Transient Stability Prediction in Multimachine System Using Data Mining Techniques

P.M. Devie, PG Student
Department of EEE,
Kamaraj College of Engineering and Technology,
Virudhunagar, India

Dr. S. Kalyani, HOD
Department of EEE,
Kamaraj College of Engineering and Technology,
Virudhunagar, India

Abstract

This paper utilizes Data Mining (DM) to be a promising tool for the accurate and quick assessment of transient stability in complex interconnected power systems. Commonly used input signals from phasor measurement units (PMU) of power system for transient stability prediction are rotor angle and speed of generators. Various data mining techniques used in this project work are Decision Tree (DT), Artificial Neural Networks (ANN), Extreme Learning Machine (ELM), and Support Vector Machine (SVM). Under various disturbances, the data samples are collected through sensors to distinguish between secure and insecure conditions of a system. The performance of the proposed DM techniques for online TSA is tested with benchmark test systems viz., Western System Coordinating Council (WSCC) 9 bus system and New England 39 bus system. Generator rotor angles during post fault condition are taken as predictors. The performance of the proposed DM techniques is tested when the system is subjected to various perturbations such as types of faults, fault locations, fault clearing times and system loading level. The simulation results are presented for different input attributes and output stability prediction.

Keywords—Decision Tree (DT), Transient Stability Assessment(TSA),Extreme Learning Machine(ELM),Support VectorMachine(SVM).

1. INTRODUCTION

With increasing loads, the existing power system becomes more and more stressed. When subjected to disturbances, the network tends to operate over the stability limit, depending on severity of the disturbance. Because of the occurrence of aleatory and epistemic uncertainties, the power system requires a more efficient methodology for the assessment of system stability, suitable for online implementation.

Various data mining methods like Decision Tree (DT) [7, 10, 11 & 13], Artificial Neural Network (ANN) [2, 8], and Support Vector Machine (SVM) [3, 5 & 6] has been proposed in recent works for on-line prediction of transient stability.

Out of step prediction can be done using DM techniques by considering different post-fault parameters as predictors, such as input power, acceleration, rotor angle, speed and apparent resistance along with its changing rate of R-R dot relay [4].

Moulin [6] generates a SVM model for the same network. The accuracy of transient stability prediction of the model however, is tested against factors such as type of fault, topology change and type of load, one at a time. Gomez [5], on the other hand, used six different contingencies to test its SVM model for the New England test system. The reported accuracies of these models can only demonstrate the robustness of the data mining models used to a certain extent, but cannot describe model's overall performance in the context of complex and uncertain network, and the reported accuracies of the models are not comparable to each other.

In this paper, the out of step prediction is carried out using generator rotor angle as a predictor variable when the system under concern is subjected to various perturbations. The necessary data and information needed for TSA for the system under study are generated by varying the system operating conditions and also by changing the fault conditions such as location of fault and fault clearing time. The simulation results have proven that maximum possible accuracy can be attained with DM classifiers. However, the proven accuracy can be neither comparable to each other under various disturbances nor describes the overall performance of tool for complex power systems. The performance of the proposed DM techniques for TSA is tested with benchmark systems namely WSCC 9 bus system and New England 39 bus system.

2. TRANSIENT STABILITY PREDICTION

Transient stability is the ability of power system to maintain its synchronism under severe fault such as three phase fault [1]. Time frame for TSA ranges from 3 to 5 sec and hence quick prediction should be performed with reasonable accuracy for taking proper corrective measures at san appropriate time. The transient stability of the generator depends on the factors namely, loading, fault location type of fault, generator reactance, generator inertia, generator internal voltage magnitude and infinite bus voltage magnitude.

Transient stability analysis of test systems is performed using classical model representation of the system. Classical model representation reduces the computational burden and the complexity of modelling [9]. The system dynamic behaviour appropriate to classical model is represented by Equations (1) and (2) given below:

$$\frac{H}{\pi f}\frac{d\omega}{dt} = P_m - P_e \quad (1)$$

$$\frac{d\delta}{dt} = \omega - \omega_S \quad (2)$$

Where

$$P_e = |E|^2 G + P_{\max} Sin(\delta - \gamma)$$

$P_{\max} = \frac{E' E_B}{X}$, maximum electrical power output in pu.

P_m – Mechanical power input in pu.

P_e – Electrical power output in pu.

ω – Angular frequency in radian per seconds.

H – Inertia constant in MW-s/MVA.

E' – Generator internal voltage magnitude in pu.

E_B – Infinite bus voltage magnitude in pu.

δ- Generator rotor angle in degrees.

f – System frequency in Hertz.

G, X – Line conductance & Reactance in pu.

A. Time Domain Simulation (TDS) Approach:

The most practical method of transient stability analysis is time-domain simulation in which the nonlinear differential equations are solved using step-by-step numerical integration techniques. The procedure for TSA using time domain simulation is:

1) Calculation of machine internal voltages and angles.
2) With the occurrence of fault, during fault & post fault reactance and electrical power output is calculated. In case of unsymmetrical faults, the fault reactance is obtained by computing positive, negative and zero sequence reactance for the appropriate fault period [1].
3) By solving the swing equation given by Equations (1) and (2) using 4th order Runge Kutta (RK) method [18], the post fault rotor angle and speed values are calculated at each time step.
4) Out of step condition of generator is predicted by inspecting the rotor angle difference of generators over regular time interval
5) Assessment of system condition as "secure" or "insecure" for varying operating and fault conditions is done based on out-of-step condition (pole slipping point), i.e., relative rotor angle exceeding 180 degrees.

Post-fault rotor angles are calculated using the above method for the prescribed test systems under various operating conditions. For these post-fault parameters, the status of stability whether it is secure or insecure are updated and samples are generated for data mining technique.

3. Data Mining (DM) For Transient Stability Prediction

A. Introduction to DM

Data mining is the process of encoding data, information, objects, etc., and representation of data in suitable form to take the appropriate decisions. DM model is a description of a specific aspect of a dataset. It produces output values for an assigned set of input values. The steps involved in the development of DM model are:

i) Data Pre processing:

Before the use of DM algorithms, a target data set must be assembled. Pre-processing is essential to analyze the multivariate data sets before data mining. The target set is cleaned to remove observations containing noise and uncertain data. In this work, the data samples are pre processed using min-max normalization technique which is the most commonly used one [4].

ii) Modeling of DM tool

iii) Performance Evaluation:

The performance of the DT classifier is validated by calculating the following performance measures for train set samples and test set samples separately.

Classification Accuracy (CA)

$$\text{CA}(\%) = \frac{\text{No. of samples classified correctly}}{\text{Total No. of samples in data set}} \times 100 \quad (3)$$

Misclassification (MC) Rate

a) Secure Misclassification (SMC) or False Dismissal

$$\text{SMC}(\%) = \frac{\text{No. of } 0's \text{ classified } as\, 1}{\text{Total No. of } Insecure\ States} \times 100 \quad (4)$$

(b) Insecure Misclassification (ISMC) or False Alarm

$$\text{ISMC}(\%) = \frac{\text{No. of } 1's \text{ classified } as\, 0}{\text{Total No. of } Secure\ states} \times 100 \quad (5)$$

In power system security evaluation, the false alarms do not bring any harm to power system operation. In case of false dismissals, system operation becomes unknown and hence failure of control actions may lead to a severe blackout. It is, therefore, important to ensure that false dismissals are kept at minimal. The classification system must be efficiently designed to meet this requirement [15].

TSA Algorithm:

The proposed algorithm consists of two parts: the first part includes the generation of training samples and the second part is to test the samples and the construction of Data Mining (DM) model. The steps involved in the above process of DM algorithm are:

Off-line Simulation:

1) Generation of data samples under various operating conditions by changing the fault clearing time, fault type, fault location and loading level for the test system under study.
2) Normalization of generated data samples in various attributed is performed using min-max normalization. Min-max normalization maps or transforms a value x_{old} in attribute A to a newly scaled value x_{new} as given by Equation (6).

$$X_{new} = \left[\frac{X_{old} - min_{old}}{max_{old} - min_{old}} * (max_{new} - max_{old})\right] + min_{new} \quad (6)$$

where min_{new} and max_{new} are the minimum and maximum values of the newly defined range. Normally, in many real problems, the data samples are linearly scaled to a binary range of $[min_{new}, max_{new}] = [0, 1]$.

3) Segregation of samples for training and testing from the state vector of generated samples.
4) Choose an appropriate data mining tool and initialize its learning parameters if any.
5) TRAINING PHASE
   (a) Train the samples so as to predict the status of stability as 'secure' or 'Insecure', based on the chosen data mining model.
   (b) Check for expected training accuracy and repeat the above step until the expected accuracy is achieved.
6) TESTING PHASE - Test the constructed and trained DM model by subjecting to unseen test samples.
7) Check for the overall classification accuracy and misclassifications.

On-line Simulation:

8) Once the training and testing process has been successfully completed, the data mining model that has been built is ready for online implementation. In online implementation, the values of selected attributes (fault location, fault clearing time, fault type and post fault rotor angle) for TSA are captured through phasor measurement units (PMU) and directly fed to the trained & validated DT model, which will directly access the transient stability status for the given operating condition without undergoing any mathematical calculations.

4. DM Techniques

A. Decision Tree

Decision tree (DT) is a type of classifier which can be applied to tasks of high dimensionality, commonly used in statistics. DT is one of the most commonly used techniques for any kind of prediction approach. In this paper, the input attributes used for DT model are post-fault generator rotor angle which are referred as 'predictors' and the classification output i.e., the status of stability is termed as 'target'.

The DT model for transient instability prediction can be performed as follows:

1) Collection of post fault attributes such as rotor angle, fault location, fault clearing time and loading level along with their status of stability after a transient disturbance.
2) Normalization of data samples using min – max normalization techniques by Equation (6).
3) Extraction of training (70%) and testing (30%) sample for validation of developed DT model.
4) Evaluation of DT model with satisfied accuracies in training and testing phase.

B. Artificial Neural Networks:

Neural networks are information processing systems, which are constructed and implemented to model the human brain. The objective is to develop a computational device for modeling the brain to perform various computational tasks at a faster rate than traditional systems. High speed digital computers are used to implement this model.

In this paper, Multilayer Feed Forward Neural Network (MLFFNN) with error back propagation learning was used. Sigmoid activation function is used for each neuron [20]. The architecture of developed neural network classifier consists of input layer, hidden layers and output layer as shown in Figure 1.

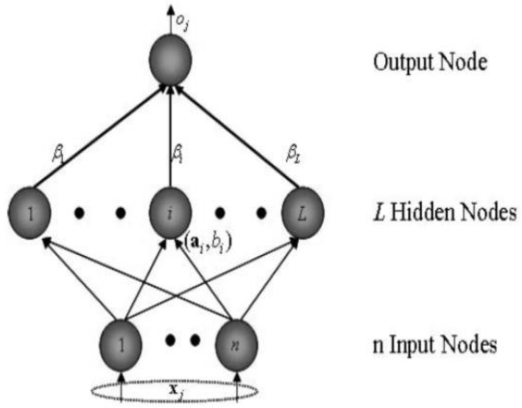

Fig.1 – Structure of feed forward neural network classifier

Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Figure shows a structure of neural network classifier in which 'n' denotes the number of input attributes which depends on the test system under concern and 'L' denotes the number of neurons used in hidden layer. For the test system under concern, n=3 with three post fault input attributes such as rotor angle, fault location and fault clearing time. For all test systems, n=30 with 30 neurons in the hidden layer. The output of network is constrained to 0(insecure) and 1(secure) using the sigmoid transfer function in output layer. The network can also be used as a general function approximator which can approximate any function with a finite number of discontinuities arbitrarily well, if sufficient neurons are given in the hidden layer. The detailed parameter setting of a neural network model is depicted in Table I.

TABLE I – PARAMETERS OF NEURAL NETWORK CLASSIFIER

Connections	MLFFNN
Learning	Supervised
Activation Function	Logsigmoid
No. Of hidden layer and Neurons	1 and 30
Training Algorithm	Trainlm

The three basic steps involved in developing a feed forward neural network classifier are:

1) Selection of suitable neural network architecture and learning algorithm.
2) Collection of state space vector containing post fault input attributes along with their stability status for transient instability prediction.
3) Training (70%) and Testing (30%) of input data samples using neural network classifier until the forecasted accuracies under training and testing phase is satisfactory.

C. Extreme Learning Machine (ELM):

It is clear that the learning speed of feed forward neural networks is in general far slower than required and it has been a major bottleneck in their applications for past decades. Two key reasons behind it may be: 1) the slow gradient based learning algorithms are extensively used to train neural networks, and 2) all the parameters of the networks are tuned iteratively by using such learning algorithms. ELM is a new algorithm which tends to provide the best generalization performance at extremely fast learning speed [16].

In this paper, the classifier type ELM is used for transient instability prediction with radial basis activation function. Twenty neurons are used in hidden layer for ELM model. The back propagation learning algorithm is chosen for feed forward neural network where gradients can be computed efficiently by propagation from the output to the input. The following steps are used to design an ELM classifier:

1) Selection of ELM architecture and learning algorithm.
2) Collection of post fault input data samples along with their security (secure / insecure) status for prediction of transient instability.
3) Data Preprocessing (Min-max normalization).
4) Extraction of training (70%) and testing (30%) samples from state space vector and writing (storing) the training & testing data samples in separate location to improve the learning speed.
5) TRAINING PHASE:

Given a training set, activation function, and the number of hidden nodes, the training phase involves basic three steps of processing as follows:

a) Assign randomly input weight vectors and hidden node bias.
b) Calculate the hidden layer output matrix.
c) Calculate the output weight

6) Training and testing of data samples by quick retrieval (reading) from specified location using ELM classifier with reasonable accuracies being maintained under training and testing phase.

D. Support Vector Machine:

The support vector machine (SVM) is a popular classification technique. A classification task usually involves separating data into training and testing sets [19]. Each instance in the training set contains one target value (i.e. the class labels) and several attributes (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given the unseen test data attributes.

In this paper, SVM classifier can be designed [17] using the following steps:

1) Data Preprocessing:

The input attributes are normalized using min-max normalization method and each attribute is scaled to the range of [0, 1].

2) Design of SVM model:

a) Choice of Kernel:

The radial basis function (RBF) kernel is used here because of its well known advantages such as improved accuracy, ability to handle linearly inseparable problems and has only one parameter (γ) with reduced model complexity.

b) Selection of SVM parameter:

Penalty parameter (C) and kernel parameter (γ) are the two parameters of SVM model with RBF kernel. Selection of SVM parameter can be performed using different techniques such as Grid Search (GS), Particle Swarm Optimization (PSO), Real Coded Genetic Algorithm (RCGA) and Differential Evolution (DE) and any other evolutionary optimization technique. In this work, the optimal value of C and γ is traced using grid search method.

c) Grid Search cross validation:

Here, the grid search using fivefold cross validation is used. All pairs of (C, γ) are tried and the one with higher cross-validation accuracy is selected. The practical method used is to identify the optimal parameters within exponentially growing sequences of C and γ. Here, the sequence used is C = $[2^{-5}, 2^{-4} \ldots, 2^{14}, 2^{15}]$ and $\gamma = [2^{-15}, 2^{-14} \ldots, 2^{4}, 2^{5}]$.

3) Training (70%) and testing (30%) of input data samples using SVM model until the expected accuracies of training and testing phase is reached.

5. TEST SYSTEMS

The performance of DM tool was tested with the benchmark test systems viz., Western System Coordinating Council (WSCC) 9 bus system and New England 39 bus system.

Probability Distribution:

The probabilities associated with the fault location and fault clearing times will be given with the system data. In the absence of such data for the test systems, the distributions are assumed as follows:

A. *Fault Location*

With the occurrence of all possible outages of buses and line tripping in test system under consideration, the large number of input data samples with their status of security is generated [12]. The post-fault attributes are calculated based on the fault location for the generation of data samples.

B. Fault Clearing Time

In this work, a discrete uniform distribution of fault clearing time, ranging from 0.10 sec to 0.58 sec with an increment of 0.02 sec is adopted for all operating conditions [14]. The post fault attributes with reasonable transient stability prediction can be achieved with this setting of clearing time.

The program code for the transient stability prediction, generation of data samples and the various DM tools were performed in MATLAB environment with processor of below specified configuration.

Processor Configuration:

The construction of DM tool model was performed in MATLAB environment using Matlab 7.8 version. The DM tool model is designed on PC with 2.5 GHz core i3 CPU and 4 GB RAM. This configuration setting is common to the construction of DM model for all test systems under concern.

6. RESULTS AND DISCUSSION

By simulating the different fault disturbances, sufficient data samples are generated for test systems. For each scenario, the transient stability assessment by conventional method i.e., 4th order Runge Kutta (RK) method [18], is carried out and the stability status (secure/insecure) is assessed. Based on the various scenarios, a set of input-output samples have been simulated for system under study. The input attributes in data set include post fault generator rotor angle, fault location & fault clearing time and the output attribute is secure/insecure status of the system. The security status is predicted using binary logic with the secure state being represented by logic ‘1’ and insecure state by logic ‘0’.

WSCC 9 - Bus System:

The data samples for test system under concern are simulated when the system is perturbed for fault disturbances. WSCC 9 bus system consists of 9 buses, 3 generating units, 6 transmission lines and 3 transformers. The performance measures of test system are evaluated during the training & testing phase and depicted in Table II.

The input-output pairs are generated for changing values of input attributes such as fault clearing time, fault location and generator rotor angle.

It is observed from Table II that for the WSCC 9 bus system, out of 8100 input-output pairs, the sample vector has 3395 secure cases & 4755 insecure cases. It can be well seen from Table II that the DT classifier gives high classification accuracy & less misclassification rate for training and testing, comparable to the other techniques. Furthermore, the time taken by DT algorithm is also quite less, of the order of few milli-seconds, making it feasible for on-line implementation.

TABLE II - PERFORMANCE ANALYSIS OF DM TECHNIQUES FOR WSCC 9 - BUS SYSTEM

	Performance Measures	**WSCC 9 – BUS SYSTEM**			
		DT	**NN**	**ELM**	**SVM**
	Total no of data samples generated	***8100***	8100	8100	8100
TRAINING PHASE	Total no of training samples	***5670***	5670	5670	5670
	No of secure samples	***2505***	2505	2505	2505
	No of insecure samples	***3165***	3165	3165	3165
	CA (%)	***99.61 (5648/5670)***	97.87 (5549/5670)	87.18 (4943/5670)	98.89 (5607/5670)
	SMC or False Dismissal (%)	***0.229 (13/5670)***	1.958 (111/5670)	6.102 (346/5670)	1.093 (62/5670)
	ISMC or False Alarm (%)	***9***	10	381	1
	Time (s)	***2.9289***	16.5417	0.9406	6780
TESTING PHASE	Total no of testing samples	***2430***	2430	2430	2430
	No of secure samples	***840***	840	840	840
	No of insecure samples	***1590***	1590	1590	1590
	CA (%)	***99.79 (2425/2430)***	98.39 (2391/2430)	89.75 (2181/2430)	99.05 (2407/2430)
	SMC or False Dismissal (%)	***0.165 (4/2430)***	1.564 (38/2430)	5.35 (130/2430)	0.946 (23/2430)
	ISMC or False Alarm (%)	***0.041 (1/2430)***	0.041 (1/2430)	4.897 (119/2430)	0
	Time (s)	***0.0576***	0.0149	0.2558	0.1868

New England 39 - Bus System:

By simulating the system under different fault disturbances, sufficient data samples are generated for New England 39 - Bus system. By considering the various scenarios of system under contingency, a set of 18525 input-output samples have been simulated for the test system under concern. The input attributes in data set include post fault generator rotor angle, fault location and fault clearing time and the output attribute is the security status of the system. The test system consists of 39 buses, 10 generating units, 34 transmission lines and 12 transformers.

The performance measures for NE 39 Bus system using different DM techniques are evaluated and incorporated in Table III. In this paper, the sample vector has 6513 secure cases & 6455 insecure cases during training and 2701 secure case & 2856 insecure cases during testing. Using DT model, out of 6455 insecure training samples the number of insecure samples which were misclassified as secure samples are only 3 samples. During testing phase, to perform transient stability prediction for unseen data samples, DT model classifies the 5554 samples correctly out of 5557 samples with the classification accuracy of 99.98 percent.

In real time systems, the DM model should perform well for both used and unseen data samples with higher classification accuracies. The developed DM model is therefore compatible for the changing operating scenarios of practical real-time systems with increased complexity and the transient stability prediction should be carried out in shorter time (milli seconds) for online implementation.

The trained DT model satisfies all the requirements and enhances the system security under various fault conditions. Hence, DT proves to be a promising tool with better results than the any other techniques of data mining.

Parameters of SVM Model:

For the above test systems under study, the SVM parameters evaluated for the model using grid search technique is depicted in Table IV.

TABLE IV – PARAMETERS OF SVM MODEL FOR THE TEST SYSTEMS

SVM Parameters	**TEST SYSTEMS USED**	
	WSCC 9 Bus System	**NE 39 – Bus System**
Best C	32768 (2^{15})	32768 (2^{15})
Best γ	4 (2^{2})	16 (2^{4})

By finding these best C and best γ values for which the cross-validation accuracy is higher, the SVM model for each test system has been developed and the transient stability prediction is performed using that model.

TABLE III - PERFORMANCE ANALYSIS OF DM TECHNIQUES FOR NEW ENGLAND 39 - BUS SYSTEM

	Performance Measures	NE 39 BUS SYSTEM			
		DT	**NN**	**ELM**	**SVM**
	Total no of data samples generated	***18525***	18525	18525	18525
TRAINING PHASE	No of secure samples	***6513***	6513	6513	6513
	No of insecure samples	***6455***	6455	6455	6455
	CA (%)	***99.98*** ***(12965/12968)***	99.46 (12898/12968)	91.15 (11820/12968)	99.72 (12931/12968)
	SMC or False Dismissal (%)	***0.023*** ***(3/12968)***	0.54 (70/12968)	3.409 (442/12968)	0.285 (37/12968)
	ISMC or False Alarm (%)	***0.0***	0.0	5.445 (706/12968)	0.0
	Time (s)	***4.8732***	40.875	1.3649	154720
TESTING PHASE	No of secure samples	***2701***	2701	2701	2701
	No of insecure samples	***2856***	2856	2856	2856
	CA (%)	***99.98*** ***(5556/5557)***	99.66 (5538/5557)	91.29 (5073/5557)	99.86 (5549/5557)
	SMC or False Dismissal (%)	***0.018*** ***(1/5557)***	0.342 (19/5557)	2.231 (124/5557)	0.144 (8/5557)
	ISMC or False Alarm (%)	***0.0***	0.0	6.478 (360/5557)	0.0
	Time (s)	***0.1411***	0.0233	0.6090	0.2365

7. CONCLUSIONS

This paper has explored the problem of Transient Stability Assessment (TSA) of power systems using data mining (DM) classifier. Every security assessment task was modeled as a binary classification problem and a DM model is developed in this paper. Various DM techniques have been employed for TSA and a suitable model has been devised.

This paper presented various DM classifier model for transient stability prediction in test systems under consideration. The simulation has been performed on benchmark systems viz., WSCC 9 – Bus system and New England 39 – Bus system with probability distributions of post-fault parameters and historical data. It has been proved through simulation results that DT can be used as a promising and reliable tool for on-line transient prediction of power system for both small scale and large scale power systems comparable to other techniques. Hence corrective control measures can be taken at appropriate time by operation personnel to retain the system stability. Finally, the simulation results presented are found to be promising and hence reliable prediction of transient instability can be made using the DT model, enhancing its feasibility for real time implementation.

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9. AUTHOR BIOGRAPHIES

P. M. Devie received her bachelor's degree in electrical and electronics engineering from K. L. N. College of Information Technology, Madurai, in the year 2012. She is currently doing her master's degree in Kamaraj College of Engineering & Technology, Virudhunagar. Her research interests are power system stability, data mining techniques for power system classification problems.

S. Kalyani is currently working as Professor and Head in the Department of Electrical & Electronics Engineering at Kamaraj College of Engineering & Technology, Virudhunagar. She obtained her PhD degree from Indian Institute of Technology Madras, Chennai in year 2011. She received her Master's Degree in Power Systems Engineering from Thiagarajar College of Engineering, Madurai in December 2002 and Bachelors Degree in Electrical and Electronics Engineering from Alagappa Chettiar College of Engineering Karaikudi, in the year 2000. She has about 11 years of teaching experience at various levels. Her research interests are power system stability, Pattern Recognition, Machine Learning, Soft Computing Techniques to Power System studies. She is a Member of IEEE since June 2009 and also life member of ISTE.