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EMPIRICAL ANALYSIS OF AVAILABLE TRANSFER CAPABILITY DETERMINATION METHODS: A FUZZY STATISTICAL PERSPECTIVE

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Abstract: **Available transfer capability (ATC) is a metric in power systems that determines the maximum amount of incremental power that can be transferred between two parts (usually seller and buyer) of the underlying power system without crossing any system thresholds. It is evaluated using 3 major metrics; i.e.; total transfer capability (TTC), transmission reliability margin (TRM) and existing transmission commitments. In order to determine these parameters, various methods are proposed by researchers, some of these methods are applicable to large scale grids, while others work effectively for small-to-medium grid deployments. In order to deploy a customized grid with effective ATC calculations, it is recommended that power system designers must select an optimum combination of these methods. For instance, Single Linear Step (SL) approach uses present state system information along with sensitivities embodied in the power transfer distribution factors (PTDF) and line outage distribution factors (LODF) in order to determine ATC values. The SL method is applicable only for small-scale power distribution systems, but can be extended via Iterated Linear Step (IL) method to incorporate controller changes for large scale systems. As system complexity increases, it becomes difficult to select the best method out of the given methods for ATC calculations. In order to reduce this complexity, the underlying text reviews different ATC calculation methods, and compares their statistical performance. Using this study, power system designers can identify most suited methods for their system deployment, and thus save time and cost for testing out different method.**

Index Terms **– Available transfer capability, grid power, linear, iterated, distribution.**

I. INTRODUCTION

In order to determine available transfer capability (ATC) values for any electrical power system a wide-variety of calculations are needed. These calculations include evaluation of transmission plans, approval of source and destination nodes, Load Generation Balance Report (LGBR) analysis, previous year report evaluations, weather forecast data processing, previous year ATC patterns, etc. All these data values are given to different processing blocks. which anticipate network topology, perform capacity additions, anticipate substation loads, anticipate thermal generation, anticipate hydro-generation, etc. These anticipation blocks are combined with various planning criterion, operating limits, previous operation experience levels & credible contingencies; and are given to a simulation and analysis block. The output of this block is the total transfer capability of the system. When reliability margins are reduced from this total transfer capability, then the available transfer capability is evaluated. A diagrammatic representation of this process can be observed from figure 1, wherein different blocks are combined in order to obtain the final ATC values.

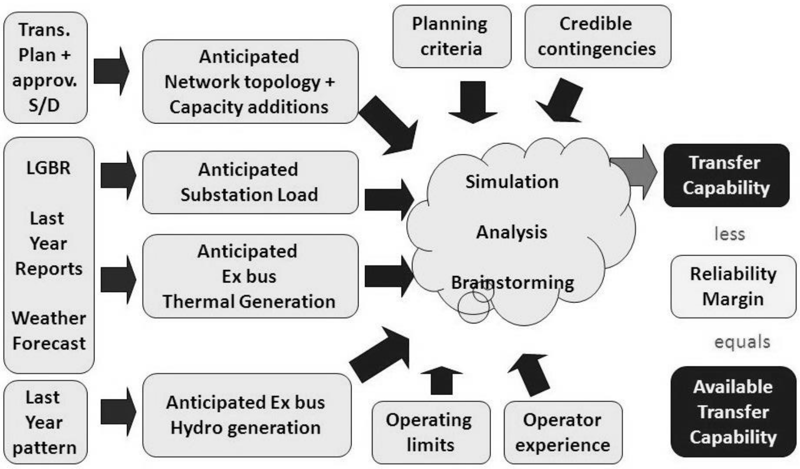

Figure 1. Exhaustive ATC calculation steps

Different algorithms are proposed by researchers over the years for network topology prediction, capacity prediction, load prediction, generation prediction, etc., which assist in improving the efficiency of ATC calculations. Moreover, different simulation, analysis and optimization algorithms are also proposed by researchers for improving ATC calculation performance. A survey of these algorithms is mentioned in the next section of this text. This is followed by a statistical evaluation of these algorithms, in order to compare their performance. Finally, this text concludes with some interesting observations about these algorithms and recommends ways in which these algorithms can be further improved for better ATC evaluation accuracy.

1. Literature Review

Available transfer capability evaluation methods range from simple linear approximations to complex machine learning based models. In this section, a review of these techniques is done and their performance is discussed. The work in [1] discusses the use of several techniques for evaluation of ATC values, for instance, the work discusses a high-speed linear approximation method. This method is 25 times faster in case of large-scale power system deployments when compared with AC power factor (PF) techniques. But its accuracy is limited to high X/R values, and degrades exponentially for low to moderate X/R values. The accuracy also reduces when there load requirements are high, or when there are sudden changes in the load demand of the system. The most common linear approximation method is DC power flow method, which is governed using incremental power and voltage angle change equations 1 and 2 as follows,

$$\Delta P = \sum_{i=1}^{N} B_{ji}\left(\emptyset_j - \emptyset_i\right) \dots (1)$$

$$\Delta\emptyset = [B']^{-1} * [\Delta P] \dots (2)$$

where, P is the power generated between buses 'i' and 'j', B is the value of susceptance, $\emptyset$ is the angle between voltage buses. This method determines the value of power on the buses, and then determines the phase angle. If the power rises above given thresholds then overload condition is triggered and corrective actions are taken as per the system's specifications.

An enhancement to this method is repetitive power flow (RPF) and continuation power flow (CPF), each of these methods are capable enough to integrate voltage breakdowns & reductions, thermal loading effects, reactive power flow values, etc. while evaluating ATC. Due to the incorporation of so many parameters, the RPF and CPF methods require larger computational delays, and might give moderate accuracy for special case power transfers. To reduce these drawbacks the optimal power flow (OPF) method is used. This method combines the advantages of linear approximation method and RPF/CPF in order to incorporate fast changes, and requires low computational delay. But an optimal solution cannot be obtained due to the combination of these methods, therefore it is recommended to use OPF as an approximate solution for ATC calculations. The stability constrained method uses dynamic system behaviour for high accuracy of ATC results, but it is not applicable to real-time online applications due to its high complexity.

To reduce these drawbacks, numerical methods are employed for ATC calculations. These methods can incorporate any level of uncertainty in the electrical power system and then too, produce accurate results. The main issue with numerical methods is the inability to deal with relativity among system components. Numerical methods must be employed for large-scale systems, because they need large amount of data for approximating their results. Small-scale systems reduce the accuracy and increase of the delay needed for numerical methods, as there are a large number of equations employed for this purpose. To reduce this computational complexity, the analytical method is employed. This method covers lesser number of uncertainties, but is faster than numerical method. But the accuracy of this method is reduced due to large number of assumptions and due to linearization. Similar to stability method, the approximate method also produces good accuracy results but is not used due to large computational delay.

It is observed that none of these methods are capable enough for reduced complexity and high accuracy ATC calculations. In order to remove this drawback, the neural network architecture is studied in [1]. Once trained the architecture can take any kind of input, and produce a highly accurate ATC output. The architecture for the said neural network can be observed from figure 2, wherein active (P) and reactive (Q) power levels are used by multiple layers of the network for improved ATC evaluations.

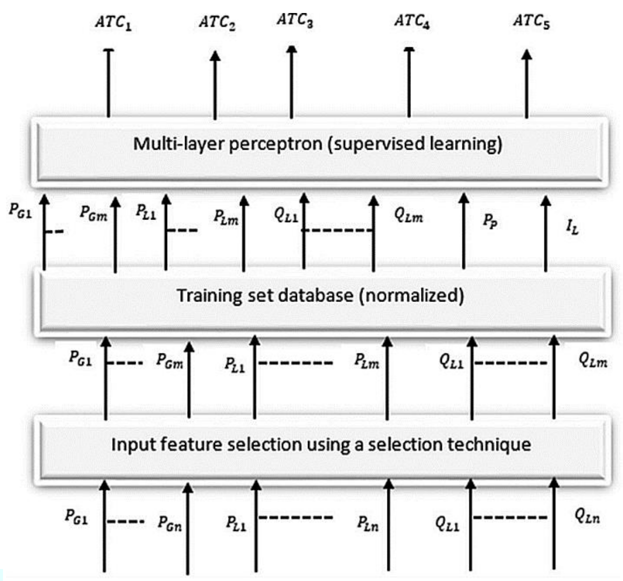

Figure 1. ATC calculations via neural networks [1]

The system requires large amount of data for ATC calculation training, but once trained the system can accurately identify ATC values for both small-scale and large-scale systems. This system uses non-linear calculations for calculation of ATC. An example of such a non-linear ATC calculation tool can be observed from [2], wherein the system is able to accurately find out ATC values for 15000 bus system. Thereby suggesting the use of neural networks and other machine learning models for such calculations.

Accuracy of neural networks can be improved via Levenberg- Marquardt (LM) algorithm as suggested in [3], wherein a high accuracy ATC evaluation system for 75 bus Indian power system and IEEE 30 bus system is discussed. The work also discusses the use of Genetic Algorithm (GA) for improving the efficiency of ATC calculations. The algorithm uses OPF method and tries to maximize the total power generated at source side and total power consumed at destination side. It also tries to reduce generation cost as well, via the following fitness equation,

$f = (P_g + P_c) * C^{-1} \dots (3)$

where, P_g is the total generated power, P_c is the total consumed power and C is the cost of power generation. The GA tries to maximize the fitness value, thereby increasing the values of power generated, power consumed and reducing the value of cost of generation in any given solution.

Another example of neural network for ATC evaluation can be observed from [4], wherein phasor measurement unit or PMU data is utilized. The system uses a radial basis function (RBF) kernel for evaluation of ATC values through parameters like current angle, current magnitude, voltage angle and voltage magnitude. Internal network diagram for the given neural network can be observed from figure 3, wherein these features along with their output ATC values can be seen.

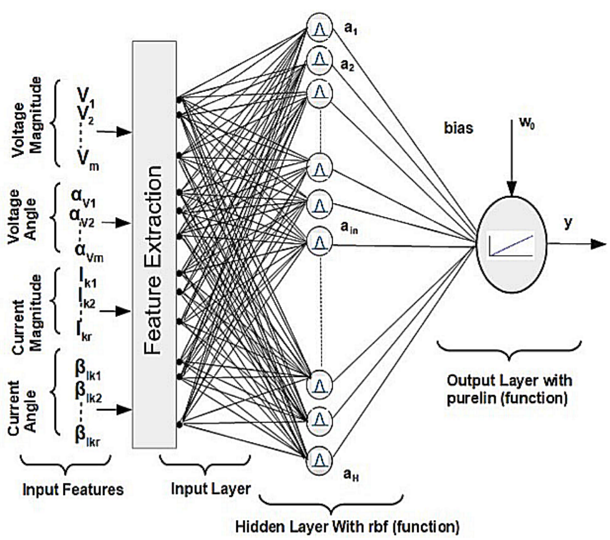

Figure 3. ATC evaluation using Neural Networks [4]

The feature extraction unit uses a sparse fitting algorithm (SFA) to select most dominant current and voltage features via Broyden–Fletcher–Goldfarb–Shanno quasi-Newton optimization. The model has low error in the range of 0.001, and large training delay, but can be applied for real-time small- and large-scale systems for ATC calculations. Similar performance is observed via the use of flexible demand response (FDR) technique as mentioned in [5], wherein deferrable demand response (DDR), switchable demand response (SDR) and flexible demand response (FDR) values are combined with renewable energy generators for day-ahead market bidding. These historical values are used on the next day for real-time market clearing in order to evaluate ATC values. The schematic diagram for these evaluations can be observed from figure 4, wherein previous day and current day response values are used to evaluate real-time ATC.

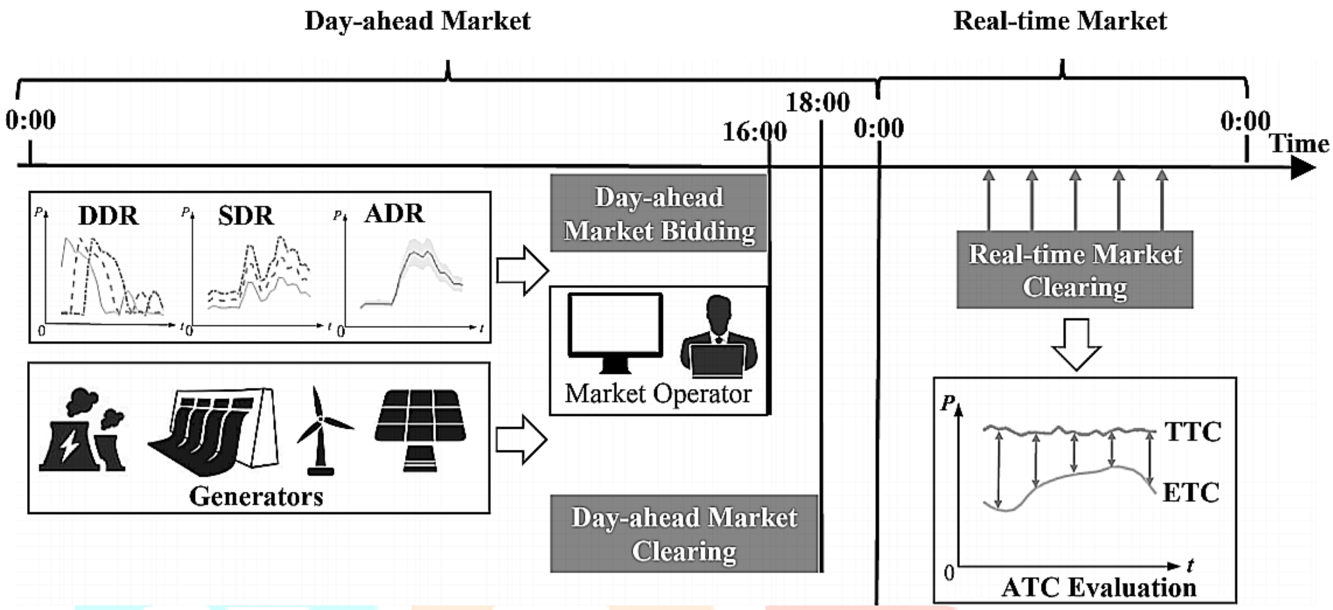

Figure 4. Market bidding for ATC evaluation [5]

Moderate level of accuracy is obtained via the use of this technique, and one day delay is incurred while using it. The overall performance of this technique can be improved via the use of neural networks.

ATC calculations are majorly affected by rapid changes in the deployed system configuration. Some of these configuration changes are described in [6], these changes include but are not limited to,

- Generator rescheduling, wherein active power rescheduling of generator nodes changes ATC levels very easily. These changes can be tackled with the help of Genetic Algorithm (GA) along with Teacher Learner based optimization (TLBO).
- Nodal pricing or location pricing for congestion management can also cause shifts in ATC, which can be handled using neural networks.
- Distributed generator placement also affects ATC calculations, and can be handled via particle swarm optimization (PSO).
- Thyristor controlled phase shift transformer for congestion management in power systems also shifts ATC values, and must be countered via the use of GA or PSO methods.

Other algorithms mentioned in [6], which include GA, PSO, NN, Gravitational Search Algorithm (GSA) and Artificial Bee Colony Optimization (ABC) can be used to further improve efficiency of ATC calculations. The effectiveness of these methods can be further improved via the use of bi-level modelling for ATC evaluation as mentioned in [7], wherein the calculation of TTC is done using mathematic program with equilibrium constraints (MPEC), and then these MPEC values are given to Karush-Kuhn-Tucher (KKT) optimality evaluation, and then to mixed-integer linear programming (MILP) model. Both these models aim at reducing the errors in TTC to improve ATC evaluation. The system divides the output of system operating point into upper and lower level as observed from figure 5, wherein at upper-level ATC is evaluated, while at lower-level economic dispatch (ED) and power flow is estimated.

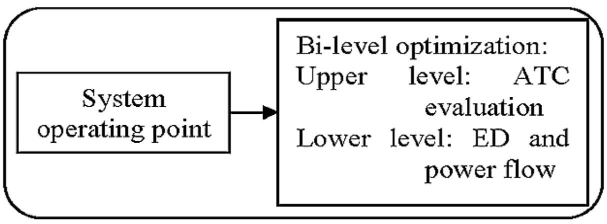

Figure 5. ATC evaluation using bi-level operations [7]

The system showcases moderate level accuracy, with moderate delay of evaluation and thus is suited for small to medium scale systems. This work can be extended via the use of probabilistic transmission capacity margins (PTCM) as discussed in [8]. Here, artificial neural networks (ANNs) are used to predict future load generation to evaluate dynamic ATC (DATC) values. The result of this ANN is given to a dragon fly algorithm for improving the efficiency of ATC calculations. It is observed that the proposed approach has moderate accuracy, high delay and is applicable only for renewable energy sources like solar & wind-based generation systems. The dragon fly algorithm works using the following steps,

- Select any hourly reading data for ATC evaluation
- Use previous temporal data for evaluation of load generation for the given hour's readings
- Initialize number of iterations, number of dragon flies, and learning rate
- Distribute the dragon flies randomly in the network, such that each dragon fly is at a different position in the network.
- Evaluate the value of ATC for this hour using standard ATC formula for each dragon fly
- Update the values of separation, alignment, cohesion and attraction in order to improve dragon fly location.
- Update the dragon fly velocity using velocity of nearby dragon flies, and repeat this process for all iterations
- At the end of the last iteration, select the output with highest ATC value, and use that configuration

The dragonfly algorithm's accuracy performance can be extended via the use of differential evolutionary algorithm and support vector machines (SVM) as suggested in [9], wherein transmission capacity margins are incorporated to ATC calculations. The work suggests iterative error reduction for ATC calculations, wherein minimum mean squared error (MMSE) is minimized iteratively in order to improve ATC evaluation accuracy. The underlying SVM uses a combination of multiple neurons at input and hidden layers along with a linear output layer in order to obtain the final ATC value as observed from figure 6, wherein connectivity between these layers is showcased.

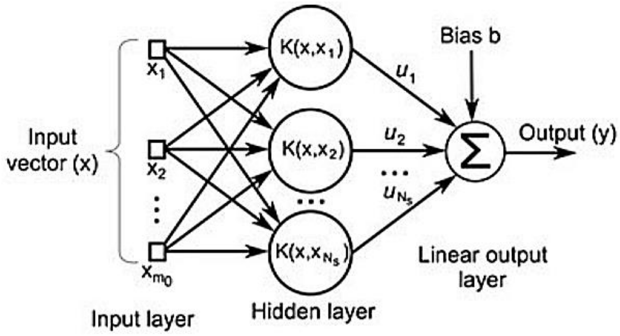

Figure 6. ATC calculations via SVM [9]

The SVM model tends to improve the accuracy for both small-scale and large-scale deployments, but requires large delays due to iterative computations and error reduction. It is observed that although SVM based differential evolution algorithm requires larger delays, but it is more accurate when compared to neural network-based ATC deployments. But the SVM model does not take into consideration small-signal stability, which reduces its accuracy under certain network load conditions. To tackle this issue, the work in [10] proposes a sequential quadratic programming (SQP) method, that combines adaptive gradient sampling (AGS) for improved ATC calculation accuracy. The work is deployed on IEEE 39 bus system, and showcases high performance in terms of ATC accuracy, and minimizes evaluation delay due to reduction and parallelization of gradient evaluation while calculating internal ATC parameters. An extension to this method, that uses particle swarm optimization (PSO) is observed from [11]. The method also takes into consideration small and large-scale changes in the power system loads, and determines values of ATC with high efficiency. Similar to [9], the PSO model also requires large training and evaluation delays due to its iterative nature. PSO, SVM and NN have similar accuracy for ATC calculations, but NN outperforms both PSO and SVM for large-scale systems, while SVM is better for small-scale systems.

A different approach to ATC calculations via network trade-off is mentioned in [12]. In this approach a two-level architecture for controlling of interconnected power systems is mentioned and observed in figure 7, wherein a control centre to receive data from all power systems is deployed. This approach works using the following steps,

- Perform state estimation to evaluate total transfer capability
- Define a single-rule base for additional loading of controlled lines on the system
- These rules are combined with initial line data and given to an Artificial Neural Network (ANN)
- Results from ANN are given to a weighting co-efficient, which results into a new value of transfer capacity
- This capacity is compared with the initial value to evaluate minimum mean squared error (MMSE)

- Based on this MMSE value, the information is sorted for each electrical power system (EPS)
- This information is given to each EPS for modification of generation instructions, procedure formation and data capture modules
- This new information is then given to a initial data generation block, to form new operation constraints
- The process is repeated, and the neural network is re-trained with these new values from each power system
- Based on these new values MMSE is evaluated, reduced and thereby accuracy of ATC evaluation is increased.

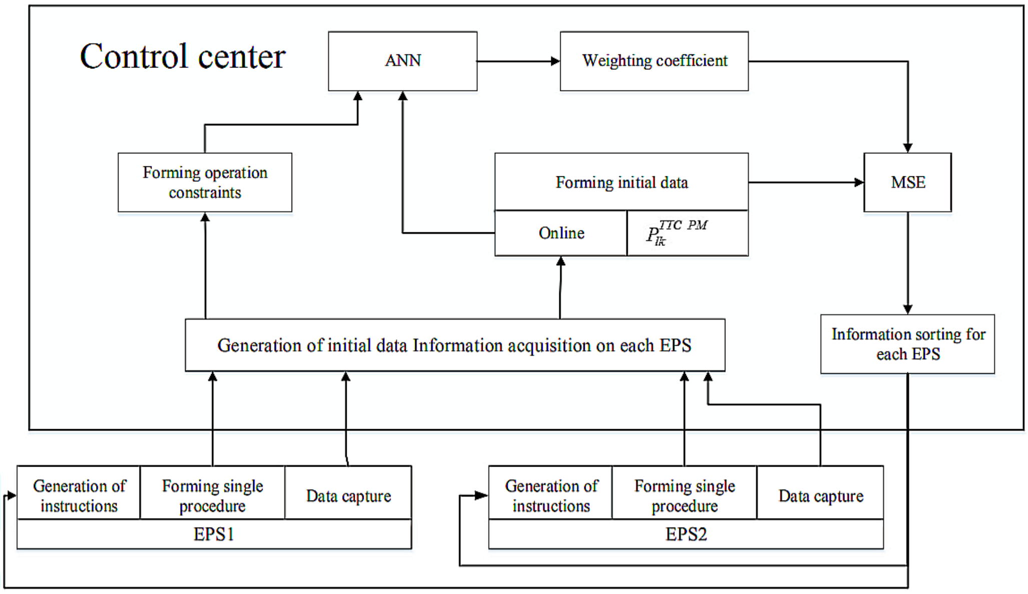

Figure 7. A control centre approach for ATC evaluation [12]

An extension to this work is mentioned in [13], wherein ANN is combined with Flexible AC Transmission System devices (FACTS devices) for improving the estimation of their online parameters. It optimizes the performance of Thyristor controlled series compensation (TCSC) and static VAR compensation (SVC) via neural network for better performance of ATC. As a result, the method possesses high accuracy for large-scale systems, but requires large delay values due to its iterative nature. Another application of TCSC for ATC evaluation is mentioned in [14], wherein Genetic Algorithm (GA) is used for optimization. When compared to NN, GA has similar accuracy performance, but has reduced delay for small-to-moderate scale systems. But the performance of NN is better for large-scale systems, due to incorporation of a large amount of network conditions. In both cases, GA has lower operation delay than NN, but NN is preferred for large-scale systems. Most of these optimization algorithms use Optimal power flow (OPF) method for evaluation of ATC, but the work in [15] suggests the use of repeated power flow (RPF) and power transfer distribution factor (PTDF) for optimization using bilateral transactions. They suggest that PTDF method can significantly reduce computational delay of any optimization method, by keeping similar ATC performance for large-scale systems. Thus, it is recommended that PTDF method be incorporated with machine learning models for improving the system's real-time performance. A similar observation is made in [16], wherein PTDF is compared with methods like DCPF, LODF, GSF, RPF, CPF and OPF. It is observed that RPF, CPF and OPF methods have better coverage for ATC evaluations as seen from table 1, and these methods are also more stable when compared with other methods.

Table 1. Comparison of different methods based on parametric coverage [16]

Method	Thermal	Voltage	Stability
DC Power Flow (DCPF)	√	×	×
Line Outage Distribution Factor (LODF)	√	×	×
Power Transfer Distribution Factor (PTDF)	√	×	×
Generation Shifting Factor (GSF)	√	×	×
Continuation Power Flow (CPF)	√	√	√
Repeated Power Flow (RPF)	√	√	√
Optimal Power Flow (OPF)	√	√	√

These methods can also be used in tandem with optimization algorithms like PSO and its variants. The work in [17] suggests combination of Metaheuristic Evolutionary Particle Swarm Optimization (MEPSO) with OPF for improving its ATC evaluation efficiency. Flow of the MEPSO algorithm can be observed from figure 8, wherein initial location optimization is done for better ATC calculations. It is observed that MEPSO method outperforms AC Power Transfer Distribution Factor (ACPTDF) and DCPTDF methods in terms of accuracy, but requires larger computational delays due to iterative error reduction. These methods are applied to FACTS devices, which makes them applicable for large-scale power system deployments. Apart from the considerations done by these methods, FACTS devices have a large number of micro and macro device considerations, which include shunt controllers, static compensation (STATCOM) controllers, unified power flow controllers (UPFC), integrated power flow controllers (IPFC), etc. Consideration of these devices for ATC calculations is done in [18], and it is observed that OPF method when combined with optimization algorithms can provide better ATC values when compared with other algorithms. Estimation of ATC can be improved via power system frequency estimation as suggested in [19], wherein finite impulse response (FIR) filters are used for frequency estimation.

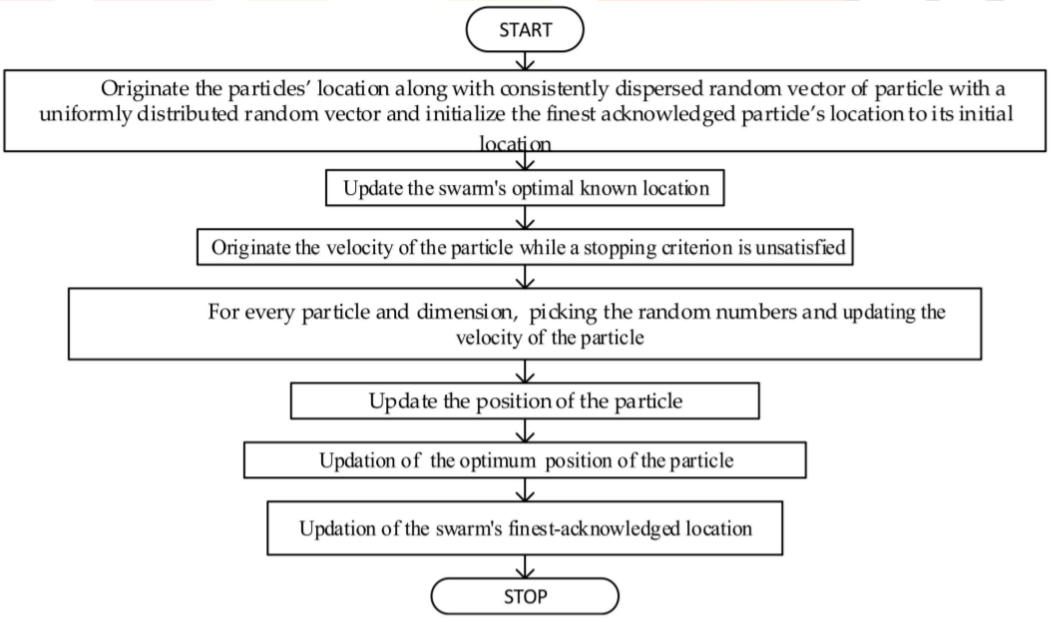

Figure 8. Flow of the MEPSO algorithm for ATC calculations [17]

Speed of ATC calculations can be improved via parallelization frameworks as mentioned in [20]. Here, Fork/Join method is combined with initialization of parameters, setting of faults, integrity detection of networks, identification of reasonableness and analysing results. This module aims at improving ATC evaluation speeds by 15% when compared with non-parallel workflows. An application of this model can be observed from [21], where it is applied to wind flow ATC calculations, but can be used for other generation sources as well. Synchro-phasor Measurements (SPM) can also be used for high-speed ATC calculations as observed from [22], wherein New England 39-bus Test System is used for testing. The SM method allow both small and large-scale systems to have moderate ATC evaluation accuracy, and low delay. It is still recommended that OPF method be combined with SM in order to improve ATC accuracy as observed in [23], wherein load flow method is compared with OPF method for different FACTS devices like STATCOM and UPFC. It is observed that OPF has better parametric efficiency, and requires similar delay when compared with load flow and other methods. OPF can be further improved via cuckoo search algorithm (CSA) as discussed in [24], wherein stochastic optimizations are applied for ATC calculations. It is further observed that CSA algorithm outperforms PSO, evolutionary programming (EP) and grey wolf optimization (GWO) for ATC evaluation.

An extension to [15] is mentioned in [25], wherein bilateral trading transactions are used for ATC evaluation via PTDF method. Flow of this system can be observed from figure 9, wherein minimum transfer limits are used for finding out ATC values. It is observed that this method is useful for IEEE 6 Bus systems, and can perform better for low-scale electrical power systems, but doesn't perform well for higher level bus systems. References of low, medium and large-scale power systems for ATC evaluation can be observed from [26], wherein California Independent System Operator Corporation (CASIO) standard for these evaluations is defined. The efficiency of PTDF method can be further extended using an intelligent Genetic Algorithm (IGA) as defined in [27], wherein FACTS devices are deployed for testing. The system also considers different outages for evaluation of ATC, and it is observed that static VAR compensation devices have good outage resilience, and thus have better ATC calculation efficiency. An extension to IGA can be observed in [28], wherein cat swarm optimization (CSO) model is used. The model is applied to IEEE 14 and 24 bus systems, and has good level of efficiency for both SVC and TCSC systems. The system also uses stochastic process modelling for reducing minimum mean square errors (MMSE), and thus has high accuracy but requires large delays for processing.

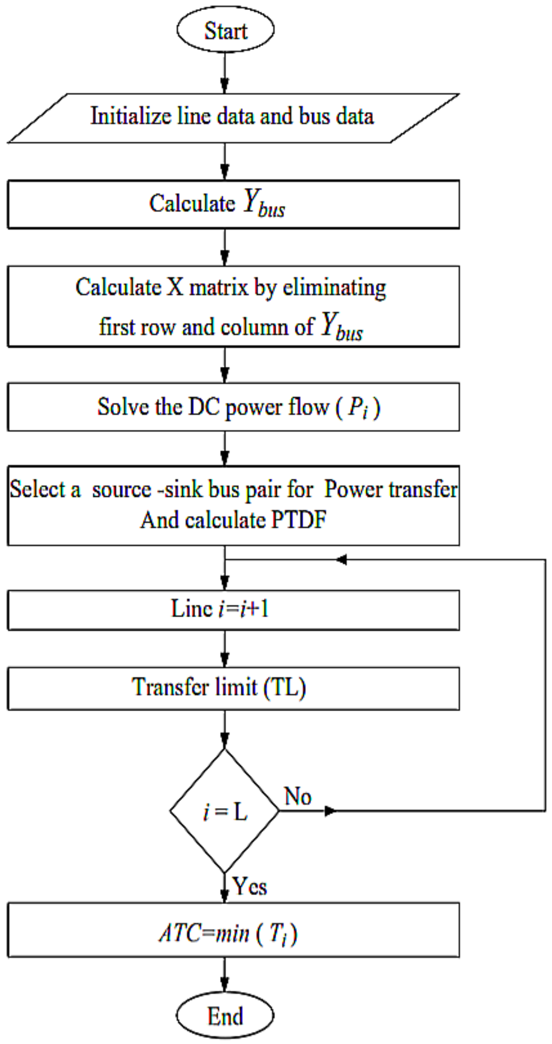

Figure 9. Bilateral transactions for ATC evaluation [25]

Other optimization models like Interval Optimization, crow search optimization, bacterial forging optimization, etc. are mentioned in [29], [30] and [31]. All these models have high accuracy for both small and large-scale systems, but requires large delays for evaluation. It can be observed that convolutional neural networks have not yet been applied for ATC evaluations due to their computational complexity, but it can be an alternative to these low-speed systems. A fuzzy statistical evaluation of these methods can be observed from the next section.

2. Fuzzy Statistical Analysis

In order to compare the reviewed methods in terms of delay, accuracy of ATC evaluation and scale of power system, this text converts the numerical values mentioned in the referred texts into fuzzy values. Delay and accuracy metrics are categorized into low, medium (M) and high (H), while scale of the system is categorized into small (S), medium (M) and large (L). This is done because all the systems are deployed on different IEEE bus systems, and thus do not have a common comparison ground. The following table 2 compares these methods and evaluates their fuzzy statistical performance.

Table 2. Fuzzy statistical comparison of different ATC evaluation methods

Method	Delay	Accuracy	Scale
High speed linear approximation [1]	L	M	S & M
RPF and CPF [1]	M	M	M
OPF [1]	M	H	M & L
Numerical method [1]	H	M	S & M
NN [1]	M	H	S, M & L
LM NN [3]	M	H	S, M & L
GA with OPF [3]	H	H	S & M
PMU with RBF [4]	H	H	M
SFA [5]	H	H	H
GA, PSO, NN, GSA & ABC [6]	H	M	S & M
Bi-level operations [7]	M	M	S, M & L
PTCM & NN [8]	H	H	M & L
SVM [9]	H	VH	S, M & L
SQP with AGS [10]	M	H	S, M & L
PSO [11]	M	M	M
ANN with 2-level architecture [12]	H	H	M & L
FACTS with NN [13]	M	H	M & L
GA [14]	H	H	M & L
RPF & PTDF [15]	L	M	M & L
MEPSO with OPF [17]	H	H	S, M & L
OPF with FACTS [18]	M	H	S, M & L
Parallelization [19]	L	H	S & M
SPM [22]	M	M	S & M
OPF with SPM [23]	M	H	S & M
CSA [24]	H	H	S & M

CSO [28]	H	H	S

From the comparison it is observed that SVM outperforms other methods like NN, CSO, CSA, GA and PSO in terms of ATC evaluation accuracy. SVM requires large delays due to its iterative behaviour, but this delay can be reduced by integration of high speed PTDF methods to SVM. Furthermore, other methods like Parallelization, linear approximation can also be integrated with SVM for reducing its delay. It is recommended that ANN methods should be extended using SVM and OPF methods for further improving their performance.

3. Conclusion and future scope

Using this review, it is observed that simple method for ATC estimation like linear approximation, OPF, RPF PTDF and CPF do not have high accuracy. Due to this, optimization algorithms like artificial neural networks, support vector machines, Genetic Algorithms, etc. have been deployed. These methods have good performance for both FACTS and non-FACTS devices, which makes them an ideal candidate for further study and exploration. These methods have large delays due to their iterative behavior, but this delay can be reduced by techniques parallelization, integration of OPF, etc. into the optimization process. It is further observed that none of these methods make use of convolutional neural networks (CNN) for ATC estimations, which provides researchers with a major research gap in this field. CNNs have proven to be high speed, low error and high consistency networks for any kind of pattern-based evaluation. It is recommended that CNN must be modelled and its performance must be evaluated in order to improve overall ATC evaluation performance.

4. References

[1] Mohammed, OO, Mustafa, MW, Mohammed, DSS, Otuoze, AO. Available transfer capability calculation methods: A comprehensive review. Int Trans Electr Energ Syst. 2019; 29:e2846. https://doi.org/10.1002/2050-7038.2846

[2] Chiang HD., Li H. (2005) On-Line ATC Evaluation for Large-Scale Power Systems: Framework and Tool. In: Chow J.H., Wu F.F., Momoh J. (eds) Applied Mathematics for Restructured Electric Power Systems. Power Electronics and Power Systems. Springer, Boston, MA. https://doi.org/10.1007/0-387-23471-3_5

[3] Mohammed,OO, Mustafa, W, Mohammed, DSS, Otuoze, AO. Available transfer capability calculation methods: A comprehensive review. *Int Trans Electr Energ Syst*. 2019; 29:e2846. https://doi.org/10.1002/2050-7038.2846

[4] Shukla, Devesh; Singh, S.P.: 'Real-time estimation of ATC using PMU data and ANN', IET Generation, Transmission & Distribution, 2020, 14, (17), p. 3604-3616, DOI: 10.1049/iet-gtd.2019.1260, IET Digital Library, https://digital-library.theiet.org/content/journals/10.1049/iet-gtd.2019.1260

[5] Yuwei Zhang & Wenying Liu & Yue Huan & Qiang Zhou & Ningbo Wang, 2020. "An Optimal Day-Ahead Thermal Generation Scheduling Method to Enhance Total Transfer Capability for the Sending-Side System with Large-Scale Wind Power Integration," Energies, MDPI, Open Access Journal, vol. 13(9), pages 1-19, May.

[6] Pooja Rani,Thakur, "Impact of deregulated power system market in congestion management of a transmission line a conceptual approach", AIP Conference Proceedings, doi: 10.1063/5.0024543

[7] Wang, B.; Fang, X.; Zhao, X.; Chen, H. Bi-Level Optimization for Available Transfer Capability Evaluation in Deregulated Electricity Market. *Energies* **2015**, *8*, 13344-13360. https://doi.org/10.3390/en81212370

[8] Karuppasamypandiyan, M, Jeyanthy, PA, Devaraj, D, Selvi, VAI. Day ahead dynamic available transfer capability evaluation incorporating probabilistic transmission capacity margins in presence of wind generators. *Int Trans Electr Energ Syst*. 2021; 31:e12693. https://doi.org/10.1002/2050-7038.12693

[9] Velusamy, AIS, Ramu, NB, Durairaj, D, Murugesan, K. Differential evolutionary algorithm-based optimal support vector machine for online dynamic available transfer capability estimation incorporating transmission capacity margins. *Int Trans Electr Energ Syst* 2017; 27:e2331. https://doi.org/10.1002/etep.2331

[10] Abedinia, Oveis, "Available Transfer Capability Calculation Constrained with Small-Signal Stability Based on Adaptive Gradient Sampling", https://doi.org/10.1155/2020/3912717

[11] P. Wongchai and S. Phichaisawat, "Determination of Transfer Capability Point by Using Adaptive Particle Swarm Optimization," 2020 8th International Electrical Engineering Congress (iEECON), Chiang Mai, Thailand, 2020, pp. 1-4, doi: 10.1109/iEECON48109.2020.230079.

[12] Anna M. Glazunova, Elena S. Aksaeva, "Estimation of Total Transfer Capability in Intersystem Tie Lines of Electric Power Systems", IFAC-PapersOnLine, Volume 51, Issue 32, 2018, Pages 331-336, ISSN 2405-8963, https://doi.org/10.1016/j.ifacol.2018.11.405.

[13] M Karuppasamy Pandiyan *et al* "Online estimation of control parameters of FACTS devices for ATC enhancement using artificial neural network", 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1055** 012146

[14] Shivakumara N, Dr. K. S. Aprameya, 2013, The Application Of TCSC To Improve ATC Of Power Transmission Network By Using Genetic Algorithm, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 02, Issue 08 (August 2013),

[15] B. Y. Bagde, Shende, P., & B. S. Umre. (2020). Assessment of Available Transfer Capability in the Electricity Market. *Helix, 10*(02), 15-20. Retrieved from https://helixscientific.pub/index.php/home/article/view/103

[16] Hojabri, Mojgan & Hizam, Hashim. (2011). Available Transfer Capability Calculation. 10.5772/21163.

[17] Gupta, Divya & Jain, Sanjay. (2021). Available Transfer Capability Enhancement by FACTS Devices Using Metaheuristic Evolutionary Particle Swarm Optimization (MEEPSO) Technique. Energies. 14. 869. 10.3390/en14040869.

[18] Albatsh, F.M., Mekhilef, S., Ahmad, S. *et al.* Enhancing power transfer capability through flexible AC transmission system devices: a review. *Frontiers Inf Technol Electronic Eng* **16,** 658–678 (2015). https://doi.org/10.1631/FITEE.1500019

[19] Chughtai, A.H., Awan, M.S. Estimation of power system frequency using a recurrent scheme. *Electr Eng* **102,** 859–868 (2020). https://doi.org/10.1007/s00202-019-00913-7

[20] CHENG, C., LUO, B., SHEN, J. *et al.* A modular parallelization framework for power flow transfer analysis of large-scale power systems. *J. Mod. Power Syst. Clean Energy* **6,** 679–690 (2018). https://doi.org/10.1007/s40565-017-0354-4
[21] Chen, H., Fang, X., Zhang, R., Jiang, T., Li, G. and Li, F. (2018), Available transfer capability evaluation in a deregulated electricity market considering correlated wind power. IET Gener. Transm. Distrib., 12: 53-61. https://doi.org/10.1049/iet-gtd.2016.1883
[22] Ch. V. V. S. Bhaskara Reddy and S. C. Srivastava and Saikat Chakrabarti, "Fast Assessment of Available Transfer Capability Using Synchrophasor Measurements", Taylor & Francis, doi:10.1080/15325008.2014.890972
[23] M. Venkateswara Rao, S. Sivanagaraju, Chintalapudi V. Suresh,Available transfer capability evaluation and enhancement using various FACTS controllers: Special focus on system security, Ain Shams Engineering Journal, Volume 7, Issue 1, 2016, Pages 191-207, ISSN 2090-4479, https://doi.org/10.1016/j.asej.2015.11.006.
[24] https://www.ijitee.org/wp-content/uploads/papers/v8i8s3/H10830688S319.pdf
[25] Duong, T. L., "Available Transfer Capability Determination for the Electricity Market using Cuckoo Search Algorithm", https://etasr.com/index.php/ETASR/article/view/3338
[26] R. Rohini, D. N. Rao, S. Ravi and V. S. Kumar, "Development of available transfer capability enhancement using intelligent genetic algorithm for ieee bus system," *Intelligent Automation & Soft Computing*, vol. 25, no.3, pp. 433–440, 2019.
[27] T. Nireekshana, G. Kesava Rao, S. Sivanaga Raju, "Available transfer capability enhancement with FACTS using Cat Swarm Optimization,", doi: 10.1016/j.asej.2015.11.011
[28] X. Kou and F. Li, "Interval Optimization for Available Transfer Capability Evaluation Considering Wind Power Uncertainty," in IEEE Transactions on Sustainable Energy, vol. 11, no. 1, pp. 250-259, Jan. 2020, doi: 10.1109/TSTE.2018.2890125.
[29] https://www.worldscientific.com/doi/10.1142/S0218126620502370
[30] K. Majumdar, P. K. Roy and S. Baneijee, "Available transfer capacity evaluation through evolutionary algorithms," 2016 International Conference on Microelectronics, Computing and Communications (MicroCom), Durgapur, India, 2016, pp. 1-6, doi: 10.1109/MicroCom.2016.7522469.