFERENT CASES OF BEAMS:

6.1 CALCULATION:

Flexural test(700*150*150mm)

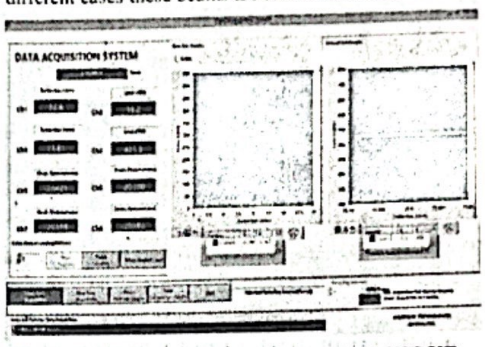
Volume	=0.01575m^3	
Cement	=1/5.5*0.01575*2400 *6	= 41.23 kg
Fine aggregate	=1.5/5.5*0.01575*2400 *6	= 61.85 kg
Coarse aggregate	= 3/5.5*0.01575*2400 *6	= 123.70 kg

6.2 CASTING:

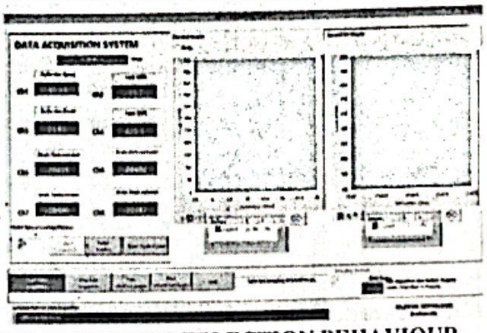
Beams with different cases of reinforcement are casted for determining the Load vs Deflection behaviour of beams.

6.3 TEST ON BEAMS:

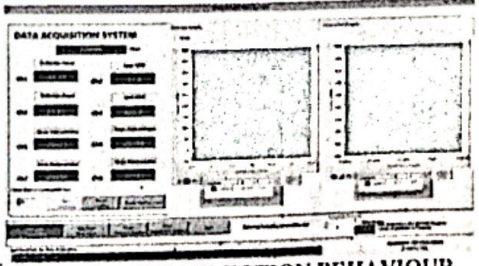
For determining the Load vs Deflection behaviour of beams with different cases these beams are tested under flexure.



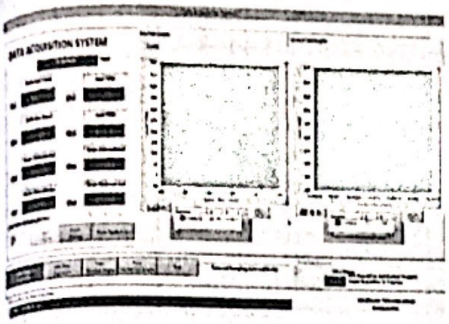
SP-1 LOAD VS DEFLECTION BEHAVIOUR



SP-2 LOAD VS DEFLECTION BEHAVIOUR



SP-3 LOAD VS DEFLECTION BEHAVIOUR



SP-4 LOAD VS DEFLECTION BEHAVIOUR

VII. RESULT-

- 7 days 28 days average compressive strength of concrete is 30.37 N/mm^2 and 45.048 N/mm^2.
- 7 days 28 days average tensile strength of concrete is 2.95 N/mm^2and 4.11 N/mm^2.
- 7 days 28 days average flexural strength of concrete is 7.516 N/mm^2 and 9.31 N/mm^2.
- 4 Beams of 700*150*150 mm are tested and results are as follows:
- Based on results of 4 specimens:

Load and deflection criteria were studied and based on the experimental results it was found that the fully welded mesh in comparison with other 3 cases the load taken by the specimen is more as well as the cracks developed it is seen that shear cracks are slowly developed with comparison with other 3 specimens and in this regard, it will be optimum to use fully welded mesh instead of conventional stirrups.

SL.NO	Different cases of beams	Ultimate load (KN)	Deflection (mm)
1	Fully conventional stirrups	533	9.8
2	Fully stirrup with welded mesh	534.7	18.17
3	From both the supports L/3 length of the specimen with welded mesh and no stirrups for remaining length	423.2	13.37
4	From both the supports L/3 length of the specimen with double welded mesh and no stirrups for remaining length	472.7	7.8

VIII. Conclusion-

1. The flexural strength of beam increases nominally and remains unaffected compared to that of control specimen for the fully welded mesh shear reinforcement provided throughout the length of the specimen.
2. Even though Shear Reinforcement was replaced with welded mesh there is no appreciable change in flexural load carrying capacity.
3. The load carrying capacity reduces in the case of specimen provided with very small volume of welded mesh shear reinforcement at the supports only.
4. In the mode of failure and crack pattern of the conventional RCC Beam specimen with welded mesh specimen are similar.
5. Failure mode and load carrying capacity depends on the volumetric ratio of welded mesh provided.
6. When the shear stirrups are completely replaced with welded mesh, when the welded mesh distribute throughout the span, behaviour of beam is better than other beam. Load vs deflection behaviour of this beam also better than other beams.
7. Out of the four specimens tested the specimens with the provision of fully welded mesh of grid configuration 25 x 25 mm exhibits better performance.
8. Since there is reduction in cost, the use if welded mesh is found to be a suitable alternative to conventional shear stirrups.
9. It reduces the workmanship of the bar bender as the welded mesh is easier to bind.
10. By reducing the number of stirrups and increasing the number of layers the ductility of the specimen can be made marginally more than the control specimen.

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ANNOCB1

ANTINEOPLASTIC EFFECTS OF *MUCUNA PRURIENS* AGAINST HUMAN COLORECTAL ADENOCARCINOMA

Sagar S[a], Rashmi K V [a]*, Vidya S M[b], Manjunatha B K[c]

[a]*Department of Biotechnology, Sir M Visvesvaraya Institute of Technology, Bengaluru – 562157, India*
[b]*Department of Biotechnology Engineering, NMAM Institute of Technology - Affiliated to NITTE (Deemed to be University), Nitte-574110, India*
[c]*Department of Biotechnology, Oxford College of Engineering, 10th Milestone, Hosur road, Bangalore-560068, India*
Email: rashmi_biotech@sirmvit.edu; rashmikvbt@gmail.com

Mucuna pruriens (MP) which is commonly called as Velvet bean is a familiar legume with medicinal and nutritional importance. This plant extracts have been proposed to have the antineoplastic effects on few cancer forms and useful for the management of several ailments. This investigation was designed to comparatively assess the anticancer and antioxidant effects two common varieties of MP, *Mucuna pruriens var. pruriens* (MPP) and *Mucuna pruriens var. utilis* (MPU) seed extracts against human colorectal cancer adenocarcinoma cells COLO-205. The highest antioxidant potential was recorded with MPP with a IC_{50} of 45.71µg/ml. The *in-vitro* anti-proliferative effects of MPP and MPU on COLO-205 showed an IC_{50} of 131.1µg/ml and 246.9µg/ml respectively. Our results revealed intervention of the MPP and MPU extracts in growth kinetics of the COLO-205 cells in concomitance with apoptosis induction up to 8.73 and 5.58 folds respectively. The AO/EtBr dual staining and the flow cytometry results also confirmed the better apoptotic efficacy of MPP over MPU. MPP at a concentration of 160µg/ml exhibited significant apoptosis and cell cycle arrest. Further, effect of the seed extracts on p53 expression was investigated by quantitative RT-PCR and a maximum upregulation of 1.12-fold was recorded with MPP.

Keywords: *Mucuna pruriens*, Velvet beans, Phytochemicals, Human colorectal carcinoma, Anticancer, Antioxidant, Flow cytometry, p53 gene, Apoptosis