# A Novel Method for ATC Computations in a Large-Scale Power System

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***Abstract*—In a restructured power system, it is the responsibility of the independent system operator (ISO) to control the power transactions and avoid overloading of the transmission lines beyond their thermal loading megavolt-ampere (MVA) limits. For this, ISO has to update periodically a real-time index termed available transfer capability (ATC). The methods reported to date for ATC determination are unable to cater to either the accuracy or the online CPU time requirements when the system is a large one. This paper proposes a novel method with the full details for determining ATC in a large power system from only three input variables through fuzzy modeling. The method is validated through extensive simulation tests on the standard IEEE 24-bus reliability test system (RTS), and comparison with an ac load flow-based conventional method using the same array of transactions, base cases, and generation/line outages.**

***Index Terms*—ATC, electricity market, fuzzy logic, large-scale power system, power system control.**

## I. Introduction

THE experience [1] gained since 1996 until now has turned the deregulation of power industry into an almost mature reality. In a deregulated system, the generation and distribution companies (i.e., market players) engage in transactions (i.e., selling or buying electricity) through a competitive bidding process administered by an agency known as power exchange apart from the transactions through bilateral negotiations. Every intended transaction is communicated to the transmission network operator termed independent system operator (ISO). The transactions are evaluated by ISO on the basis of an index termed available transfer capability (ATC) [2]. The bus at which a generation company sells (injects) power is termed source, and the one at which a distributor buys (extracts) power is called "sink." ATC between a given source-sink pair is the highest allowable size of a transaction over and above the already committed uses of the transmission system (i.e., existing base case) so that no line is overloaded in excess of its thermal loading limit megavolt-ampere (MVA) when the system is in steady-state condition.

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ATC is computed in real time at periodic intervals for each source-sink pair separately considering the base case that exists just before the current interval. Notably this base case is the outcome of the transactions that have already taken place between the current interval and the immediately preceding one. Also, various contingencies (anticipated outage scenarios) selected from a ranked list are considered one by one along with a base case while computing ATC between a source-sink pair. Having completed the ATC computations for all the source-sink pairs in the current interval, the intended transactions are ranked in descending order of available transfer margin (ATM). The difference between ATC and the size (in megawatts) of an intended transaction is termed "ATM." The transaction having the highest ATM is deemed honored first [3] leading to a change in the base-case scenario that warrants recalculation of ATC in the same interval corresponding to the transaction with the second highest ATM, and so on. Thus, ATC computation for a large system with many pairs of source-sink buses is a dimensional process.

A number of methods have been reported to date in literature for ATC determination. The continuation power-flow (CPF) methods [4]–[7] repeat full-scale ac load flow solution for each increment (above the base case value) of the load at sink bus until any line in the system is overloaded. Although accurate, these are not real-time compatible for large systems. The dc load-flow-based methods [3], [8], [9] are a bit faster than their ac counterparts but model only real power flow (in megawatts) in the lines rather than MVA, and assume the network to be loss free. The methods based on power transfer/outage distribution factors [10]–[12] can cater to only the scenarios that are too close to the base case from which the factors are derived. The stochastic methods [13], [14] are more suited to planning stage. The reported [15] artificial neural network (ANN) method requires a large input vector so that it has to oversimplify determination of ATC by limiting it to a special case of power transfer to a single area from all of the remaining areas. So this method is unable to track down the bus-to-bus transactions, which is the true spirit of deregulation.

The authors have deliberated on the drawbacks of the reviewed methods, and developed an idea that if ATC could be determined in one shot (without any repetition) using a reduced set of input variables and trivial online computations, then this would hold potential for a large-scale power network. To meet this goal, the authors have chosen fuzzy logic [16] as a tool. It has two main advantages. The way fuzzy logic tackles the dimensionality of a problem is computationally more efficient than that by other artificial intelligence (AI) techniques (such as ANN, expert system, etc.). Another advantage is that fuzzy logic can capture uncertainties inherent in an incomplete or reduced set of data. It is noteworthy that rigorous mathematics intensive conventional methods have none of these two advantages.

Fuzzy logic has successfully been used in many power system problems [17]. Of course, the way this is applied and exploited to advantages depends on the problem in particular. However, to date, no results appear to have been reported on the application of fuzzy logic for ATC determination.

In this paper, the authors have developed a method that applies fuzzy logic in the determination of ATC in a large system. The proposed fuzzy method has been tested extensively for computing ATCs between a number of source-sink pairs in the standard IEEE 24-bus reliability test system (RTS). The method has also been compared with a full-scale ac load flow-based method in terms of accuracy and CPU time for evaluating ATCs considering the same array of transactions, base cases, and outages.

## II. Proposed Method

The development process of the method proposed for determining ATC in a large system can best be illustrated beginning with a small (three-bus) power network shown in Fig. 1. Let the ATC between buses 1 (source) and 2 (sink bus) be evaluated. Power injected at bus 1 will flow to bus 2 through path '1–2' as well as through '1–3–2'. The authors introduce path '1–2' as the "direct path," '1–3–2' as the "indirect path," and bus 3 as the "neighboring bus." Notably the direct path has the less impedance and it shares more flow. The indirect path via the neighboring bus has the higher impedance, and it shares less flow. Consideration of the existing (base case) loads/generations at sink and neighboring buses (i.e., only two inputs can help fuzzy determination of the ATC between a pair of source-sink in an exclusively three-bus system). But in any large system with a higher number of buses, usually more than one electrical path shares the flow of power from a source bus to a sink one. This gives rise to a number of major differences that impacts ATC determination in a large system.

### A. Differences Between a Large and a Three-Bus System

The following are the major differences.

i) There are a number of candidate paths and buses that can be labeled as "indirect path" and "neighboring bus" corresponding to a given source–sink pair in a large system.
ii) For a given system topology, a transaction (power transfer) between any two buses of a large system is influenced by loads at various buses, and affects the flows in many lines to different extents depending upon the operating condition.
iii) Consideration of only sink and neighboring bus data will not be able to provide the required minimum information on the operating condition and outage scenarios (if any) of a large system. On the contrary, too many input variables will require a large rule base and mar the real-time compatibility of even a fuzzy method.

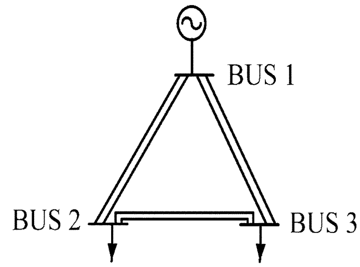


Fig. 1. Three-bus sample power system.

iv) The physical characteristics of an exclusively three-bus power system are easily tractable so that a set of rules can be developed to infer a fuzzy value (i.e., linguistic attribute) of ATC directly from fuzzy values of inputs. Eventually a single crisp (i.e., numerical) value of ATC is obtained combining the fired rules through a process what is known as defuzzification. This way of making inference is termed Mamdani fuzzy model [16]. But the characteristics and interactions among many buses and lines in a large system are not tractable simply on the basis of intuition. So ATC evaluation in a large system entails an alternative rule-base.

### B. Identification of Indirect Path and Neighboring Bus

For a given source–sink pair, the least "indirect path" is traced using line impedance data. The one having the least impedance among all the possible indirect paths is chosen.

If there are a number of buses on the chosen indirect path between a source and a sink then the bus immediately after the source is labeled as the neighboring bus. However, if this bus has mere a load but no generator connected to it whereas a next bus on the same path is generator connected, then the latter will be preferred as the neighbor. This is because a generator connected bus influences a transaction more than what simply a load bus does. So its choice as the neighbor will provide more explicit information that will enhance accuracy in the determination of ATC.

It should be noted that tracing the indirect path and the neighboring bus for each source–sink pair can always be made in offline mode by an algorithm that would use the network topology and parameters available in the database of a system.

### C. Catering to System Operating Conditions and Outages

A unified index has been proposed and labeled as "loading index" ($L$) to represent a given operating scenario of a large power system taking into account demands at all the buses and information on generation/line outages. This index is defined as in (1)

$$L = \frac{\sum_{i=1}^{N} P_{\mathrm{di}}}{1.5 A_{\max}} + 2C \tag{1}$$

where $P_{\mathrm{di}}$ is demand (MW) at bus $i$, $N$ is the total number of buses, and $A_{\max}$ is the thermal loadability (MVA) of the line having the highest limit in the system.

Various operating conditions and outages are considered by categorizing those. The variable $C$ in (1) is assigned a discrete integer value (e.g., $1, 2, 3, \ldots$) corresponding to the particular category under which ATC is being determined.

It is noteworthy that if the system demand that may have a large MW value is added with a small integer $C$ the latter's entity will be masked. So the former is normalized through division by a factor 1.5 $\mathrm{A_{max}}$ as in (1). The choice of 1.5 as multiplier reflects a fact that if there were only one candidate as the indirect path between a certain source–sink pair, and the base case were with no load at any bus, then the transferable maximum power would have been about 1.5 times the thermal loading limit of the direct path. Multiplication of $C$ by "2" in (1) is mainly to make two successive categories' loading indexes ($L$) distinct.

### D. Number of Input Variables

Based on the details explained in Sections II-A to II-C, ATC between a given pair of source-sink buses in a large system is determined using only three inputs. These are, respectively, the sink bus injection $(P_s)$, the neighboring bus injection $(P_n)$, and the loading index $(L)$ under the corresponding base case. The sink and neighboring bus injections are the differences between respective local generation and demand in MW.

### E. Fuzzification of Inputs

Fuzzy method is presented in literature using a more descriptive form rather than formal mathematics. The authors have presented precisely various steps using a coherent and unified set of mathematical expressions in this and subsequent sections.

Each of the inputs is converted from a single crisp value into a maximum of two fuzzy values using the widely used [16] triangular functions that may overlap with one another as in Fig. 2. The $x$-axis in Fig. 2 represents the crisp values of $i$th input $(I_i)$ while the $y$-axis shows "membership grade" $(\mu_{\mathrm{i}})$ that may vary from 0.0 to 1.0. Each triangle has a fuzzy attribute that can be coded by a linguistic variable (e.g., "low") or a number implying level of fuzziness (e.g., 1). However, for the sake of mathematical representation, a number is used. The total number of such attributes or triangles for $i$th input is denoted by $\mathrm{m}_i$. The $x$ coordinates of three vertices of each triangle are, respectively, $a_{\mathrm{ij}}, c_{\mathrm{ij}}$, and $b_{\mathrm{ij}}$ when $j = 1, 2, \ldots, m_{\mathrm{i}}$. Equation (2) shows crisp $(I_i)$ to fuzzy $(I_i^f)$ conversion for $i$th input.

$$
\begin{aligned}
&I_i^f = \{1\}, \quad I_i \le c_{i1} \\
&I_i^f = \{m_i\}, \quad I_i > c_{im_i} \\
&I_i^f = \{(1,2),(2,3)\ldots(m_i-1,m_i)\}, \\
&\qquad\qquad c_{i1} < I_i \le c_{im_i}
\end{aligned} \tag{2}
$$

where $i = 1, 2, 3$ (i.e., for ATC determination), $I_1, I_2$, and $I_3$ are, respectively, $P_s, P_n$, and $L$.

The membership grade $(\mu_i)$ corresponding to each fuzzy value of a given crisp input can be obtained using (3)

$$
\begin{aligned}
(\mu_i)_j &= \frac{I_i - a_{ij}}{c_{ij} - a_{ij}} a_{ij} \le I_i \le c_{ij}, \quad j \in I_i^f \\
(\mu_i)_j &= \frac{I_i - b_{ij}}{b_{ij} - c_{ij}}; \quad c_{ij} < I_i \le b_{ij}, \quad j \in I_i^f
\end{aligned} \tag{3}
$$

where j implies the numbers picked up by the $i$th input's fuzzy value $I_i^f$ as in (2).

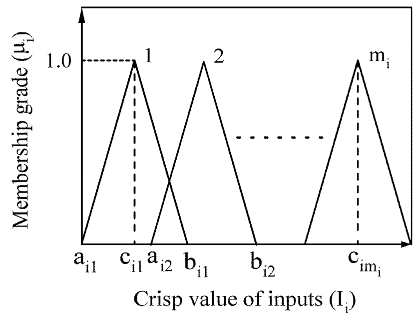


Fig. 2. Triangular membership function for $i$th input.

### F. Inference on ATC

Due to the reasons mentioned in Section II-A, the rule-base relating ATC to the inputs for a large system is developed using Sugeno fuzzy model [16]. A set of first-order polynomial equations is used to infer a crisp value of ATC from crisp values of three inputs. Each polynomial has four (i.e., one more than the number of inputs) coefficients ($r$'s), and is applied subject to a particular combination of fuzzy values (attributes) of the inputs. Equation (4) shows the full set of rules

$$
\text{If } \left(I_1^f = k \cdot \mathrm{AND} \cdot I_2^f = l \cdot \mathrm{AND} \cdot I_3^f = n\right) \text{ Then}
$$

$$
\mathrm{ATC}_o = \sum_{i=1}^{3} (r_{io} I_i) + r_{4o} \tag{4}
$$

where $\mathrm{k} = 1, 2, \ldots, m_1, l = 1, 2, \ldots, m_2, n = 1, 2, \ldots, m_3, o = 1, 2, \ldots, \prod_{i=1}^{3} m_i$.

The total number of rules represented in (4) is $\prod_{i=1}^{3} m_i$ (i.e., product of the number of fuzzy attributes for each input).

It should be noted that a given set of crisp values for the three inputs will not fire all of the $\prod_{i=1}^{3} m_i$ rules rather $q$ number of rules when $1 \le q \le 2^3$ (i.e., one to eight rules). This is because, as shown in (2), each input's crisp value has a maximum of two fuzzy values. The required overall crisp value $\mathrm{ATC}'$ is obtained as in (5) that uses weighted average of the individual crisp outputs from each of the fired rules, that is $\mathrm{ATC_o}$

$$
\mathrm{ATC}' = \frac{\sum_{o \in q} (\mu_o \mathrm{ATC}_o)}{\sum_{o \in q} \mu_o} \tag{5}
$$

where "$o$" implies each of the fired $q$ rules, and $\mu_o$ is as in (6)

$$
\mu_o = \prod_{\mathrm{i}=1}^{3} \mu_{\mathrm{i}} \tag{6}
$$

where $\mu_1, \mu_2$, and $\mu_3$ are the membership grades calculated using (3), respectively, for the three inputs' fuzzy values (i.e., $I_1^f, I_2^f$, and $I_3^f$) that are also used in the conditional part (termed fuzzy premise) of rules given by (4).

### G. Determination of Polynomial Coefficients

ATC for a given source–sink pair can be obtained by online implementation of (1) to (6). However, "$r$" coefficients as required in (4) should be made available. The total number of these coefficients is $4\prod_{i=1}^{3} m_i$.

The $r$ coefficients are determined by an offline procedure [16] that is termed adaptive network-based fuzzy inference systems (ANFIS). A set of training patterns (total number is $P$)

each comprising three inputs and an already known ATC is used. The sum of the square of the difference between the available ATC and that computed by (5) for each pattern (i.e., $E = \sum_{p=1}^{P}(\mathrm{ATC} - \mathrm{ATC}^{/})_p^2$) is minimized in the least square sense to solve for the set of r coefficients in a noniterative way as in (7). However, this time (5) considers all the rules (i.e., now $o \in q = \prod_{i=1}^{3} m_i$). It means $\mu_o$ will be zero for some of the rules which are actually not fired if a given pattern (combination) of inputs does not satisfy the fuzzy premises of those rules

$$[X] = ([A]^T[A])^{-1}[A]^T[B] \tag{7}$$

where

[X] $= 4\mathrm{q} \times 1$ vector termed consequent parameter vector; $[r_{11}\ r_{21}\ r_{31}\ r_{41}\ \ldots\ r_{1q}\ r_{2q}\ r_{3q}\ r_{4q}]^T$

[B] $= \mathrm{P} \times 1$ target (known) ATC vector; $[\mathrm{ATC}_1\ \mathrm{ATC}_2\ \ldots\ \mathrm{ATC}_P]^T$

[A] $\quad P \times 4q$ sparse matrix with each $p$th row as follows:

$$[A]_p = [(\bar{u}_o I_{1p} \quad \bar{u}_o I_{2p} \quad \bar{u}_o I_{3p}\ \bar{u}_o \ldots)_{o=1,2,\ldots,q}]$$

when $p = 1, 2, \ldots, P, I_1 = P_s, I_2 = P_n, I_3 = L$, and $\bar{u}_o$ is as in (8)

$$\bar{u}_o = \frac{\mu_o}{\sum_{t=1}^{q} \mu_t} \tag{8}$$

[i.e., $\bar{u}_o$ (the normalized firing strength of a particular $o$th rule) is $\mu_o$ expressed as a ratio of the sum of the firing strengths of all the rules].

It should be noted that determination of $r$ coefficients (also termed consequent parameters) as in (7) assumes that the membership triangles' vertices [i.e., $a$, $b$, $c$ (also termed premise parameters)] for all of the inputs are already fixed (i.e., chosen). However, using the same training patterns the premise parameters can also be determined offline assuming that consequent parameters are fixed. But this involves an iterative steepest decent gradient minimization of the same index $E$ to solve for the premise parameters one by one as in (9). The total number of premise parameters is $3\sum_{i=1}^{3} m_i$. Of course this time, $E$ involves an expression in terms of the relevant premise parameters through ATC$^{/}$ as calculated by (5) for each pattern

$$\alpha_h^{\mathrm{iter}+1} = \alpha_h^{\mathrm{iter}} - \left(\frac{\partial E}{\partial \alpha_h}\right)^{\mathrm{iter}} \tag{9}$$

where $\alpha_h$ denotes $h$th premise parameter, and $h = 1, 2, \ldots, 3\sum_{i=1}^{3} m_i$.

For greater accuracy, another scheme known as hybrid learning ANFIS is evolved in which a set of initial values is chosen for the premise parameters. Using this set (7) is solved to obtain a set of consequent parameters. These are then used by (9) to update the premise parameter set. In this way, (7) and (9) are solved alternatively using one's outputs as inputs for the other. This is continued until the updates of each set of parameters between two successive iterations converge within a tolerance margin. Each update is termed "epoch" that comprises a forward pass [i.e., solution of (7)], and a backward pass [i.e., solution of (9)]. Notably, the backward pass is similar to ANN back propagation learning so that the hybrid learning ANFIS is also termed "adaptive neuro fuzzy inference systems."

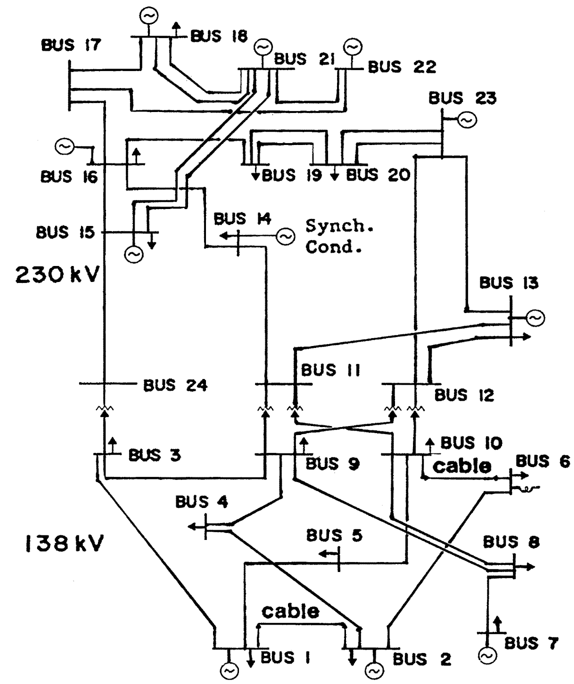


Fig. 3. IEEE 24-bus test system.

TABLE I
CATEGORIZATION OF THE SYSTEM STATUS

| Particulars of base case | Category index 'C' |
|---|---|
| Off-Peak hours | 1 |
| Peak hours | 2 |
| Outage of a generator compensated by generators neighboring source-sink buses | 3 |
| Outage of a generator compensated by generators distant from source-sink buses | 4 |
| Outage of a non crucial line | 5 |
| Outage of a crucial line | 6 |

## III. PRESENTATION OF RESULTS

The IEEE 24-bus RTS, shown in Fig. 3, has been used to compare the performance of the proposed method with that of an ac load flow-based ATC determination method [7]. Notably, this system has long been accepted in literature [3], [8] as the true representative of the characteristics of a large power network. The test system's line parameters and thermal loading limits (MVA) are given in [18]. The results of the comprehensive study are presented in the limited space of this paper, mainly in the form of general comments while highlighting the outputs for a representative source-sink pair with typical scenarios.

Table I shows the values of category index ($C$) required by the proposed method for use in (1).

### A. Illustration for a Representative Source–Sink Pair

The pair of buses 23 (source) and 16 (sink) is considered for illustrating the determination of ATC. Following the procedure mentioned in Section II–B, the path 23–13–11–14–16 has been identified as the one having the least impedance among all of the indirect paths that connect 16 to 23. This has led to selection of bus 13 as the neighbor to this source–sink.

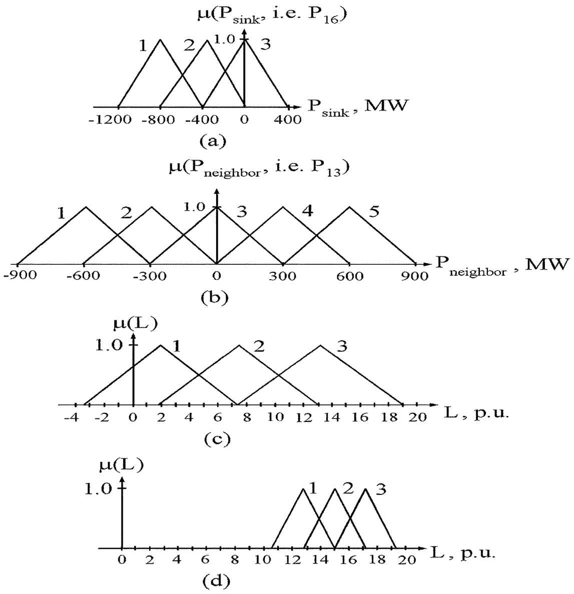


Fig. 4. Fuzzy levels for (a) sink bus load, (b) neighboring bus injection, (c) loading index for categories 1 to 4, and (d) loading index for categories 5 and 6.

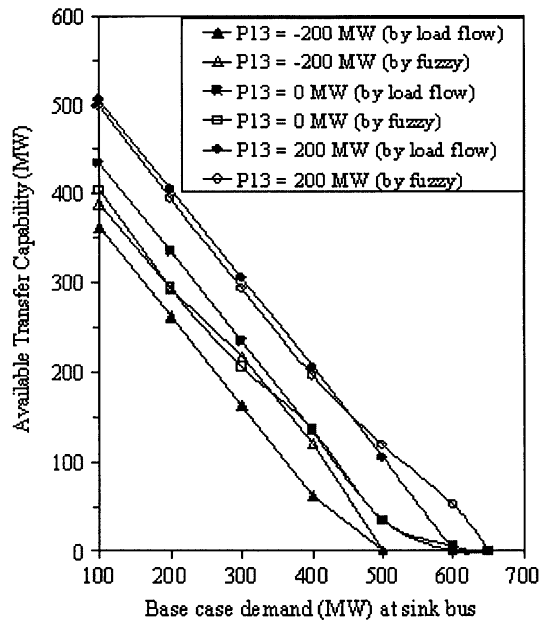


Fig. 5. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 500 MW (category 1, $\mathrm{L} = 2.66$).

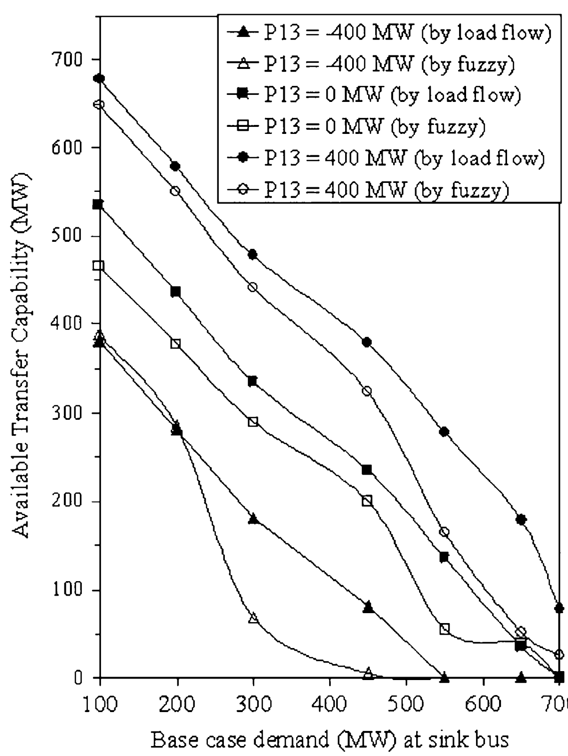


Fig. 6. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 2000 MW (category 2, $L = 6.66$).

The proposed method has been tested separately on 336 base cases (i.e., 42 for each of the categories 1 to 4, and 84 for each of the categories 5 and 6). The test patterns varied from each other in respect of any of the inputs (i.e., sink bus injection $(P_{16})$), the neighboring bus injection $(P_{13})$, and the loading index $(L)$. Demands at other buses were also changed when L was required to be varied in some base cases. The system demand used in (1) was normalized using the thermal loadability of the line having the highest one among all of the lines in the test system, which was 500 MVA. Fig. 4 shows the fuzzy membership functions for the three inputs. The number of fuzzy levels (attributes) chosen was respectively 3, 5, and 3 for $P_{16}$, $P_{13}$, and $L$. The linguistic attributes corresponding to three levels are, respectively, low, medium, and high. Since the neighboring bus may also have generation in excess of its local load, its membership levels are five implying negative high, negative low, zero (including positive low), positive medium, and positive high, respectively.

### *B. Comparison With Load-Flow-Based Method*

The load-flow-based ATC method has also been applied on each of the same 336 cases by treating bus 23 as slack, 16 and 13 both as PV (i.e., bus with specified real power and voltage) buses. The other bus types were retained as what those should be in a normal load flow. The load at sink bus (no. 16) was incremented in steps of 100 MW to repeat the load flow until thermal limit is exceeded in any line of the test system. The maximum possible increment achieved above base-case load at the sink bus was the ATC for the corresponding case.

Figs. 5 to 8 compare the ATC between buses 23 and 16 obtained by the proposed and the load-flow methods for a number of typical patterns belonging to categories 1 to 4, respectively. In category 3, outage of generator at bus 21 was compensated by generators at buses 18 and 22. In category 4, the compensation was made by generators at buses 1 and 2. Fig. 9 shows the comparison for test patterns under category 5 with one circuit of line 15-21 out. This line was noncrucial for transaction between 23 and 16 buses. Fig. 10 compares ATCs by both methods under category 6 for outage of a crucial line (i.e., 2–4).

The ATCs, by the proposed fuzzy method, compare well with those by the load-flow method. In general, the difference was

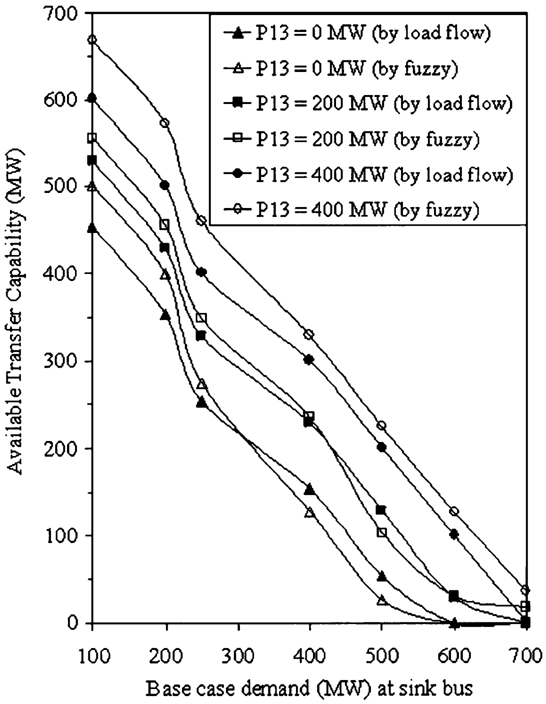


Fig. 7. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 3000 MW (category 3, $L = 10.00$).

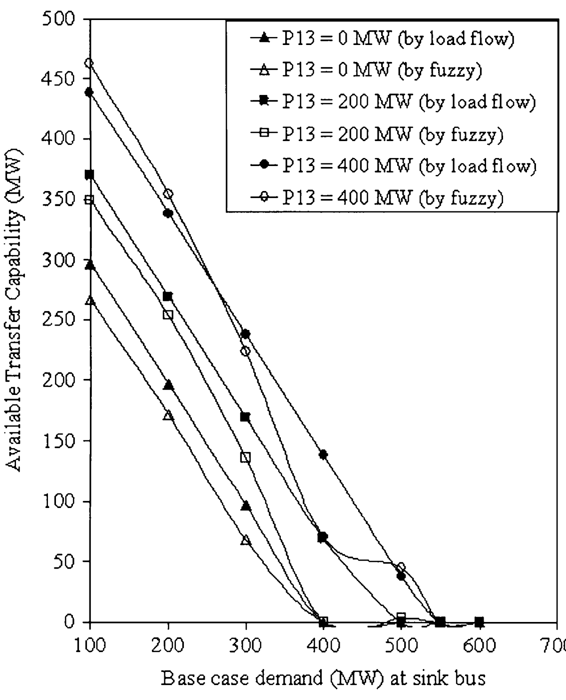


Fig. 8. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 3000 MW (category 4, $L = 12.00$).

found to be around 100 MW only while it was 150 to 250 MW in a few cases.

### C. ANFIS Training

It should be noted that $4\prod_{i=1}^{3} m_i$ (i.e., $4(3 \times 5 \times 3) = 180$) polynomial coefficients (i.e., $r$'s) required in (4) were ob-

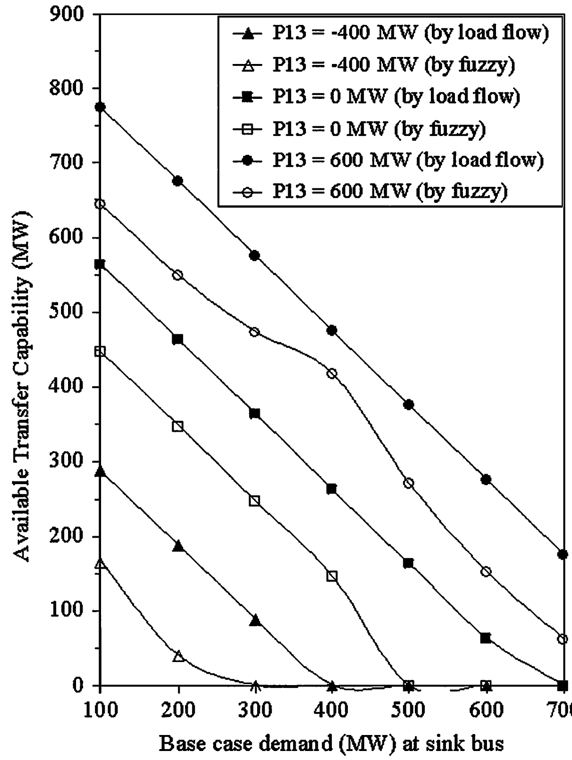


Fig. 9. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 2650 MW (category 5, $L = 13.53$).

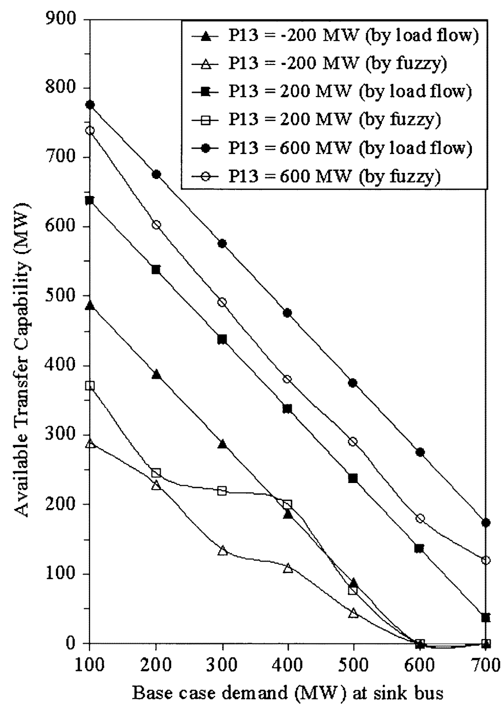


Fig. 10. Bus 23 to 16 ATC by the proposed fuzzy and the conventional load-flow-based methods for various sink bus loads and neighboring bus injections under a base system demand of 2650 MW (category 6, $L = 15.53$).

tained by the hybrid learning ANFIS procedure mentioned in Section II-G. For this, 300 training patterns (50 for each of the 6 categories mentioned in Table I) were created. It is noteworthy that the 336 patterns used to test and compare the proposed method are different from the 300 training patterns. The target ATCs for training patterns were obtained by subjecting each of the patterns to the load-flow-based method as above. However, for a real power system, the required training patterns and corresponding target (known) ATCs can always be taken from past history maintained in the database. So the rule-base of Sugeno fuzzy model becomes able to take fully into account the physical laws of a network on power flow and thermal loading limits of the lines through the set of $r$ coefficients that is tuned using ATCs from load flow or real operational data.

For training by ANFIS, the widely used MATLAB Fuzzy Toolbox [19] was used. The toolbox required that the number of fuzzy levels for each input be chosen, and this was done as specified in Section III-A. However, all of the 300 patterns for six categories were not presented to ANFIS as a single cluster. The 200 training patterns under categories 1 to 4 were used together to obtain one set of $r$ coefficients. The remaining 100 training patterns belonging to categories 5 and 6 were used together to derive another set of $r$ coefficients. The authors have found through trial that when only one set of $r$ coefficients, obtained from intermingling all six categories' training patterns, is used, the ATCs for the test patterns by the proposed method do not match well those by load flow. This is because the line outages (categories 5 and 6) [i.e., topological changes] are more nonlinear than generation outages or base load changes and, hence, require separate training.

Only three epochs were required in the training procedure for each group (i.e., categories 1 to 4 together, and categories 5 plus 6). The training for each group provided not only the 180 r coefficients but also $3\sum_{i=1}^{3} m_i$ [i.e., $3(3+5+3) = 33$] membership triangular vertices ($a$, $b$, $c$) for $P_{16}, P_{13}$, and $L$. The values obtained for these triangular vertices were used in Fig. 4. The sets of $r$ coefficients for two groups were substantially different from each other. The membership parameters ($a$, $b$, $c$) were almost the same in both groups for $P_{16}$ and $P_{13}$ but different for $L$. This is because the $r$ coefficients (consequent parameters) depend more on the ranges of outputs (i.e., target ATCs of the training patterns) whereas the $a$, $b$, $c$ vertices (premise parameters) depend more on the ranges of the inputs (i.e., $P_{16}, P_{13}$, and $L$). Notably, the ranges of ATCs and $L$ for categories 1 to 4 were not close to their respective counterparts for categories 5 to 6.

### D. ATC for Other Pairs of Source-Sink Buses

The proposed method has also been trained and tested for a variety of source sink pairs (e.g., 18–15, 2–9, 23–24, and 21–1) in the same way as mentioned, respectively, in Sections III-C and III-A. The ATCs by load-flow-based method were found for each of those pairs in the way mentioned in Section III-B. A comparison of ATCs for each pair by the two methods for the same test patterns and categories revealed a close match.

### E. Comparison of CPU Time

The commercial programs available for load flow are not in editable form (i.e., no source code provided) and, hence, cannot be customized to the specific input-output and repetitive autoexecution requirements for each increment of sink bus load for a given source-sink pair. So the fast decoupled version of Newton–Raphson load-flow solution together with an exploitation [20] of sparse structure of the involved Jacobian matrices has been programmed using Fortran 77.

For a fair comparison, the computations in (1) to (6) that need to be done by the proposed method when implemented online, have also been coded in Fortran 77. The $r$ coefficient sets for each source-sink pair obtained from offline training using MATLAB Fuzzy Toolbox were saved in a file for use by the Fortran code.

The coded programs for both methods have been compiled and executed using Microsoft Fortran Power Station version 1.0 on a 1.6-GHz Pentium 4 PC under Windows XP operating system. The average CPU time per case/category/source sink pair of the considered 24-bus test system turned out to be 0.06 and 0.12 s, respectively, by the proposed and the load-flow methods.

### F. Generality in the Performance of the Proposed Method

The proposed method has been able to retain generality in its performance as evident from the following findings.

i) The method gave satisfactory outputs (ATCs) using only three input signals for a variety of source sink pairs, which differ widely from one another in respect to characteristics of the paths and other buses that exist between each pair.

ii) The method used a single set of $r$ coefficients for test on patterns belonging to four different categories (1 to 4). It used just another set of r coefficients for patterns belonging to categories 5 to 6 that are of more nonlinear nature than the first four categories.

iii) The test patterns for each category were widely different than those used for training. For instance, the standard deviations of sink bus load in the test patterns under each of the categories 1 to 4 for the 23–16 source–sink bus pair were 195 MW on average vis-à-vis 264 MW for the same in training patterns. This was 247 MW versus 371 MW for the neighboring bus injections, respectively, in test and training patterns for those four categories.

iv) The method gave satisfactory outputs even when tested on line-outage category patterns in which the lines considered as out were not same as those in the training patterns. For instance, the 50 training patterns for crucial line outage (category 6) were obtained for the 23–16 source–sink bus pair considering one circuit of the line 20–23 as out. But the 42 test patterns considered line 2–4 as out. Of course, the method was also tested on another 42 patterns in which the line considered as out was the same as that in training patterns. In a limited space of this paper, only the ATCs for typical test patterns that consider a line outage different from the one in training patterns have been plotted in Figs. 9 and 10.

## IV. Conclusion

This paper has proposed a method that applies for the first time ever, fuzzy logic in determining ATC in a large deregulated power system. The substantial differences between a small and large power network have been taken into account through identifying only three input signals (i.e., sink bus load, neighboring bus injection, and an appropriately defined loading index) for ATC between each source-sink pair, and using Sugeno fuzzy model. The proposed method has adequately been able to exhibit generality in its performance when tested extensively on the standard IEEE 24-bus RTS, and compares well against a full-scale ac load-flow-based method for the same array of source-sink pairs, base case loadings, and generation/line outage scenarios.

The developed method determines in one shot the ATC between a source-sink pair requiring only three input signals, firing a maximum of 8 out of 45 rules, and using two sets of 180 output coefficients (consequent parameters) irrespective of system size. The general characteristics that exist in any large network have been exploited by the proposed method in choosing only three inputs, five fuzzy attributes for the injection input, and three attributes for each of the other two inputs. This limits the number of rules to only 45. The neighboring bus can always be predetermined (i.e., offline) for each source-sink pair in a given system. The two sets of 180 consequent parameters are also obtained offline, respectively, using a mixed set of only about 200 training patterns on base load variations and generation outage categories, while another mixed set of only 100 training patterns on crucial and noncrucial line outage categories. The proposed method's requirement of two separate sets of coefficients, respectively, for line outage and other categories is quite normal just as the conventional load-flow method which also requires separate Jacobian matrices whenever the topology changes.

The test system used in this paper is an IEEE standard system, and has all of the features typical of a large system (e.g., meshed transmission lines, dual voltage levels with interfacings between them, and a significant number of generators, etc.). The way the proposed method has been developed, does not lack generality and can always be applied to another test or real power system of any size. The CPU time requirement of the proposed method is independent of the system size while the load-flow-based ATC determination method's CPU time is directly proportional to the size despite exploitation of sparse structure of the system. This is because the load-flow method requires for ATC between each source-sink pair $2N$ number of inputs when $N$ is the total number of buses in the system. But the proposed fuzzy method requires only three inputs irrespective of system size. Even the numbers of rules and parameters related to fuzzy model are system size independent. So when applied on a larger system, the proposed method's speedup ratio relative to a load-flow method will definitely escalate far above 2 in proportion to the size of the system. This will enable the proposed method to determine ATC considering more cases and contingencies than the conventional load-flow method in a given interval of time when using the same processor.

Use of more than 100-MW increment in sink bus load by the conventional method may reduce its CPU time but will seriously compromise its accuracy in ATC determination. On the contrary, use of a small increment (e.g., 10 MW will enhance its accuracy but increase the CPU time requirement by a factor of about 10). But the proposed method's accuracy can always be further improved without any increase in its CPU time irrespective of system size. This is because the output coefficients (consequent parameters) it requires can be obtained offline using training patterns taken from past real data or a load-flow method that uses 10-MW increment in sink bus load.

The proposed method can easily be extended to provide additional outputs besides ATC at trivial computational costs. Currently, the authors are investigating into extending the method to determine the VAR supports that may be required occasionally to avoid any voltage collapse while a transaction takes place between a source-sink pair.

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