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Available Transfer Capability Maximization by using Genetic Model

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Abstract: Available Transfer Capability (ATC) between two points of a power system determines the maximum incremental power transfer that is possible while considering circuit limitations. It is estimated via a combination of existing commitments of transmission (ETC), total transfer capability (TTC) and transmission reliability margin (TRM), which are controlled via generator participation factors. Thus, efficient control of these participation factors can assist in improving ATC between different points of electrical circuits. Researchers have proposed multiple optimization models to perform this task, but most of these models use static rules, thus cannot be deployed for dynamically changing load requirements. To overcome this limitation, a novel Genetic Model for Maximization of ATC via optimum selection of participation factors is proposed in this text. The model uses line data, source bus, destination bus, and minimum participation needed for different sources in order to train a dynamic Genetic Model (GM), which assists in estimation of participation factors. These factors are optimized via continuous evaluation of Power Transfer Distribution Factor (PTDF), which is estimated by stochastic differential power factor calculations. Based on these stochastic calculations, different participation factors (PFs) for obtaining Maximum ATC levels are estimated, and each of these PFs are further evaluated for quality maximization under different bus configurations. The model also proposes a novel Learning Rate (LR) optimization method, which assists in selection of circuit-specific GM parameters. Due to use of the LR optimization method, transmission system designers can directly reconfigure underlying GM model by providing circuit parameters. This further reduces delay needed to identify optimum PF values for different circuit types. The model was tested & deployed under different standard bus configurations, and its efficiency was evaluated in terms of ATC improvement, Total Harmonic Distortion (THD), Power Efficiency, and computational delay performance. Based on this evaluation, the model was compared with various state-of-the-art models, and it was observed that the proposed model showcased 8.5% better ATC, 3.8% lower THD, 8.3% better power efficiency, and 19.2% lower delay under different configurations. This performance was observed to be consistent across different bus systems, thereby suggesting that the proposed model has high scalability, and can be used for a wide variety of deployments.

Keywords: Available, Transfer, Capacity, Genetic, Optimization, Learning, Rate, PTDF, Participation, Factor, ETC, TRM, TTC

1. Introduction

Multiple bus power systems require efficient transmission of power between different circuit points with maximum power efficiency. To achieve this task, a series of multidomain models are deployed, which include line flow calculations, active & reactive power estimation, wheeling transaction analysis, environment-specific evaluations, etc. A typical ATC estimation model deployed under CEED (combined economic emission dispatch) environment can be observed from figure 1, wherein initially base-case load flows are used to determine optimal settings of generators [1]. These settings are combined with wheeling transactions, generalized distribution factors, line current flows, power limits, etc. for dispatching efficient transactions. Based on these dispatches ATC is evaluated via equation 1,

$$ATC = M_t(TRM, TTC, CBM) \dots (1)$$

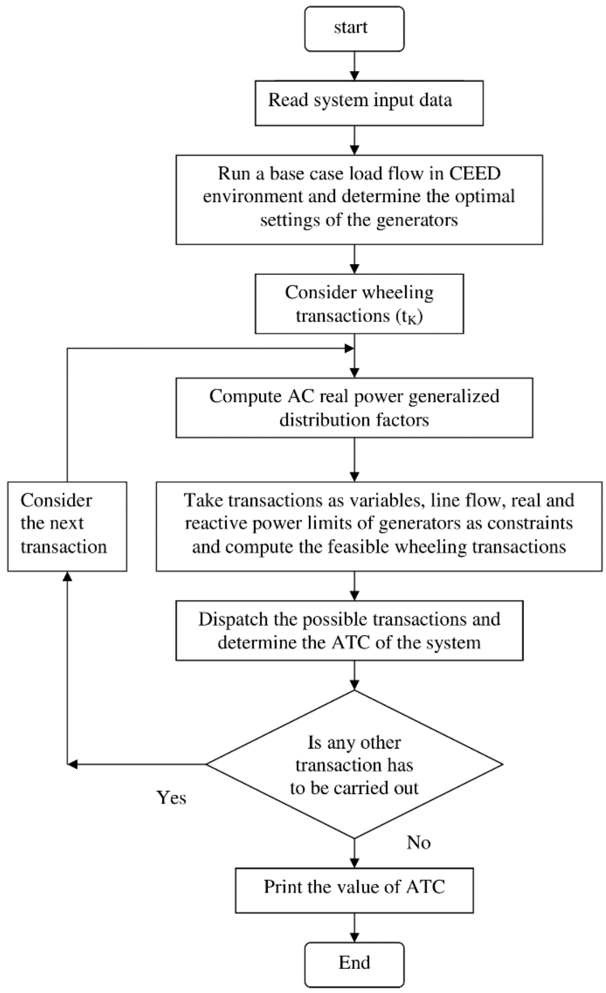

Figure 1. A typical ATC estimation model for CEED environments

Where, TTC represents total transfer capability (TTC), and is evaluated via equation 2, TRM represents transmission reliability margin and is estimated using equation 3, while CBR represents capacity benefit margin, and is estimated using equation 4 as follows,

$$TTC = \left(\sum_{i=1}^{N_T} B_{T_i} + C_{T_i} \right) + ETC \dots (2)$$

$$TRM = P_U * TTC \dots (3)$$

$$CBM = L_{exp} * LF \dots (4)$$

In these equations, B_{T_i} & C_{T_i} represents base case, and commercial network transfers, N_T represents count of transfers, ETC represents existing transfer commitments, which are evaluated by checking number of transfers remaining in the network, P_U represents probability of load uncertainty, while, L_{exp}, & LF represents load expected, & loss function for the underlying circuit deployments. Models that utilize these calculations [2, 3, 4] for optimization of ATC levels, along with their circuit-specific nuances, model specific advantages, application specific limitations, and future research scopes are discussed in the next section of this text. Based on this discussion, it was observed that most of these models use static rules, thus cannot be deployed for dynamically changing load requirements. To overcome this limitation, section 3 proposes design of Genetic Model to Maximize Available Transfer Capability via optimum Participation Factor selection, that can be used for multiple types of power transfer circuits. The proposed model's performance was evaluated in section 4, wherein ATC improvement, Total Harmonic Distortion (THD), Power Efficiency, and computational delay were compared with various state-of-the-art methods. Finally, this text concludes with some circuit-specific observations about the proposed model, and recommends model specific optimizations to improve their performance under different bus types.

2. Literature Review

A wide variety of models are proposed by researchers for maximization of ATC levels, and each of these models have their own characteristics and deployment capabilities. For instance, work in [1, 2, 3] propose use of particle swarm optimization (PSO), Newton-Raphson with Holomorphic embedding load flow (NR HELF), and Grey Wolf Optimization Algorithm (GWO) which assist in stochastic selection of internal components for efficient estimation of ATC levels. These models showcase lower error performance than linear estimation models, and thus can be used for a wide variety of large-scale application deployments. Similarly, work in [4, 5, 6], propose use of sequential quadratic programming with gradient sampling (SQPGS), Machine Learning Methods (MLMs), and Online Power Control which enable controlled estimation of ATC under static load requirements. These models are capable of showcasing lower THD performance, but cannot be scaled to larger deployments. To overcome this limitation, work in [7] proposes use of Teaching Learning based Optimization (TLbO) for estimation of voltage stability under dynamic bus configurations. The model is capable of achieving high efficiency and low error ATC estimation performance with better stability analysis. Extensions to this model are discussed in [8, 9, 10], wherein use of optimal power flow (OPF) with its variants, and production capacity-based optimizations are discussed by researchers. These models are highly context-sensitive and cannot be scaled to different bus configurations.

To improve scalability of ATC maximization models, work in [11, 12, 13] propose use of probabilistic day ahead dynamic ATC (PDA-DATC), canonical low-rank approximation (LRA), and performance index (PI) with particle swarm optimisation (PSO), and deep belief network (DBN), which assist in capturing large-scale load variations, and estimate ATC levels with good efficiency. These models require large delays due to their complex internal working characteristics. To reduce this complexity, work in [14, 15, 16] proposes use of active distribution network (ADN), Adaptive Particle Swarm Optimization (APSO), and big-M model which assist in improving computation speed via redundancy reduction under different bus configurations. Similar models that include novel data-driven sparse polynomial chaos expansion (DDSPCE) [17, 18], reliability test system (RTS) [19], energy injection [20], Sequential Game-Theory [21], Optimal Bayesian Transfer Learning (OBTL) [22], and hybrid Genetic Algorithm (GA) with Firefly (FF) [23, 24] are discussed & deployed for a large number of applications. These models are capable of solving ATC issues under static loads, but cannot be extended to dynamic loads due to their internal characteristics. To overcome this limitation, next section proposes a Genetic Model to Maximize Available Transfer Capability via optimum Participation Factor selection, which can be applied to small, medium & large-scale loads. Performance of the model was also evaluated under different bus configurations, and compared with various state-of-the-art methods under different scenarios.

3. Proposed Genetic Model to Maximize Available Transfer Capability via optimum Participation Factor selection

Based on the literature review it can be observed that existing models for selection of participation factor use static allocation rules, thus cannot be deployed for dynamically changing load requirements. Due to this limitation, existing models are not useful for loads that have frequent temporally changing current requirements. To overcome this limitation, a novel Genetic Model for Maximization of ATC via optimum selection of participation factors is proposed in this text. The model processes ratings of source bus, destination bus, line current requirements, and minimum participation per bus which is needed for different sources. This information is used to train a Genetic Model (GM), which assists in optimum estimation of participation factors. Overall flow of the model is depicted in figure 2, wherein it can be observed that these factors are optimized via continuous evaluation of Power Transfer Distribution Factor (PTDF) levels.

These levels are estimated via stochastic differential power factor calculations which assist in evaluation of different participation factors (PFs) to obtain Maximum ATC levels. The model also proposes a novel Learning Rate (LR) optimization method, which assists in selection of circuit-specific GM parameters. Due to use of the LR optimization method, transmission system designers can directly reconfigure underlying GM model by providing circuit parameters. This further reduces delay needed to identify optimum PF values for different circuit types. The model design is segregated into different sub modules, and each of these modules are described in different sub-sections of this text.

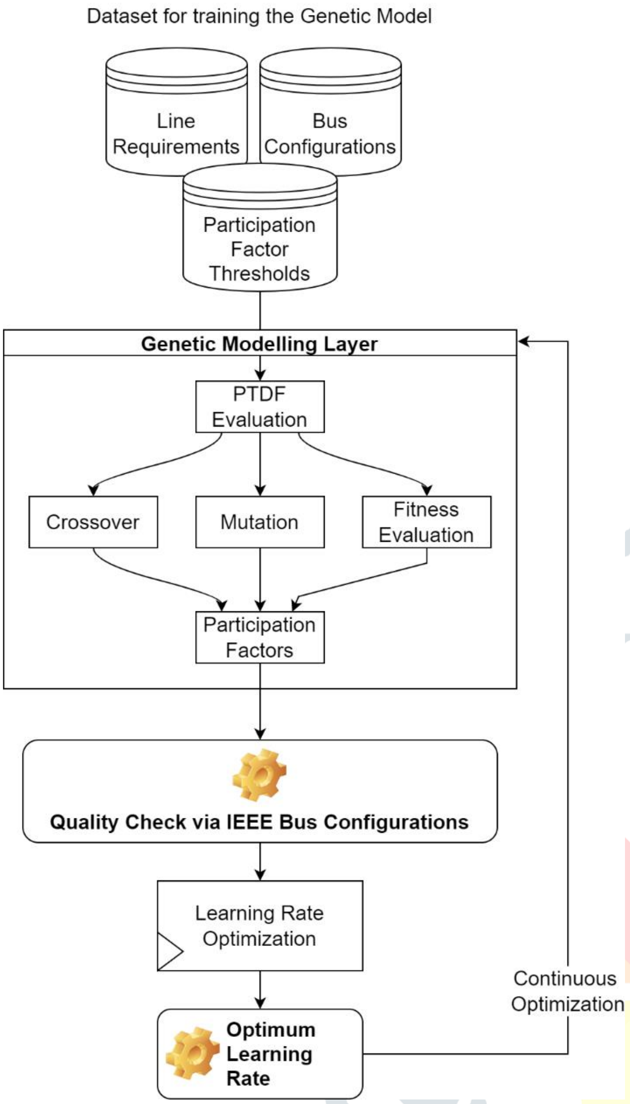

Figure 2. Overall flow of the proposed model

Readers can refer these sub sections to implement the underlying model in part(s) or as a whole, depending upon their circuit requirements.

3.1. Design of the Genetic Optimization Model for estimation of participation factors

The proposed Genetic Optimization model uses bus connections, reactance between buses, and their power specifications in order to estimate initial participation factors. This initial estimation model works via the following process,

- Initialize Genetic Optimization Parameters,
  - Source Bus (S_{bus})
  - Destination Bus (D_{bus})
  - Maximum power capacity of the circuit ($Max(P)$)
  - Minimum participation factor of each generator ($Min(PF)$)
  - Number of Iterations (N_i)
  - Number of Solutions (N_s)
  - Initial Learning Rate (L_r)
- Initially mark all solutions as 'to be mutated'
- For each solution in 1 to N_s, perform the following tasks,
  - For each iteration in 1 to N_i, perform the following tasks,
    - If solution is marked as 'not to be mutated', then go to the next solution, else generate new solution via the following process,
- Stochastically select participation factors (PF) for all generators via equation 4,

$$PF(i) = STOCH(Min(PF), 1)_i \ldots (4)$$

Where, $STOCH$ & $NumGen$ represents a stochastic Markovian process, and number of generators respectively.

- For the final generator, calculate participation factor via equation 5,

$$PF(NumGen) = 1 - \sum_{i=1}^{NumGen-1} PF(i) \ldots (5)$$

- Based on these factors, evaluate residual bus power (RP) via equation 6,

$$RP = PF \pm 0.1 \ldots (6)$$

- Using this residual power, evaluate PTDF via equation 7,

$$PTDF = (PF_2 - PF_1) * Max(P) \ldots (7)$$

Where, PF_1 & PF_2 represent updated power factors, and are estimated via equation 8 as follows,

$$PF_i = P_i * RP_i \ldots (8)$$

- Estimate solution fitness via equation 9,

$$f = \max\left[\frac{L - PF_1}{PTDF}\right] \ldots (9)$$

Where, L represents line power between the buses which are selected for power transfers.

- Based on this evaluation, estimate fitness threshold via equation 10,

$$f_{th} = \sum_{i=1}^{N_s} f_i * \frac{L_r}{N_s} \dots (10)$$

- At the end of each iteration, identify solutions where $f_i < f_{th}$, and mark them as 'to be mutated', while mark all others as 'not to be mutated'

- Repeat this process for all iterations, and select solution with maximum fitness

The selected solution contains initial participation factors for each generator, which are further optimized via quality checks and learning rate optimizations. Design of these tasks is discussed in the next section of this text.

3.2. Design of the Quality check layer for learning rate optimization

Upon estimation of initial participation factors, an iterative Quality check process is used to fine tune these factors. This process uses a continuous Q-Learning model which assists in optimization of Genetic Optimization learning rate, thereby improving selection of participation factors. This model works via the following process,

- Iterate the Genetic Optimization Model with 2 stochastic learning rates, and estimate their fitness levels.
- Based on these levels, evaluate Q factor via equation 11,

$$Q = F_2 + \partial[r + \emptyset * \max(F_1, F_2) - F_1] \dots (11)$$

Where, ∂ represents learning rates, r represents reward factor, $\emptyset$ represents discount factor, F_1 & F_2 represents consecutive fitness values estimated for different stochastic levels.

- Based on this Q value, estimate new learning rate via equation 12,

$$LR(New) = \frac{LR_{old}}{Q} \dots (12)$$

- Using the new LR value estimate participation factors & new fitness value F_3, and re-evaluate Q value via equation 13,

$$Q(New) = Max(F_3, F_2) + \partial\left[r + \emptyset * \max\left(Max(F_1, F_2), Max(F_3, F_2)\right) - Max(F_1, F_2)\right] \dots (13)$$

- Repeat this process if $Q(New) < Q$, else use the same value of learning rate which was evaluated via equation 12 to find optimum participation factors.

This process is used to continuously tune learning rate for evaluation of optimum participation factors. These factors were used to estimate ATC levels for different bus configurations. Results of these estimations are discussed in the next section of this text.

4. Result analysis & comparison

The proposed model uses a combination of Genetic Optimization with Learning Rate estimation to evaluate participation factors for evaluation of available transfer capability (ATC) levels. To estimate performance of the proposed model, it was tested on IEEE 14 Bus, IEEE 30 Bus, and IEEE 57 Bus configurations. Based on these configurations, values for percentage estimation error, processing delay, and total harmonic distortion (THD) were averaged and compared with GWO [3], SQP GS [4], and DBN [13] models under same configurations. These values for percentage estimation error (E) are tabulated in table 1, where source buses & destination buses combinations (NBC) were varied between 1 to 1000, which indicates all possible combinations of power transfer instances.

NBC	**E (%) GWO [3]**	**E (%) SQP GS [4]**	**E (%) DBN [13]**	**E (%) GMMA TPCF**
2	2.93	1.55	10.24	1.14
5	3.03	1.58	10.46	1.17
7	3.18	1.61	10.69	1.21
11	3.30	1.64	10.92	1.23

23	3.24	1.64	10.90	1.21
34	3.17	1.63	10.84	1.21
46	3.22	1.65	10.96	1.22
69	3.25	1.67	11.06	1.23
92	3.26	1.68	11.13	1.23
115	3.26	1.69	11.18	1.24
172	3.26	1.70	11.23	1.24
207	3.28	1.71	11.31	1.25
230	3.30	1.72	11.39	1.26
276	3.31	1.74	11.46	1.26
322	3.32	1.75	11.52	1.27
368	3.33	1.76	11.59	1.27
414	3.34	1.77	11.67	1.28
460	3.35	1.78	11.74	1.28
506	3.36	1.79	11.81	1.29
552	3.37	1.80	11.88	1.30
598	3.38	1.82	11.95	1.30
644	3.40	1.83	12.03	1.31
690	3.41	1.84	12.10	1.31
747	3.42	1.85	12.17	1.32
805	3.43	1.87	12.25	1.33
862	3.44	1.88	12.32	1.33
920	3.45	1.89	12.40	1.34
943	3.46	1.90	12.47	1.34
989	3.48	1.92	12.55	1.35
1000	3.50	1.93	12.63	1.41

Table 1. Average ATC estimation error for different models

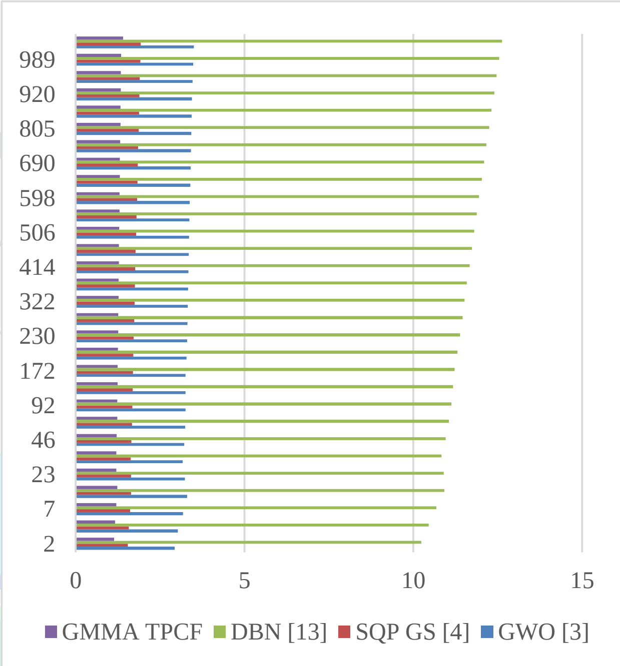

Figure 3. Average ATC estimation error for different models

Based on this evaluation, and figure 3, it can be observed that the proposed model showcases an error reduction of 18.5% when compared with GWO [3], 8.3% when compared with SQP GS [4], and 26.8% when compared with DBN [13], under different operating conditions. The reason for this enhancement is use of Genetic Optimization with continuous learning with assists in estimation of optimal participation factors for better circuit response under different deployment scenarios. Similar observations were made for computational delay, and can be observed from table 2 as follows,

NBC	**D (ms)** **GWO [3]**	**D (ms)** **SQP GS [4]**	**D (ms)** **DBN [13]**	**D (ms)** **GMMA TPCF**

2	7.66	10.66	7.38	4.61
5	7.75	10.78	7.45	4.65
7	7.82	10.88	7.51	4.69
11	7.87	10.95	7.55	4.72
23	7.90	11.00	7.59	4.74
34	7.94	11.06	7.63	4.77
46	8.00	11.14	7.69	4.80
69	8.05	11.22	7.73	4.83
92	8.10	11.29	7.78	4.86
115	8.15	11.36	7.83	4.89
172	8.20	11.43	7.88	4.92
207	8.25	11.51	7.92	4.95
230	8.30	11.58	7.97	4.98
276	8.35	11.66	8.02	5.02
322	8.40	11.73	8.07	5.05
368	8.45	11.80	8.12	5.08
414	8.50	11.88	8.17	5.11
460	8.56	11.96	8.22	5.14
506	8.61	12.03	8.27	5.18
552	8.66	12.11	8.32	5.21
598	8.71	12.19	8.37	5.24
644	8.77	12.27	8.42	5.27
690	8.82	12.35	8.47	5.31
747	8.87	12.42	8.52	5.34
805	8.93	12.50	8.58	5.37
862	8.98	12.58	8.62	5.41
920	9.04	12.67	8.66	5.44
943	9.09	12.75	8.70	5.48
989	9.15	12.83	8.75	5.51
1000	9.19	12.89	8.80	5.53

Table 2. Computation delay for different models

Based on this evaluation, and figure 4, it can be observed that the proposed model reduces computational delay by 19.4% when compared with GWO [3], 23.5% when compared with SQP GS [4], and 19.8% when compared with DBN [13], under different operating conditions.

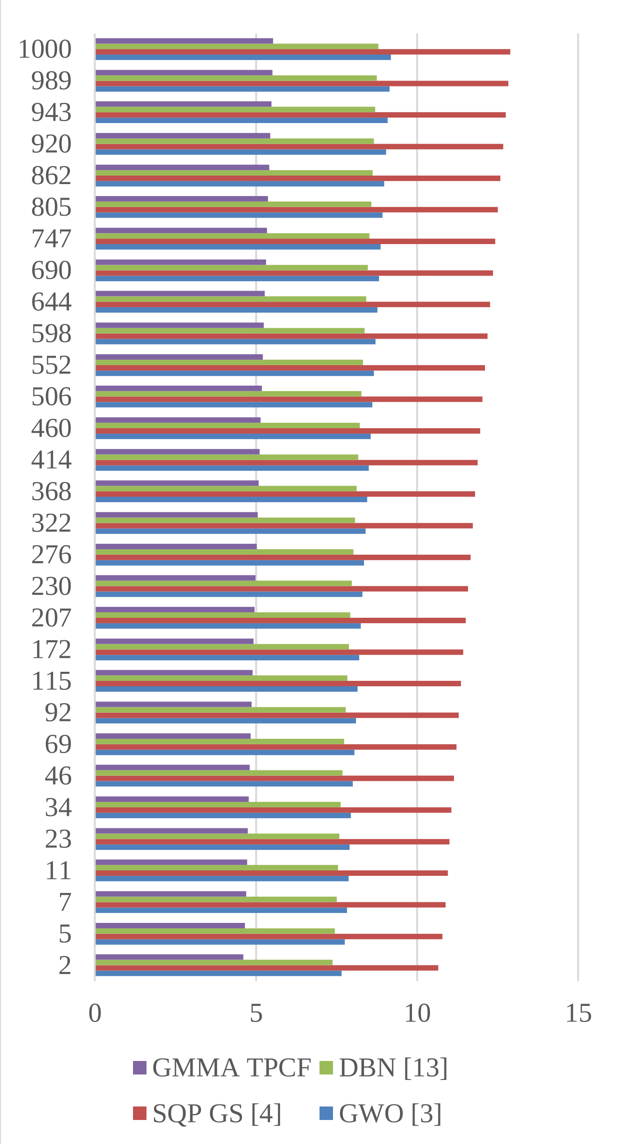

Figure 4. Computation delay for different models

The reason for this reduction in delay is use of incremental learning that assists in evaluation of optimum learning rates for efficient estimation of participation factors, which provide better circuit response under different deployment scenarios. Similar observations were made for THD levels, and can be observed from table 3 as follows,

NBC	**THD GWO [3]**	**THD SQP GS [4]**	**THD DBN [13]**	**THD GMMA TPCF**
2	2.55	3.27	1.84	1.41
5	2.58	3.31	1.86	1.43
7	2.60	3.34	1.87	1.44
11	2.62	3.36	1.89	1.45
23	2.63	3.38	1.89	1.46
34	2.64	3.40	1.90	1.46
46	2.66	3.42	1.92	1.47
69	2.68	3.45	1.93	1.48
92	2.69	3.47	1.94	1.49
115	2.71	3.49	1.95	1.50
172	2.73	3.51	1.97	1.51
207	2.74	3.53	1.98	1.52
230	2.76	3.56	1.99	1.53
276	2.78	3.58	2.00	1.54
322	2.79	3.60	2.01	1.55
368	2.81	3.62	2.03	1.56
414	2.83	3.65	2.04	1.57
460	2.85	3.67	2.05	1.58
506	2.86	3.70	2.06	1.59
552	2.88	3.72	2.08	1.60
598	2.90	3.74	2.09	1.61
644	2.92	3.77	2.10	1.62
690	2.93	3.79	2.11	1.63
747	2.95	3.82	2.13	1.64
805	2.97	3.84	2.14	1.65

862	2.99	3.86	2.15	1.66
920	3.01	3.89	2.16	1.67
943	3.03	3.92	2.17	1.68
989	3.04	3.94	2.18	1.69
1000	3.06	3.96	2.20	1.70

Table 3. Average THD levels for different models

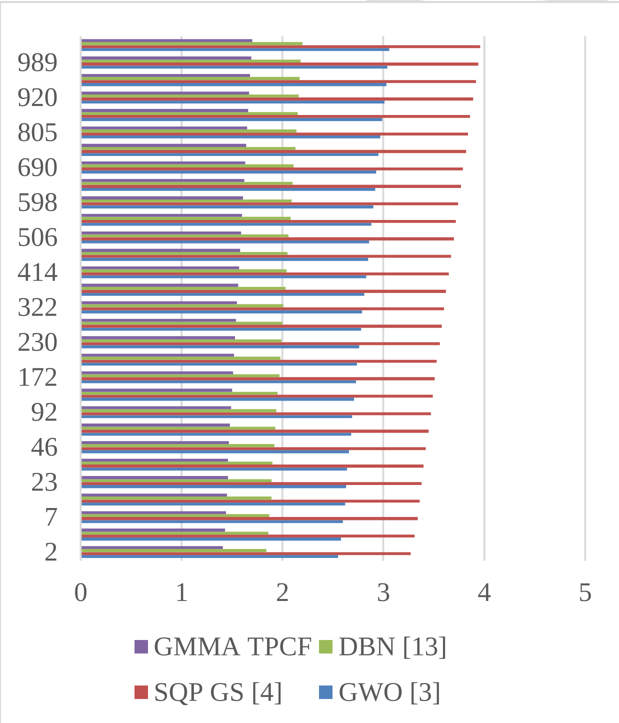

Table 5. Average THD levels for different models

From this evaluation and figure 5, it can be observed that the proposed model reduces THD by 7.5% when compared with GWO [3], 8.3% when compared with SQP GS [4], and 6.5% when compared with DBN [13], under different operating conditions. The reason for this reduction in THD is use of Genetic Optimization with incremental learning that assists in evaluation of optimum learning rates for efficient estimation of participation factors, which provide better circuit response under different deployment scenarios. Thus, the proposed model has lower error, faster response, and lower THD levels when compared with existing models, which makes it highly useful for a wide variety of power system applications.

5. Conclusion and future scope

The proposed GMMATCPF model uses a combination of continuous learning with Genetic Optimization for estimation of generator participation factors. The proposed model was tested under IEEE 14 Bus, IEEE 30 Bus, and IEEE 57 Bus configurations to estimate ATC calculation error, computational delay, and THD performance. Based on this evaluation, it was observed that the proposed model showcased an error reduction of 18.5% when compared with GWO [3], 8.3% when compared with SQP GS [4], and 26.8% when compared with DBN [13], it also showcased reduction in computational delay by 19.4% when compared with GWO [3], 23.5% when compared with SQP GS [4], and 19.8% when compared with DBN [13], while, the proposed model was observed to reduce THD by 7.5% when compared with GWO [3], 8.3% when compared with SQP GS [4], and 6.5% when compared with DBN [13], under different operating conditions. Thus, making the proposed model highly useful for a wide variety of real-time deployments. Performance of this model must be validated for other bus systems in order to estimate its scalability & applicability for larger configurations. In future, researchers can replace Genetic Optimization by other bioinspired models like Grey Wolf Optimization (GWO), Bacterial Foraging Optimization (BFO), Firefly Optimization, etc. and estimate their performance under various circuit conditions. Researchers can also incorporate deep learning methods including Long-Short-Term-Memory (LSTM), & Gated Recurrent Unit (GRU) to further optimize circuit performance under dynamic load requirements & circuit conditions.

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