International Journal of Soft Computing 9 (6): 425-433, 2014
ISSN: 1816-9503

Power Transactions Based Available Transfer Capability Estimation Using Support Vector Machine

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Abstract: Vertically Integrated Power System around the world is being restructured into Horizontally Distributed Deregulated Power System. In the deregulated power system, the power transactions plays a major role. Effective management of power transactions decides the secure and economic operation of power system. As the real time operation and control of deregulated power system is mainly based on transactions, it would be better if the system studies are also based on the power transactions. This study analyses the technical feasibility of ATC estimation using real power transactions. This study proposes a Support Vector Machine (SVM) based method for ATC estimation using real power transactions as inputs. To the best of the knowledge this is the first attempt to use real power transactions as inputs for ATC estimation using SVM. The proposed methods are tested on IEEE 24 bus Reliability Test System (RTS) and IEEE 118-bus System. The results are compared with Repeated Power Flow (RPF) results and the results of SVM Model developed using real power loads as inputs.

Key words: Available transfer capability, deregulation, operation and control, support vector machine, artificial intelligence

INTRODUCTION

With a view to optimally utilize the existing transmission capacities and minimize the number of infeasible transactions, electric utilities intend to accommodate more number of transactions. The hurdles faced by the System Operators (SO) in carrying out this task are the system operating and stability limits. It is very important to assess the power that can be transferred in addition to the already committed transactions for a given interface to determine the feasibility of proposed transactions. For this purpose it is necessary to estimate Available Transfer Capability (ATC) for the operating state which will indicate the available transmission margin and if this margin is found to be inadequate, appropriate corrective measures should be taken to improve the margin. The assessment and enhancement of ATC have to be carried out during the real-time operation and planning of restructured power system. Luo *et al*. (2000) proposed a neural network solution methodology for the problem of ATC calculations. Based on the optimal power flow formulation of the problem, the inputs for a neural network are generator status, line status and load status and the output is the transfer capability. The Quickprop algorithm is used to train the neural network.

Khairuddin *et al*. (2004) proposed a fuzzy logic approach for determining ATC in a large deregulated power system. The proposed fuzzy method is tested for computing ATC between a numbers of source-sink pairs. The method is also compared with a full-scale AC power flow based method in terms of accuracy and CPU time for evaluating ATCs considering the same array of transactions, base cases and outages. The CPU time requirement of the proposed method is independent of the system size while the power flow based ATC Determination Method's CPU time is directly proportional to the size despite exploitation of sparse structure of the system. The proposed fuzzy method requires only three inputs irrespective of system size. Berizzi *et al*. (2007) proposed a new methodology to reduce the arbitrariness related to the mid and long term ATC computation using a probabilistic approach. A Monte Carlo Method is applied to sample many different reference scenarios in terms of generation patterns to be adopted for the ATC computation. Eventually, the probability density function of the ATC is built (Stahlhut and Heydt, 2007) a stochastic calculation of ATC is proposed. A stochastic power flow algorithm is used to quantify and evaluate the uncertainties involved in the ATC estimation. Othman *et al*. (2005) presented computationally fast and

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accurate method for evaluating available transfer capability based on curve fitting technique called as the cubic-spline interpolation technique. This method traces the curves of voltage magnitude and power flow variations with respect to the increase of real power transfer. Srinu Naik *et al.* (2010) proposed a method for determination of ATC with PTDF using linear methods in presence of TCSC. IEEE 14-bus System was used to test the feasibility of the model. Hahn *et al.* (2008) described a fuzzy logic approach to parallelizing contingency-constrained optimal power flow. The fuzzy multi objective problem is formulated for ATC estimation. A model for ATC calculations accorded with trade-off mechanism in electricity market was set up (Pan and Xu, 2005). The impact of branch outage contingency on the static voltage stability margin is analyzed and contingency ranking is performed through sensitivity indices of branch flows with respect to the loading margin. Ichikawa *et al.* (2009) proposed a method for estimation of ATC from the view point of power system transient stability. Wu (2007) proposed a Novel algorithm for contingency ATC computation and a sensitivity analysis for system uncertainties. It incorporates linear distribution factors and AC load flow sensitivity based method in order to calculate ATC. Vaithilingam and Kumudini Devi (2013) proposed support vector machine based ATC Estimation Method. Three indices were used to estimate ATC. From the literature, it is clear that in restructured power system the ISO analyzes all the proposed transactions sequentially for their feasibility. Each proposed transactions is evaluated based on their respective ATC values.

The conventional methods reported in the literature can estimate ATC for one set of input that is the ATC of one operating condition can be obtained in a single run. But in the restructured power system the number of proposed transactions will be more and hence the ATC estimation has to be carried out sequentially. Hence, it will be easier if an ATC estimator can estimate ATC for more than one operating condition simultaneously. This study proposes a method for ATC estimation using SVM which has the unique feature of estimating the ATC values for more than one operating condition simultaneously.

SELECTION OF INPUTS

Proper selection of inputs decides the accuracy and computation time of any AI based method. Inclusion of less significant variable as input increases the number of inputs unnecessarily rather omission of the most significant variable reduces the accuracy. Hence, only the variables influencing the ATC values need to be identified and should be considered.

ATC ESTIMATION USING REAL POWER LOADS AS INPUTS

The technical feasibility of ATC estimation using transactions as inputs can be verified by comparing the results of ATC values obtained using conventional inputs. In the literature real power loads were used as one of the inputs for ATC estimation. Hence, a model is developed for ATC using real power loads as inputs. ATC is the power that can be transferred through specified interface in addition to the already committed transactions. Normally the power transactions through an interface can be varied by changing real power demand and real power generation at sink and source buses respectively. The line or generator outages can also cause some change in interface transactions. But in the large scale power system, all the sink bus loads and line outages may not have influence on a specified interface transaction. Hence, the bus loads, generations and the outages having significant influence on the transaction of selected interface should be identified. The influential buses are identified by varying the bus loads sequentially. The change in bus load which causes significant change in the interface transaction is selected as influential bus. The outages which cause significant influence on the interface transaction will be selected as critical outages. The AI Model to estimate ATC is developed by considering all the possible operating conditions.

AI Model developed without considering any contingency cannot be used under contingency condition since the network condition will be changed. Therefore, for each critical contingency, a separate AI Model has to be developed.

ATC ESTIMATION USING TRANSACTIONS AS INPUTS

The technical correctness and the accuracy of any AI based model mainly depend on the inputs used. This study focuses on developing an AI model for ATC estimation using a new set of inputs. The necessity for selecting new set of inputs and the theoretical facts to substantiate the selection are explained in the preceding study. This study explains the process of selecting the influential branches in detail. An operating condition is chosen in such a way that it causes no limit violation. This operating condition is considered as base case. The N-R load flow is conducted for the base case and the transactions of the branches are obtained. The transactions of the branches are changed by varying the loads at the buses. The changes in the transactions of the branches are compared with the change in interface

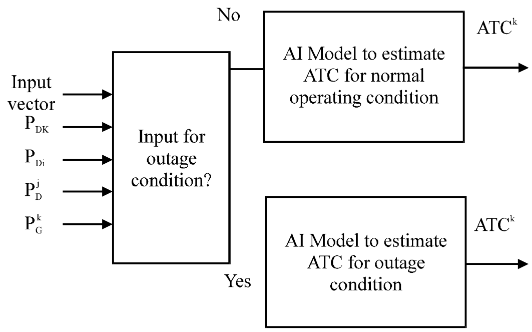

Fig. 1: AI Model for ATC estimation. P_{DK}: The real power transactions of interface D-K; P_{Di}: The real power transactions of influential branch I where, i∈J; P^J_D: The set of influential branch transactions; P^G_K: The real power injection at source bus of interface K; the output of AI Model is ATC^K and ATC^K: ATC of interface K

transaction. The branches having similar changes in their transaction as that of interface transactions are selected as influential transactions. The loading of influential branches will have significant effect on the ATC of a given interface. If the influential branches are lightly loaded then the ATC value will be higher and vice-versa. Especially in a practical power system where the number of branches and hence the number of transactions is more, selection of influential branches is essential and it can be done in off-line. The AI Model to estimate ATC should be developed by considering all the possible operating conditions. Figure 1 shows the proposed SVM Model for ATC estimation.

The network condition and hence the ATC value will not be the same for outage and non-outage conditions, the need for a separate ATC estimators for each critical outage is warranted.

In this study, SVM is used to estimate ATC. The AI technique require more number of data patterns covering all possible operating conditions of the given system. The lines whose outage causes significant changes in the interface transactions are selected as critical lines. Separate ATC estimators are developed for each critical outage.

DATASET GENERATION USING REPEATED POWER FLOW

The ATC value of an interface for an operating condition can be obtained using repeated power flow. The operating limits considered while estimating ATC are voltage magnitudes and power flow limits of the transmission lines. The ATC can be obtained by satisfying these system limits using repeated power flow algorithm. The real and reactive power load at the sink bus is increased by a pre-specified value. The source bus injection is also increased by the same pre-specified value. The load flow analysis is carried out and checked for constraints violations. The sink bus load and source bus injection are increased till the operating limits are violated. The maximum possible increase in demand in addition to the already committed demands which causes no limit violation is the ATC of the given operating condition. The ac load flow is modified as follows to run repeatedly with incremented loads at sink bus till any operating limit violation occurs. ATC of an interface connected between the source bus, k and sink bus, m can be computed as follows:

$$P_{Dm} = P_{Dm0} + k\,P_{Dm0} \tag{1}$$

$$Q_{Dm} = Q_{Dm0} + kQ_{Dm0} \tag{2}$$

$$P_{Gk} = P_{Gk0} + kP_{Gk0} \tag{3}$$

where, $kP_{Dm0} = kP_{Gk0}$.

$$(P_{Gi} - P_{Di}) - \sum_{i \in N} V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) = 0 \tag{4}$$

$$(Q_{Gi} - Q_{Di}) - \sum_{i \in M} V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) = 0 \tag{5}$$

These load flow equations are solved using N-R method and the following constraints are checked after the solution is converged:

$$P_{gmin} \le P_g \le P_{gmax} \tag{6}$$

$$Q_{gmin} \le Q_g \le Q_{gmax} \tag{7}$$

$$\delta_{ij} \le \delta_{ijmax} \tag{8}$$

$$V_{imax} \le V_j \le V_{jmax} \tag{9}$$

Where:

N = Set of PV buses except slack bus
M = Set of PQ buses
P_{dk} = Real power load at sink bus, ‘m’
Q_{dk} = Reactive load at sink bus, ‘m’
P_{gm} = Real power injection at source bus, ‘k’
Y_{ij}, θ_{ij} = Y bus matrix elements
V_i, δ_i = Magnitude and angle of voltage at bus, ‘i’

ALGORITHM FOR GENERATING DATA PATTERNS USING RPF

The effective estimation of ATC values using AI techniques depends on the datasets. Data pattern generation is one of the important stages of any AI based method. This study explains the steps involved in generation of datasets. The RPF algorithm is used to generate the necessary datasets for the method proposed in this study the real power loads are varied in such a way that it causes some significant change in the influential branch transactions. The real power loads are varied by keeping the power factor constant. The real power generations at the generators buses are also increased to maintain the power balance. From the load flow results the influential transactions are obtained. For the same operating condition ATC is obtained by RPF. A dataset will have influential transactions and real power generation at source bus as input and the output will be ATC value corresponding to that operating condition. This study summarizes the process of dataset generation:

- Step 1: specify the interface for which the ATC has to be computed
- Step 2: vary the bus loads such a way that the influential branch transactions are varied
- Step 3: run AC power flow for the given operating condition state
- Step 4: obtain power transactions through the influential branches and the interface
- Step 5: increase the sink bus load and source bus injection by the same amount in steps and run repeated power flow till the operating limit violation
- Step 6: from the maximum possible increase which causes no limit violations the ATC of that operating condition is estimated
- Step 7: steps 1-6 are repeated for different operating conditions. The influential power transactions and the respective ATC values are obtained
- Step 8: the necessary input and output values are used to develop the AI models. The same steps are followed to generate datasets for critical outage condition

SUPPORT VECTOR MACHINE

WKNN algorithm finds the unknown value with a weighted average of the K-Nearest Neighbor as given in Eq. 1.

Let's assume that the value of the jth variable of the ith dataset, x_{ij} is unknown. The unknown value can be calculated using the Eq. 10:

$$x_{ij} = \frac{\sum_{k=1}^{k} w_k x_{kj}}{\sum_{k=1}^{k} w_k} \tag{10}$$

Where:
K = The number of nearest neighbors
k = The nearest neighbor
w_k = The weight associated to the kth nearest neighbor which is the reciprocal of d_{ik}
d_{ik} = The Euclidean distance between the ith dataset and the kth nearest neighbor dataset

The process of imputation can be understood by the following example. The example with five datasets and three features A, B and C is given in Table 1. The dataset by removing the column corresponding to feature B is presented in Table 2.

Assume that for the fifth dataset the Bth feature value is not known. Let this unknown value be 'X'. The dataset by removing the column corresponding to feature B is presented in Table 2. The ED between the fifth dataset and the first dataset is calculated as:

$$ED_{5\text{-}1} = \sqrt{\{(4\text{-}5)^2 + (5\text{-}2)^2\}} = 3.16$$

Similarly the EDs are calculated between the 5th dataset and dataset 1, 2, 3 and 4 are given in Table 3. The weight for the dataset 1 is computed as:

Table 1: The original dataset with unknown value (X)

Datasets	Features A	B	C
1	5	7	2
2	2	1	1
3	7	7	3
4	2	3	4
5	4	X	5

Table 2: Dataset by ignoring the column corresponding to the unknown value

Datasets	Features A	C
1	5	2
2	2	1
3	7	3
4	2	4
5	4	5

Table 3: Datasets with Euclidean Distance (ED)

Datasets	A	C	Euclidean distance to the fifth dataset	Weights (W_k)
1	5	2	3.16	0.31
2	2	1	4.47	0.22
3	7	3	3.60	0.27
4	2	4	2.23	0.44

$$w_1 = \frac{1}{3.16} = 0.316$$

The weights for each dataset are calculated and presented in Table 3. From Table 3, it is observed that datasets 1, 3 and 4 are closer to the dataset 5 as their Euclidean distances are small. Therefore the number of nearest neighbors is chosen as 3. The value for the unknown 'X' is computed as:

$$a_{52} = \frac{0.31\times 7+0.27\times 7+0.44\times 0.3}{0.31+0.27+0.44} = 5.27$$

The SVM can compute more than one unknown value simultaneously by choosing datasets based on ED. This thesis uses the WKNN algorithm for ATC estimation because the WKNN algorithm uses both the distance and weights to estimate the unknown value. As the weights are the reciprocal of the Euclidean distance the closer instance will be given more weightage and the farther neighbor will be given the lesser weightage. Hence, the WKNN algorithm will give better results compared to the other imputation methods.

SYSTEM STUDY AND RESULTS

IEEE 24 bus RTS: IEEE 24 bus Reliability Test System (RTS) and IEEE 118 bus system is used to test the feasibility of proposed method. The IEEE 24 and 118 bus data and single line diagrams are available at www.ee.washington. edu/research/pstca.

IEEE 24-bus RTS is used to demonstrate the feasibility of the proposed model. Bus 23 is considered as source bus and the bus 3 is considered as sink bus. The power injection will be at the bus 23. The influential sink bus loads are identified as 3, 4, 8, 9, 10, 14, 15 and 16.

ATC values obtained using RPF and SVM Model for normal and outage conditions are given in Table 4. The dataset 1 given in Table 4 corresponds to a system loading of 130%. The real power injection at the source bus is 200 MW. The ATC for the test dataset 1 using RPF is obtained as 70 MW and for the same dataset the ATC by SVM Model is found to be 75 MW. The percentage error is calculated as 7%. ATC is bounded by the voltage constraint at 24th bus. The voltage magnitude at this bus is 0.9 p.u.

From the Table 4, it is observed that ATC for normal operating condition is 140 MW for sets 9 and 10. But their respective ATCs for outage conditions were 80 and 70 MW. The degree of loading of datasets 9 and 10 is 81 and 84%, respectively on the base of base case loading. The marginal variation in the ATC was due to the fact that the degree of loading of set 10 was slightly higher than set 9 which was less significant during normal operating condition and slightly more significant in the outage condition. This was the reason for the marginal variation in the ATC values. The test data sets pertaining to sets 9 and 10 are given in Table 4 for further clarification.

The ATC of the interface (23-3, corresponding to dataset 1) is also obtained by removing the line connecting the buses 15 and 24. The ATCs are 20 and 18 MW with RPF and SVM, respectively. The absolute error is found to be 10%. From the ATCs obtained for normal and outage conditions, it can be noted that the ATC for the outage condition is lesser than the ATC of normal operating condition. This is due to the fact that following an outage the system will be more stressed than the normal operating condition. Hence, the possible increase in the load and hence the ATC will be lesser than the normal operating condition.

In the real time operation of power system the ATCs should be updated at regular intervals to enable the market participants to plan their transactions. Therefore, the computation time involved in the estimation of ATC

Table 4: ATC obtained by RPF and SVM for the bilateral transaction between 23-3 of IEEE 24 bus RTS

	ATC for normal operating condition (MW)			ATC with outage of line 15-24 (MW)		
Test datasets	RPF	SVM	Error (%)	RPF	SVM	Error (%)
1	70	75	7.00	20	18.0	10.0
2	130	127	2.00	80	83.0	3.0
3	70	75	7.00	40	39.0	2.0
4	120	128	6.00	70	65.0	7.0
5	120	121	0.80	60	67.0	11.0
6	90	92	2.00	50	50.0	0.0
7	90	90	0.00	70	72.0	2.0
8	80	79	1.00	40	38.0	5.0
9	140	144	2.00	80	81.0	1.0
10	140	131	6.00	70	72.0	2.0
Average absolute error (%)			3.38			4.3

Table 5: Comparison of computation time of SVM and RPF (sec)

	Computation time (sec)	
Test datasets	RPF	SVM
1	0.904	0.0042
2	0.736	0.0044

Table 6: ATC obtained for three operating conditions by SVM

	ATC (MW)		
Transactions	RPF	SVM	Error (%)
1	70	67	4
2	130	124	5
3	70	71	1

Table 7: ATC obtained for five operating conditions by SVM

	ATC (MW)		
Transactions	RPF	SVM	Error (%)
1	70	72	3
2	100	95	5
3	90	97	7
4	90	86	4
5	70	70	0

is equally important besides the accuracy. The computation time of the proposed SVM Model is compared with RPF Model.

Table 5 shows the comparison of RPF and SVM Methods in terms of their computation time. The computation time of SVM Model given in the Table 5 is single execution time. The computation time of SVM found to be much lesser than RPF Method.

Feasibility of estimating the ATC of more than one operating condition simultaneously using SVM is verified with respect to average absolute error and computation time. The necessary datasets are generated with different load patterns. Table 6 is presented to show that the accuracy of SVM Model is not reduced when ATC of more than one operating condition is obtained simultaneously. The three operating conditions mentioned here are the different operating conditions with different degree of loading. The degree of loading of the test dataset 1, 2 and 3 are 138, 89 and 134%, respectively.

The percentage errors of SVM model to estimate ATC for three and five operating conditions simultaneously are given in Table 6 and 7, respectively. The three operating conditions mentioned here are the different operating conditions with different degree of loading. The degree of loading of the test dataset 1, 2 and 3 are 138, 89 and 134%, respectively.

From Table 6 and 7, it is inferred that the accuracy of the SVM Model is not reduced much when the ATC is estimated for more than one operating condition simultaneously.

Table 8: Computation time of RPF and SVM for five operating conditions

Test case	RPF (sec)	SVM (sec)
1	4.72	0.0058
2	3.91	0.0051

From Table 6 and 7, it is inferred that the average absolute error of SVM Model while estimating the ATCs of three and five operating conditions are 3.3 and 3.8, respectively.

Table 8 compares the time taken by RPF and SVM to estimate ATC of five operating conditions. The SVM model estimates the ATC simultaneously but the RPF model estimates sequentially. Hence, the computation time of RPF is much higher than SVM Model. From the Table 6-8, it can be noted that the proposed SVM Model can estimate ATC of more than one operating condition simultaneously with good accuracy in lesser computation time.

ATC estimation using transactions as inputs: The influential branch transactions are selected as 1-3, 3-24, 9-12, 9-11, 10-11 and 14-16. The critical line is identified as 15-24.

IEEE 118 bus system: The effectiveness of the proposed model is tested on IEEE 118 bus system. The interface is connected between 46 and 80. The influential bus loads are identified as 45, 46, 47, 48, 49, 74, 76, 77, 78, 79, 80, 82, 88, 90, 92, 93, 94, 95 and 100. The influential branch transactions are identified as 43-34, 44-43, 45-44, 46-45, 69-77, 66-65, 68-81, 77-82, 81-80, 80-99, 99-100, 80-97, 97-96 and 96-95.

The SVM Model is developed using the MATLAB Bio Informatics toolbox. The ATC estimation is carried out on Intel (R) core (TM) 2 Duo CPU T7100 at the rate of 1.8 GHz processor.

ATC ESTIMATION USING TRANSACTIONS AS INPUTS

IEEE 24 bus RTS: The influential transactions and the source bus injection are given as inputs and the respective ATC value will be treated as unknown value.

Table 9 shows the percentage error of ATC calculated using SVM model with respect to RPF results. It is observed that the SVM Model gives reasonably accurate results. The average error of SVM Models is 4.2%.

The results of SVM Model developed for the line outage 15-24 is compared with the RPF results and presented in Table 9. It is clear that the ATC value of the outage condition is lesser compared to the non-outage

Table 9: Comparison of ATC obtained by RPF and SVM-IEEE 24 bus

	ATC for normal operating conditions (MW)			ATC with outage of line 15-24 (MW)		
Test datasets	RPF	SVM	Error (%)	RPF	SVM	Error (%)
1	70	74	6.0	20	19	5.0
2	130	127	2.0	80	80	0.0
3	70	72	3.0	23	24	4.0
4	120	131	9.0	70	67	4.0
5	120	126	5.0	60	55	8.0
6	90	85	5.0	50	58	4.0
7	90	92	2.0	70	74	5.0
8	80	82	2.0	40	43	7.0
9	140	150	7.0	80	77	3.0
10	140	142	1.0	70	74	6.0
Average absolute error (%)			4.2			4.6

Table 10: Comparison of computation time (secs)

Test case	RPF	SVM
1	0.904	0.0041
2	0.736	0.0044

Table 11: ATC of three operating conditions for IEEE 24-bus

ATC (MW)		
RPF	SVM	Error (%)
70	66	5
130	127	2
70	77	10

Table 12: ATC of five operating conditions for IEEE 24-bus

ATC (MW)		
RPF	SVM	Error (%)
70	74	5
100	96	4
90	92	2
90	97	7
70	66	5

condition. The percentage error calculated for outage condition is also given in Table 9. The average error for outage condition is calculated as 4.6%.

Table 10 shows the comparison of RPF and SVM Methods in terms of their computation time. The computation time of SVM Model is much lesser than the RPF Model.

Another unique feature of SVM is its ability to estimate ATC values for more than one operating condition simultaneously. The percentage errors of SVM Model which estimates ATC for three and five operating conditions simultaneously is given in the Table 11 and 12, respectively.

From Table 11 and 12, it is observed that the average absolute error of SVM Model while estimating the ATCs of three and five operating conditions are 5.6 and 4.6 respectively. As ATCs of more than one operating condition is estimated simultaneously the absolute error is slightly higher than the absolute error shown in Table 9 but the average error is almost same. The accuracy can be improved by adding some more datasets.

Table 13: Comparison of computation time for five operating conditions (sec)

Test case	RPF	SVM
1	4.72	0.0055
2	3.91	0.0042

Table 13 compares the time taken by RPF and SVM to estimate ATC of five operating conditions. The SVM Model estimates the ATC simultaneously but the RPF Model estimates sequentially. Hence the computation time of SVM is much lesser than RPF Method.

A new method is proposed in this study for ATC estimation which uses power transactions as inputs. The technical correctness of the proposed model can be verified by comparing the ATC values obtained using real power loads as inputs and power transactions as inputs. The results and the respective absolute error are presented in Table 14.

From the Table 14, it is observed that the average absolute error of the method proposed in this study is found to be 4.2%. The average error is slightly higher than the method which uses real power loads as inputs. Therefore it is verified that the ATC can be estimated using power transaction as one of the inputs instead of real power loads.

From the Table 14, it is inferred that the ATC can be estimated using transaction as one of the inputs estimates the ATC with reasonably good accuracy. Even though the error (%) is slightly higher than the other method, it can be used in the deregulated power system for ATC estimation.

IEEE 118 BUS SYSTEM

The technical feasibility of the proposed model for large scale power system is tested by applying the proposed model on IEEE 118 Bus System. Table 15 shows the percentage error of ATC calculated using SVM Model with respect to RPF results. It is observed that the SVM Model give reasonably accurate results. The average error of SVM Models is 3.5%.

Table 14: Percentage error of two methods with two different inputs

	ATC (MW)				
	Real power loads as inputs				
Test data	RPF	SVM	Error (%)	Transactions as inputs (SVM)	Error (%)
1	70	75.00	7.0	74	6.0
2	130	127.00	2.0	127	2.0
3	70	75.00	7.0	72	3.0
4	120	128.00	6.0	131	9.0
5	120	121.00	0.8	126	5.0
6	90	92.00	2.0	85	5.0
7	90	90.00	0.0	92	2.0
8	80	79.00	1.0	82	2.0
9	140	144.00	2.0	150	7.0
10	140	131.00	6.0	142	1.0
Average absolute error (%)		3.38			4.2

Table 15: Comparison of ATC obtained by RPF and SVM for the bilateral transaction between 46 and 80-IEEE 118 Bus System

	ATC (MW)		
Test datasets	RPF	SVM	Error (%)
1	230	233	1
2	310	317	2
3	170	179	5
4	370	378	2
5	60	63	5
6	100	97	3
7	40	37	7
8	165	171	4
9	270	263	2
10	230	221	4

Table 16: Comparison of computation time (sec)

	Computation time (sec)	
Test case	RPF	SVM
1	11.32	0.0046
2	26.64	0.0044

The real time operation and control of restructured power system mainly depends on the computation time of various studies. Hence any new method suggested must be tested with a large scale power system for its computation time. Therefore, the computation time of the proposed SVM Model is compared with the RPF Method.

By comparing the Table 16, it is evident that as the system size increases computation time taken by RPF is also increases. Whereas the computation time of SVM Model is not increased much. Hence, the SVM Models will be very effective for large scale practical power systems where the number of buses will be in terms of thousand.

CONCLUSION

The first method explained in this study used conventional inputs for ATC estimation. One of the unique features of SVM based method was its ability to estimate ATC value for more than one operating condition. From the results, it was observed that the proposed SVM Model can estimate ATC for more than one operating condition without compromising the accuracy. This reduces the computation time by many folds. In a real time operation of deregulated power system, the ISO has to estimate ATC values for many possible proposed transactions. As the SVM can estimate ATC value for more than one proposed transactions simultaneously the ISO can evaluate many transactions in short time. This enhances the performance of ISO.

Further it is very evident that the complexity of system and hence the computation time will increase as the number of buses increases. Hence for large scale practical power systems the proposed SVM Model can estimate ATC in lesser computation time with reasonably good accuracy. This makes the SVM Model suitable for real time applications.

The second method suggested in this study used power transactions as one of the inputs. The test results shows ATC can be estimated using power transactions. The computation time of the proposed SVM Model is much lesser than the RPF based method. The computation time is further reduced as SVM Model can estimate ATC of more than one operating cases in a single shot. This enables the ISO to evaluate the feasibility all the proposed transactions in a lesser time compared to the ac power flow based conventional methods. For any given interface identification of influential bus loads, influential transactions and critical lines can be identified off-line. The data patterns can be obtained from load flow studies hence developing an ATC estimator for any given interface can be done off-line.

Even though the developed method can estimate ATC of more than one operating condition, it is suggested that not to be more optimistic by trying to find ATC for more operating cases in a single run as it may reduce the accuracy. But keeping on amending the data pattern might help in retaining the accuracy to the desired level.

REFERENCES

Berizzi, A., C. Bovo, M. Delfanti, M. Merlo and M.S. Pasquadibisceglie, 2007. A Monte Carlo approach for TTC evaluation. IEEE Trans. Power Syst., 22: 735-743.

Hahn, T.K., M.K. Kim, D. Hur, J.K. Park and Y.T. Yoon, 2008. Evaluation of available transfer capability using fuzzy multi-objective contingency-constrained optimal power flow. Electr. Power Syst. Res., 78: 873-882.

Ichikawa, T., K. Ichiyanagi, R. Watanabe, K. Yukita and Y. Goto *et al*., 2009. An estimation method of available transfer capabilities from viewpoint of power system transient stability under deregulated environment. Electr. Eng. Japan, 167: 66-73.

Khairuddin, A.B., S.S. Ahmed, M.W. Mustafa, A.M. Zin and H. Ahmad, 2004. A novel method for ATC computations in a large-scale power system. IEEE Trans. Power Syst., 19: 1150-1158.

Luo, X., A.D. Patton and C. Singh, 2000. Real power transfer capability calculations using multi-layer feed-forward neural networks. IEEE Trans. Power Syst., 15: 903-908.

Othman, M.M., A. Mohamed and A. Hussain, 2005. Fast evaluation of available transfer capability using cubic-spline interpolation technique. Electric Power Syst. Res., 73: 335-342.

Pan, X. and G. Xu, 2005. Available transfer capability calculation considering voltage stability margin. Electr. Power Syst. Res., 76: 52-57.

Srinu Naik, R., K. Vaisakh and K. Anand, 2010. Determination of ATC with PTDF using linear methods in presence of TCSC. Proceedings of the 2nd International Conference on Computer and Automation Engineering, Volume 5, February 26-28, 2010, Singapore, pp: 146-151.

Stahlhut, J.W. and G.T. Heydt, 2007. Stochastic-algebraic calculation of available transfer capability. IEEE Trans. Power Syst., 22: 616-623.

Vaithilingam, C. and R.P. Kumudini Devi, 2013. Available transfer capability estimation using Support Vector Machine. Int. J. Elect. Power. Energy Syst., 47: 387-393.

Wu, Y.K., 2007. A novel algorithm for ATC calculations and applications in deregulated electricity markets. Int. J. Electr. Power Energy Syst., 29: 810-821.