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Application of Relevance Vector Machine for Static Security Assessment of Power Systems

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ABSTRACT

Recently, Machine learning techniques have become popular and broadly used in the area of power system data analysis. In this paper, a more efficient Relevance Vector Machine (RVM) based algorithm for Static Security Assessment (SSA) of a large scale power system has been presented. The main objective of this paper is to investigate the requirements of the SSA in predicting the security status of power system from serious intrusions during operations in real time for quick decision making and remedial actions. The proposed RVM classifier was used to classifying the power system states as secure and insecure classes under a given operating condition with contingencies. Nonetheless, an f-value feature selection algorithm combines with RVM classifier is necessary to reduce the larger dimension of input variables into small size thus validates the potential of the whole data representation. The proposed approach has been tested on an Indian Utility 62 Bus system. The results of this proposed technique have been compared with and without f-value feature selection for selected test system and are found satisfactory within an acceptable range of accuracy and error rate with smaller computation time. Simulation results prove that the RVM classifier with a contributed feature subset selection effects the highly uncorrelated features on the training as well as on testing. The feasibility of implementation of the proposed classifier system for online static security evaluation is also discussed. From the analysis, it has been observed that the proposed SSA-RVM classifier provides very high class accuracy with minimum number of variables hence reducing complexity of data analysis and quicker results.

KEYWORDS: Feature selection Power system security Relevance vector machine Static security assessment

INTRODUCTION

Presently, Security evaluation is a major concern in real time monitoring to determine the current state of the modern power systems. The current movements towards deregulation have needed modern electric utilities to function their systems under stressed operating situation nearer to their security limits. First and foremost, the Static Security Assessment (SSA) addresses mainly to the question about the competence of generation and transmission capacity to meet load demand .A system is supposed to be functioning in a normal mode which is a preferred mode when load and operating constraints are satisfied i.e., all the loads are met within acceptable voltage , frequency limits and all system components are loaded within the secure specified limits. So, Static security evaluation is needed to perceive any potential overloads with system branch and voltage violations on buses, following a given set of contingencies [1,2].

Over the years, the SSA problem has been solved by simulation approaches, probabilistic approaches and pattern recognition approaches. In the simulation approaches such as Newton Raphson, Decoupled or Fast Decoupled Load Flow methods, a variety of contingencies are hypothetically simulated using digital computer thus resulting in the computation intensiveness and large amount of results generated makes these methods unacceptable to on-line applications [3]. Similarly, the probabilistic approaches to SSA are not acceptable due to

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the difficulty of assessing the probability of various events. But these conventional security analyses rely on mathematical models and sophisticated programming techniques. However, the complexity and size of modern power system is such that complete computational solutions usually cannot be obtained in a timely fashion, and doubtful for emergency conditions.

In recent years, use of many Artificial Intelligence (AI) techniques have been proposed for security evaluation problems [4,5,6] overcoming the demerits of traditional SSA. The use of AI techniques similar to Kohonen Neural Network [7], Multilayer feed forward with back propagation algorithm, self organizing NN [8,9,10], fuzzy logic combined, Genetic-based neural network for static security evaluation process. Application of Artificial Neural Network (ANN) based pattern recognition approach has also been widely exploited in the literature. Although ANN is the most popular SSA classifier to classifying patterns, it requires extensive training process with complicated design procedure. Moreover, ANNs are good in interpolation but not so good in extrapolation, decreasing its generalization ability too. Owing to these drawbacks, it becomes necessary to devise a more efficient pattern classifier system for solving the problem of security evaluation.

But these procedures concern some hassles similar to the conventional methods. Hence to overcome this crisis, Machine learning based classification has been suggested for security assessment problems. A very successful approach over supervised learning is the Support Vector Machine (SVM) [12]. SVM, which is based on statistical learning have also been successfully applied in highly linear and nonlinear feature space. Results have reported that, the Number of support vectors grows linearly along with the increase of training samples size, which entails for extra calculation of setting of parameters.

Therefore, how to shrink the time intricacy is a key issue for SVM in SSA [13]. On the basis of SVM based SSA and evaluation, Core Vector Machine (CVM) [14] and Ball Vector Machine (BVM) [15] have been suggested. Nevertheless, these Machine learning algorithms have some drawbacks due to absence of Probabilistic Interpretation. To overcome above drawbacks, a Probabilistic Bayesian framework termed as Relevance Vector Machine (RVM) [16] has been proposed for power system static security classification with feature selection.

Alternatively, the avoidance of similar data's in the dataset will make better performance of the proposed RVM classifier. So, it is necessary to determine a minimal feature subset from a problem domain while retaining a suitably high accuracy in representing the original features. In literature, many Feature selection procedures such as Fisher Discrimination Analysis, Entropy Maximization, and Divergence Maximization, Rough set theory based feature selection etc, have been applied [18,10,11]. The major problem with the existing feature selection algorithms is that they are mainly adopted for linearly separable classes and not well established on non-linearly separable classes. In this paper, the process of feature selection is highlighted by a simple approach called F-value selection method.

This paper presents the suitability of RVM based SSA classifier, by improving its performance using feature selection and feature subset selection process. RVM-SSA classifier can accurately identify the status of the power system, even in harmful contingencies, within a very short computational time with much better adoptability for online assessments. The proposed method is trained and tested for an Indian Utility 62 bus system.

Power System Security Assessment:

Power System Operation:

A momentous factor in power system operation is the hope to preserve system security. So, it must be designed to keep system operation safer when failure occurs. Besides economizing on some factors, the power system should be operationally "secure". It is clear that, an operationally secure power system is one with low probability of blackouts. In order to achieve the safer power transactions, some basic elementary studies such as load flow studies, stability studies, fault analysis, economic dispatch, unit commitment, maintenance planning, spinning reserve requirement, load frequency control, etc., are needed [19].

For better appraisal, Load flow studies are premeditated thus providing the status of the entire system, considering a set of electric network equations which represents load flow studies and its results depends on the load and the generation distributions and the network configuration. The amount of power generated by each unit is constrained by it capacity. The power flowing in each line is limited by its rating and so is that handled by each transformer.

Power System Security and Types:

In practice, it is not sufficient just to maintain a system in the normal operating state always. Under certain conditions, the occurrence of some disturbance may cause the system to go in to an emergency such as the overloading of lines and violation of voltage limits. A set of most probable disturbances as contingencies consist of the following effects such as a single line out, a loss of a generator, sudden loss of a load, sudden change of flow in an inter-tie and a 3Φ fault in the system.

The capability to maintain stable power transactions under the influence of contingencies without violating normal operating limits is defined as power system security and it may be alienated as follows, Steady State Security which deals with the Steady State condition of the system, Transient Security, which deals with the transient stability of the system when it is subjected to disturbance, and Dynamic security which pertains to the system responses of the order of a few minutes. In this paper, only a study on static security assessment is considered.

Static Security Assessment (SSA):

Static security of a power system addresses whether, after a disturbance, the system reaches a steady state operating point without violating system operating constraints called 'Security Constraints'. These constraints ensure that the bus voltage magnitudes and thermal limit of transmission lines are within the acceptable limits given by following equations (1) and (2). If all the constraints are satisfied for a specified contingency, the system operating state is labeled as 'Static Secure' (1) or else if any violation is identified, the system operating state is labeled as 'Static Insecure' (0).

$$|V|_k^{min} \leq |V|_k \leq |V|_k^{max} \quad \text{where } k = 1,2,\ldots,N_b \tag{1}$$

$$S_{km} \leq S_{km}^{max} \quad \forall \text{ Branches k-m} \tag{2}$$

Where, $|V|_k$ - Voltage magnitude at bus k, S_{km} - Complex power flow in branch k-m, and N_b - Number of buses.

During simulation, the system load and generation have been changed to permissible percentage with base case. For each case, Load Flow has been used to obtain the operating state defined by variables Pgen, Qgen, Pflow, Qflow, Pload, Qload, Vbus & Vangle, which are then used to run load flow under contingent condition and the violations of operating limits of various components are checked [20].

Usually, static security using conventional technique requires that load flow studies be performed time to time. Hence it takes long amount of computer time and the volume of data generated needs significant and difficult human decision to assess the security of the system. In order to overcome these difficulties, Machine Learning based RVM technique has been chosen.

Relevance Vector Machine:

The relevance vector machine introduced by tipping [21] is truly a special case of a Gaussian process which helps for classification. RVMs have the identical functional form as SVMs but are trained within a Bayesian framework. The compelling characteristic of RVMs is that they typically use fewer training vectors, termed ''relevance vectors,'' associated with non-zero weights, while achieving generalization performance similar to that of SVMs.

Given a set of input-target pairs $\{X_n, t_n\}_{n=1}^{N}$, the output $t_i = y(X_i; w) + \varepsilon_i$ and ε_i is assumed to be mean-zero Gaussian with variance σ^2, that is $N(0, \sigma^2)$.Kernel function $k(x, x_n)$ has been considered in RVM which makes prediction by the function,

$$Y(x; w) = w^T \phi(x) = \sum_{n=1}^{M} w_n k(x, x_n) + w_0 \tag{3}$$

Where, $\phi(x)$ is vector of basis function; $w = (w_1, w_2, w_3, \ldots, w_M)$ is the weight vector.

Therefore, the probabilistic formulation of RVM Model is defined as in eqn.4 (Tipping, 2001),

$$P(t_n|x) = \prod_{i=0}^{N} N(w_{in}|y(x_n), \sigma^2) \tag{4}$$

Where, N represents a Gaussian distribution over t_n with mean of $y(x_n)$ and variance σ^2

Let's, consider a likelihood function of whole samples,

$$P(t|w, \sigma^2) = (2\pi\sigma^2)^{-N/2} e^{\{-(\frac{1}{2\sigma^2}) \| t - \phi w \|^2\}} \tag{5}$$

To overcome over-fitting from implement of maximum-likelihood estimation for w and σ^2, constraint on weights w_i has been imposed [22], that is 'prior' probability distribution function is written in eqn. (6).,

$$P(w|\alpha) = \prod_{i=0}^{N} N(w_i|0, \alpha_i^{-1}) \tag{6}$$

Where, α is N+1 vector termed 'hyper parameters'

Furthermore, the posterior over unknown samples could be obtained from proceeds of Bayes inference is given in eqn.(7),

$$P(w, \alpha, \sigma^2 \mid t) = \frac{P(t|w, \alpha, \sigma^2) \times P(w, \alpha, \sigma^2)}{P(t)} \quad (7)$$

Assuming that new test target is t_* new test input x_* are used to make predictions. Then, predictive distribution can be written as,

$$P(t_* \mid t) = \int P(t_* \mid w, \alpha, \sigma^2) P(w, \alpha, \sigma^2 \mid t) dw \, d\alpha \, d\sigma^2 \quad (8)$$

and Posterior distribution over weights could be consequently rewritten as

$$P(w \mid t, \alpha, \sigma^2) = \frac{P(t|w, \sigma^2) \times P(w \mid \alpha)}{P(t \mid \alpha, \sigma^2)} \quad (9)$$

Therefore, the learning process of RVM becomes on search for α and σ^2 ,which make the maximization of P $(\alpha, \sigma^2 \mid t) \propto P(t|\alpha, \sigma^2) p(\alpha) p(\sigma^2)$ by maximum marginal likelihood estimation methods

$$P(t|\alpha, \sigma^2) = \int P(t|w, \sigma^2) P(w|\alpha) \, dw = (2\pi)^{-N/2} \left| \sigma^2 I + \Phi A^{-1} \right|^{(-1/2)} \exp\left\{-\frac{1}{2} t^T (\sigma^2 I + \Phi A^{-1} \Phi^T)^{-1} t\right\} \quad (10)$$

It can compute α and σ^2 by equating the differentiation over α , σ^2 of function in eqn.(10) to zero. When α_i approaches extremely large, w_i goes to zero because of constrain by the prior. For w_i interrelated with small α_i, it fits the sample data better. Iteration would be preceded until the convergence condition is fulfilled . During the process of parameters estimation, most of α_i belongs to ∞, where corresponding $w_i = 0$. It leads to non-participation of prediction calculation for many terms of kernel matrix. This is why RVM could achieve Sparsity [22].

Consequently, Iterative estimation of hyper parameters proceeds to make predictions based on each weights of posterior distribution which adjusts to maximizing values α_{MP}, σ^2_{MP} , with new inputs x_* . Predictive results could be described as follow ,

$$P(t_* \mid t, \alpha_{MP}, \sigma^2_{MP}) = \int P(t_* \mid w, \sigma^2_{MP}) P(w \mid t, \alpha_{MP}, \sigma^2_{MP}) dw = N(t_* \mid y_*, \sigma^2_*). \quad (11)$$

Where,

$$y_* = \mu^T \Phi(x_*) \quad (12)$$

$$\sigma^2_* = \sigma^2_{MP} + \Phi(x_*)^T \Sigma \Phi(x_*) \quad (13)$$

The weights depend on two classes of hyper parameters α, σ that are assumed to be Gaussian distributed. These hyper parameters are iteratively optimized to maximize Eqn.(11) Finally, the model only depends on the subset of Relevance Vectors (RV) $\subset X$ of non-zero elements in *w*. However, unlike the SVs, the RVs are not the points closest to the respective other classes but samples from the center of the distribution, considered most typical for their class. The model can be adapted naturally to the multi-class case.It is claimed that it needs considerably less RVs thus speeding up the system classification [23,24]. In this paper, the Bayesian principle based RVMs have been employed in the security assessment of power systems.

The most important evaluator of the RVM performance is the accuracy which is defined as the ratio of successfully classified operating points (OPs) to the number of OPs in Data set (DS).

$$\text{Accuracy} = \frac{\text{OPs successfully classified by the RVM}}{\text{Total number of OPs in the DS}} \quad (14)$$

For a two class partition (Secure-Insecure) there can be two distinguished types of error, depending on the actual class of the misclassified OP,

$$\text{Misclassification} = \frac{\text{OPs Wrongly classified by the RVM}}{\text{Total number of OPs in the DS}} \quad (15)$$

$$\text{False Alarm} = \frac{\text{Secure OPs misclassified as Insecure by the RVM}}{\text{Total number of Secure OPs in the DS}} \quad (16)$$

$$\text{False dismissal} = \frac{\text{Insecure OPs misclassified as secure by the RVM}}{\text{Total number of Insecure OPs in the DS}} \quad (17)$$

Application Of Rvm For Static Security Assessment:

RVM is a relatively pioneering method for learning separating functions in classification problem. The success of RVM classification relies on a good feature set thus, gathering information about the behavior of the system obtained from off-line studies. These simulations need two data sets, the training and the testing data sets. The training data set is used to originate the security evaluation structure and the testing data set is used for validating the developed arrangement. This data handling Scenario has been explained in the following sub sections.

Sample Detection / Generation:

A training set consists of input vector and target vector and is combined together with learning methods to train a knowledge database. This set must adequately represent the entire range of power system operating states. All variables describing an operating condition constitute the components of the Pattern vector represented as $X = \{x_1, x_2 \ldots x_n\}$. These variables include Real and Reactive Power generations at buses, loads at buses, Power flows in lines, Voltage magnitude and angle at buses, Real and Reactive power losses in the system, etc., which may be determined directly by measurement or may be computed. Having defined the static security variables, the different operating scenarios are considered by varying the total system load and generation from 80% to 130% of its base case. For each operating scenario, single line outages are simulated and load flow solution by Newton–Raphson method is obtained for each contingency. Evaluating the security constraints such as line flow limits, voltage limits and generation limits, each pattern is labeled as secure or insecure class.

Feature Selection:

In Pattern Classification, Feature Selection is an exceptional appearance of dimensionality reduction. Feature selection involves simplifying the amount of resources required to describe a large set of data accurately. Generally, the number of variables representing a pattern vector is very large and analysis with a large number of variables normally requires large amount of memory and computation power, thus leading to over- fitting of training samples and poor generalization ability for unseen test samples. As a result, it becomes necessary to determine relatively small number of variables, called features, which will be distinctive for each of the two classes.Feature selection is the process of selecting a subset of original features, by removing redundant and irrelevant variables [17]. The selected features form the components of a vector called feature vector represented as $Z = \{z_1, z_2, \ldots, z_m\}$. It should be noted that m is smaller than n, m and n being number of components in feature vector and pattern vector, respectively.

Features may be selected by engineering judgment. But such selections will be subjective with the possibility of important variables getting rejected. In this paper, Correlation based F-value approach, a filter model, which seeks an optimal linear separation for two classes of data has been used. The selection of features begins with the computation of F-values for all Components (variables) of pattern vector in the training set.

The F-value for each attribute is defined as given in eqn. (18),

$$F = \frac{|m_s - m_f|}{\left(\sigma_s^2 + \sigma_f^2\right)} \quad (18)$$

The variable with the largest F value is selected as the first feature. Let this variable be z_1. When selecting other features, redundant information is omitted by discarding these variables which are correlated to z_1, i.e. those variables having a correlation coefficient greater than ,say,0.8, From the remaining variables, the one with the largest F-value is selected as the second feature,z_2. The procedure is repeated until all the variables are considered. It is extended to reform *n* number of subsets of features within the ranked feature space thus validating higher accuracy on classification in sequence. This method has been chosen due to its simplicity and relies only on the general characteristics of the data without involving any mining algorithm [19].

Procedure of RVM for Static Security Assessment:

1. Training samples selection phase:

To classify the SSA, samples are selected by load flow analysis with contingencies were taken as training samples with concern to neglecting the constant and zero values.

2. Training and classification phase:

Step1: To input selected training samples and optimized parameters into RVM engine and to initialize iteration conditions;

Step2: To calculate the posterior distribution over weights:

$$P(w|\ t, \alpha,\ \sigma^2) = (2\pi)^{-(N+1/2)} |\Sigma|^{-(1/2)}\ e^{\{-(\frac{1}{2})(w-\mu)^T \Sigma^{-1}(w-\mu)\}} \quad (19)$$

Step3: To update the mean and variance of posterior μ and Σ, respectively:

$$\mu = \sigma^{-2} \Sigma \varnothing^T t \quad (20)$$

$$\Sigma = (\sigma^{-2} \varnothing^T \varnothing + A)^{-1} \quad (21)$$

Step 4: To precede iteration of function α_i^{new} and $(\sigma^2)^{new}$ until the convergence condition is fulfilled:

$$\alpha_i^{new} = \frac{1-\alpha_i \Sigma_{ii}}{\mu_i^2} \quad (22)$$

$$(\sigma^2)^{new} = \frac{t-\varnothing \mu^2}{N-\sum_i (1-\alpha_i \Sigma_{ii})} \quad (23)$$

where, μ_i is the i^{th} mean of posterior from function in eqn.(20); Σ_{ii} is the i_{th} diagonal element of posterior covariance from function in eqn.(21), and computed by α ,σ^2 from current iteration results; N indicates the number of sample data.

Step 5: To delete those $w_i = 0$ in the iteration process. The vector corresponding to remaining w_i is termed as 'Relevance Vector'. Consequently, RVM largely reduces model complexity and computing costs. Model parameters α_{MP} ,σ_{MP}^2 would be achieved when model training is completed.

3. To import test data and model parameters into classification mode. After calculation and anti-normalization process, prediction value and its possible fluctuation are obtained. Not only could RVM model provide an individual prediction value, but also calculate variance of the prediction value in eqns. (20, 21) which is also the possible prediction error. Term of variance comprises two kinds of error: one is from error of estimation while another is from uncertainty of weights calculation. This probabilistic mechanism for classification problem of SSA largely improves the accuracy.

Use of kernel function:

Having realised the concepts of feature selection and classification in the previous sections, the preceding step is to improve the performance of RVM classifier with the choice of kernel function. In many classifications, computational problems occur due to the large vectors and the danger of over fitting may happen due to the high dimensionality. The latter problem is solved with application of the maximal margin classifier, and a so-called kernel gives a solution. It is clear that, a function that returns a dot product of the Feature space mappings of original data points is called a kernel.

These kernel functions are polynomial, Gaussian radial basis function (RBF) and sigmoid kernels, which are presented in Eqns (24),(25),(26) and (27).

Polynomial	$K = (x^t(\eta * x_2)^T + 1)^P$	(24)
Laplace	$K=\exp(-\sqrt{(\eta * (x_t - x_i)^2)})$	(25)
Cubic	$R_2 = \eta * (x^t - x_i)^2$, $K = r_2 * \sqrt{r_2}$	(26)
Gaussian	$K = \exp(-\eta * (x^T - x_i)^2)$	(27)

Where x is input patterns, x_i is support vectors, σ^2 is variance, $1 \leq i \leq Ns$, Ns is number of support vectors and p is degree of the polynomial. Despite its simplicity, RVM greatly reduces the time and space complexities compared with the SVM, CVM and BVM algorithms.

RESULTS AND DISCUSSION

Case Study:

The proposed RVM based classification approach to SSA is performed with Indian utility 62 Bus power system. The required data set for training and testing phases be subject to a specified load flow analysis is performed by MATPOWER toolbox with MATLAB 7.1(Zimmerman and Murillo-Sanchez, 2007). This data set is obtained by varying the generation and load from 80% to 130% of their base case value. The security limit of

bus voltage magnitude is taken as 0.95 to 1.05 p.u and The MVA limit of system branches is assumed as 130% of its base case values.

The details of an Indian Utility 62 Bus power system has been shown in Table 1 and 2, One at a time, outage studies are performed and form the set of disturbances to be utilized for steady state security in the power system. So, the patterns or variables are generated from load flow results. The generated variable set consists of 42 numbers of voltage magnitude variables except Slack and PV buses (Vi), 61 numbers of voltage angle (δi), 19 numbers of real power generation variables (Pgi), 18 numbers of reactive power generation variables (Qgi), 32 numbers of real power demand variables (PDi), 33 numbers of reactive power demand variables (QDi), 89 numbers of active real power flow variables (Pi-j) , 89 numbers of reactive power flow variables (Qi−j) and 89 numbers of line MVA variables (Si-j). The trivial variables at certain buses such as zero load, zero generation and constant values are neglected and finally 472 patterns are considered for classification process. All feasible 472 patterns are subjected to static security check with voltage limit and line flow limit.

Table 1: Components of Indian utility 62 bus system

Indian 62 bus system	
Buses	62
Generators	20
Loads	33
Branches	89
Transformers	11
Areas	1

Table 2: Capacity of Indian Utility 62 bus system

Indian 62 bus system	*P (MW)*	*Q (MVAr)*
Total Gen Capacity	6350.0	-550.0 to 6165.0
On-line Capacity	6350.0	-550.0 to 6165.0
Generation (actual)	2904.3	679.8
Load	2845.0	1284.0
Losses (I^2 * Z)	59.29	300.36
Branch Charging (inj)	-	904.6

Table 1 and 2 Show the complete details about an Indian utility 62 Bus system. It can be seen that, for a possible 924 operating scenarios, 782 operating scenarios are found to be secure and the remaining 142 cases are found to be insecure. The training and testing samples are split in random by the ratio of 90 % (831 cases) for training phase and 10% (93 cases) for testing phase as given in Table 3.

Table 3: Data set for Training and Testing Phases

Scenarios	*Overall*	*Training*	*Testing*
Total No of Cases	924	831	93
Secure Cases	782	702	80
Insecure Cases	142	129	13
Attributes/Patterns	472	472	472

Hence, the RVM classifier is obtained by use of the splitted training and test data sets to provide better classification results with important features from input attributes. Table 4 shows an optimal set of patterns selected using F-Value feature selection process. The effectiveness of the dimensionality reduction is determined with a threshold value of 0.8 and the highly correlated variables are discarded from the total pattern variables.

Table 4: Feature Selection Process

Case study	Indian Utility 62Bus system
No. of pattern variables	472
No. of features selected	104

Analysis and discussion:

It can observed from Table 5 that the training accuracy of RVM classifier without feature selection gives better performance by choosing the proper control parameters. In order to justify this training result, any good classifier desires to ensure higher value of accuracy and less error rate always. From Table 6, it is clearly evident that the performance of RVM classifier is improved with selection of good feature set and elimination of redundant data.

Table 5: Choice of kernel parameters for better accuracy

Model (kernel)	Alpha max	epsilon	Noise model	Training accuracy (%) without feature selection
	e^{12}	e^{4}	7	99.72
Gaussian	e^{12}	e^{5}	9	100

Table 6: Classification accuracy of RVM classifier with feature selection

Performance Evaluation of RVM	Training Phase	Testing Phase	
	With and Without feature selection (472 attributes / 104 attributes)	*Without feature selection (472 attributes)*	*With feature selection (104 attributes)*
Accuracy (%)	*100 (831/831)*	*92.4731 (86/93)*	*96.7741 (90/93)*
Misclassification (%)	*0 (0/831)*	*7.526 (7/93)*	*3.2258 (3/93)*
False alarm (%)	*0 (0/702)*	*2.50 (2/80)*	*1.25 (1/80)*
False dismissal (%)	*0 (0/129)*	*38.46 (5/13)*	*15.38 (2/13)*

With this result, the performance of RVM model is improved by reducing the number of variables was being selected for classification. During the concept of reduction in input variables, main variables such as generation linked and power flow based variables has been fixed probably. The proposed classifier could be efficient whenever directs in to a correct path and that should be reason for insecure in most of the situations.

Table 7: Comparative results of Static Security classification with 104 attributes

Performance	*RVM classifier*	*SVM classifier*
Accuracy (%)	*96.77*	*95.23*
Misclassification (%)	*3.22*	*4.76*
False alarm (%)	*1.25*	*4.16*
False Dismissal (%)	*15.38*	*5.5*

Table 7 shows the comparative results of RVM and SVM classifier. The Results prove that RVM is a preeminent classifier within a preselected contingent environment. Here false dismissal value 15.38 %(2/13) is noticeable value as compared with SVM. This was happen due to number of insecure samples used on testing. In future, review of this analysis with different test system must have minimum patterns required for understanding the classes of the system during training and testing.

Table 8: Results of RVM-SSA classifier with a set of highly ranked features

Performance Evaluation RVM	*Training with highly ranked (2,3, 5,6,7,8) features*	*Testing With first 2 attributes on ranking*	*Testing With first 3 attributes on ranking*	*Testing With first 5 attributes on ranking*	*Testing With first 6 attributes on ranking*	*Testing With first 7 attributes on ranking*	*Testing With First 8 attributes on ranking*
Accuracy (%)	*100 (831/831)*	*86 (86/93)*	*89 (86/93)*	*90.3 (84/93)*	*90.3 (84/93)*	*90.3 (84/93)*	*90.3 (84/93)*
Misclassification (%)	*0 (0/831)*	*7.526 (7/93)*	*7.526 (7/93)*	*9.6774 (9/93)*	*9.6774 (9/93)*	*9.6774 (9/93)*	*9.6774 (9/93)*
False alarm (%)	*0 (0/702)*	*2.50 (2/80)*	*2.50 (2/80)*	*1.25 (1/80)*	*1.25 (1/80)*	*1.25 (1/80)*	*1.25 (1/80)*
False dismissal (%)	*0 (0/129)*	*38.46 (5/13)*	*38.46 (5/13)*	*61.5 (8/13)*	*61.5 (8/13)*	*61.5 (8/13)*	*61.5 (8/13)*

Furthermore, In this paper, a comprehensive analysis of the selected features based on their f-value correlation Ranking has been done. In this analysis, initially the first 2 highly ranked features were selected as input variables for training and testing of RVM classifier and its classification accuracy was observed which was found to be approximately 86%. Then the same procedure was repeated with first 3 highly ranked features and its accuracy was found to be approximately 89%. Similarly by repeating the procedure it was observed that there was an increase in accuracy up to 90.3% with first 7 highly ranked features after which the classification accuracy got saturated. From this extensive analysis, it has been observed that, even though SSA classifier accuracy using RVM with 104 features is 96.77 %, classification accuracy using feature subset selection is 90.3% which is acceptable as it has utilized only first 7 variables namely PD_{15}, QG_{25}, SL_{70}, PL_{57}, SL_{38}, SL_{49}, QD_{34}. Results prove the effects of highly uncorrelated feature sub set on the training as well as on the test result

accuracies as given in Table 8. Static security classification accuracy of RVM is enhanced because of the highly uncorrelated discriminating data subset feature management. Accordingly, the data classification could be tested in the new subset selection. It is observed that the performance of RVM is improved and limited with powerful feature subset. A little error reduction is obtained with feature selection and subset selection is a unique contribution of mine.

Conclusion:

The presence of RVM algorithm in classification of SSA does contribute the prediction of real situation in large interconnected power system. The basic implementation and modification of results in SSA are provided with feature selection algorithm. These algorithms are tested with a standard Indian utility system and results are analysed. Results of the Indian utility 62 bus systems proves that, the classification accuracy and misclassification rate of the proposed model are 96.77 % and 3.22% which are lower than those of existing familiar classifier, like SVM. Furthermore, the proposed model effectively provides quantitative assessment of uncertainty and outperforms well in terms of feature selection and feature subset selection. A well fitting Gaussian based kernel engine has been established to segregate the data space which is relevant to current condition of the system into several classes, thus improving accuracy and to minimize error rate. The selected Gaussian kernel can identify the resemblance of distinctive input and outputs of the dataset quickly. This will help enhance the representativeness of secure and insecure data in a certain data space so as to improve performance. RVM with feature subset selection proves to be an optimal approach for SSA of power system as it provides acceptable classification accuracy with a minimum number of uncorrelated features. This method makes more suitable to on-line static security assessment of power system so as to significantly improve classification accuracy, very less false rate as compared to other classifiers. Future work will focus on further improving the performance of RVM classifier by fine tuning its parameters through optimization of recent techniques and application of RVM classifier with optimizer for real time transient and dynamic security assessment is possible.

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