



รายงานวิจัยฉบับสมบูรณ์

การประยุกต์ใช้อุปกรณ์ควบคุมแพ็คทส์หลายชนิด
เพื่อเพิ่มสมรรถภาพการถ่ายโอนกำลังไฟฟ้าในระบบไฟฟ้ากำลังของประเทศไทย
โดยใช้เทคนิคการคำนวณเชิงวิวัฒนาการแบบผสมผสาน

โดย

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มิถุนายน 2555

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สนับสนุนโดยสำนักงานกองทุนสนับสนุนการวิจัย

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บทสรุปสำหรับผู้บริหาร

เนื่องจากความต้องการใช้พลังงานไฟฟ้าที่เพิ่มขึ้นอย่างต่อเนื่อง ทำให้ต้องมีการพัฒนาระบบไฟฟ้าให้มีประสิทธิภาพและสามารถส่งจ่ายพลังงานไฟฟ้าได้อย่างต่อเนื่องและเพียงพอต่อความต้องการดังกล่าว แต่การขยายตัวของระบบไฟฟ้าถูกจำกัดด้วยปัจจัยหลายประการ เช่น เงินลงทุน ผลกระทบต่อสิ่งแวดล้อม และข้อจำกัดภายในระบบไฟฟ้าเอง ด้วยเหตุนี้จึงได้มีการพัฒนาอุปกรณ์ควบคุมระบบส่งจ่ายไฟฟ้ากระแสสลับแบบยืดหยุ่นได้ หรือเรียกว่า อุปกรณ์ควบคุมเฟลิกซ์ นำมาประยุกต์ใช้ควบคุมการไหลของกำลังไฟฟ้าและเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าในระบบไฟฟ้ากำลัง แต่การเลือกใช้งานและควบคุมอุปกรณ์ดังกล่าวมีความซับซ้อนและอาจส่งผลกระทบต่อระบบไฟฟ้าได้หากติดตั้งและควบคุมไม่เหมาะสม

งานวิจัยนี้จึงได้พัฒนาวิธีการคำนวณเชิงวิวัฒนาการแบบผสมผสาน โดยมีพื้นฐานจากวิธีการโปรแกรมเชิงวิวัฒนาการ การค้นหาแบบทาบ และการจำลองการอบอุ่น เพื่อหาวิธีการจัดวางอุปกรณ์ควบคุมเฟลิกซ์ที่มีความเหมาะสมที่สุด โดยพิจารณาจาก ชนิด จำนวน ตำแหน่ง และขนาด ของอุปกรณ์ควบคุมเฟลิกซ์หลายชนิด ที่จะถูกใช้งานในระบบไฟฟ้ากำลังเพื่อเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าให้ได้มากที่สุด และลดกำลังไฟฟ้าสูญเสียให้น้อยที่สุดพร้อมกัน โดยไม่ส่งผลกระทบต่อข้อจำกัดของระบบไฟฟ้าเดิม ปัญหาการหาค่าเหมาะสมที่สุดของการจัดวางอุปกรณ์ควบคุมเฟลิกซ์ ได้ถูกสร้างเป็นสมการฟังก์ชันวัตถุประสงค์ทางคณิตศาสตร์ และหาคำตอบโดยใช้อัลกอริทึมการคำนวณเชิงวิวัฒนาการแบบผสมผสานที่ได้ถูกพัฒนาขึ้น ผลที่ได้จากการทดสอบกับระบบทดสอบมาตรฐานและระบบไฟฟ้าจริงของประเทศไทย รวมถึงการเปรียบเทียบกับวิธีการวิเคราะห์ด้วยวิธีการอื่น แสดงให้เห็นว่าการเลือกใช้ การจัดวาง และการควบคุมอุปกรณ์ควบคุมเฟลิกซ์หลายชนิดด้วยวิธีการที่นำเสนอในงานวิจัย ทำให้สามารถเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าและลดกำลังไฟฟ้าสูญเสียในระบบไฟฟ้าเดิมได้มากกว่าวิธีการอื่น นำไปสู่การใช้ประโยชน์ระบบไฟฟ้ากำลังที่มีอยู่เดิมให้มีประสิทธิภาพและสมรรถภาพเพิ่มมากขึ้น

ผลลัพธ์จากงานวิจัยได้รับการตรวจสอบและยอมรับให้ตีพิมพ์ลงในวารสารวิชาการระดับนานาชาติ ที่มีคณะผู้ทรงคุณวุฒิเป็นผู้พิจารณาจำนวน 1 บทความ นอกจากนี้ยังได้มีการเชื่อมโยงกับนักวิจัยทั้งภายในและต่างประเทศ รวมถึงมีการขยายขอบเขตงานวิจัยเพื่อเชื่อมโยงกับสำนักงานนโยบายและแผนพลังงาน กระทรวงพลังงาน ในการพัฒนานักวิจัยรุ่นใหม่ ในระดับนักศึกษาปริญญาโทและเอก โดยมีผลการศึกษาและงานวิจัยที่ได้นำเสนอต่อที่ประชุมวิชาการระดับนานาชาติ รวมถึงบทความตีพิมพ์เผยแพร่ในวารสารการประชุมวิชาการระดับนานาชาติจำนวน 5 บทความ ตลอดช่วงเวลาที่ผู้ดำเนินการวิจัยได้รับการสนับสนุนจาก สำนักงานกองทุนสนับสนุนการวิจัย สำนักงานคณะกรรมการการอุดมศึกษา และมหาวิทยาลัยเชียงใหม่

Abstract

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Project Title : Applications of Multi-type FACTS Controllers for Power Transfer Capability Enhancement of Thailand Electrical Power System Using Hybrid Evolutionary Computation Technique

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With the advent of flexible AC transmission system (FACTS), FACTS devices are used to provide flexible control of power flows over designated transmission routes and increase power transfer capability of transmission networks. The extent of these benefits depends upon where these devices are placed and how they are controlled in the systems. This research proposes a new hybrid evolutionary algorithm (HEA) based on evolutionary programming (EP), tabu search (TS), and simulated annealing (SA) to determine the optimal allocation of multi-type FACTS controllers to simultaneously maximize the electrical power transfer capability and minimize system real power loss of power transactions in power systems. The optimally placed optimal power flow with FACTS controllers is formulated as a combined objective function including power transfer capability and system power loss to evaluate the feasible maximum power transfer value. The HEA approach simultaneously searches for types, number, locations, and parameters of FACTS controllers, real power generations in a source area, real power loads in a sink area, and generation bus voltages to solve the optimal power flow with FACTS problem. Test results on the test systems and practical Thailand power systems indicate that optimally placed FACTS controllers by the HEA could enhance power transfer far more than those from EP, TS, hybrid TS/SA, and improved EP algorithms, leading to much efficient utilization of the existing Thailand transmission systems.

Keywords: Evolutionary Algorithm; FACTS Controllers; Power Transfer Capability; Optimal Power Flow

บทคัดย่อ

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จากการคิดค้นและพัฒนาระบบส่งจ่ายไฟฟ้ากระแสสลับแบบยืดหยุ่นได้ หรือเรียกชื่อย่อว่า แฉีกหลายชนิด ทำให้มีการประยุกต์ใช้งานอุปกรณ์ควบคุมแฉีกหลายชนิดเพื่อนำไปควบคุมการไหลของกำลังไฟฟ้าในทิศทางที่กำหนด อีกทั้งยังสามารถนำไปเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าในระบบส่งจ่ายไฟฟ้ากำลังได้อีกด้วย แต่ประโยชน์ที่ได้รับจะมากหรือน้อยขึ้นอยู่กับวิธีการออกแบบ ติดตั้ง และควบคุมอุปกรณ์เหล่านี้ได้อย่างเหมาะสมเพียงใด งานวิจัยนี้จึงได้นำเสนออัลกอริทึมการคำนวณเชิงวิวัฒนาการแบบผสมผสาน โดยมีพื้นฐานมาจากวิธีการโปรแกรมเชิงวิวัฒนาการ การค้นหาแบบทาบ และการจำลองการอบอุ่น เพื่อหาวิธีการจัดวางอุปกรณ์ควบคุมแฉีกหลายชนิดที่มีความเหมาะสมที่สุด สำหรับเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าให้ได้มากที่สุดและลดกำลังไฟฟ้าสูญเสียให้น้อยที่สุดพร้อมกัน ปัญหาการหาค่าเหมาะสมที่สุดของการจัดวางอุปกรณ์ควบคุมแฉีกหลายชนิด ได้ถูกสร้างเป็นสมการฟังก์ชันวัตถุประสงค์ทางคณิตศาสตร์ และหาคำตอบโดยใช้วิธีการที่ได้ถูกพัฒนาขึ้น ซึ่งจะทำให้ทราบถึงชนิด จำนวน ตำแหน่ง และขนาด ที่เหมาะสมที่สุดของอุปกรณ์ควบคุมแฉีกหลายชนิดพร้อมกัน ผลที่ได้จากการทดสอบวิธีการจัดวางอุปกรณ์ควบคุมแฉีกหลายชนิด กับระบบทดสอบมาตรฐานและระบบไฟฟ้าจริงของประเทศไทย รวมถึงการเปรียบเทียบกับวิธีการหาคำตอบที่เหมาะสมด้วยวิธีการโปรแกรมเชิงวิวัฒนาการ วิธีการค้นหาแบบทาบ วิธีการผสมผสานระหว่างการค้นหาแบบทาบและการจำลองการอบอุ่น และวิธีการโปรแกรมเชิงวิวัฒนาการที่มีการปรับปรุง แสดงให้เห็นว่าการใช้อัลกอริทึมการคำนวณเชิงวิวัฒนาการแบบผสมผสานที่ได้นำเสนอใหม่นั้น ทำให้สามารถจัดวางอุปกรณ์ควบคุมแฉีกหลายชนิดเพื่อเพิ่มความสามารถในการถ่ายโอนกำลังไฟฟ้าและลดกำลังไฟฟ้าสูญเสียในระบบไฟฟ้ากำลังได้มากกว่าวิธีการอื่น ๆ นำไปสู่การใช้ประโยชน์ระบบส่งจ่ายไฟฟ้ากำลังที่มีอยู่เดิมให้มีประสิทธิภาพเพิ่มมากขึ้น

คำหลัก: อัลกอริทึมเชิงวิวัฒนาการ; อุปกรณ์ควบคุมแฉีก; ความสามารถในการถ่ายโอนกำลังไฟฟ้า; การไหลของกำลังไฟฟ้าที่เหมาะสม

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List of Abbreviations

AI	Artificial intelligence
APOPF	Active power optimal power flow
ATC	Available transfer capability
BESS	Battery energy storage system
CBM	Capacity benefit margin
CPF	Continuation power flow
EA	Evolutionary algorithm
EC	Evolutionary computation
ED	Economic dispatch
EP	Evolutionary programming
ES	Evolutionary strategy
ETC	Existing transmission commitments
FACTS	Flexible ac transmission system
FERC	Federal energy regulatory commission
GA	Genetic algorithm
GODF	Generator outage distribution factor
GSDF	Generation shift distribution factor
HEA	Hybrid evolutionary algorithm
IEP	Improved evolutionary programming
IP	Interior point
LATC	Linear available transfer capability
LODF	Line outage distribution factor
LOLE	Loss of load expectation
LP	Linear programming
MFT	Mean field theory
MINLP	Mixed integer non-linear programming
MIP	Mixed integer programming
NERC	North American reliability council
NLP	Non-linear programming
NR	Newton-Raphson

List of Abbreviations

OASIS	Open access same time information system
OPF	Optimal power flow
ORPD	Optimal reactive power dispatch
PAR	Phase angle regulator
PCPDIPLP	Predictor-corrector primal-dual interior point linear programming
PHEA	Parallel hybrid evolutionary algorithm
PIM	Power injection model
PSAT	Power system analysis toolbox
PSO	Particle swarm optimization
PTDF	Power transfer distribution factor
PTS	Parallel tabu search
QP	Quadratic programming
RPF	Repetitive power flow
RPOPF	Reactive power optimal power flow
RTS	Reliability test system
SA	Simulated annealing
SAEP	Self adaptive evolutionary programming
SCOPF	Security constrained optimal power flow
SHEA	Sequential hybrid evolutionary algorithm
SQP	Sequential quadratic programming
SSSC	Static synchronous series compensator
STATCOM	Static synchronous compensator
SVC	Static var compensator
TCPS	Thyristor controlled phase shifter
TCPST	Thyristor controlled phase shifting transformer
TCSC	Thyristor controlled series capacitor
TCVL	Thyristor controlled voltage limiter
TCVR	Thyristor controlled voltage regulator
TRM	Transmission reliability margin
TS	Tabu search

List of Abbreviations

TSCOPF	Transfer-based security constrained optimal power flow
TS/SA	Hybrid Tabu search and simulated annealing
TSSC	Thyristor switched series capacitor
TTC	Total transfer capability
UC	Unit commitment
UPFC	Unified power flow controller
VCPI	Voltage collapse proximity indicator
VSM	Voltage source model

Chapter 1

Introduction

1.1 Background

In competitive electric power markets and open access transmission systems, electric utilities have to operate closer to their limits, causing unpredictable line loading, voltage variations, and stability problems. To solve these difficulties, flexible AC transmission system (FACTS) devices have been used to increase power transfer capability of transmission networks and provide direct control of power flows over designated transmission routes, resulting in a lower system loss, stability enhancement, operating cost reduction, and fulfilled contractual requirements (Edris et al., 1998). The extent of these benefits depends upon where these devices are placed and how they are controlled in the systems, which in turn requires efficient methodologies to solve the optimally placed FACTS problem. This is an important aspect in the context of growing energy demand and the emergence of energy trading markets.

Available transfer capability (ATC) is used as a market signal of the capability of a transmission network to deliver electric energy in deregulated power systems. ATC is defined as a measure of the transfer capability remaining in a physical transmission network for further commercial activity over and above already committed uses (NERC, 1996). It is required to be calculated for each control area and posted on a public communication system called open access same time information system (OASIS) to enhance the open access transmission network and make competition reasonable and effective (FERC, 1996a; FERC, 1996b). Mathematically, ATC is defined as the total transfer capability (TTC) less the transmission reliability margin (TRM), less the sum of the capacity benefit margin (CBM) and existing transmission commitments. TTC is the main

component of the ATC calculation, which is defined as the amount of electric power that can be transferred over the transmission network in a reliable manner while meeting all of a specific set of defined pre- and post-contingency system conditions. TRM and CBM are two transmission margins considering the inherent uncertainty and reliability in the transmission system.

Accurate determination of ATC is essential to maximize utilization of the existing transmission network while maintaining system security. Underestimated ATC may lead to under-utilization of transmission systems, while overestimated ATC could lower system reliability. Wide varieties of mathematical methods such as: i) linear ATC (LATC) method (Ejebe et al., 2000), ii) continuation power flow (CPF) (Ejebe et al., 1998), iii) repetitive power flow (RPF) (Gravener and Nwankpa, 1999), and iv) dynamic ATC (Kumar et al., 2004) have been developed for ATC computations. In addition, optimal power flow (OPF)-based methods, which can be implemented by many optimization techniques such as interior point algorithm (Dai et al., 2000), sequential quadratic programming (SQP) (Shaaban et al., 2003), and transfer-based security constrained OPF (TSCOPF) (Ou and Singh, 2002) have been proposed to calculate ATC with various degrees of success.

These methods require convexity of objective function to obtain the optimal solution. However, the OPF-based ATC calculation is generally non-linear and non-convex optimization problem and, as a result, many local solutions may exist especially in power systems with embedded FACTS controllers (Wong et al., 2003). FACTS parameters are additional control variables which can not be solved effectively by conventional optimization methods because these parameters will change the admittance matrix. Moreover, the ability of interconnected transmission networks to reliably transfer electric power is limited by physical and electrical characteristics including line thermal limits, voltage limits, and stability limits (NERC, 1996). The limiting condition on some portions of the systems can shift among these constraints as the network operating conditions change over time. Such variations further complicate the ATC computation. Therefore, conventional techniques may converge to local solutions or diverge altogether (Lai, 1998).

With the advent of evolutionary computation (EC) techniques, many heuristic methods e.g. genetic algorithm (GA) and evolutionary programming (EP) are efficiently applied for solving the optimal FACTS placement problems to determine global or near global optimum solution. These algorithms are not sensitive to starting points and are capable of handling non-convex optimization problems. A GA combined with CPF method is used to determine the optimal placement of thyristor-controlled series capacitor (TCSC) for maximizing TTC (Feng and Shrestha, 2001). The GA is used to search for the optimal location and parameter of TCSC while CPF is used to evaluate the TTC value with the optimally placed TCSC subject to thermal and voltage limits. For the optimal placement of multi-type FACTS controllers, a floating point GA is used to simultaneously search for locations, types, and parameters of TCSC, static var compensator (SVC), thyristor-controlled phase shifting transformer (TCPST), and

thyristor-controlled voltage regulator (TCVR) (Gerbex et al., 2001). The optimization strategy based on RPF method is performed to determine the maximum system loadability subject to thermal and voltage limits. However, using CPF and RPF may lead to a conservative TTC value because these methods do not result in the optimal generation, loading, and generator bus voltages.

Furthermore, the optimally placed OPF with FACTS controllers is a mixed integer non-linear programming (MINLP) problem with continuous and discrete variables. Solving MINLP problems is difficult for two reasons. Firstly, the presences of non-linearity in the objective and constraint function imply non-convexity in MINLP problems with multiple local solutions, which are still far from the global solution. Secondly, the presence of both continuous and discrete variables in a large combinatorial problem, combining the mixed-integer programming (MIP) and non-linear programming (NLP) significantly increase the complexity of MINLP problems. Therefore, the optimally placed OPF with FACTS problem may not be effectively solved by either conventional methods or a single EC technique.

Since the initiative of FACTS concept in the late 1980s (Hingorani, 1988a), FACTS controllers have provided strategic benefits for power system planning and operation. In addition to ATC enhancement (Ou and Singh, 2001; Xiao et al., 2003), FACTS controllers have been effectively used to control power flow especially for controlling reactive power flow over designated transmission routes. One of the main aims of reactive power control is to provide appropriate placement of FACTS controllers to minimize power loss of transmission networks (Baskarana and Palanisamy, 2006). The problems of reactive power control with FACTS controllers using conventional optimization methods and artificial intelligence (AI) techniques have been studied and widely reported in the literature. Moreover, sensitivity index approaches have been commonly used to determine suitable locations of FACTS controllers for minimizing power loss (Preedavichit and Srivastava, 1998) and maximizing ATC (Leonidaki et al., 2001; Orfanogianni and Bacher, 2003). However, these methods may not lead to the optimal solution because of dependency to system topology and loading conditions.

To achieve the main objectives of FACTS controllers utilization and deal with the complicated combinatorial optimization problem, this research proposes a novel hybrid evolutionary algorithm (HEA) based on evolutionary programming (EP), tabu search (TS), and simulated annealing (SA) to determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize system real power loss of power transactions between different control areas in deregulated power systems.

1.2 Statement of the Problem

ATC computations present a major challenge for power system engineers. Wide varieties of mathematical methods have been proposed for ATC calculations with various degrees of success. There are still issues associated with their implementation.

1. The LATC method takes account only of thermal limits on line flows. Ignoring voltage and reactive power effects may lead to unacceptable error especially in a stressed system with insufficient reactive power support and voltage control.
2. To increase a certain power transfer, CPF and RPF methods use a common loading factor for a specific cluster of generators and loads, which may lead to a conservative ATC value since the optimal generation, loading, and generator bus voltages are ignored.
3. The applications of dynamic ATC methods are limited to the evaluation of a large scale non-linear programming problem that results in a problem formulation of huge dimension.
4. OPF-based ATC determinations mostly take only line thermal and voltage limits into consideration. However, the limiting condition of transmission network can shift among thermal, voltage, and stability limits. Ignoring any one of these constraints may lead to unsecured system operation.
5. OPF-based ATC determination is generally non-linear and non-convex optimization problem and, as a result, many local solutions may exist especially in power systems with embedded FACTS controllers. Therefore, conventional optimization methods may converge to local optimal solutions or diverge altogether.

In addition to the ATC computation aspect, determination of the optimally placed OPF with FACTS problem is an essential topic in power system operation and planning studies. A number of issues associated with this optimization problem are listed as follows:

1. The optimally placed OPF with FACTS is a MINLP problem, which may not be solved effectively by conventional optimization methods or a single EC technique.
2. Sensitivity index approaches that provide suitable locations of FACTS controllers may not lead to the optimal solution because of dependency to system topology and loading conditions.

3. A number of EC techniques combined with conventional methods have been proposed to solve the optimal FACTS allocation problems. Nevertheless, the obtained results are far from the optimal solutions due to the use of OPF with local search algorithms.
4. For a simple system with a number of FACTS controllers, many optimization techniques have been adequately reported. However, for more complicated power systems with multiple and multi-type FACTS controllers, a few techniques have been developed for solving the optimization problems.
5. Even though a combined objective function including ATC maximization and power loss minimization is not new, it is treated as one of the most important problems in using FACTS controllers.

1.3 Objectives

The main objectives of the study are as follows:

1. To develop an efficient HEA approach for determining ATC of power transactions in deregulated power systems, considering thermal, voltage, and stability limits.
2. To apply the HEA approach for determining the optimal placement of multiple and multi-type FACTS controllers to simultaneously maximize ATC and minimize system real power loss of the power transactions without violating system constraints.
3. To compare the effectiveness of the HEA approach to CPF, EP, TS, hybrid TS/SA, and improved EP (IEP) methods.

1.4 Scope and Limitations

The scope and limitations of the study are as follows:

1. Dynamic properties, and dynamic stability limits of FACTS controllers are out of scope of the research.
2. Five optimization techniques including EP, TS, hybrid TS/SA, IEP, and HEA are considered. The proposed optimization methods are developed in MATLAB programming language.

3. The modified IEEE 24-bus reliability test system (RTS), modified IEEE 30-bus system, modified IEEE 118-bus system, and the modified Thai power 160-bus system are used as test systems.
4. The proposed HEA approach has capabilities to:
 - i. determine ATC of bilateral and multilateral transactions,
 - ii. incorporate thermal limits, voltage limits, voltage and angle stability limits, and FACTS controllers steady-state operating limits into system constraints,
 - iii. accommodate other constraints including the most critical single contingency outage condition,
 - iv. simultaneously maximize ATC and minimize system real power loss,
 - v. incorporate multiple and multi-types FACTS controllers into the OPF problem,
 - vi. perform sequential run on one computer or parallel run on multiple computers.

1.5 Structure of the Report

The organization of this report is as follows: Statement of the problem and objectives of the research are presented in Chapter 1. In Chapter 2, a review of literature related to ATC determination, FACTS controllers, OPF problems, and heuristic optimization techniques is presented. In Chapter 3, the OPF-based ATC determination is formulated as an optimization problem. The HEA approach is proposed to solve the optimization problem. In Chapter 4, the HEA method is proposed to determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize power loss. Test results from the HEA are compared with those from EP, TS, TS/SA, and IEP methods. Lastly, Chapter 5 gives the conclusion of this research.

Chapter 2

Literature Review

This chapter presents a literature review of available transfer capability, FACTS controllers, optimal power flow problems, and modern heuristic optimization techniques.

2.1 Available Transfer Capability

2.1.1 Principles and definitions of ATC

The movement towards competitive electric power markets and open access transmission systems has added considerable emphasis to the interest in quantifying transmission transfer capability (NERC, 1995a; Williams, 1996). In 1996, the North American Electric Reliability Council (NERC) published a technical report regarding available transfer capability (ATC) definitions and determination to provide a uniform framework for determining ATC and related terms (NERC, 1996). The report also provides ATC principles under which ATC values are to be calculated. All transmission provider and user entities are expected to abide by the following principles:

1. ATC calculations must produce commercially viable results.
2. ATC calculations must recognize time-variant power flow conditions and the effects of simultaneous transfers and parallel path flow throughout the network.

3. ATC calculations must recognize the dependency of ATC on the points of electric power injection, the directions of transfers, and the points of power extraction.
4. Regional or wide-area coordination is necessary to develop and post information that reasonably reflects the ATC.
5. ATC calculations must conform to regional, subregional, power pool, and individual system reliability planning and operating policies, criteria, or guides.
6. The determination of ATC must accommodate reasonable uncertainties in system conditions and provide operating flexibility to ensure the secure operation.

ATC is defined as a measure of the transfer capability remaining in a physical transmission network for further commercial activity over and above already committed uses (NERC, 1996). It is required to be calculated for each control area and posted on a public communication system called open access same time information system (OASIS) to enhance the open access transmission network and make competition reasonable and effective by providing a market signal of the capability of the transmission network to deliver electric energy in deregulated power systems (FERC, 1996a; FERC, 1996b).

Mathematically, ATC is defined as the total transfer capability (TTC) less the transmission reliability margin (TRM), less the sum of the capacity benefit margin (CBM) and existing transmission commitments. TTC is the amount of electric power that can be transferred over the interconnected transmission network in a reliable manner while meeting all of a specific set of defined pre- and post-contingency system conditions. TRM is the amount of transmission transfer capability necessary to ensure that the interconnected transmission network is secure under a reasonable range of uncertainties in system conditions. CBM is the amount of transmission transfer capability reserved by load serving entities to ensure access to generation from interconnected systems to meet generation reliability requirements.

2.1.2 Considerations in ATC computations

ATC calculation is a complicated task involving determination of TTC and two margins, TRM and CBM. Accurate determination of ATC is essential to maximize utilization of the existing transmission networks while maintaining system security. Underestimating ATC may lose business opportunities, while overestimating it can compromise system reliability. Wide varieties of mathematical methods have been proposed to determine ATC with various

degrees of success. Methods based on AC load flow models are slower than methods using DC load flow models but do allow for consideration of additional system limits and more accurate accounting of the operation guides and control actions that accompany the increasing transfers. Moreover, the ability of interconnected transmission networks to reliably transfer electric power is limited by physical and electrical characteristics including thermal limits, voltage limits, and stability limits (NERC, 1996). The limiting condition on some portions of the systems can shift among these constraints as the network operating conditions change over time. Such variations further complicate the ATC computation (Gisin et al., 1999; Ilic et al., 1997).

Sauer (1997) presents several concepts for dealing with the technical challenges of ATC computation, such as definition of a base case, specification of contingencies, finding the maximum transfer, and interpretation of results. Various types of uncertainty and error that can impact ATC calculations and their use in power system operations are discussed in (Sauer, 1999; Sauer and Grijalva, 1999). In addition, reactive power considerations in ATC computation are also presented in (Grijalva and Sauer, 1999).

Both TRM and CMB, which account for uncertainties and reliability of power systems, are seldom mentioned in the papers associated with ATC computation. Sauer (1998) propose four methods for calculating TRM. The first method is based on repeated computation of TTC using variations in the base case data. The second one is a single repeat computation of the TTC using limitations reduced by a fixed percentage (i.e. 4%). The next one is simply to reduce the TTC by a fixed percentage (i.e. 5%). The last method is a probabilistic approach using statistical forecast error and other systematic reliability concepts. CBM can be determined either by deterministic or probabilistic methods (NERC, 1999; Othman et al., 2006), both of which are used in reliability evaluation. Ou and Singh (2002) propose two methods for incorporating CBM into ATC. In one method, CBM is subtracted from TTC directly to derive the ATC, while in the other method CBM is taken as firm transfers. Moreover, test results from the study indicate that ignoring CBM will lead to a considerable risk of losing transfer or generation unreliability.

Transmission management in deregulated power systems is another issue facing system operators to provide optimal power transactions (Christie et al., 2000; Fang and David, 1999). Dispatch methodologies including pool, bilateral, and multilateral transactions for open access transmission systems are presented in (David, 1998a; David, 1998b; Hamoud, 1999). ATC determinations of power transactions between different control areas have to conform to these concepts.

2.1.3 Determination of ATC

ATC calculations are generally based on computer simulations of the operation of interconnected transmission networks under a specific set of assumed operating conditions. Wide varieties of mathematical methods have been developed for calculating ATC, which can be summarized into four types as follows:

1. **Linear approximation method** based on DC power flow model considering only thermal limits.
2. **Continuation power flow method** based on AC power flow model considering thermal, voltage, and voltage stability limits.
3. **Stability-constrained ATC method** based on time domain simulations with dynamic model considering stability limits.
4. **Optimal power flow method** based on AC power flow model considering thermal and voltage limits.

A. Linear approximation method

Linear method is based on linear incremental power flow approximation, which calculates network sensitivity indices to determine the transfer capabilities of power systems. Initial concepts for applying sensitivity index to transfer capability calculations are presented in (Greene et al., 1997). Christie et al. (2000) propose a power transfer distribution factor (PTDF) based on DC load flow for ATC determination. In addition, Ejebe et al. (2000) also propose a linear ATC (LATC) method, which calculates three sets of linear sensitivity indices including PTDF, line outage distribution factor (LODF), and generator outage distribution factor (GODF) for calculating ATC values. For each ATC case, power transfer is non-simultaneous because it only considers power transfer from a single source to a single sink. Greene et al. (2002) present a network sensitivity index approach for the first order sensitivity of the transfer capability with respect to the variation of any parameters. This method uses the sensitivity of transfer capability margins to calculate ATC.

These methods are attractive because the network sensitivity indices are easy to calculate and they quickly provide estimated ATC values. However, these methods are based on dc load flow, considering only thermal limits. Ignoring voltage and reactive power effects may lead to unacceptable error especially in a stressed system with insufficient reactive power support and voltage control.

B. Continuation power flow and Repetitive power flow methods

Continuation power flow (CPF) is a general method for finding the maximum value of a scalar parameter in a linear function of changes in real power at a set of buses in a power flow problem (Ajjarapu and Christy, 1992). CPF method traces the power flow solution curve, starting at a base load, leading to the steady-state voltage stability limit or the maximum loading point of power systems. The main advantage of CPF is that it can overcome the singularity of the Jacobian matrix near the saddle-node bifurcation point, or the critical point (Chiang et al., 1995). Originally introduced for determining maximum loadability, CPF is adaptable without change in principle for ATC computation. In (Ejebe et al., 1998), a CPF method with adaptive localization is proposed to calculate ATC considering reactive power and voltage stability effects.

In (Gravener and Nwankpa, 1999), a repetitive power flow (RPF) technique is proposed to calculate ATC. The RPF method, based on a generalized search method, repeatedly solves conventional power flow equations, where the successive power flow solutions are conducted to establish the maximum transfer capability. RPF enables transfers by increasing the complex load with uniform power factor at every load buses in a sink area, and by increasing the injected real power at generator buses in a source area in incremental steps until limits are incurred. A generalized search algorithm is implemented to first find the thermal limit of non-simultaneous transfers between those two control areas. Once the thermal limit of the transfers is determined, AC contingency checking for the voltage limit is performed.

For both CPF and RPF methods, the total load in the sink area is taken as TTC value of the power transaction. However, to increase a certain power transfer, CPF and RPF methods use a common loading factor for a specific cluster of generators and loads, which may lead to a conservative TTC value because these methods do not result in the optimal generation, loading, and generator bus voltages.

C. Stability-constrained ATC method

Dynamic ATC is concerned with calculating the maximum increase in power transfers such that the transient response remains stable and viable. There are a number of constraints on transient behavior considered in dynamic ATC such as saddle node bifurcation, loss of stability mechanisms associated with phase angle behavior, and electromechanical swing modes (DeMarco, 1998; Tuglie et al., 1999).

Hiskens et al. (1998) and Hiskens et al. (2000) propose an iterative approach for computing dynamic ATC. This method uses trajectory sensitivities and a set of differential-algebraic-discrete equations for the power system model. The

application of this method is limited to the evaluation of a single free parameter that can be used to yield marginally stable trajectories and computational complexity for application to large systems. In (Yuan et al., 2003), a dynamic ATC problem is formulated as an OPF-based optimization problem by integrating transient stability constraints into conventional steady-state ATC determination. An interior point algorithm is used to solve the optimization problem. The application of this method is limited to the evaluation of a large scale non-linear programming problem, which results in a problem formulation of huge dimension. An application of bifurcation criteria for ATC calculation with bilateral and multilateral power transactions is developed by Kumar et al. (2004). The Hopf bifurcation limit is used for determining dynamic ATC while the saddle node bifurcation and bus voltage limits are used for static ATC determination.

D. Optimal power flow-based methods

In this category, ATC determination is formulated as OPF problems which can be implemented by many optimization techniques such as conventional OPF calculations and artificial intelligence (AI) techniques.

Conventional OPF calculations

Conventional security constrained OPF (SCOPF) methods are commonly used to solve the OPF-based ATC problem to maximize power transfer capability between two control areas, assuming all OPF optimized parameters can be centrally dispatched (Bresesti et al., 2002; Hur et al., 2001). To overcome the deficiency of the conventional SCOPF, a transfer-based SCOPF (TSCOPF) is developed in (Ou and Singh, 2002). It is assumed that only OPF optimized parameters involving the selected source and sink area can be dispatched, which can be satisfied in deregulated power systems.

A sequential quadratic programming (SQP) algorithm (Shaaban et al., 2000a; Shaaban et al., 2003) and a Bender decomposition method (Shaaban et al., 2001) are propose to determine TTC values considering reactive power and voltage limits. The objective function is to maximize power transfers between specific generators and loads subject to constraints of load flow equations and system operating limits. Linear programming (LP) (Berizzi et al., 2000) and non-linear programming (Tuglie et al., 2000) methods are also used to solve the OPF-based ATC problem. Even though LP method is fast and reliable, the power flow equations are largely simplified, which may result in unacceptable results. The non-linear programming approach has some disadvantages associated with the insecure convergence properties and algorithmic complexity.

Dai et al. (2000) propose a direct interior point algorithm to calculate maximum loadability and minimum load curtailment. The algorithm can only be used to compute ATC values from one generation company to a customer. In (Xiao et al., 2001) a hybrid stochastic technique is proposed to calculate ATC of prescribed interfaces in transmission networks.

These methods require convexity of objective function to obtain the optimal solution. However, the OPF problem is generally non-linear and non-convex optimization problem and, as a result, many local solutions may exist. Therefore, conventional optimization methods may converge to local optimal solutions or diverge altogether. Moreover, these methods consider only thermal and voltage limits. Ignoring power system stability limits may lead to unsecured system operation.

Artificial intelligence techniques

A multi-layer feed-forward neural network approach is used to calculate ATC values by Luo et al. (2000). The inputs for the neural network are generator status, line status, and load status and the output is the transfer capability. Quickprop algorithm is used to train the neural network. Test results show that the proposed method can determine power transfer capability between system areas with variations in load levels and the status of generator and transmission lines.

In the advent of modern heuristic techniques, evolutionary computation (EC) methods such as GA and EP are implemented to solve the OPF-based ATC problem. Shaaban et al. (2000b) propose a GA approach to determine TTC values of prescribed point-to-point power transactions on a 4-bus test system. In (Ongsakul and Jirapong, 2004), an EP approach combined with Newton-Raphson (NR) power flow method is used for calculating TTC values of power transactions between different control areas. To improve the robustness of the existing EC techniques, an improved EP (IEP) approach is proposed in (Ongsakul and Jirapong, 2005) to calculate TTC values. Test results on a modified IEEE 30-bus system from the proposed method are compared favourably with those from LATC, RPF, and EP methods.

2.2 Flexible AC Transmission System

2.2.1 Principles and definitions of FACTS

Flexible AC Transmission System (FACTS) is an evolving technology-based solution envisioned to help electric utilities to deal with changes in modern power system planning and operation. The main objectives of FACTS controllers are as follows (Lai, 2001):

1. To provide direct control of power flow over designated transmission routes
2. To increase the power transfer capability of transmission networks.

According to the IEEE definitions (Edris et al., 1997), FACTS and FACTS device (controller) are defined as follows:

- **FACTS:** Alternating current transmission systems incorporating power electronic-based and other static controllers to enhance controllability and increase power transfer capability.
- **FACTS device:** A power electronic-based system and other static equipment that provide control of one or more AC transmission system parameters.

FACTS controllers can be categorized into four types according to the connection and operating criteria as follows (Hingorani and Gyugyi, 1999):

1. **Shunt connected controllers:** battery energy storage system (BESS), static synchronous compensator (STATCOM), and static var compensator (SVC).
2. **Series connected controllers:** thyristor controlled series capacitor (TCSC), thyristor switched series capacitor (TSSC), phase angle regulator (PAR), and static synchronous series compensator (SSSC).
3. **Combined shunt and series connected controllers:** thyristor controlled phase shifter (TCPS) or thyristor controlled phase shifting transformer (TCPST), and unified power flow controller (UPFC).
4. **Other controllers:** thyristor controlled voltage limiter (TCVL).

TCSC, SVC and UPFC are the main commercially available FACTS controllers. TCSC is a series compensation component which consists of a series capacitor bank shunted by thyristor controlled reactor. With the firing control of the thyristor, it can change its apparent reactance smoothly and rapidly (Mathur and Varma, 2002). SVC is a shunt compensation component which can be used as a shunt connected static var generator or absorber, whose output is adjusted to exchange capacitive or inductive current so as to control specific parameters of electrical power systems. UPFC is a novel power transmission controller. UPFC provides a full control of transmission parameters, voltage, line impedance, and phase angle. It allows real-time control and dynamic compensation of interconnected transmission systems.

Nowadays FACTS technologies have been moving ahead at an increasing pace. Very significant long-term benefits of FACTS controllers are now recognized on a worldwide basis (Hingorany, 1998*a*; Hingorany, 1998*b*). To extend these benefits, many researchers have developed methodologies for incorporating FACTS controllers into power system operation. The following sections provide an overview of previous works on power flow calculation and optimal power flow control with FACTS controllers.

2.2.2 Power flow calculations with FACTS controllers

Determination of load flow solutions in the presence of FACTS controllers is essential in power system operation and planning studies. Incorporating FACTS models in load flow algorithms can be either dynamic or static.

A. Dynamic models of FACTS controllers

Dynamic models of various FACTS controllers for voltage and angle stability studies are developed in (Canizares and Faur, 1999; Canizares, 2000). These models are based on the assumption that voltages and currents are sinusoidal, balanced, and operated near fundamental frequency. However, they have several limitations, especially when studying large system changes according to these FACTS controllers.

B. Static models of FACTS controllers

Static or steady-state models of FACTS controllers can be classified into decoupled model and coupled model.

Decoupled model

In a decoupled model, FACTS controllers are replaced with fictitious PQ- and PV-bus (Niaki and Iravani, 1996). Standard load flow calculations are then carried out to determine the load flow solution of the system with the above modifications. Esquivel and Acha (1997) and Esquivel et al. (2000) consider FACTS control parameters as independent variables and their values are found through traditional load flow iterative process. These methods result in the modification of Jacobian matrix structure to incorporate the additional independent variables. It is found that the convergence pattern of these methods is very sensitive to the initial value of FACTS control parameters (Gotham and Heydt, 1998). In addition, the modified load flow algorithm may not converge, particularly when voltage magnitudes are significantly less than rating (Haque and Yam, 2003).

Coupled model

A coupled model consists of two major models: voltage source model (VSM) and power injection model (PIM). The VSM is formulated as a series or shunt inserted voltage source according to the device's operating principle (Gyugyi, 1999; Padhy and Moamen, 2005). It can represent the corresponding device in a more intuitive way. However, it destroys the symmetrical characteristics of admittance matrix (Han, 1982). Moreover, trigonometric functions involved will inevitably lead to an oscillation of power flow control (Noroozian and Andersson, 1993). Derived from the VSM, the PIM is proposed by Han (1982). With the conversion of inserted voltage source to power injections to the related busses, the PIM is allowed to keep the symmetry of admittance matrix. According to this advantage, the applications of this model are extended to nearly all FACTS controllers and are widely spread in most of the literature of operation and control of FACTS-equipped power systems (Armin and Goran, 1998; Singh and David, 2001a; Verma et al., 2001b; Xiao et al., 2003).

2.2.3 Optimal power flow with FACTS controllers

A. Optimal power flow control with FACTS controllers

Power flow control aims at controlling active and reactive power flows through certain transmission lines and bus voltage magnitudes at specified levels. When FACTS controllers are integrated in OPF problem, the power flow control of specific lines is treated as the constraints. Many conventional optimization methods and metaheuristic techniques such as Newton method (Perez et al., 1998), LP method (Ge and Chung, 1999), GA (Leung and Chung, 2000), and a hybrid TS/SA approach (Ongsakul and Bhasaputra, 2002) are successfully used to

solve OPF with FACTS controllers to minimize generation costs. In recent years, power loss minimization and power transfer capability enhancement utilizing multi-type FACTS controllers have received significant attention because these aspects enhance competition and efficiently utilize the existing power systems. A review of literature focused on these two kinds of objective functions is summarized in this section.

Minimize power loss

Conventional optimization methods are commonly used to solve the OPF with FACTS controllers. Noroozian et al. (1997) demonstrate the application of UPFC for OPF control through numerical examples. Test results indicate that UPFC has the capability of regulating the power flow and minimizing the power losses simultaneously. Chung and Shaoyun (1998) propose an algorithm to solve the OPF with UPFC. The problem is decomposed into an active power OPF (APOPF) subproblem which is solved by LP to minimize the total production cost and a reactive power OPF (RPOPF) subproblem which is solved by successive quadratic programming (QP) to minimize the total active power loss. In (Xiao et al., 2002), a predictor-corrector primal-dual interior point linear programming (PCPDIPLP) is developed for solving an OPF with multi-type FACTS controllers. The objective function is to minimize the total mismatch of control targets of active and reactive power flows over designated transmission lines.

On the other hand, modern heuristic optimization techniques such as GA (Paterni et al., 1999) are also successfully used to solve the optimization problem. Lai and Ma (1995) proposed an EP approach coupled with P-Q decoupled power flow to solve the OPF with FACTS controllers to minimize real power loss and keep power flows in their secure limits. UPFC is used as a phase shifter and/or series compensator to regulate both angles and magnitude of bus voltages. A GA approach is also proposed to solve the same optimization problem in (Lai and Ma, 1996). A micro GA combined with fuzzy logic (FGA) is developed in (Baskarana and Palanisamy, 2006) for solving OPF with TCSC, TCPAR, UPFC, and SVC to minimize power loss. Test results from the proposed method are compared favorably with those from GA alone.

Maximize power transfer capability

Ou and Singh (2001) propose a general procedure based on RPF method to maximize TTC with FACTS controllers installed in power systems. Test results on a 4-bus test system indicate that TCSC is more effective than SVC in improving TTC. In (Liu et al., 2002), a transportation model combined with matrix computational technique is proposed to evaluate the impact of TCSC on TTC enhancement. However, the proposed method has a disadvantage of accuracy

related to the reactive power flow in the solution. Moreover, a stochastic programming technique (Xiao et al., 2000) and a PCPDIPLP method (Xiao et al., 2003) are also proposed to maximize ATC in the OPF with multi-type FACTS controllers. The OPF-based ATC enhancement model is formulated to achieve the maximum power transfer by controlling multi-type FACTS controllers while increasing all the complex loads and generations in current situation using a scalar loading factor. Test results demonstrate the effective of SVC, TCPS, and UPFC on ATC enhancement.

B. Optimal placement of FACTS controllers to control power flow

The optimally placed OPF with FACTS controllers is a combinatorial optimization problem, which is determining the optimal types, locations, and parameters of FACTS controllers in the OPF problem. Many optimization techniques such as a decomposition-coordination method combined with network compensation technique (Lie and Deng, 1997), LP-based method (Oliveira et al., 1999), GA (Cai et al., 2004), a real power flow performance index combined with SQP (Singh and David, 2001b; Singh et al., 2001), and a hybrid TS/SA approach (Bhasaputra and Ongsakul, 2006) are effectively used to determine the optimal placement of FACTS controllers to minimize system operating costs. On the other hands, wide varieties of mathematical methods have been made on the optimal placement of FACTS controllers to minimize system power loss and maximize power transfer capability, which can be summarized in the following paragraphs.

Minimize power loss

Preedavichit and Srivastava (1997) and Preedavichit and Srivastava (1998) propose an algorithm to minimize system real power loss in an optimal reactive power dispatch (ORPD) with FACTS controllers. A sensitivity based method is used to determine suitable locations of SVC, TCSC, and TCPAR. The ORPD with fixed FACTS problem is solved by a successive QP algorithm. In (Yu and Lusan, 2004), a generalized decomposition method is proposed to determine the optimal placement of FACTS controllers based on multiple time periods to maximize social welfare with real power losses considered. Test results indicate that transmission losses can affect the optimal FACTS placement.

Maximize power transfer capability

Sensitivity index approaches are commonly used to determine approximate locations of FACTS controllers for power transfer capability enhancement. However, these methods may not lead to the optimal solution because of dependency to system topology and loading conditions. A sensitivity approach

based on the real power flow performance index is developed in (Verma et al., 2001a) for finding suitable locations of TCSC and TCPAR to enhance TTC. Test results indicate that the FACTS controllers should be placed on the most sensitive lines. Schnurr and Wellssow (2001) propose a sensitivity analysis based on the generation shift distribution factor (GSDF) to determine possible locations of FACTS controllers to maximize ATC. Moreover, Orfanogianni and Bacher (2003) propose a sensitivity method to find suitable locations of TCSC and UPFC to maximize power transfers from a group of generating plants or exporting areas to a consumption bus or importing area.

To overcome the deficiency of the sensitivity index approaches, a few conventional optimization techniques and a number of heuristic techniques have been developed. Sharma et al. (2005) propose a mixed integer linear programming approach to determine the optimal location of TCPAR and TCSC to enhance system loadability. The proposed method is based on DC load flow equations. A parallel TS (PTS) algorithm is developed in (Mori and Goto, 2000) for determining the optimal locations and parameters of UPFC to simultaneously maximize incremental load rate and minimize transmission loss. A two-phased optimization technique is implemented to deal with the allocation of UPFC using TS and handle tuning up the parameters using PTS. Feng and Shrestha (2001) propose a GA approach combined with CPF to determine the optimal placement of TCSC to maximize TTC. GA is used as the optimization tool to determine the location and parameter of TCSC and CPF is used to determine TTC values.

In (Gerbex et al., 2001), a GA approach is used to determine the optimal locations, types, and parameters of TCSC, TCPST, TCVR, and SVC to maximize system loadability. Test results show that the simultaneous use of several kinds of controllers is the most efficient solution to increase the system loadability. Farahmand et al. (2004) propose a GA combined with RPF to determine optimal location of SVC to improve voltage profile and maximize TTC. Moreover, a self-adaptive evolutionary programming (SAEP) is developed in (Hao et al., 2004) for determining the optimal locations and parameters of UPFC to maximize the system loadability.

2.3 Optimal Power Flow

Optimal power flow (OPF) is an optimization problem of power system operation, which is expressed as the maximization or minimization of an objective function subject to equality and inequality constraints which define the boundaries of technical feasibility. An OPF solution gives the optimal active and reactive power dispatch for a static power system condition. Computationally, it is a very demanding non-linear programming problem, due to a large number of variables and in particular to the much larger number and types of limit constraints (Alsac

and Stott, 1974; Stott, 1974). Moreover, the presence of discrete control variables such as FACTS parameters further complicates the OPF solution.

Since the OPF was successfully implemented by Dommel and Tinney (1968), it has been widely used in power system planning and operation. As the power industry moves into a more competitive environment, uses of the OPF become increasingly more important in maximizing the capability of the existing power systems. Considerable amounts of research toward the development of different optimization methods have been done, especially in the last three decades (Momoh et al., 1997). These approaches are mainly classified into conventional optimization methods and artificial intelligence (AI) techniques.

2.3.1 Conventional optimization methods

The main existing optimization methods for solving OPF problems are conventional methods such as non-linear programming (NLP) (Dommel and Tinney, 1968), quadratic programming (QP) (Reid and Hasdorf, 1973), gradient method (Alsac and Stott, 1974), linear programming (LP) method (Stott and Marinho, 1979), Newton method (Sun et al., 1984), mixed integer programming (MIP) (Contaxis et al., 1986), and interior point (IP) method (Clements et al., 1991; Momoh et al., 1992; Momoh and Zhu, 1999). Each method has its own advantages and disadvantages, but all of them have their own capabilities for solving OPF problems.

Conventional optimization methods have been widely used to solve OPF problems. However, they are not guaranteed to converge to the global optimum of the general non-convex OPF problem. There are some empirical evidences on the uniqueness of the OPF solution within the domain of interest (Papalexopoulos et al., 1989). Moreover, these methods rely on convexity to obtain the global optimal solution and as such are forced to simplify relationships to ensure convexity. Several disadvantages of traditional optimization techniques are summarized in the following paragraph.

NLP deals with problems involving non-linear objective function and system constraints. This method has many drawbacks such as insecure convergence properties and algorithmic complexity (Abido and Bakhashwain, 2005). QP is a special form of NLP whose objective function is quadratic with linear constraints. This method has some disadvantages associated with the piecewise quadratic cost approximation (Bakirtzis et al., 2002). The gradient and Newton methods have some drawbacks such as the convergence characteristic, which is sensitive to the initial condition and they suffer from the difficulty in handling inequality constraints (Sood, 2007). LP treats problems with constraints and objective function formulated in linear forms. The input-output function is expressed as a set of linear functions, which may lead to loss of accuracy (Devaraj and Yegnanarayana, 2005). MIP is a particular type of LP whose constraint

equations involve variables restricted to being integers. This method is known to exhibit numerical difficulties when penalty factors become extremely large (Abido, 2002a; Abido, 2002b). IP-based methods have been reported as computationally efficient, however, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original non-linear domain (Yan and Quintana, 1999). In addition, IP-based methods suffer from bad initial, termination, and optimality criteria and, in most cases, are unable to solve non-linear and quadratic objective functions (Momoh and Zhu, 1999). For more discussions on these techniques, a comprehensive survey is presented in (Momoh et al., 1999a; Momoh et al., 1999b).

2.3.2 Artificial intelligence optimization techniques

Artificial intelligence (AI) techniques, which promise a global optimum solution, or nearly so, have in recent years emerged as a complement tool to conventional approaches (Bansal et al., 2003). Recent attempts to overcome the limitations of conventional optimization methods, many AI techniques such as neural network (Nguyen, 1995), evolutionary computation, and heuristic optimization techniques have been employed to solve OPF problems. A brief review of these algorithms is summarized in this section.

A. Genetic algorithm (GA)

GA is a heuristic search based on natural evolution theory. GA-based approaches are successfully used to solve OPF problems with various objectives such as economic dispatch (ED) (Bakirtzis et al., 1994), minimize power loss (Lai and Ma, 1996), generator unit commitment (UC) (Swarup and Yamashiro, 2003), and minimize total system cost (Osman et al., 2004).

B. Evolutionary programming (EP)

EP is a general global optimization algorithm based on the natural evolution theory similar to GA. However, EP works on real value coded strings rather than binary strings used by GA. EP-based methods are used to solve economic dispatch (ED) problems for units with non-smooth fuel cost functions (Yang et al., 1996) and also applied to the environmentally-constrained ED problems to minimize the emissions and power production cost subject to the emission constraints (Wong and Yuryevich, 1998). An EP approach is also used to solve the optimal reactive power planning (Lee and Fang, 1998). Moreover, an EP enhanced by the gradient information to increase the speed of search in the neighborhood area to candidate solutions is used to solve OPF problems in (Yuryevich and Wong, 1999).

C. Evolutionary strategy (ES)

ES is mainly applied to solve various optimization problems with continuously changeable parameters. An ES approach is used to solve the reactive power dispatch problem in (Gomes and Saavedra, 2002). The ES algorithm is improved by the control of mutations and by using of Cauchy-based mutation rather than the classical Gaussian mutation. In addition, a hybrid ES is proposed to solve reactive power dispatch problem to minimize the total real power transmission losses (Das and Patvardhan, 2003).

D. Tabu search (TS)

TS is a higher level heuristic algorithm called metaheuristic for solving combinatorial optimization problems. TS is characterized by its ability to avoid the entrapment in local optimal solution and prevent cycling by using flexible memory of search history. TS-based approaches are successfully used to solve many OPF problems (Abido, 2002*b*; Kulvorawanichpong and Sujitjorn, 2002; Lin et al., 2002).

E. Simulated annealing (SA)

Based on the annealing process in the statistical mechanics, SA is used to solve the OPF problem simultaneously composed by the load flow and economic dispatch (Sepulveda and Lazo, 2002; Wong and Fung, 1993). The main drawback of SA procedure is that the annealing procedure is very CPU consuming although its convergence has been theoretically improved. To enhance the performance of SA, the mean field theory (MFT) which aims at approximating the SA with a set of deterministic equations, is introduced in (Chen et al., 1997).

F. Particle swarm optimization (PSO)

PSO is an efficient and reliable evolutionary-based approach which combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO-based methods are used for solving OPF problems with various objectives such as fuel cost minimization, voltage profile improvement, and voltage stability enhancement (Abido, 2002*a*; Jeyakumar et al., 2006; Yoshida et al., 2000).

In addition, an extensive list of references to works in evolutionary algorithm is presented in (Miranda et al., 1998). It is indicated that the vast majority of the applications use GA. However, the interest in the use of other techniques is rising fast. Moreover, the applications of hybrid algorithms in the

solution of multi-objective optimization problems have generated significant research interest in recent years. A number of hybrid algorithms have been developed and are being continuously improved to achieve better performance.

2.4 Heuristic Optimization Techniques

Several heuristic tools have evolved in the last decades that facilitate solving many optimization problems that are previously difficult or impossible to solve. These tools include GA, EP, TS, SA, PSO, etc. Reports of applications of each of these methods have been widely published. Recently, these new heuristic techniques have been combined among themselves and with other traditional approaches to solve complicated optimization problems. Principles of the main heuristic optimization techniques are summarized in this section.

2.4.1 Classification of heuristic optimization techniques

A. Evolutionary computation

Natural evolution is a hypothetical population-based optimization process. Simulating this process on a computer results in stochastic optimization techniques that can often outperform conventional optimization methods when applied to difficult real-world problems. EC-based techniques have received significant attention during the last decade, although the origins can be traced back to the late 1950's (Fogel, 2000). EC is a general adaptable concept for problem solving, especially well suited for solving difficult optimization problems. The main advantage of evolutionary search compared to other approaches lies in the gain of flexibility and adaptability to the task at hand, in combination with robust performance and global search characteristics (Back et al., 1997).

The majority of current implementations of evolutionary algorithms descend from three strongly related but independently developed approaches: genetic algorithms (GA), evolutionary programming (EP), and evolution strategies (ES). The main differences of the three approaches lie in the representation of individuals, the design of the variation operators, and the selection mechanism.

Genetic algorithms

GA, introduced by Holland (1962) and subsequently studied by Goldberg (1985) and others such as Koza (1989) and Eshelman and Schaffer (1993), is a heuristic search based on natural evolution theory. GA works on binary strings of candidate

solutions. It can discover optimal point for complicated and uncertain area by evolving its genetic material during the search process (Holland, 1975). The crossover, mutation, and selection mechanisms are used in the evolution. It can deal with non-smooth, discontinuous, and non-differentiable objectives as well as constraints. However, Wright (1991), Back (1993), and Lai et al. (1997) indicate that the binary representation has some disadvantages. The coding function may introduce an additional multimodality, thus making the combined objective function more complex than the original problem.

Evolutionary programming

EP, introduced by Fogel (1962) and extended by Burgin (1974), Fogel (1994), Eiben et al. 1999, and others, is a stochastic optimization strategy similar to GA, which places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature. EP is a useful method of optimization when other techniques such as gradient descent or direct analytical discovery are not possible. Combinatorial and real-valued function optimization problems are well suited for EP (Fogel, 2000).

Evolution strategies

ES, developed by Rechenberg (1973) and extended by Herdy (1992), Ostermeier (1992), and others, employs real-coded variables and, in its original form, it relied on mutation as the search operator. It has evolved to share many features with GA. The major similarity between these two types of algorithms is that they maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences are as follows: ES operate directly on floating point vectors while classical GA operates on binary strings. GA relies mainly on recombination to explore the search space, while ES uses mutation as the dominant operator. In addition, ES is an abstraction of evolution at individual behavior level, stressing the behavioral link between an individual and its offspring, while GA maintains the genetic link.

B. Particle swarm optimization

PSO is a new methodology in evolutionary algorithm that is somewhat similar to GA in that the system is initialized with a population of random solutions (Abido, 2002a). Unlike other algorithms, each potential solution, called a particle, is assigned a randomized velocity and then flown through the problem hyperspace. PSO has been found to be extremely effective in solving a wide range of engineering problems. It is easy to implement and it solves problems very quickly.

C. Ant colony search algorithm

Ant colony search algorithms mimic the behavior of real ants. It is known that real ants are capable of finding shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the environment, for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle (Dorigo et al., 2006). The studies by ethnologists reveal that these capabilities are essentially due to what is called pheromone trails which ants use to communicate information among individuals regarding path and to decide where to go. Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

D. Tabu search

TS is a gradient-descent search with memory (Abido, 2002b). The memory preserves a number of previously visited states along with a number of states that might be considered unwanted. This information is stored in a tabu list. The definition of a state, the area around it and the length of the tabu list are critical design parameters. In addition to these tabu parameters, two extra parameters are often used: aspiration and diversification. Aspiration is used when all the neighboring states of the current state are included in the tabu list. In that case, the tabu obstacle is overridden by selecting a new state. Diversification adds randomness to this otherwise deterministic search. If the tabu search is not converging, the search is reset randomly.

E. Simulated annealing

SA is based on local search in which each movement is accepted if it improves the system energy. Other possible solutions are also accepted according to a probabilistic criterion. Such probabilities are based on the annealing process and they are obtained as a function of the system temperature (Wong and Fung, 1993). In a large combinatorial optimization problem, an appropriate perturbation mechanism, cost function, solution space, and cooling schedule are required to find an optimal solution with SA.

2.4.2 The structure of an evolutionary algorithm

Evolutionary algorithms mimic the process of natural evolution, which is the driving process for the emergence of complex and well-adapted organic structures. Evolution is the result of the interplay between the creation of new genetic information and its evaluation and selection. A single individual of a

population is affected by other individuals of the population, as well as by the environment. The better an individual performs under these conditions, the greater is the chance for the individual to live for a longer while and generate offspring. This neo-Darwinian model of organic evolution is reflected by the structure of the following general evolutionary algorithm (Back et al., 1997).

Main algorithm:

```

    t=0;
    initialize P(t);
    evaluate P(t);
    while not terminate do
        P'(t) = variation [P(t)];
        evaluate [P'(t)];
        P(t+1) = select [P'(t) ∪ Q];
        t = t + 1;
    end

```

In this algorithm, $P(t)$ denotes a population of μ individuals at generation t . Q is a special set of individuals that might be considered for selection, e.g., $Q = P(t)$. An offspring population $P'(t)$ of size λ is generated by means of variation operators such as recombination or mutation from the population $P(t)$. The offspring individuals are then evaluated by calculating the objective function values for each of the solutions represented by individuals in $P'(t)$, and selection based on the fitness values is performed to drive the process toward better solutions. It should be noted that $\lambda=1$ is possible, thus including so-called steady-state selection schemes, if used in combination with $Q = P(t)$. Furthermore, by choosing $1 < \lambda < \mu$, an arbitrary value of the generation gap is adjustable, such that the transition between strictly generational and steady-state variants of the algorithm is also taken into account by the formulation offered here. It should also be noted that $\lambda > \mu$, i.e., a reproduction surplus, is the normal case in nature.

2.5 Mixed-Integer Nonlinear Programming

Mixed integer nonlinear programming (MINLP) refers to mathematical programming with continuous and discrete variables and nonlinearities in the objective function and constraints. The general form of a MINLP is:

$$\begin{array}{ll}
 \text{minimize} & f(x, y) \\
 \text{subject to} & g(x, y) \leq 0 \\
 & x \in X \\
 & y \in Y
 \end{array}$$

The function $f(x, y)$ is a nonlinear objective function and $g(x, y)$ a nonlinear constraint function. The variables x, y are the decision variables, where y is required to be integer valued. X and Y are bounding-box-type restrictions on the variables. MINLP problems are precisely so difficult to solve, because they combine all the difficulties of both of their subclasses: the combinatorial nature of mixed integer programs (MIP) and the difficulty in solving nonconvex nonlinear programs (NLP). Methods for solving MINLP include innovative approaches and related techniques taken and extended from MIP. Outer Approximation (OA) methods (Duran and Grossmann, 1986), Branch-and-Bound (BB) (Quesada and Grossmann, 1992), Extended Cutting Plane methods (Westerlund and Petersson, 1995), and Generalized Bender's Decomposition (GBD) (Geoffrion, 1972) for solving MINLP have been discussed in the literature since the early 1980's.

BB starts out forming a pure continuous NLP problem by dropping the integrality requirements of the discrete variables. In addition, OA and GBD require the successive solution of a related MIP problem. Both algorithms decompose the MINLP into an NLP subproblem that has the discrete variables fixed and a linear MIP master problem. The main difference between GBD and OA is in the definition of the MIP master problem. OA relies on linearizations, effectively reducing each subproblem to a smaller feasible set, whereas the master MIP problem generated by GBD is given by a dual representation of the continuous space.

2.6 Conclusion

ATC calculation is a complicated task involving determination of TTC and two margins, TRM and CBM. Wide varieties of mathematical methods have been proposed for ATC calculations with various degrees of success. Methods based on OPF receive significant attention because of flexibility of objective function, which can be implemented by many optimization techniques. For the optimally placed OPF with FACTS problem, it is a MINLP problem with continuous and discrete variables. Conventional optimization methods could not be solved MINLP problem effectively. Therefore, AI techniques are used to solve the MINLP problem for better solutions than those from conventional methods.

In the next chapter, a new hybrid evolutionary algorithm based on EP, TS, and SA is proposed to solve the OPF-based ATC problem. The algorithm is based on full ac OPF solution to account for the effects of active and reactive power flows, voltage limits, and line flow limits. The real power output of generators in source area, real and reactive load in sink area, and bus voltage of generators can be adjusted to obtain the maximum transfer capability. Test results from the proposed HEA approach are compared with those from LATC, CPF, EP, TS, hybrid TS/SA, and IEP methods.

Chapter 3

Optimal Power Flow-Based Available Transfer Capability Determination

In this chapter, ATC determination is formulated as an OPF problem. The objective function is to maximize power transfers between different control areas constrained by load flow equations and system operating limits. A novel hybrid evolutionary algorithm (HEA) is proposed to solve the optimization problem. Test results on three test systems from the proposed method are compared with those from LATC, CPF, EP, TS, hybrid TS/SA, and IEP methods.

3.1 OPF-Based ATC Problem Formulation

3.1.1 Objective function

An ATC function in (3.1) is used as an objective function of the OPF-based ATC determination. The optimal solution provides a feasible ATC value that can be transferred from a specific set of generators in a source area to loads in a sink area within real and reactive power generation limits, line thermal limits, voltage limits, and voltage and angle stability limits. State variables are dependent variables of NR power flow. Output variables which account for solutions of the proposed optimization methods are parts of the state variables.

$$\text{Maximize} \quad F = ATC = TTC - TRM - CBM \quad (3.1)$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (3.2)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^N V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (3.3)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (3.4)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (3.5)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (3.6)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (3.7)$$

$$VCPI_i \leq 1 \quad \forall i \in N \quad (3.8)$$

$$|\delta_{ij}| \leq \delta_{ij}^{crit} \quad \forall i \in NL \quad (3.9)$$

Where

F	objective function,
ATC	available transfer capability,
TTC	total transfer capability,
TRM	transmission reliability margin,
CBM	capacity benefit margin,

Input Variables

Y_{ij}, θ_{ij}	magnitude and angle of the ij th element in bus admittance matrix,
$P_{Gi}^{\min}, P_{Gi}^{\max}$	lower and upper limits of real power generation at bus i ,
$Q_{Gi}^{\min}, Q_{Gi}^{\max}$	lower and upper limits of reactive power generation at bus i ,
$V_i^{\min}, V_i^{\max}$	lower and upper limits of voltage magnitude at bus i ,
$S_{Li}^{\max}$	i th line or transformer loading limit,
δ_{ij}^{crit}	critical angle difference between bus i and j ,
N, NL	number of buses and branches,
NG	number of generator buses,

State Variables

P_{G1}, Q_{G1}	real and reactive power generations at slack bus,
V_i, V_j	voltage magnitudes of bus i and j ,
δ_i, δ_j	voltage angles of bus i and j ,

Output Variables

P_{Gi}, Q_{Gi}	real and reactive power generations at bus i ,
P_{Di}, Q_{Di}	real and reactive loads at bus i ,
$ S_{Li} $	i th line or transformer loading,
$VCPI_i$	voltage collapse proximity indicator at bus i , and
$ \delta_{ij} $	angle difference between bus i and j .

Voltage collapse proximity indicator (VCPI) in (3.8) is used to directly determine voltage collapse conditions within voltage stability limits. VCPI is a general constraint which could be static and dynamic. In addition, it provides accurate voltage collapse conditions without solving dynamic equations which consumes more computation time. Based on the optimal impedance solution of an equivalent 2-bus system in Figure 3.1, VCPI at a load bus i is defined as the ratio of the Thevenin's equivalent impedance, $Z_{ii} \angle \beta_i$, looking into the port between bus i and ground, and the impedance of the load at bus i , $Z_i \angle \phi_i$ (Chebbo et al., 1992). The load at bus i can be increased to the maximum value at the voltage collapse point or critical point when Z_{ii} is equal to Z_i as shown in Figure 3.2. Therefore, for the maximum power transfer to a load at bus i without violating voltage stability limits, VCPI at the load bus i in (3.10) must equal to or less than one.

$$VCPI_i = \frac{Z_{ii}}{Z_i} \leq 1 \quad (3.10)$$

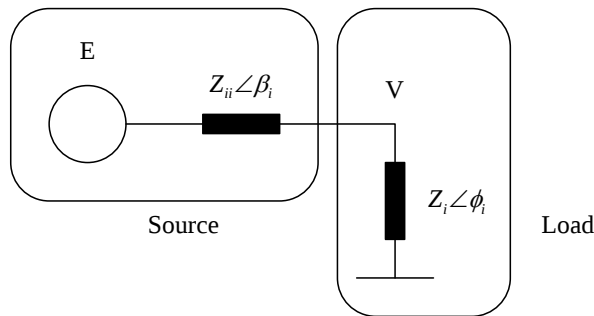


Figure 3.1 An equivalent 2-bus system.

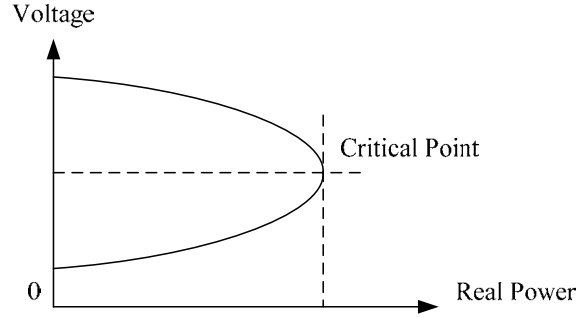


Figure 3.2 Power-voltage curve.

Angle stability constraints considered can be either steady-state (Singh et al., 2001) or dynamic (Yuan et al., 2003). This research considers only steady-state angle stability constraint. Critical angle displacement in (3.9) is used as a criterion to determine steady-state angle stability limit. The system stability limit is defined in term of the stability margin in (3.11). The amount of margin, which is desirable in a given situation, is dependent on many factors. For a reasonable level of typical heavy line loading situations, it is assumed that the stability margin is in the range of 30-35% as shown in Figure 3.3. Therefore, the angle difference between buses i and j across a transmission line is kept within a critical angle difference, which is 44° as recommended in (Dunlop et al., 1979; Taylor, 1994).

$$\text{Stability margin} = \frac{P_{\max} - P_{\text{rated}}}{P_{\max}} \times 100 \% \quad (3.11)$$

Where

$P_{\max}$ maximum power transfer ability of a system and
 P_{rated} operating level of power transfer.

Voltage and angle stability limits are treated as OPF constraints in (3.8) and (3.9), respectively. During the optimization, inequality constraints of state variables including bus voltage magnitudes, real power generation at slack bus, reactive power generation, line or transformer loading, angle and voltage stability limits are enforced using a penalty function in (3.12) (Wood and Wollenberg, 1996).

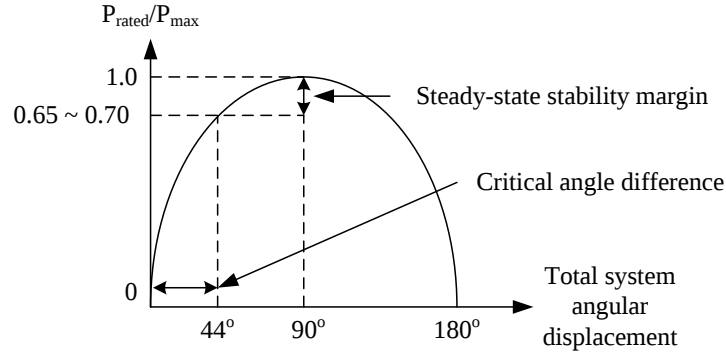


Figure 3.3 Power-angle curve.

$$PF = k_p \left[h(P_{G1}) + \sum_{i=1}^{NG} h(Q_{Gi}) + \sum_{i=1}^N h(V_i) + \sum_{i=1}^{NL} h(|S_{Li}|) + \sum_{p=1}^{NL} h(|\delta_{ij,p}|) + \sum_{i=1}^N h(VCPI_i) \right] \quad (3.12)$$

$$h(x) = \begin{cases} (x - x^{\max})^2 & \text{if } x > x^{\max} \\ (x^{\min} - x)^2 & \text{if } x < x^{\min} \\ 0 & \text{if } x^{\min} \leq x \leq x^{\max} \end{cases} \quad (3.13)$$

Where

$x^{\min}, x^{\max}$

lower and upper limits of variable x ,

k_p

penalty weighting coefficient. By experiments, the penalty coefficient is set to 10^6 since the lower coefficient value results in an oscillation of HEA solution. The suggested range of penalty coefficient is between 10^3 - 10^6 (Wood and Wollenberg, 1996).

3.1.2 ATC determination

ATC calculation in (3.1) involves determination of TTC and two margins, TRM and CBM. Mathematically, ATC is defined in (3.14).

$$ATC = TTC - TRM - CBM \quad (3.14)$$

To determine ATC value of a power transaction between different control areas, an interconnected power system is divided into three kinds of areas: source or sending area, sink or receiving areas, and external areas. An area can be defined in an arbitrary fashion. It may be an individual electric system, power pool,

control area, subregion, etc (Yuan et al., 2003). Two types of transactions (Kumar et al., 2004) are considered.

Bilateral transaction

A bilateral transaction is made directly between a seller and a buyer. The seller injects a certain amount of power at one generator bus and the buyer receives this power at the other load bus. Each bilateral transaction between a seller at bus i and a buyer at bus j satisfies the power balance equation in (3.15).

$$P_{Gi} - P_{Dj} = 0 \quad (3.15)$$

Where

P_{Gi} real power generation at bus i and
 P_{Dj} real power load at bus j .

Multilateral transaction

A multilateral transaction trading among several parties is arranged by a scheduling coordinator. Mathematically, a multilateral transaction involving several sellers and buyers can be expressed in (3.16). To facilitate the multilateral transaction, a weighting factor or a relative participation factor of generators involved on seller bus side and loads on sink bus side is set to 1.0. The optimization methods simultaneously search for the maximum allowable individual generation and load in each areas. Using pre-specified participation factors, HEA will converge faster due to the reduced search space, but it may lead to a lower ATC value.

$$\sum_{i \in S} P_{Gi} - \sum_{j \in B} P_{Dj} = 0 \quad (3.16)$$

Where

S set of sellers who sell the power to buyers and
 B set of buyers who buy the power from the sellers.

To define a specific power transaction from a source to a sink area without curtailing existing ones, it is assumed that in each area, generators belong to the same owner and loads belong to the same load serving entity. The utility in a sink area wants to import power from source area. Only generations in the source area and loads in the sink area are adjusted to create a generation excess in the source

area and an increasing load in the sink area, thereby automatically resulting in an electric power transfer from the source to the sink area. These differential adjustments in each area's generation and load levels are increased until equipment or system limit is reached, or a transfer test level is achieved, taking into account the system thermal, voltage, and stability effects.

3.1.3 TTC determination

TTC is the maximum electric power that can be transferred over the network in a reliable manner. It is the main component of the ATC computation. The OPF-based ATC determination defined in (3.1) enables transfers by increasing the complex load with uniform power factor at every load buses or a group of load buses in a sink area, ND_SNK , and increasing the injected real power at generator buses in a source area, NG_SCE , until a system limit is incurred. The total real power load in the sink area is used in the objective function to determine the maximum feasible TTC value similar to that defined in the CPF and RPF methods. Therefore, TTC is defined in (3.17).

$$TTC = \sum_{i=1}^{ND_SNK} P_{Di} \quad (3.17)$$

3.1.4 TRM determination

TRM is the amount of transmission transfer capability necessary to ensure that the transmission network is secure under a reasonable range of uncertainties in system conditions. For TTC determination considering TRM, load uncertainty is taken into consideration as random load increased within 2% of base case values in every load flow evaluations. Considering base case configuration, let TTC_0 be the maximum amount of power transfer without contingency constraints. Similarly, let TTC_k be the maximum amount of power transfer under the contingency k . Therefore, a feasible contingency TTC value considering TRM is given in (3.18).

$$TTC = \text{Min}\{TTC_0, TTC_1, \dots, TTC_k\} \quad (3.18)$$

The contingency k to be analyzed will depend on the pre-specified contingency ranking. If the number of contingencies goes up to ensure more reliable transfers, the transfer capability will obviously be smaller. For a large power system, contingency screening and ranking techniques may be used to find those critical contingencies whose unavailability will have the largest effect on transfer capability for a particular area to area transfer. In this research, only the outage of the largest generator in each area and the outage of tie lines are included in the contingency list.

3.1.5 CBM determination

CBM is the amount of transmission transfer capability reserved by load serving entities to ensure access to generation from interconnected systems to meet generation reliability requirements. Allocation of CBM to individual areas can be determined either by deterministic or probabilistic methods (NERC, 1995b; NERC, 1999). This research considers CBM determination based on single area generation reliability evaluation using a probabilistic method proposed in (Ou and Singh, 2002). For hourly load model, loss of load expectation (LOLE) < 2.4 hour per year is selected as a reliability criterion. To meet the specific reliability criterion, additional installed capacity is required. This additional capacity is considered as the CBM. To incorporate CBM into ATC, CBM is subtracted from TTC directly.

The generation model required in the loss of load approach is known as a capacity outage probability table, which is an array of capacity level and cumulative probability. The cumulative probability of a particular capacity outage state of X MW after a unit of capacity C MW and forced outage rate U is added is given in (3.19) (Billinton and Allan, 1996). The expression is initialized by setting $P'(X)=1.0$ for $X \leq 0$ and $P'(X)=0$ otherwise.

$$P(X) = (1-U)P'(X) + (U)P'(X - C) \quad (3.19)$$

Where $P'(X)$ and $P(X)$ are cumulative probabilities of the capacity outage state of X MW before and after the unit are added, respectively.

LOLE index can be obtained using daily peak load variation curve depicted in Figure 3.4. The total LOLE made by capacity outage O_k in the study interval is calculated in (3.20).

$$LOLE = \sum_{k=1}^n (t_k - t_{k-1}) P_k \quad (3.20)$$

Where

- n number of unit states,
- t_k number of time units that an outage O_k would result in a loss of load,
- P_k cumulative outage probability for capacity state O_k , and
- O_k magnitude of the k th outage in the system capacity outage probability table.

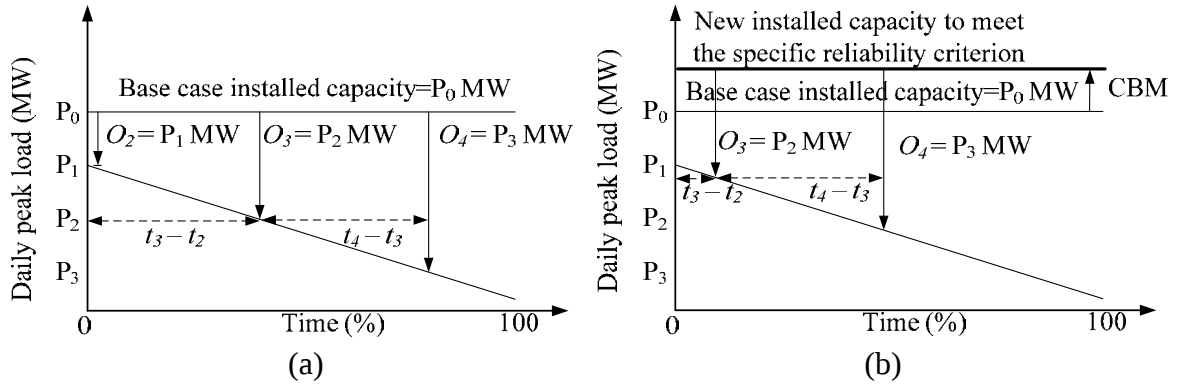


Figure 3.4 Time periods (a) before and (b) after CBM is added.

3.2 Hybrid Evolutionary Algorithm for OPF-Based ATC Determination

To improve the robustness of evolutionary computation techniques, a new hybrid evolutionary algorithm (HEA) integrating EP, TS, and SA methods is proposed. The HEA starts with random generation of initial individuals in multi-populations and then the mutation and reassignment are proceeded until the best individual, which has the highest fitness, is found (Jirapong and Ongsakul, 2007a). The HEA approach has special features and merits described as follows:

1. Multiple population search with various mutation operators is designed to enhance search diversity and improve population update, providing higher quality of solutions than those from single population search.
2. Reassignment strategy is carried out to fuse and exchange the search information of all subpopulations so that premature convergence caused by consistency of individuals in a single population will be alleviated.
3. Selection with a probabilistic updating strategy based on TS and annealing schedule of SA is applied to avoid dependency on fitness function and to avoid being trapped in local optimal solutions.
4. The algorithm can easily facilitate parallel implementation on parallel computers to reduce the elapsed time without sacrificing the quality of solution.

The HEA approach is used to simultaneously search for real power generations in a source area excluding slack bus, generation bus voltages, and real power loads in a sink area for determining the optimal solutions of the objective function defined in (3.1). A procedure to determine ATC value using the HEA is shown in Figure 3.5. A flowchart of the HEA is depicted in Figure 3.6, which can be explained as follows:

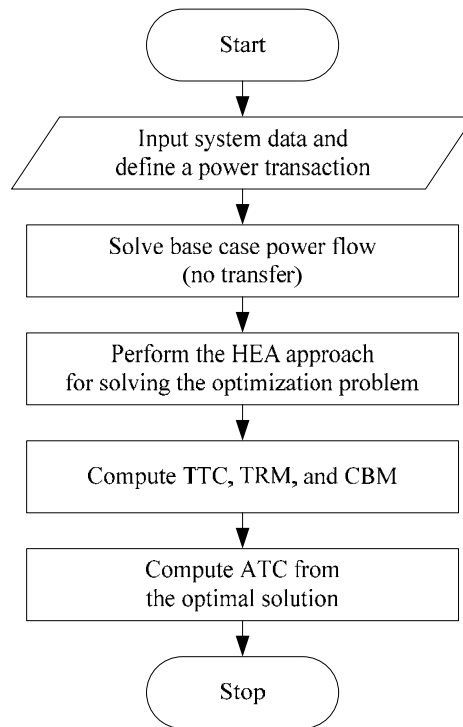


Figure 3.5 Flow chart of ATC determination using the HEA approach.

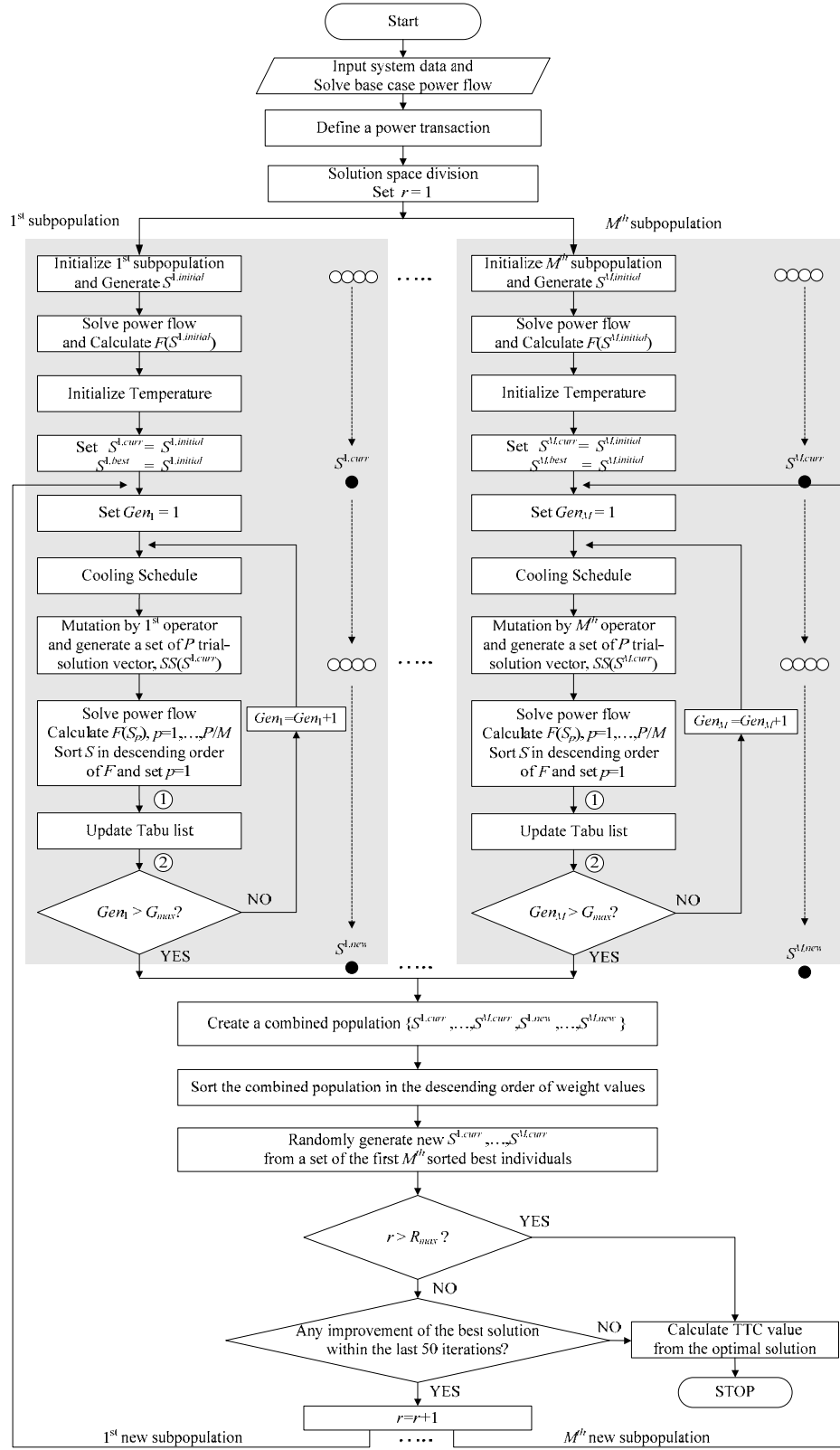


Figure 3.6 Flow chart of OPF-based ATC determination using the HEA approach.

Representation of solution

An individual in a population represents a candidate of OPF solution. Each individual consists of OPF control variables coded by real number. The coded control variables employed in the algorithm are real power generation output of all generator buses in the source area, voltage magnitudes of all generator buses including slack bus, and real power demand of all load buses in the sink area. The p th individual in a population is represented by a trial solution vector in (3.21).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \quad (3.21)$$

Where

S_p	trial solution vector of the p th individual,
P_{Gi}	real power generation at bus i in the source area,
V_{Gi}	voltage magnitude of generator at bus i including slack bus, and
P_{Dj}	real power load at bus j in the sink area.

Space division

Space division strategy is used to divide the whole population size P into M subpopulations according to the number of mutation operators used. Therefore, the search process can be performed in parallel to enhance performance of exploration and speed of convergence.

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number distribution ranging over the feasible limits of each control variable in (3.22).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.22)$$

Where

x_i	i th element of the individual in a population,
$x_i^{\min}, x_i^{\max}$	lower and upper limits of the i th element of the individual, and
u	uniform random number in the interval $[0,1]$.

Power flow solution

During iterations, a full AC Newton-Raphson (NR) power flow analysis is used to check the feasibility of each individual solution. If the power flow of any individuals fails to converge, such individuals will be removed and replaced by new randomly created individuals.

Fitness function

Fitness function is used to measure the optimality or quality of each candidate solution with respect to the objective being optimized. The objective function in (3.1) is taken as the fitness function of the HEA approach.

Cooling schedule procedure

The initial temperature of each subpopulation is determined from the objective value of the best and the worst individual, and the probability of accepting the worst individual with respect to the best individual expressed in (3.23). After reassignment strategy, the temperature is cooled down by the temperature annealing function or cooling schedule in (3.24).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (3.23)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (3.24)$$

Where

$T_{0,m}$	initial temperature of the m th subpopulation,
$F_m^{\min}, F_m^{\max}$	objective value of the worst and best individuals in the m th subpopulation,
p_r	probability of accepting the worst individual with respect to the best individual,
$T_{r,m}$	annealing temperature of the m th subpopulation after the r th reassignment,
λ	rate of cooling, and
r	iteration counter of reassignment strategy.

Mutation

In different subpopulations, different mutation operators are used to create new offspring subpopulation so that many hybrid operators are applied to enhance the search diversity. Two mutation operators including Gaussian and Cauchy are applied. A set of trial solution vectors, $SS(S^{curr})$, is generated by perturbing the current solution vector, S^{curr} , using the uniform probability distribution function. Each element of the offspring is calculated in (3.25). If any mutated value exceeds its limits, it will be recalculated until it is within the limits. Mutation intensifies with the increasing number of iterations. The term $a^{(r-1)}$ in (3.26) is employed to reduce mutation step size when the iteration number is increased. The reason is to diversify the search at the beginning and intensify when the iteration counter is increased.

$$x'_{k,i} = x_{k,i} + \sigma_{k,i} \cdot \xi_m \quad (3.25)$$

$$\sigma_{k,i} = T_{r,m} \cdot a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \quad (3.26)$$

Where

$x'_{k,i}$	i th element of the k th offspring individual,
$x_{k,i}$	i th element of the k th parent individual,
$\sigma_{k,i}$	mutation step size for the i th element of the k th individual,
ξ_m	mutation operator of the m th subpopulation e.g. $N(0,1)$, $C(0,1)$,
$N(0,1)$	Gaussian random number with mean 0 and standard deviation 1,
$C(0,1)$	Cauchy random number,
a	positive number slightly less than one, and
$x_i^{\max}, x_i^{\min}$	subinterval's or interval's upper and lower limits of i th element of the individual.

Tabu list

Tabu list is used to prevent the entrapment in local optima. It is a finite length first-in first-out structure, which records a set of current best solutions visited. Tabu list may be viewed as a 'meta-heuristic' superimposed on other heuristic methods. It is designed to jump local optima and prevent the cycling movement. A new trial solution vector classified as tabu is placed on top of the list and the oldest trial vector is taken out from the list.

Aspiration criterion

Aspiration criterion is a rule used to override a tabu restriction. If a certain move is forbidden by tabu restriction, the aspiration criterion, when satisfied, can make this move allowable. The aspiration criterion in (3.27) adopts a probabilistic acceptance criterion of SA. When the probabilistic acceptance criterion is higher than a uniform randomly generated variable in the interval [0,1], the tabu restriction is overruled.

$$p_{k,m} = \frac{1}{1 + \exp(-\Delta / T_{r,m})} \quad (3.27)$$

Where

$p_{k,m}$ probabilistic acceptance criterion of the k th offspring individual within the m th subpopulation, and
 Δ difference of objective values between the k th offspring individual and its corresponding parent individual, i.e. the k th parent individual.

If $p_{k,m}=1$, the k th offspring individual of the m th subpopulation will be selected to be a new parent individual for next generation. Otherwise, a uniform random number, U , in the interval [0,1] is generated and compared to $p_{k,m}$. If $p_{k,m} > U$, the k th offspring individual will be accepted, otherwise, their corresponding parent will be selected.

Reassignment strategy

To perform the reassignment strategy, tournament scheme is used to select new current parent population from the combined population of current parent ($S^{1,curr}, \dots, S^{M,curr}$) and new offspring ($S^{1,new}, \dots, S^{M,new}$) individuals of all subpopulations. Each individual in the combined population is assigned a weight value according to the competition in (3.28). Each individual has to compete with Nt randomly-selected individuals in one-by-one basis. If the individual wins a selected opponent, it will obtain one from this competition. Otherwise, it will obtain zero. The summation of scores from Nt competitions is a competition score, w_k , of the k th individual. After sorting the combined population of $2M$ individuals in the descending order of weight values, each new current parent solution individual of all subpopulations will be randomly selected from a set of the first M th sorted best solution individuals.

$$w_k = \sum_{t=1}^{N_t} \begin{cases} 1 & \text{if } F_k > F_r \\ 0 & \text{otherwise} \end{cases} \quad (3.28)$$

Where

w_k	weight value of k th individual in combined population,
F_k	fitness value of k th individual in combined population,
F_r	fitness value of r th opponent randomly selected from the combined population based on $r = \lfloor 2 \cdot M \cdot u + 1 \rfloor$,
N_t	number of competitors.

Termination criteria

There are three termination criteria used in the proposed HEA approach. It will stop whenever any one of three criteria is met. The first termination criterion is set as the maximum number of generations of each subpopulation and the second termination criterion is the number of reassignment required. The algorithm will be stopped if there is no improvement of the best fitness within 50 generations as the third termination criterion. In addition, these criteria are applied to all the methods for a fair comparison.

3.3 Evolutionary Computation Methods for ATC Determination

3.3.1 Evolutionary programming

Based on EP approach (Lai, 1998), an EP-based algorithm proposed for solving the OPF-based ATC determination is depicted in Figure 3.7. Main components of the algorithm are described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (3.29).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \quad (3.29)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (3.30).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.30)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Fitness function

The objective function in (3.1) is taken as the fitness function of the EP approach.

Mutation

Each element of the offspring individual is mutated by using the Gaussian mutation operator in (3.31).

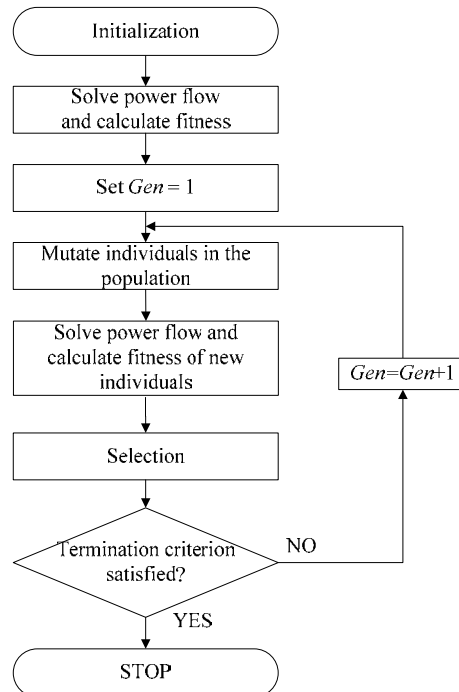


Figure 3.7 Flow chart of OPF-based ATC determination using the EP approach.

$$x'_{k,i} = x_{k,i} + N(0, \sigma_{k,i}^2) \quad (3.31)$$

$$\sigma_{k,i} = (x_i^{\max} - x_i^{\min}) \left(\frac{F^{\max} - F_k}{F^{\max}} + a^g \right) \quad (3.32)$$

Where

$N(0, \sigma_{k,i}^2)$ Gaussian random number with a mean of 0 and a standard deviation of $\sigma_{k,i}$,

f_k fitness value of the k th individual,

$f_{\max}$ the maximum fitness of the parent population, and

g iteration counter.

Selection

Each individual in the combined population of parent and offspring individuals is assigned a weight value according to the tournament scheme competition in (3.33). A set of the first P th sorted best weight values individuals from the combined population of $2P$ individuals will be selected as a new current parent population.

$$w_k = \sum_{t=1}^{N_t} \begin{cases} 1 & \text{if } F_k > F_r \\ 0 & \text{otherwise} \end{cases} \quad (3.33)$$

Termination criterion

There are two termination criteria used in the EP algorithm. It will stop whenever any one of two criteria is met. The first termination criterion is set as the maximum number of generations. The algorithm will be stopped if there is no improvement of the best fitness within 50 generations as the second termination criterion.

3.3.2 Tabu search

Based on TS approach (Abido, 2002b), a TS-based algorithm proposed for solving the OPF-based ATC determination is shown in Figure 3.8. Main components of the algorithm are described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (3.34).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \quad (3.34)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (3.35).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.35)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Perturbation

A set of trial neighbourhood solution vectors is generated by perturbing the current solution vector using the uniform probability distribution function in (3.36).

$$x'_{k,i} = x_{k,i} + \frac{1}{g} \cdot u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.36)$$

Tabu list

A new trial solution vector classified as tabu is placed on top of the list and the oldest trial vector is taken out from the list.

Aspiration criterion

The aspiration criterion is used to override the tabu status of a move if this move yields a solution which has better objective function value than the aspiration level, which is the objective value of current trial solution vector from previous iteration.

Termination criterion

There are two termination criteria in the TS approach similar to those used in the EP approach.

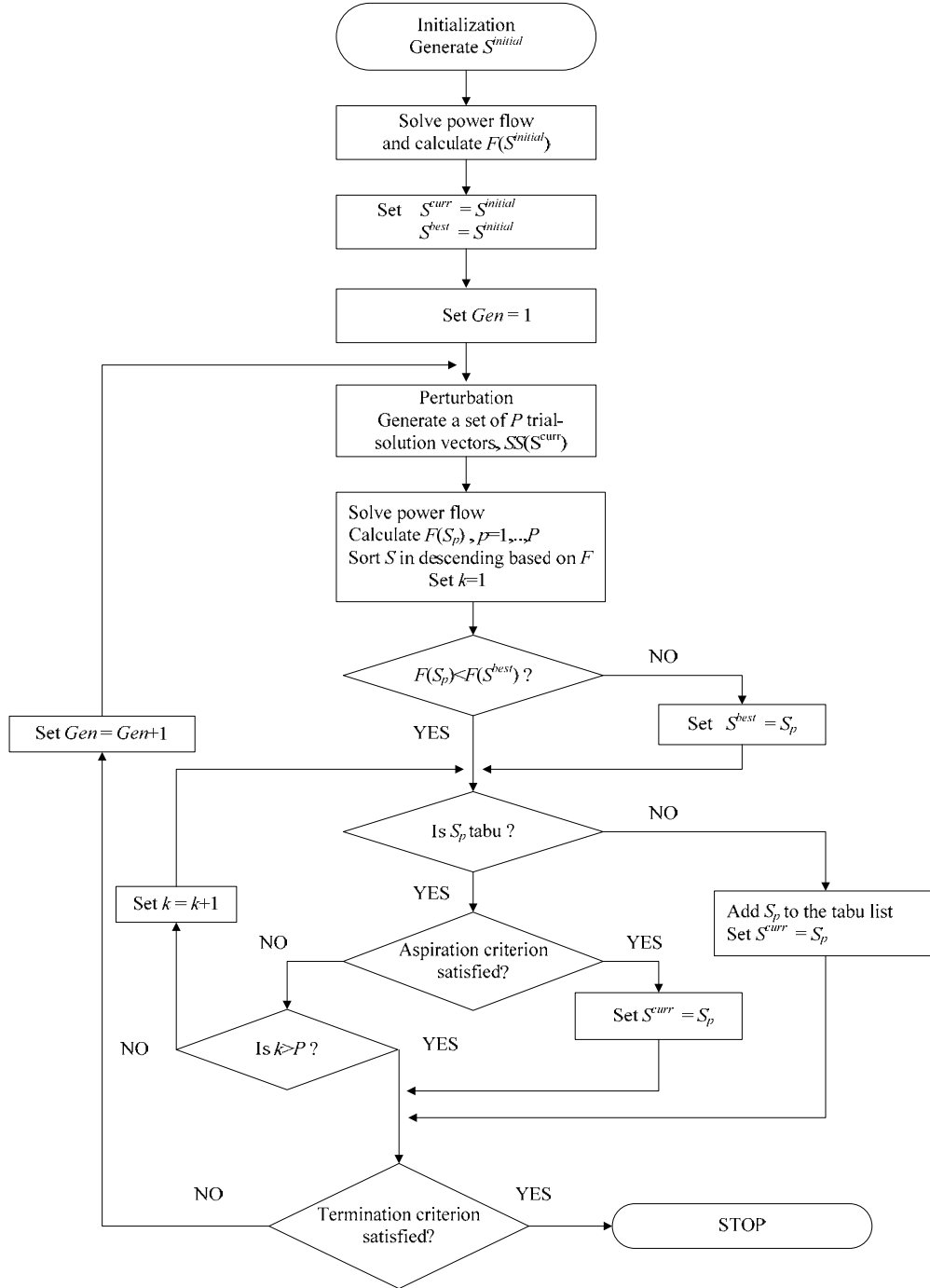


Figure 3.8 Flow chart of OPF-based ATC determination using the TS approach.

3.3.3 Hybrid tabu search and simulated annealing

A hybrid TS/SA approach is a hybrid algorithm of TS and SA by using TS as the main algorithm (Bhasaputra and Ongsakul, 2006). The perturbation of the TS/SA imitates from SA algorithm and the aspiration criterion is adapted by using probabilistic acceptance criterion of SA instead of aspiration level of TS. The cooling schedule of SA is also applied in the perturbation. The hybrid TS/SA algorithm shown in Figure 3.9 can be described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (3.37).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \quad (3.37)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (3.38).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.38)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Cooling schedule

The initial temperature of each subpopulation is determined in (3.39). The temperature is cooled down by the temperature annealing function or cooling schedule in (3.40).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (3.39)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (3.40)$$

Perturbation

Each element of the offspring individual is generated by using the uniform probability distribution function in (3.41).

$$x'_{k,i} = x_{k,i} + T_{r,m} \cdot u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.41)$$

Tabu list

The tabu list utilized in the hybrid TS/SA approach is the same as that used in the TS algorithm.

Aspiration criterion

The aspiration criterion employed adopts a probabilistic acceptance criterion of SA similar to that used in the TS approach as shown in (3.42).

$$p_{k,m} = \frac{1}{1 + \exp(-\Delta / T_{r,m})} \quad (3.42)$$

Termination criterion

There are two termination criteria in the hybrid TS/SA approach similar to those used in the EP approach.

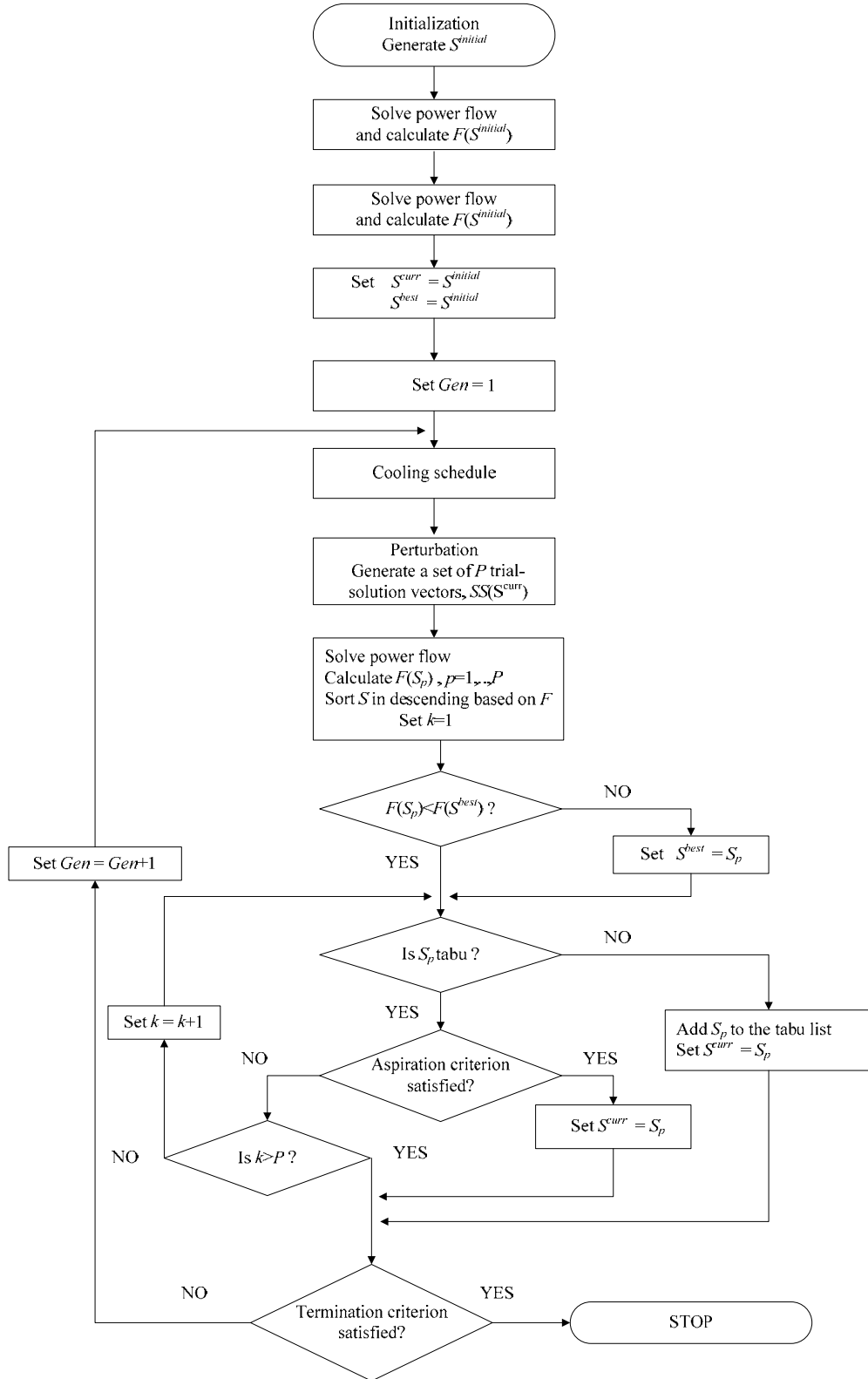


Figure 3.9 Flow chart of OPF-based ATC determination using the TS/SA.

3.3.4 Improved evolutionary programming

An IEP approach is a hybrid algorithm of EP and SA by using EP as the main algorithm (Jirapong and Ongsakul, 2007b). Based on IEP approach, an IEP-based algorithm for solving the OPF-based ATC determination is shown in Figure 3.10. Main components of the algorithm are described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (3.43).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \quad (3.43)$$

Space division

Space division strategy is used to divide the search space into subspaces. The division can be made in a certain way. For example, if there are two subpopulations, the first control variable's interval ranging from its minimum limit to its maximum limit can be divided equally into two subintervals while the interval of other control variables will be used throughout their feasible range.

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (3.44).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (3.44)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Fitness function

The objective function in (3.1) is taken as the fitness function of the IEP algorithm.

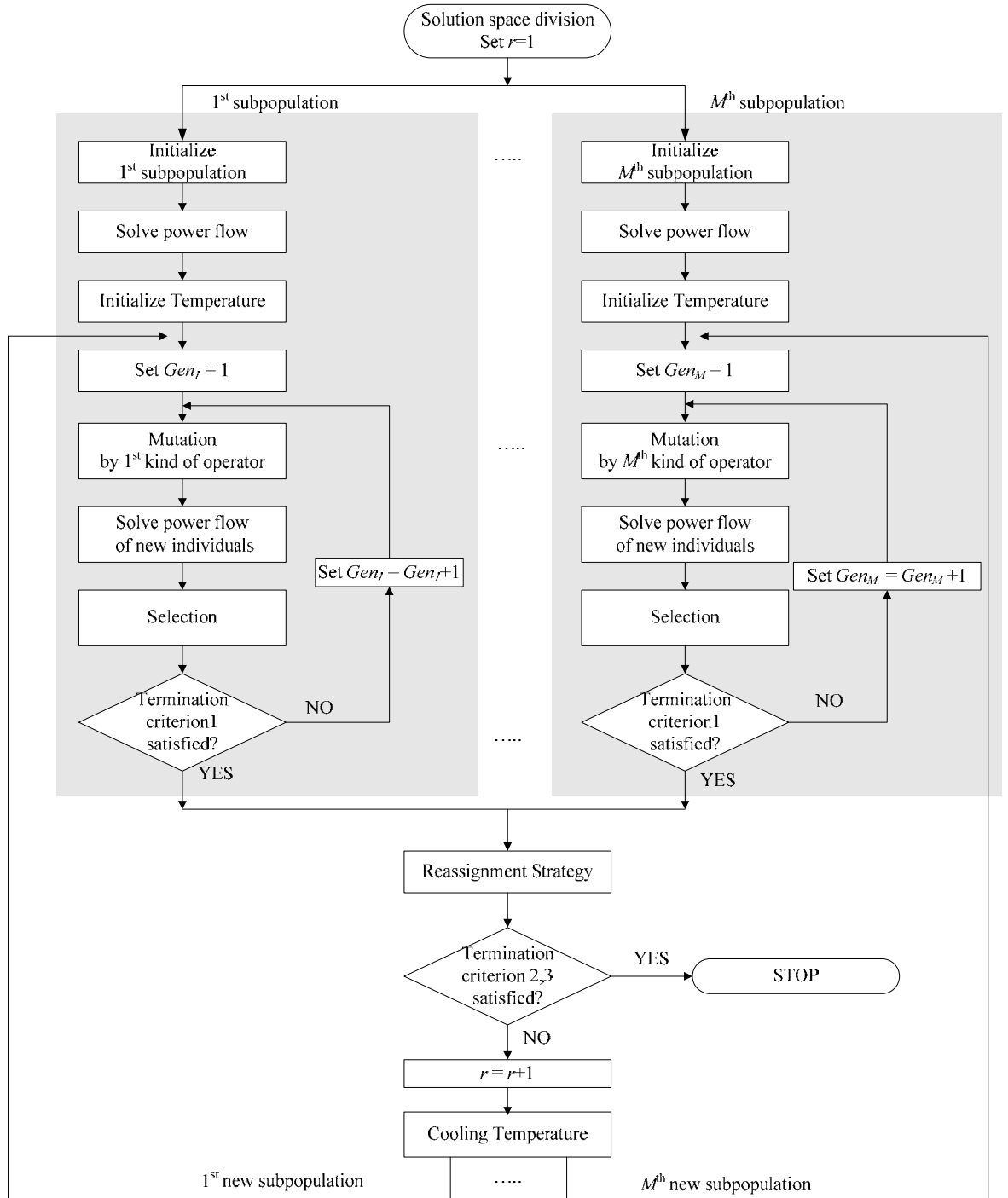


Figure 3.10 Flow chart of OPF-based ATC determination using the IEP approach.

Cooling schedule

The initial temperature of each subpopulation is determined in (3.45). The temperature is cooled down by the temperature annealing function in (3.46).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (3.45)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (3.46)$$

Mutation

Two mutation operators including Gaussian and Cauchy are applied for each subpopulation. Each element of the offspring individual is determined in (3.47).

$$x'_{k,i} = x_{k,i} + \sigma_{k,i} \cdot \xi_m \quad (3.47)$$

$$\sigma_{k,i} = a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \quad (3.48)$$

Selection

Each offspring individual is accepted to be a new parent individual for next generation according to its probabilistic acceptance criterion. The probabilistic acceptance criterion of the k th offspring individual can be expressed in (3.49).

$$p_{k,m} = \min\{1, \exp(-\Delta/T_{r,m})\} \quad (3.49)$$

Reassignment strategy

The individuals of all subpopulations are merged and then the whole population will be randomly divided to form new subpopulations.

Termination criteria

The termination criteria utilized in the IEP algorithm are similar to those used in the HEA approach.

3.4 Continuation Power Flow for TTC Determination

Continuation power flow (CPF) method enables transfers by increasing the complex load with uniform power factor at every load buses in the sink area and increasing the injected real power at generator buses in the source area in incremental steps until limits are incurred. Mathematically, TTC determination using CPF method can be expressed as follows:

$$\text{Maximize} \quad \lambda \quad (3.50)$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (3.51)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^N V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (3.52)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (3.53)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (3.54)$$

Where

λ	scalar parameter representing the increase in bus load or generation. $\lambda = 0$ corresponds to no transfer (base case) and $\lambda = \lambda_{\max}$ corresponds to the maximum transfer,
P_{Gi}, Q_{Gi}	real and reactive power generations at bus i ,
P_{Di}, Q_{Di}	real and reactive loads at bus i ,
V_i, V_j	voltage magnitudes at bus i and j ,
δ_i, δ_j	voltage angles of bus i and j ,
Y_{ij}, θ_{ij}	magnitude and angle of the ij th element in bus admittance matrix,
$V_i^{\min}, V_i^{\max}$	lower and upper limits of voltage magnitude at bus i ,
$S_{Li}^{\max}$	i th line or transformer loading limit,
$ S_{Li} $	i th line or transformer loading,
N	number of buses,
NL	number of branches, and

Real power generations in source area, and real and reactive loads in sink area are changed in (3.55) – (3.57).

$$P_{Gi} = P_{Gi}^0 \cdot (1 + \lambda \cdot k_{Gi}) \quad (3.55)$$

$$P_{Di} = P_{Di}^0 \cdot (1 + \lambda \cdot k_{Di}) \quad (3.56)$$

$$Q_{Di} = Q_{Di}^0 \cdot (1 + \lambda \cdot k_{Di}) \quad (3.57)$$

Where

P_{Gi}^0 base case real power generation at bus i in source area,
 P_{Di}^0, Q_{Di}^0 base case real and reactive loads at bus i in sink area, and
 k_{Gi}, k_{Di} constant values used to specify the change rate in generation and load.

According to (3.55) – (3.57), generations in the source area and loads in the sink area are increased in successive steps with constant power factor until a system limit is reached, or a transfer test level is achieved. The maximum real power which can be delivered from the source area to the sink area through the transmission network is defined as TTC value of the power transaction.

3.5 Simulation Results of ATC determination

The modified IEEE 6-bus system, modified IEEE 30-bus system, and the modified IEEE 24-bus reliability test system (RTS) are used to demonstrate the ATC determination using the proposed HEA method. The HEA is implemented using MATLAB version 6.5 on an AMD Athlon64 X2 3600+ computer with 1.0 GB memory. Loads are modelled as constant power factor loads. Power System Analysis Toolbox (PSAT) (Milano, 2005) and Power World Simulator Software are used to perform the CPF and LATC analysis, respectively.

3.5.1 The modified IEEE 6-bus system

The modified IEEE 6-bus system in Figure 3.11 is utilized to illustrate the TTC determination with stability limits. Thermal and voltage limits checking are enabled for all TTC determinations. TRM and CBM are not considered in the ATC determination. Five different combinations of power transactions including three bilateral transactions (from bus 1 to bus 4, 5, and 6) and one multilateral transaction (from bus 1-3 to bus 4-6) are considered.

A. TTC determination using LATC and CPF methods

For the transaction from bus 1 to 4, using LATC method, TTC value is 1,019.64 MW and the transmission branch that causes the limit is line 1-4. Using CPF method, TTC value is 693.36 MW and the limiting condition is the expected voltage stability limit, if further transfers take place. CPU time of the LATC and CPF are 1.85 sec and 3.97 sec, respectively. LATC method calculates linear sensitivity factors for determining power transfer capability taking into account only thermal limits on line flows. Therefore, TTC value from LATC may be higher than that from CPF, which takes thermal, voltage, and voltage stability limits into consideration.

Test results of other transactions shown in Table 3.1 indicate that, ignoring voltage, reactive power, and stability effects, LATC method determines higher TTC values than those from CPF method, which may lead to unacceptable error in a stressed system with insufficient reactive power support and voltage control.

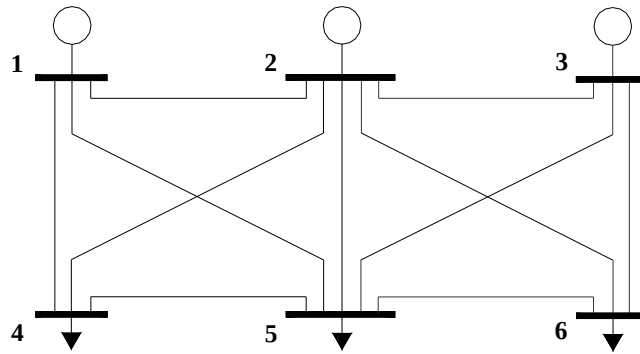


Figure 3.11 Diagram of the modified IEEE 6-bus system.

Table 3.1 TTC Results of the Modified IEEE 6-bus System Using LATC and CPF Methods

Transaction		LATC		CPF	
From	To	TTC (MW)	Limit	TTC (MW)	Limit
Bus 1	Bus 4	1,019.64	Line 1-4	693.36	Vcrit
Bus 1	Bus 5	1,237.20	Line 1-5	624.55	Vcrit
Bus 1	Bus 6	1,271.32	Line 1-2	612.79	Vcrit
Bus 1-3	Bus 4-6	2,307.55	Line 3-6	1,507.53	Vcrit

B. TTC determination using EP and HEA methods

In Table 3.2, for all bilateral transactions, the proposed HEA method can determine the same TTC values and binding conditions as those from the CPF and EP methods. However, for multilateral transaction, using HEA method, TTC is 2,013.17 MW, which is 33.54% and 0.28% more than those from CPF and EP methods, respectively. The limiting component is line 3-6, if expected further transfers take place, similar to the binding condition of the EP method. The optimal solutions of the multilateral transaction are shown in Table 3.3 and a rapid HEA convergence characteristic of the transaction is shown in Figure 3.12.

Table 3.2 TTC Results of the Modified IEEE 6-bus System Using EP and HEA Methods

Transaction		EP		HEA	
From	To	TTC (MW)	Limit	TTC (MW)	Limit
Bus 1	Bus 4	693.36	Vcrit	693.36	Vcrit
Bus 1	Bus 5	624.55	Vcrit	624.55	Vcrit
Bus 1	Bus 6	612.79	Vcrit	612.79	Vcrit
Bus 1-3	Bus 4-6	2,007.53	Line 3-6	2,013.17	Line 3-6

Table 3.3 Optimal Solutions of Bilateral Transaction on the Modified IEEE 6-bus System

Parameter	CPF	EP	HEA
VG1 (p.u.)	1.05 /0.0	1.05 /0.0	1.05 /0.0
VG2 (p.u.)	1.05 /-50.85	1.05 /-18.39	1.05 /-21.50
VG3 (p.u.)	1.07 /-57.12	1.07 /-23.77	1.07 /-29.00
PG1 (MW)	1234.74	832.27	878.78
PG2 (MW)	358.93	995.57	999.82
PG3 (MW)	430.72	761.38	723.55
PD4 (MW)	502.51	681.19	692.01
PD5 (MW)	502.51	626.40	592.26
PD6 (MW)	502.51	699.94	728.91

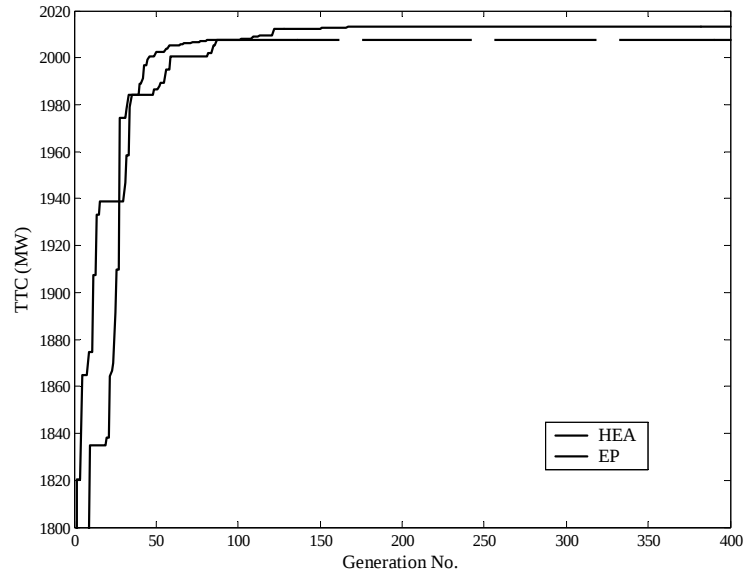


Figure 3.12 HEA convergence characteristic.

Table 3.4 TTC Results and CPU Times of Bilateral Transaction on the Modified IEEE 6-bus System

TTC (MW)	EP	HEA
Best	2007.53	2013.17
Average	2006.34	2012.01
Worse	2001.60	2009.77
Standard Deviation	1.93	1.15
Average CPU Time (min)	0.23	0.38

To increase a certain power transfer, CPF uses a common loading factor for a specific cluster of generators and loads. For all bilateral transactions, CPF can give the same TTC values as those from EP and HEA methods. However, for the multilateral transaction, using a common loading factor may lead to a conservative TTC value. Since the objective function is to maximize the power transfer from source to sink areas, EP and HEA can optimize generation and loading in each area resulting in the maximum transfer capability.

The comparison of TTC results from 20 runs shown in Table 3.4 indicate that HEA method gives better solutions than EP method because HEA uses the probabilistic updating strategy of SA to avoid the dependence on fitness function and to escape from the entrapment in local optimum solutions that can occur with EP. Furthermore, the variation of HEA best solutions is smaller as evidenced by a smaller standard deviation than EP, leading to a more stable HEA approach.

3.5.2 The modified IEEE 30-bus system

The modified IEEE 30-bus system in Figure 3.13 has three areas with two generators in each area. Generators in each area are assumed to belong to the same company and the loads belong to the same load serving entity. Five different combinations of power transactions including T1 (from bus 1 to 10), T2 (from bus 2 to 12), T3 (from area 1 to 2), T4 (from area 2 to 3), and T5 (from area 3 to 1) are considered.

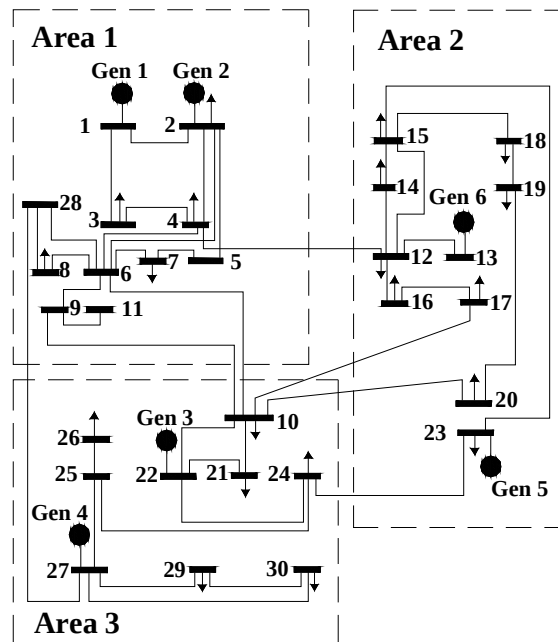


Figure 3.13 Diagram of the modified IEEE 30-bus system.

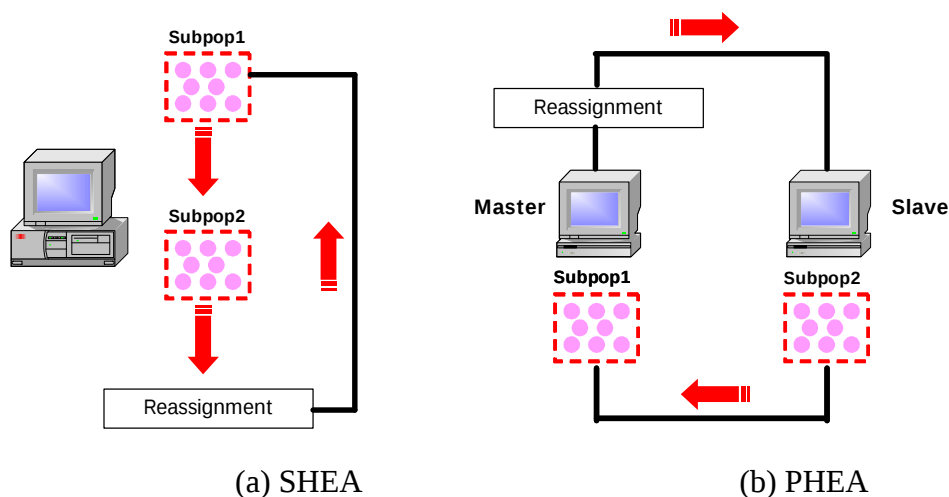


Figure 3.14 Implementation of HEA on (a) sequential and (b) parallel computations.

In this case study, CPF, EP, and HEA methods are used to determine TTC values of the predefined power transactions. To speed up the HEA approach, parallel implementation of HEA (PHEA) using 2 CPUs as shown in Figure 3.14 is utilized and test results are compared to those from sequential HEA (SHEA).

For the transaction T1, using CPF method, TTC value is 17.48 MW. The limiting condition is line flow limit at line 22-21, if expected further transfers take place. Using EP method, TTC is 24.68 MW and the limiting condition is line flow limit at line 22-21 similar to the binding condition of the CPF method. Using SHEA method, TTC value is 39.79 MW, which is 127.63% and 61.22% more than those from the CPF and EP methods, respectively. The limiting condition is generation upper limit at bus 1. Using PHEA method, TTC value is 39.77 MW, and the limiting component is similar to the binding condition of the SHEA method.

For the transaction T3, using CPF method, TTC value is 60.71 MW. The limiting condition is line flow limit at line 22-21, if expected further transfers take place. Using EP method, TTC is 102.65 MW and the limiting component is line 27-25. Using SHEA method, TTC value is 114.86 MW, which is 89.19% and 11.89% more than those from the CPF and EP methods, respectively. The limiting component is line 27-25, similar to the binding condition of the EP method. Using PHEA method, TTC is 115.35 MW and the limiting component is line 27-25, similar to the binding condition of the EP and SHEA methods. Test results of other transactions shown in Table 3.5 indicate that TTC values from CPF are more conservative than those from the EP and HEA-based methods. To increase a certain power transfer, CPF uses a common loading factor for a specific cluster of generators and loads. Therefore, CPF does not lead to the optimal generation, loading, and generator bus voltages.

The comparisons of TTC results and CPU times evaluated by EP, SHEA, and PHEA methods from 20 runs are shown in Table 3.6. Test results indicate that the SHEA and PHEA methods can obtain better solutions on the best, average, and the worst solutions than those from EP method. The HEA-based algorithms use the probabilistic updating strategy of SA to avoid the dependence on fitness function and to escape from the entrapment in local optimum solutions that can occur with EP algorithm. Furthermore, the variation of the SHEA and PHEA best solutions are smaller as evidenced by a smaller standard deviation than EP, leading to a more stable HEA approach.

CPU times of SHEA and PHEA methods are higher than that from EP because the best solution of HEA-based algorithm is obtained based on its acceptance probability, which depends on the improvement of the offspring's objective value and the annealing procedure of SA algorithm. In addition, the reassignment strategy of HEA-based method requires additional computing effort. However, PHEA method can easily facilitate parallel implementation, reducing elapsed time without sacrificing the quality of solution. The elapsed time including the communication overhead of PHEA is reduced by 32.89%.

Table 3.5 TTC Results of the Modified IEEE 30-bus System

Transaction	CPF		EP		SHEA		PHEA	
	TTC (MW)	Limit	TTC (MW)	Limit	TTC (MW)	Limit	TTC (MW)	Limit
T1	17.48	Line 22-21	24.68	Line 22-21	39.79	PG 1	39.77	PG 1
T2	43.61	Line 23-15	59.51	Line 23-15	60.62	Line 23-15	60.77	Line 23-15
T3	60.71	Line 22-21	102.65	Line 27-25	114.86	Line 27-25	115.35	Line 27-25
T4	79.87	Line 22-21	91.90	Line 6-8	96.90	Line 27-25	95.43	Line 6-8
T5	87.02	Line 22-21	124.76	Line 27-25	191.05	Line 27-25	191.47	Line 27-25

Table 3.6 TTC Results and CPU Times of the Transaction T3 on the Modified IEEE 30-bus System

TTC (MW)	EP	SHEA	PHEA
Best	102.65	114.86	115.35
Average	101.70	113.57	113.91
Worst	100.20	112.12	113.62
Standard Deviation	1.32	1.10	1.13
Average CPU Time (min)	1.08	2.28	1.53

3.5.3 The modified IEEE 24-bus RTS

The modified IEEE 24-bus RTS is used to demonstrate ATC calculation using the proposed HEA method. The modified test system is partitioned into 3 areas as shown in Figure 3.15. A multilateral transaction from area 1 to 2 with contingency constraints is considered. Only the outage of the largest generator in each area and the outage of tie lines are included in the contingency list. ATC results without and with considering TRM from the proposed HEA approach are compared to those from EP, TS, TS/SA and IEP methods.

A. ATC Calculation without considering TRM

Base case TTC using HEA method is 718.89 MW. Considering the pre-specified contingency constraints as shown in Table 3.7, contingency TTC value using HEA approach is 632.09 MW without violating network constraints, which is 0.59%, 1.05%, 0.44%, and 0.14% higher than those from EP, TS, TS/SA, and IEP methods, respectively. In addition, the TTC value is decreased by 12.07% compared to that without contingency constraints. The critical contingency case is the interconnected line 14-11 between those two areas outage. It is evident that neglecting the effects of contingency constraints on TTC evaluation will inevitably lead to insecure system operation. To meet the specific reliability criterion, which is $LOLE < 2.4$ hour/year, area 1 needs to import 60 MW from

area 2. Therefore, CBM for the critical contingency case is 60 MW. ATC value using HEA method is 572.09 MW, which is 0.65%, 1.16%, 0.48%, and 0.16% higher than those from EP, TS, TS/SA, and IEP methods, respectively.

Test results in Table 3.8 indicate that single-population search of EP, TS, and TS/SA is less effective than multi-population search of IEP and HEA methods. Even though CPU times of IEP and HEA methods are higher than those from EP, TS and TS/SA because the best solutions of IEP and HEA are obtained based on the acceptance probability, which depends on the improvement of the offspring's objective value and the annealing procedure of SA algorithm. In addition, the reassignment strategy requires additional computing effort. However, both IEP and HEA methods can easily facilitate parallel implementation using more than 2 CPUs, reducing elapsed time without sacrificing the quality of solution.

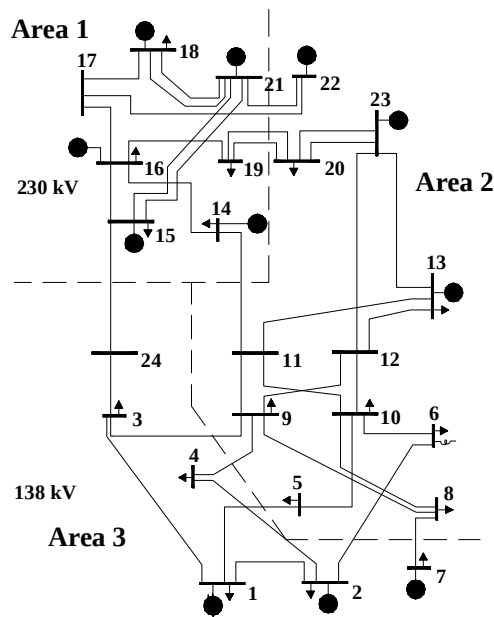


Figure 3.15 Diagram of the modified IEEE 24-bus RTS.

Table 3.7 ATC Results of Multilateral Transaction on the Modified IEEE 24-bus RTS Without Considering TRM

Case	TTC Level (MW)				
	EP	TS	TS/SA	IEP	HEA
Normal	714.03	712.48	716.41	714.62	718.89
Largest gen. in area 1 outage	711.46	711.69	713.09	713.80	716.78
Largest gen. in area 2 outage	711.67	711.59	715.74	714.71	717.24
Line 21-22 outage	713.07	709.00	714.11	716.77	717.84
Line 17-22 outage	715.79	708.99	717.33	717.22	720.09
Line 19-20 outage	691.93	697.69	709.37	710.76	713.50
Line 14-11 outage	628.38	625.54	629.34	631.18	632.09
Contingency TTC Value (MW)	628.38	625.54	629.34	631.18	632.09
CBM of the contingency case	60.00	60.00	60.00	60.00	60.00
ATC Value (MW)	568.38	565.54	569.34	571.18	572.09

Table 3.8 ATC Results and CPU Times of Multilateral Transaction on the Modified IEEE 24-bus RTS Without Considering TRM

TTC Value (MW)	EP	TS	TS/SA	IEP	HEA
Best	628.38	625.54	629.34	631.18	632.09
Average	618.49	614.57	615.48	618.66	624.32
Worst	567.63	587.53	584.94	566.47	607.81
Standard Deviation	16.88	13.83	12.74	15.5	10.01
CPU Time (minute)	0.65	0.65	0.63	1.04	0.99

To compare the convergence characteristic, IEP and HEA approaches utilize a probabilistic updating strategy based on annealing schedule of SA, resulting in more generations required and slower convergence characteristic than EP, TS and TS/SA methods as shown in Figure 3.16. However, the convergence speed of HEA is improved by introducing a flexible memory of search history of TS to prevent cycling and to avoid entrapment in local optima compared to IEP algorithm.

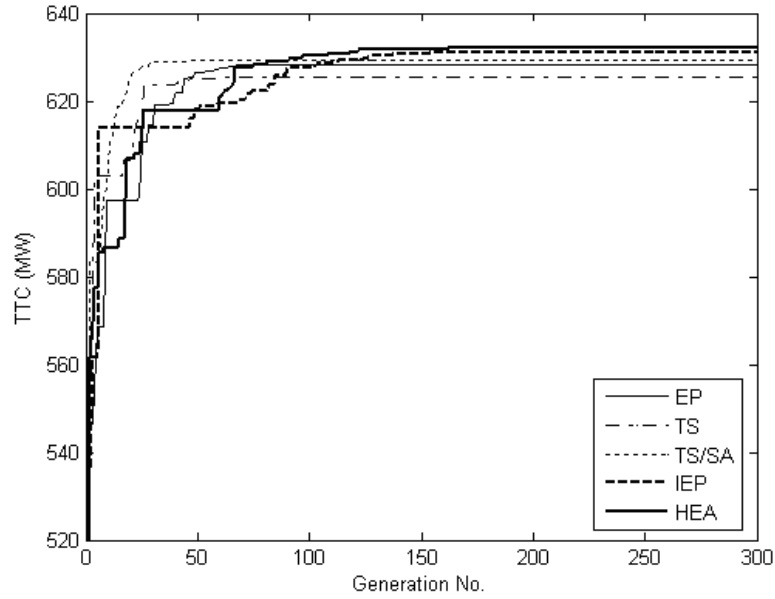


Figure 3.16 Convergence characteristic of solutions.

B. ATC Calculation considering TRM

Base case TTC with TRM using HEA method is 715.33 MW. Considering the pre-specified contingency constraints as shown in Table 3.9, contingency TTC value using HEA approach is 626.18 MW without violating network constraints, which is 0.35%, 0.55%, 0.32%, and 0.33% higher than those from EP, TS, TS/SA, and IEP methods, respectively. In addition, the TTC value is decreased by 12.46% compared to that without contingency constraints. The critical contingency case is the interconnected line 14-11 between those two areas outage. CBM for the critical contingency case is 60 MW. Therefore, ATC value using HEA method is 566.18 MW, which is 0.39%, 0.61%, 0.35%, and 0.37% higher than those from EP, TS, TS/SA, and IEP methods, respectively. Test results indicate that HEA approach can effectively re-dispatch real power generations except slack bus in a source area, increment of real power loads in a sink area, and optimal setting of generation bus voltages. Even though test results show a marginal improvement of HEA over the other optimization methods, the higher ATC for power transfer of HEA than the other methods could lead to a substantial cost savings of daily energy trading between different control areas.

Comparisons of TTC results and CPU times evaluated by EP, TS, TS/SA, IEP, and HEA methods from 20 runs are shown in Table 3.10. The proposed HEA method can obtain better results on the best, average, and the worst TTC values than those from the other optimization methods because HEA approach uses the selection mechanism with a probabilistic updating strategy based on TS and SA

algorithms to avoid dependency on fitness function and to escape from the entrapment in local optimal solutions.

Table 3.9 ATC Results of Multilateral Transaction on the Modified IEEE 24-bus RTS Considering TRM

Case	TTC Level (MW)				
	EP	TS	TS/SA	IEP	HEA
Normal	706.44	708.39	708.82	711.90	715.33
Largest gen. in area 1 outage	707.58	701.93	711.76	708.77	711.57
Largest gen. in area 2 outage	710.76	710.86	714.91	711.98	714.31
Line 21-22 outage	705.07	706.43	706.52	712.24	705.07
Line 17-22 outage	712.05	705.18	708.83	713.34	713.53
Line 19-20 outage	679.50	688.83	691.56	697.95	700.09
Line 14-11 outage	623.99	622.76	624.19	624.12	626.18
Contingency TTC Value (MW)	623.99	622.76	624.19	624.12	626.18
CBM of the contingency case	60.00	60.00	60.00	60.00	60.00
ATC Value (MW)	563.99	562.76	564.19	564.12	566.18

Table 3.10 ATC Results and CPU Times of Multilateral Transaction on the Modified IEEE 24-bus RTS Considering TRM

TTC Value (MW)	EP	TS	TS/SA	IEP	HEA
Best	623.99	622.76	624.19	624.12	626.18
Average	616.91	567.96	606.05	599.82	617.23
Worst	558.4	561.59	567.21	580.31	605.15
Standard Deviation	17.53	15.45	18.86	16.39	6.41
CPU Time (minute)	0.65	0.64	0.53	0.81	0.78

Table 3.11 Comparison Between Without and With Considering TRM (Considering Contingency and CBM)

Method	ATC (MW)		Difference
	without TRM	with TRM	
EP	568.38	563.99	- 0.77 %
TS	565.54	562.76	- 0.49 %
TS/SA	569.34	564.19	- 0.90 %
IEP	571.18	564.12	- 1.24 %
HEA	572.09	566.18	- 1.03 %

Table 3.12 Comparison Between Without and With Considering Contingency Constraints (Considering TRM and CBM)

Method	ATC (MW)		Difference
	without contingency	with contingency	
EP	646.44	563.99	- 12.75 %
TS	648.39	562.76	- 13.21 %
TS/SA	648.82	564.19	- 13.04 %
IEP	651.90	564.12	- 13.47 %
HEA	655.33	566.18	- 13.60 %

Table 3.13 Comparison Between Without and With Considering CBM (Considering Contingency and TRM)

Method	ATC (MW)		Difference
	without CBM	with CBM	
EP	623.99	563.99	- 9.62 %
TS	622.76	562.76	- 9.63 %
TS/SA	624.19	564.19	- 9.61 %
IEP	624.12	564.12	- 9.61 %
HEA	626.18	566.18	- 9.58 %

From the comparison between without and with considering TRM as shown in Table 3.11, test results show that the effect of TRM on ATC value is quite small but contingency constraints and CBM have more effect on ATC value than TRM as shown in Table 3.12 and 3.13. Test results indicate that without considering contingency constraints or CBM may lead to unsecured power systems or cause risk of having generation unreliability.

3.6 Conclusion

In this chapter, the HEA approach is effectively implemented to determine ATC values of power transfers between different control areas constrained by load flow equations and system operating limits. Test results on three test systems from the proposed method are compared favourably with those from the other heuristic methods. It is indicated that the HEA can effectively re-dispatch real power generations except slack bus in a source area, increment of real power loads in a sink area, and optimal setting of generation bus voltages, leading to an efficient utilization of the existing power systems. In the next chapter, the HEA approach is proposed to determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize system real power loss of power transfers in deregulated power systems.

Chapter 4

Optimal Placement of Multi-Type FACTS controllers for Available Transfer Capability Enhancement

In this chapter, the HEA approach is proposed to determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize system real power loss of power transfers in deregulated power systems. The optimally placed OPF with FACTS controllers is formulated as a MINLP problem. A combined objective function including ATC and system real power loss is used to evaluate the feasible maximum ATC value and minimum power loss within real and reactive power generation limits, line thermal limits, voltage limits, stability limits, and FACTS controllers steady-state operating limits. Four types of FACTS controllers are included: TCSC, TCPS, UPFC, and SVC. Test results on three test systems from the proposed method are compared with those from EP, TS, TS/SA, and IEP methods.

4.1 OPF with Multi-Type FACTS Problem Formulation

4.1.1 Objective function

The optimally placed OPF with FACTS controllers is formulated as a MINLP problem with continuous and discrete variables. Real power generations, generator bus voltages, real power loads, and FACTS parameters are continuous variables. Type, location, and number of FACTS components are discrete variables of the MINLP problem. A combined objective function including ATC and system real power loss functions in (4.1) is used to evaluate the feasible ATC value that can be transferred from a specific set of generators in a source area to loads in a sink area within real and reactive power generation limits, line thermal limits, voltage limits, steady-state stability limits, and FACTS controllers operating limits.

$$\text{Maximize} \quad F = ATC - \sum_{i=1}^N (P_{Gi} - P_{Di}) \quad (4.1)$$

Subject to

$$P_{Gi} - P_{Di} + \sum_{k=1}^{m(i)} P_{Pi}(\alpha_{Pk}) + \sum_{k=1}^{n(i)} P_{Ui}(V_{Uk}, \alpha_{Uk}) - \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \cos(\theta_{ij}(X_s) - \delta_i + \delta_j) = 0 \quad (4.2)$$

$$Q_{Gi} - Q_{Di} + \sum_{k=1}^{m(i)} Q_{Pi}(\alpha_{Pk}) + \sum_{k=1}^{n(i)} Q_{Ui}(V_{Uk}, \alpha_{Uk}) + Q_{Vi} + \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \sin(\theta_{ij}(X_s) - \delta_i + \delta_j) = 0 \quad (4.3)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (4.4)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (4.5)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (4.6)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (4.7)$$

$$VCPI_i \leq 1 \quad \forall i \in N \quad (4.8)$$

$$|\delta_{ij}| \leq \delta_{ij}^{\text{crit}} \quad \forall i \in NL \quad (4.9)$$

$$X_{Si}^{\min} \leq X_{Si} \leq X_{Si}^{\max} \quad (4.10)$$

$$\alpha_{Pi}^{\min} \leq \alpha_{Pi} \leq \alpha_{Pi}^{\max} \quad (4.11)$$

$$V_{Ui}^{\min} \leq V_{Ui} \leq V_{Ui}^{\max} \quad (4.12)$$

$$\alpha_{Ui}^{\min} \leq \alpha_{Ui} \leq \alpha_{Ui}^{\max} \quad (4.13)$$

$$Q_{Vi}^{\min} \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (4.14)$$

$$0 \leq n_{CFk} \leq n_{CFk}^{\max} \quad (4.15)$$

$$0 < location_k \leq N \text{ or } NL \quad (4.16)$$

Where

F	objective function,
ATC	available transfer capability,

Input Variables

$P_{Gi}^{\min}, P_{Gi}^{\max}$	lower and upper limits of real power generation at bus i ,
$Q_{Gi}^{\min}, Q_{Gi}^{\max}$	lower and upper limits of reactive power generation at bus i ,
$V_i^{\min}, V_i^{\max}$	lower and upper limits of voltage magnitude at bus i ,
$S_{Li}^{\max}$	i th line or transformer loading limit,
δ_{ij}^{crit}	critical angle difference between bus i and j ,
$X_{Si}^{\min}, X_{Si}^{\max}$	lower and upper limits of TCSC at line i ,
$\alpha_{Pi}^{\min}, \alpha_{Pi}^{\max}$	lower and upper limits of TCPS at line i ,
$V_{Ui}^{\min}, V_{Ui}^{\max}$	lower and upper limits of UPFC at line i ,
$\alpha_{Ui}^{\min}, \alpha_{Ui}^{\max}$	lower and upper limits of UPFC at line i ,
$Q_{Vi}^{\min}, Q_{Vi}^{\max}$	injected reactive power of SVC at bus i ,
$n_{CFk}^{\max}$	maximum allowable number of FACTS components,
N	number of buses,
NL	number of branches,
NG	number of generator buses,

State Variables

P_{G1}, Q_{G1}	real and reactive power generations at slack bus,
V_i, V_j	voltage magnitudes at bus i and j ,
δ_i, δ_j	voltage angles of bus i and j ,

Output Variables (continuous and discrete variables)

P_{Gi}, Q_{Gi}	real and reactive power generations at bus i ,
P_{Di}, Q_{Di}	real and reactive loads at bus i ,
Y_{ij}, θ_{ij}	magnitude and angle of the ij th element in bus admittance matrix,
$P_{Pi}(\alpha_{Pk})$	injected real power of TCPS at bus i ,
$Q_{Pi}(\alpha_{Pk})$	injected reactive power of TCPS at bus i ,
$P_{Ui}(V_{Uk}, \alpha_{Uk})$	injected real power of UPFC at bus i ,
$Q_{Ui}(V_{Uk}, \alpha_{Uk})$	injected reactive power of UPFC at bus i ,
$Y_{ij}(X_s)$	magnitude of the ij th element in bus admittance matrix with TCSC included
$\theta_{ij}(X_s)$	angle of the ij th element in bus admittance matrix with TCSC included,

$ S_{Li} $	i th line or transformer loading,
$VCPI_i$	voltage collapse proximity indicator at bus i ,
$ \delta_{ij} $	angle difference between bus i and j ,
X_{Si}	reactance of TCSC at line i ,
α_{Pi}	phase shift angle of TCPS at line i ,
V_{Ui}	voltage magnitude of UPFC at line i ,
α_{Ui}	voltage angle of UPFC at line i ,
Q_{Vi}	injected reactive power of SVC at bus i ,
$m(i)$	number of TCPS connected at bus i ,
$n(i)$	number of UPFC connected at bus i ,
n_{CFk}	integer value of number of FACTS components, $n_{CFk} \in \{0, 1, 2, \dots, n\}$, and
$location_k$	integer value of line or bus location of FACTS type k .

VCPI is used to directly determine voltage collapse conditions within voltage stability limits. For every iteration, VCPI at a load bus i in (4.8) must equal to or less than one. Critical angle displacement is used as a criterion to determine steady-state angle stability limit. The angle difference between buses i and j across a transmission line is kept within a critical angle difference, which is 44° . Voltage and angle stability limits are treated as OPF constraints in (4.8) and (4.9), respectively. During the optimization, inequality constraints of state variables including real power generation at slack bus, reactive power generation, bus voltage magnitudes, line or transformer loading, angle and voltage stability limits are enforced using a penalty function in (4.17).

$$PF = k_p \left[h(P_{G1}) + \sum_{i=1}^{NG} h(Q_{Gi}) + \sum_{i=1}^N h(V_i) + \sum_{i=1}^{NL} h(|S_{Li}|) + \sum_{p=1}^{NL} h(|\delta_{ij,p}|) + \sum_{i=1}^N h(VCPI_i) \right] \quad (4.17)$$

$$h(x) = \begin{cases} (x - x^{\max})^2 & \text{if } x > x^{\max} \\ (x^{\min} - x)^2 & \text{if } x < x^{\min} \\ 0 & \text{if } x^{\min} \leq x \leq x^{\max} \end{cases} \quad (4.18)$$

Where

P_{G1}	real power generations at slack bus,
k_p	penalty weighting coefficient, $k_p = 10^6$, and
$x^{\min}, x^{\max}$	lower and upper limits of variable x .

4.1.2 ATC determination

ATC calculation is defined in (4.19).

$$ATC = TTC - TRM - CBM \quad (4.19)$$

To determine ATC value of a power transaction between different control areas, an interconnected power system is divided into three kinds of areas: source or sending area, sink or receiving areas, and external areas. Two types of transactions including bilateral and multilateral transactions are considered. Each bilateral transaction satisfies the power balance relationship in (4.20). A multilateral transaction involving several sellers and buyers can be expressed in (4.21).

$$P_{Gi} - P_{Dj} = 0 \quad (4.20)$$

$$\sum_{i \in S} P_{Gi} - \sum_{j \in B} P_{Dj} = 0 \quad (4.21)$$

Where

P_{Gi}	real power generation at bus i ,
P_{Dj}	real power load at bus j ,
S	set of sellers who sell the power to buyers, and
B	set of buyers who buy the power from the sellers.

4.1.3 TTC determination

To determine TTC values of a power transaction between different control areas, the optimization methods enable transfers by increasing the complex load with uniform power factor at every load buses or a group of load buses in a sink area and increasing the injected real power at generator buses in a source area until a system limit is incurred. The total real power load in the sink area is used in the objective function to determine the maximum feasible TTC value. Therefore, TTC is defined in (4.22).

$$TTC = \sum_{i=1}^{ND_SNK} P_{Di} \quad (4.22)$$

Where

ND_SNK	number of load buses in a sink area.
-----------	--------------------------------------

4.1.4 TRM and CBM determination

For TTC determination considering TRM, load uncertainty is taken into consideration as random load increased within 2% of base case values in every load flow evaluations. Contingency analysis is also considered in the TRM determination. Only the outage of the largest generator in each area and the outage of tie lines are included in the contingency list. CBM determination is based on single area generation reliability evaluation using a probabilistic method. For hourly load model, LOLE < 2.4 hour per year is selected as a reliability criterion. To incorporate CBM into ATC, CBM is subtracted from TTC directly.

4.2 Modeling of FACTS controllers

Four types of FACTS controllers are included: thyristor-controlled series compensator (TCSC), thyristor-controlled phase shifter (TCPS), unified power flow controller (UPFC), and static var compensator (SVC). The TCSC is modeled by the adjustable series reactance. The TCPS, UPFC, and SVC are modeled using the power injection (PI) model (Ongsakul and Bhasaputra, 2002).

4.2.1 Thyristor controlled series compensator

TCSC is modeled by the adjustable series reactance X_s as shown in Figure 4.1. TCSC is integrated in the OPF problem by modifying system line data. A new line reactance is given in (4.23).

$$X_{new} = X_{ij} - X_s \quad (4.23)$$

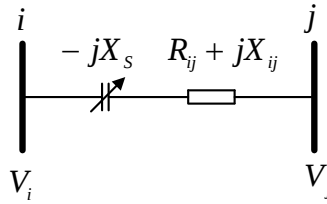


Figure 4.1 Model of TCSC.

The power flow equations of the line with a new line reactance are given as follows:

$$P_{ij} = V_i^2 G'_{ij} - V_i V_j (G'_{ij} \cos \delta_{ij} + B'_{ij} \sin \delta_{ij}) \quad (4.24)$$

$$Q_{ij} = -V_i^2 B'_{ij} - V_i V_j (G'_{ij} \sin \delta_{ij} - B'_{ij} \cos \delta_{ij}) \quad (4.25)$$

$$P_{ji} = V_j^2 G'_{ij} - V_i V_j (G'_{ij} \cos \delta_{ij} - B'_{ij} \sin \delta_{ij}) \quad (4.26)$$

$$Q_{ji} = -V_j^2 B'_{ij} + V_i V_j (G'_{ij} \sin \delta_{ij} + B'_{ij} \cos \delta_{ij}) \quad (4.27)$$

Where

$$G'_{ij} = \frac{R_{ij}}{R_{ij}^2 + X_{new}^2} \quad \text{and}$$

$$B'_{ij} = \frac{-X_{new}}{R_{ij}^2 + X_{new}^2}.$$

4.2.2 Thyristor controlled phase shifter

The static model and power injection model of a TCPS placed in a line connected between bus i and j are shown in Figure 4.2. The injected real and reactive power at bus i and j of the line having a phase shifter are as follows:

$$P_{is} = -V_i^2 K^2 G_{ij} - V_i V_j K (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (4.28)$$

$$Q_{is} = V_i^2 K^2 B_{ij} + V_i V_j K (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (4.29)$$

$$P_{js} = -V_j V_i K (G_{ij} \sin \delta_{ij} + B_{ij} \cos \delta_{ij}) \quad (4.30)$$

$$Q_{js} = -V_i V_j K (G_{ij} \cos \delta_{ij} - B_{ij} \sin \delta_{ij}) \quad (4.31)$$

Where

$$K = \tan \alpha_p.$$

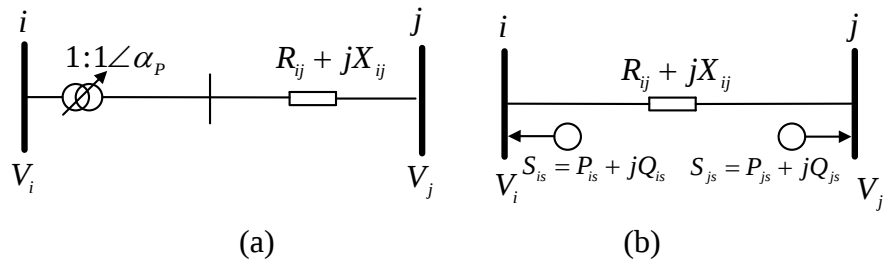


Figure 4.2 (a) Model of TCPS. (b) Power injection model of TCPS.

4.2.3 Unified power flow controller

The static model and power injection model of a UPFC placed in a line connected between bus i and j are shown in Figure 4.3. The injected real and reactive power of UPFC at bus i and j are as follows:

$$P_{is} = -V_U^2 G_{ij} - 2V_i V_U G_{ij} \cos(\alpha_U - \delta_i) + V_j V_U (G_{ij} \cos(\alpha_U - \delta_j) + B_{ij} \sin(\alpha_U - \delta_j)) \quad (4.32)$$

$$Q_{is} = V_i I_q + V_i V_U (G_{ij} \sin(\alpha_U - \delta_i) + B_{ij} \cos(\alpha_U - \delta_i)) \quad (4.33)$$

$$P_{js} = V_j V_U (G_{ij} \cos(\alpha_U - \delta_j) - B_{ij} \sin(\alpha_U - \delta_j)) \quad (4.34)$$

$$Q_{js} = -V_j V_U (G_{ij} \sin(\alpha_U - \delta_j) + B_{ij} \cos(\alpha_U - \delta_j)) \quad (4.35)$$

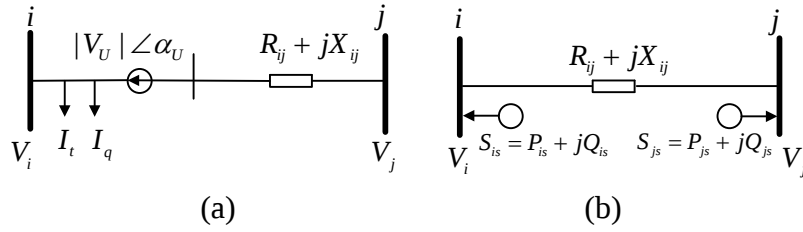


Figure 4.3 (a) Model of UPFC. (b) Power injection model of UPFC.

4.2.4 Static var compensator

SVC is modeled as shunt-connected static var generator or absorber with the value Q_V as shown in Figure 4.4.

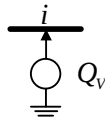


Figure 4.4 Model of SVC.

4.3 Hybrid Evolutionary Algorithm for Optimal Placement of FACTS controllers

The HEA approach is a hybrid algorithm of EP, TS, and SA. HEA balances the explosion by dividing the population into subpopulations. Multiple mutation operators are employed to enhance the search diversity. The selection mechanism with Tabu list and probabilistic updating strategy based on annealing schedule of SA is utilized to avoid being trapped in local optimum. Reassignment strategy for individuals is designed for every subpopulation to fuse information and enhance population diversity. The HEA approach is used to simultaneously search for real power generations in a source area excluding slack bus, generation bus voltages, real power loads in a sink area, and optimal placement of multi-type FACTS controllers for determining the optimal solutions of the objective function defined in (4.1). A flowchart of the HEA approach is shown in Figure 4.5, which can be explained as follows:

Representation of solution

An individual in a population represents a candidate of OPF solution. Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial solution vector in (4.36). There are four types of FACTS controllers with maximum allowable n_{CFk} component for each type, which is assigned as input data. The placement configuration depicted in Figure 4.6 is represented by three parameters: n_{CFk} , $location_k$, and $parameter_k$ given in (4.37). For FACTS type $k \in \{1,2,3,4\}$ representing placement configuration of TCSC, TCPS, UPFC and SVC, respectively, the number of FACTS component type k , $n_{CFk} = \{0,1,...,n\}$. More specifically, there is either no FACTS type k if $n_{CFk}=0$ or a number of FACTS type k if $n_{CFk} \neq 0$. Therefore, number of FACTS components, locations, and parameters of each type of FACTS controllers are simultaneously searched by the HEA. Note the searched locations and parameters of FACTS type k is valid only when $n_{CFk} \neq 0$.

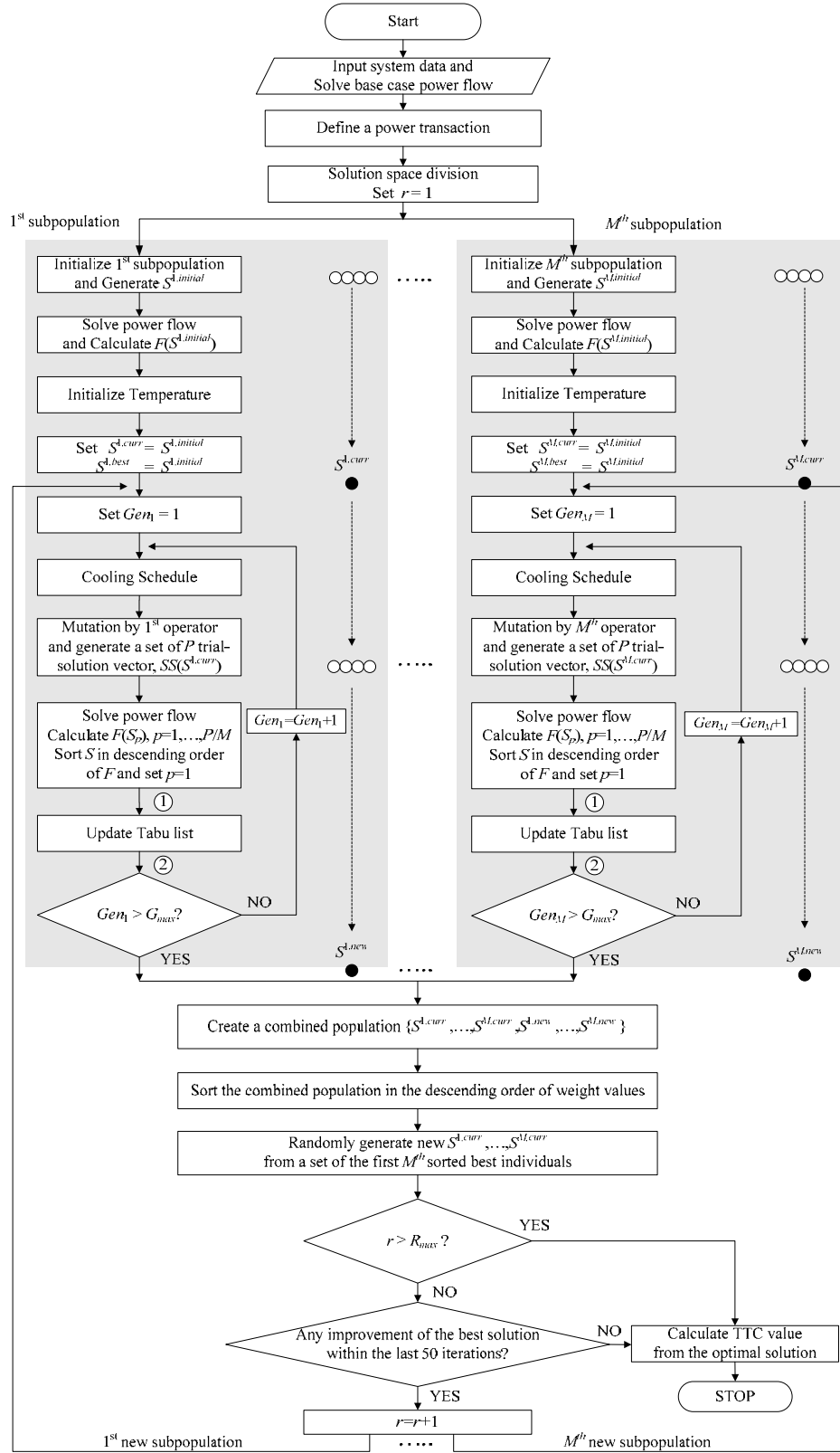


Figure 4.5 Flow chart of the HEA approach for OPF with FACTS problem.

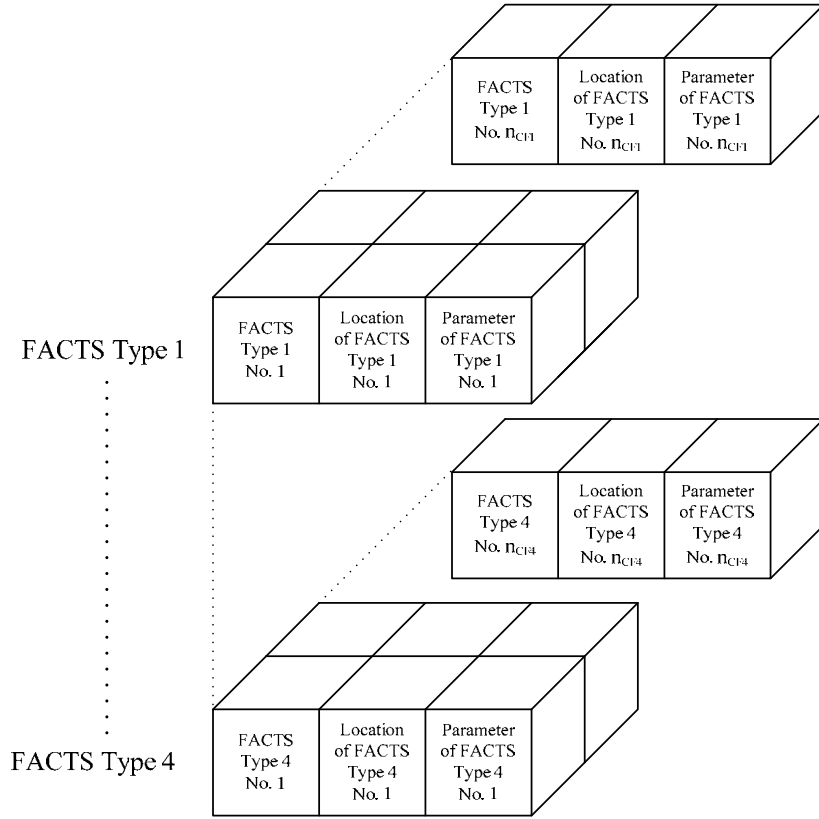


Figure 4.6 Structure of the trial solution vector of multi-type FACTS placement.

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (4.36)$$

$$Loc_k = [n_{CFk}, location_k, parameter_k] \quad (4.37)$$

Where

S_p	trial solution vector of the p th individual,
P_{Gi}	real power generation at bus i in the source area,
V_{Gi}	voltage magnitude of generator at bus i including slack bus,
P_{Dj}	real power load at bus j in the sink area,
Loc_k	allocation vector of FACTS device type k , where $k=1, \dots, 4$ representing placement configuration of TCSC, TCPS, UPFC and SVC, respectively,
n_{CFk}	number of FACTS components, $n_{CFk} \in \{0, 1, 2\}$,
$location_k$	line or bus location of FACTS type k , and
$parameter_k$	parameter settings of FACTS type k .

Space division

Space division strategy is used to divide the whole population size P into M subpopulations according to the number of mutation operators used. Therefore, the search process can be performed in parallel to enhance performance of exploration and speed of convergence.

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number distribution ranging over the feasible limits of each control variable in (4.38).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.38)$$

Where

x_i	i th element of the individual in a population,
$x_i^{\min}, x_i^{\max}$	lower and upper limits of the i th element of the individual, and
u	uniform random number in the interval $[0,1]$.

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution. If the power flow of any individuals fails to converge, such individuals will be removed and replaced by new randomly created individuals.

Fitness function

Fitness function is used to measure the optimality or quality of each candidate solution with respect to the objective being optimized. The objective function in (4.1) is taken as the fitness function of the HEA approach.

Cooling schedule procedure

The initial temperature of each subpopulation expressed in (4.39) is determined from the objective value of the best and the worst individual, and the probability of accepting the worst individual with respect to the best individual. After

reassignment strategy, the temperature is cooled down by the temperature annealing function or cooling schedule in (4.40).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (4.39)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (4.40)$$

Where

$T_{0,m}$	initial temperature of the m th subpopulation,
$F_m^{\min}, F_m^{\max}$	objective value of the worst and best individuals in the m th subpopulation,
p_r	probability of accepting the worst individual with respect to the best individual,
$T_{r,m}$	annealing temperature of the m th subpopulation after the r th reassignment,
λ	rate of cooling, and
r	iteration counter of reassignment strategy.

Mutation

In different subpopulations, different mutation operators are used to create new offspring subpopulation so that many hybrid operators are applied to enhance the search diversity. Two mutation operators including Gaussian and Cauchy are applied. A set of trial solution vectors, $SS(S^{curr})$, is generated by perturbing the current solution vector using the uniform probability distribution function. Each element of the offspring is calculated in (4.41). If any mutated value exceeds its limits, it will be recalculated until it is within the limits. Mutation intensifies with the increasing number of iterations.

$$x'_{k,i} = x_{k,i} + \sigma_{k,i} \cdot \xi_m \quad (4.41)$$

$$\sigma_{k,i} = T_{r,m} \cdot a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \quad (4.42)$$

Where

$x'_{k,i}$	i th element of the k th offspring individual,
$x_{k,i}$	i th element of the k th parent individual,
$\sigma_{k,i}$	mutation step size for the i th element of the k th individual,
ξ_m	mutation operator of the m th subpopulation e.g. $N(0,1)$, $C(0,1)$,

$N(0,1)$	Gaussian random number with mean 0 and standard deviation 1,
$C(0,1)$	Cauchy random number,
a	positive number slightly less than one, and
$x_i^{\max}, x_i^{\min}$	subinterval's or interval's upper and lower limits of i th element of the individual.

Tabu list

Tabu list is a finite length first-in first-out structure, which records a set of current best solutions visited. Tabu list may be viewed as a ‘meta-heuristic’ superimposed on another heuristic method. Tabu list is used to prevent the entrapment in local optima. It stores movement of solution and forbids backtracking to previous movement. A new trial solution vector classified as tabu is placed on top of the list and the oldest trial vector is taken out from the list.

Aspiration criterion

Aspiration criterion is a rule used to override a tabu restriction. If a certain move is forbidden by tabu restriction, the aspiration criterion, when satisfied, can make this move allowable. The aspiration criterion in (4.43) adopts a probabilistic acceptance criterion of SA. When the probabilistic acceptance criterion is higher than a uniform randomly generated variable in the interval [0,1], the tabu restriction is overruled.

$$p_{k,m} = \frac{1}{1 + \exp(-\Delta / T_{r,m})} \quad (4.43)$$

Where

$p_{k,m}$	probabilistic acceptance criterion of the k th offspring individual within the m th subpopulation, and
Δ	difference of objective values between the k th offspring individual and its corresponding parent individual, i.e. the k th parent individual.

If $p_{k,m} = 1$, the k th offspring individual of the m th subpopulation will be selected to be a new parent individual for next generation. Otherwise, a uniform random number, U , in the interval [0,1] is generated and compared to $p_{k,m}$. If $p_{k,m} > U$, the k th offspring individual will be accepted, otherwise, their corresponding parent will be selected.

Reassignment strategy

To perform the reassignment strategy, tournament scheme is used to select new current parent population from the combined population of current parent ($S^{1,curr}, \dots, S^{M,curr}$) and new offspring ($S^{1,new}, \dots, S^{M,new}$) individuals of all subpopulations. Each individual in the combined population is assigned a weight value according to the competition in (4.44). Each individual in the combined population has to compete with Nt randomly-selected individuals in one-by-one basis. If the individual wins a selected opponent, it will obtain one from this competition. Otherwise, it will obtain zero. The summation of scores from Nt competitions is a competition score, w_k , of the k th individual. After sorting the combined population of $2M$ individuals in the descending order of weight values, each new current parent solution individual of all subpopulations will be randomly selected from a set of the first M th sorted best solution individuals.

$$w_k = \sum_{t=1}^{Nt} \begin{cases} 1 & \text{if } F_k > F_r \\ 0 & \text{otherwise} \end{cases} \quad (4.44)$$

Where

w_k	weight value of k th individual in combined population,
F_k	fitness value of k th individual in combined population,
F_r	fitness value of r th opponent randomly selected from the combined population based on $r = \lfloor 2 \cdot M \cdot u + 1 \rfloor$,
Nt	number of competitors.

Termination criteria

There are three termination criteria used in the proposed HEA approach. It will stop whenever any one of three criteria is met. The first termination criterion is set as the maximum number of generations of each subpopulation and the second termination criterion is the number of reassignment required. The algorithm will be stopped if there is no improvement of the best fitness within 50 generations as the third termination criterion. In addition, these criteria are applied to all the methods for a fair comparison.

4.4 Evolutionary Computation Methods for Optimal Placement of FACTS controllers

4.4.1 Evolutionary programming

Based on EP approach, an EP-based algorithm proposed for solving the optimally placed OPF with FACTS problem can be described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (4.45).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (4.45)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (4.46).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.46)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Fitness function

The objective function in (4.1) is taken as the fitness function of the EP approach.

Mutation

Each element of the offspring individual is mutated by using the Gaussian mutation operator in (4.47).

$$x'_{k,i} = x_{k,i} + N(0, \sigma_{k,i}^2) \quad (4.47)$$

$$\sigma_{k,i} = (x_i^{\max} - x_i^{\min}) \left(\frac{F^{\max} - F_k}{F^{\max}} + a^g \right) \quad (4.48)$$

Where

$N(0, \sigma_{k,i}^2)$ Gaussian random number with a mean of 0 and a standard deviation of $\sigma_{k,i}$,

f_k fitness value of the k th individual,

$f_{\max}$ the maximum fitness of the parent population, and

g iteration counter.

Selection

Each individual in the combined population is assigned a weight value according to the tournament scheme competition in (4.49). A set of the first M th sorted best weight values individuals from the combined population of $2M$ individuals will be selected as a new current parent population.

$$w_k = \sum_{t=1}^{N_t} \begin{cases} 1 & \text{if } F_k > F_r \\ 0 & \text{otherwise} \end{cases} \quad (4.49)$$

Termination criterion

There are two termination criteria used in the EP. It will stop whenever any one of two criteria is met. The first termination criterion is set as the maximum number of generations. The algorithm will be stopped if there is no improvement of the best fitness within 50 generations as the second termination criterion.

4.4.2 Tabu search

Based on TS approach, an TS-based algorithm proposed for solving the optimally placed OPF with FACTS problem can be described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (4.50).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (4.50)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (4.51).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.51)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Perturbation

A set of trial neighborhood solution vectors is generated by perturbing the current solution vector using the uniform probability distribution function in (4.52).

$$x'_{k,i} = x_{k,i} + \frac{1}{g} \cdot u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.52)$$

Tabu list

A new trial solution vector classified as tabu is placed on top of the list and the oldest trial vector is taken out from the list.

Aspiration criterion

The aspiration criterion is used to override the tabu status of a move if this move yields a solution which has better objective function value than the aspiration level, which is the objective value of current trial solution vector from previous iteration.

Termination criterion

There are two termination criteria in the TS approach similar to those used in the EP approach.

4.4.3 Hybrid tabu search and simulated annealing

Based on hybrid TS/SA approach, an TS/SA-based algorithm proposed for solving the optimally placed OPF with FACTS problem can be described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (4.53).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (4.53)$$

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (4.54).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.54)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Cooling schedule

The initial temperature of each subpopulation is determined in (4.55). The temperature is cooled down by the temperature annealing function or cooling schedule in (4.56).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (4.55)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (4.56)$$

Perturbation

Each element of the offspring individual is generated by using the uniform probability distribution function in (4.57).

$$x'_{k,i} = x_{k,i} + T_{r,m} \cdot u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.57)$$

Tabu list

The tabu list utilized in the hybrid TS/SA approach is the same as that used in the TS algorithm.

Aspiration criterion

The aspiration criterion employed adopts a probabilistic acceptance criterion of SA as shown in (4.58).

$$p_{k,m} = \frac{1}{1 + \exp(-\Delta / T_{r,m})} \quad (4.58)$$

Termination criterion

There are two termination criteria in the hybrid TS/SA approach similar to those used in the EP approach.

4.4.4 Improved evolutionary programming

Based on IEP approach, an EP-based algorithm proposed for solving the optimally placed OPF with FACTS problem can be described as follows:

Representation of solution

Each individual consists of OPF control variables coded by real number. The p th individual in a population is represented by a trial vector in (4.59).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (4.59)$$

Space division

Space division strategy is used to divide the search space into subspaces. The division can be made in a certain way. For example, if there are two subpopulations, the first control variable's interval ranging from its minimum limit to its maximum limit can be divided equally into two subintervals while the interval of other control variables will be used throughout their feasible range.

Initialization

Each element of the trial vector is initialized randomly within its search space by using uniform random number in (4.60).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (4.60)$$

Power flow solution

During iterations, a full AC NR power flow analysis is used to check the feasibility of each individual solution.

Fitness function

The objective function in (4.1) is taken as the fitness function of the IEP algorithm.

Cooling schedule

The initial temperature of each subpopulation is determined in (4.61). The temperature is cooled down by the temperature annealing function in (4.62).

$$T_{0,m} = -\frac{(F_m^{\max} - F_m^{\min})}{\ln p_r} \quad (4.61)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (4.62)$$

Mutation

Two mutation operators including Gaussian and Cauchy are applied for each subpopulation. Each element of the offspring individual is determined in (4.63).

$$x'_{k,i} = x_{k,i} + \sigma_{k,i} \cdot \xi_m \quad (4.63)$$

$$\sigma_{k,i} = a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \quad (4.64)$$

Selection

The probabilistic acceptance criterion of the k th offspring individual can be expressed in (4.65).

$$p_{k,m} = \min\{1, \exp(-\Delta/T_{r,m})\} \quad (4.65)$$

Reassignment strategy

The individuals of all subpopulations are merged and then the whole population will be randomly divided to form new subpopulations.

Termination criteria

The termination criterions utilized in the IEP algorithm are similar to those used in the HEA approach.

Table 4.1 Parameter Setting of the Optimization Methods

Test Systems	Parameter Setting Value	EP	TS	TS/SA	IEP	HEA
The modified IEEE 6-, 24- and 30-bus systems	<i>P-pop size</i>	30	30	30	30	30
	<i>M-subpop</i>	-	-	-	2	2
	N_t	20	-	-	20	20
	<i>Tabu size</i>	-	20	20	-	20
	K_p	10^6	10^6	10^6	10^6	10^6
	p_r	-	-	0.01	0.01	0.01
	λ	-	-	0.8	0.8	0.8
	a	-	-	-	0.9	0.9
	G_{max}	400	400	400	10	10
	R_{max}	-	-	-	40	40
The modified IEEE 118- bus and Thai power 160- bus systems	<i>P-pop size</i>	40	40	40	40	40
	<i>M-subpop</i>	-	-	-	2	2
	N_t	20	-	-	20	20
	<i>Tabu size</i>	-	20	20	-	20
	K_p	10^6	10^6	10^6	10^6	10^6
	p_r	-	-	0.01	0.01	0.01
	λ	-	-	0.8	0.8	0.8
	a	-	-	-	0.9	0.9
	G_{max}	600	600	600	10	10
	R_{max}	-	-	-	60	60

4.5 Simulation Results of Optimal Placement of FACTS controllers

The modified IEEE 30-bus, 24-bus, 118-bus, and the modified practical Thai power 160-bus systems are used to demonstrate the optimal placement of multi-type FACTS controllers for ATC enhancement using the proposed HEA method. The HEA is implemented using MATLAB version 6.5 on an AMD Athlon64 X2 3600+ computer with 1.0 GB memory. Parameter settings of the HEA are shown in Table 4.1. The reactance limit of TCSC is $0 \leq X_{Si} \leq 60\%$ of line reactance; phase shifting angle limit of TCPS is $-\pi/4 \leq \alpha_{Pi} \leq \pi/4$ radian; voltage limit of UPFC is $0 \leq V_{Ui} \leq 0.1$ p.u.; angle limit of UPFC is $-\pi \leq \alpha_{Ui} \leq \pi$ radian; and reactive power injection limit of SVC is $-10 \leq Q_{Vi} \leq 10$ MVar. Loads are modeled as constant power factor loads.

4.5.1 The modified IEEE 30-bus system

The modified IEEE 30-bus system in Figure 4.7 is partitioned into three areas with two generators in each area. TRM and CBM are not included in the ATC determination. Three transactions including one bilateral transaction and two multilateral transactions are considered. A multilateral transaction from area 1 to 2 is presented in section A. In addition, a bilateral transaction from bus 2 to 21 and a multilateral transaction from area 1 to 3 are presented in section B.

A. Optimal placement of FACTS controllers using loss sensitivity index, EP, and HEA

In this section, four methods are used to solve the optimally placed OPF with FACTS problem to simultaneously maximize ATC and minimize power loss as shown in Table 4.2. For method I and II, the loss sensitivity index proposed in (Preedavichit and Srivastava, 1998; Verma et al., 2001) is used to determine the suitable locations of multi-type FACTS controllers. EP and HEA methods are used to determine parameter settings of FACTS controllers and the objective function defined in (4.1). For method III and IV, the EP and HEA are used to simultaneously determine the locations, types, and parameters of FACTS controllers and the objective function.

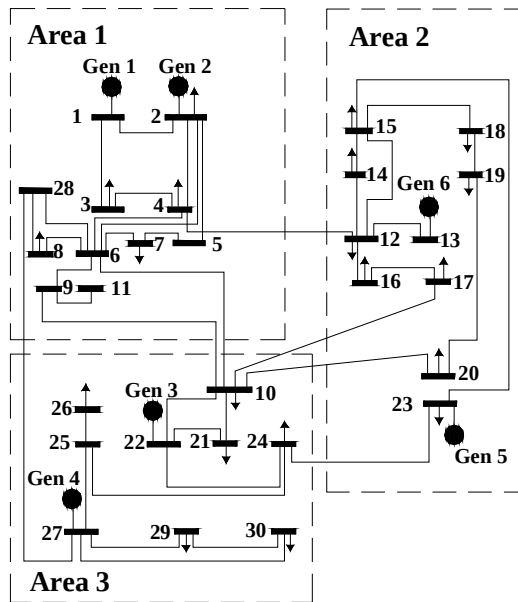


Figure 4.7 Diagram of the modified IEEE 30-bus system.

Table 4.2 Optimization Methods for the Modified IEEE 30-bus System

Method	FACTS controllers		Objective Function
	Location	Type & Parameters	
I	Loss Index	EP	EP
II	Loss Index	HEA	HEA
III	EP	EP	EP
IV	HEA	HEA	HEA

Table 4.3 Base Case TTC Values Without FACTS controllers of the Transaction From Area 1 to 2 on the Modified IEEE 30-bus System

Method	TTC (MW)	Loss (MW)	Limit condition
CPF	60.71	3.18	Line 22-21
EP	102.65	6.00	Line 27-25
HEA	114.86	7.25	Line 27-25

Table 4.4 TTC Values With Optimally Placed FACTS controllers of the Transaction From Area 1 to 2 on the Modified IEEE 30-bus System

Method	TTC (MW)	Loss (MW)	Limit Condition	FACTS Location			
				TCSC	TCPS	UPFC	SVC
I	162.63	11.67	Line 27-25	Line 2-6	Line 12-15	Line 22-24	Bus 18
II	189.15	12.41	Line 27-25	Line 2-6	Line 12-15	Line 22-24	Bus 18
III	174.31	10.71	Line 27-25	Line 15-23	Line 12-15	Line 27-30	Bus 20
IV	197.52	11.96	Line 27-25	Line 10-20	Line 12-15	Line 4-12	Bus 17

Base case TTC without FACTS controllers are calculated using CPF method. Power System Analysis Toolbox (PSAT) (Milano, 2005) is used to perform the CPF analysis. For the transaction from area 1 to 2, using CPF method, TTC value without FACTS controllers is 60.71 MW as shown in Table 4.3. The expected limiting condition is line flow limit at line 22-21, if further transfers take place. Using EP method, TTC is 102.65 MW and the limiting condition is the line flow limit at line 27-25. Using HEA method, TTC is 114.86 MW, which is 89.19% and 11.89% more than those from the CPF and EP methods, respectively. The limiting component is line 27-25, similar to the binding condition of the EP method.

For method IV, HEA has optimally placed each type of FACTS controllers to simultaneously maximize TTC and minimize loss. The TTC is 197.52 MW without violating system limits, which is increased by 71.97% compared to that without FACTS controllers. In addition, the TTC value is 21.45%, 4.43%, and 13.32% higher than those from method I, II, and III, respectively. For either method II and IV, optimally placed OPF with FACTS controllers by HEA could also significantly enhance TTC values far more than those from EP approach in method I and II.

Test results in Table 4.4 indicate that the loss sensitivity index is mainly used to determine the locations of FACTS controllers to minimize the total system real power losses. This method is easy to calculate and computationally fast. However, it may not lead to the optimal solution because of the dependency to system topology and loading conditions. The placement of FACTS controllers using the loss sensitivity index (method I and II) gives conservative TTC values and a higher power losses than those from EP and HEA (method III and IV) because sensitivity approach does not result in the optimal locations of FACTS controllers, leading to a loss of business opportunities.

B. Optimal placement of FACTS controllers using EP, TS, TS/SA, IEP and HEA methods

In this case study, two transactions including a bilateral transaction from bus 2 to 21 and a multilateral transaction from area 1 to 3 are considered. Test results from HEA are compared to those from EP, TS, hybrid TS/SA, and IEP methods.

For bilateral transaction with optimally placed FACTS controllers using HEA method, TTC value is 43.65 MW without violating system constraints, which is increased by 89.62% compared to that without FACTS controllers shown in Table 4.5. In addition, the TTC value is 41.45%, 51.04%, 40.72%, and 10.39% more than those from EP, TS, TS/SA, and IEP methods, respectively.

For multilateral transaction with optimally placed FACTS controllers using HEA method, TTC value is 111.92 MW, which is increased by 40.59% compared to that without FACTS controllers. In addition, the TTC value is

23.65%, 10.66%, 7.66%, and 7.51% more than those from EP, TS, TS/SA, and IEP, respectively. The optimal placements of FACTS controllers are shown in Table 4.6.

Comparisons of TTC results and average CPU times from 20 runs are shown in Table 4.7. The reported CPU time is the total computation time of HEA approach from starting to ending including the NR power flow of all individuals. The HEA can obtain better results on the best, average, and the worst TTC values than those from the other methods because HEA uses the selection mechanism with a probabilistic updating strategy based on SA and tabu list to avoid dependency on fitness function and to escape from the entrapment in local optimal solutions. To compare the convergence characteristic, IEP and HEA utilize a probabilistic updating strategy based on annealing schedule of SA, resulting in more generations required and slower convergence characteristic than EP, TS, and TS/SA methods as shown in Figure 4.8.

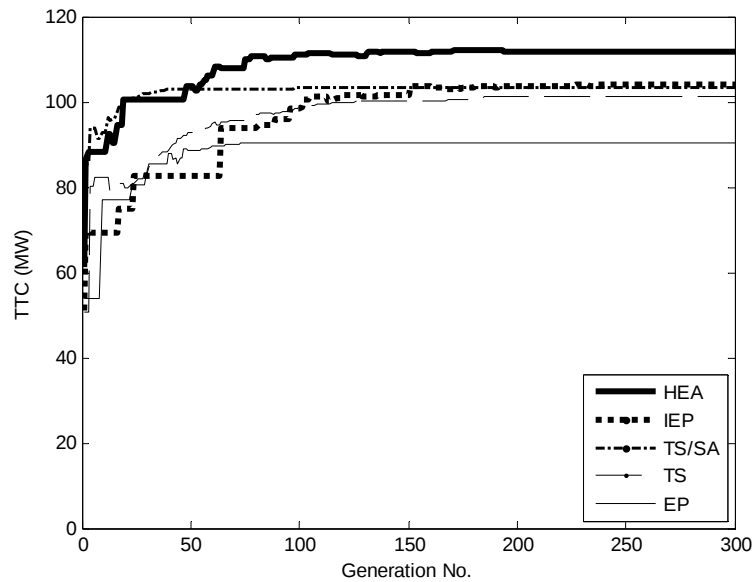


Figure 4.8 Convergence characteristic of solutions.

Table 4.5 TTC Values With Bilateral and Multilateral Transactions on the Modified IEEE 30-bus System

Method	Bilateral Transaction				Multilateral Transaction			
	Without FACTS		With FACTS		Without FACTS		With FACTS	
	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)
EP	23.02	2.63	30.86	2.67	79.48	4.03	90.51	4.98
TS	23.02	2.63	28.90	2.78	78.84	4.23	101.14	5.71
TS/SA	23.02	2.63	31.02	2.89	79.44	3.97	103.96	5.79
IEP	23.02	2.63	39.54	1.89	79.45	3.99	104.10	4.17
HEA	23.02	2.63	43.65	2.15	79.61	3.98	111.92	5.85

Table 4.6 Optimal Placement of Multi-Type FACTS controllers of Multilateral Transaction on the Modified IEEE 30-bus System

Method	TCSC			TCPS			UPFC			SVC		
	n_{CF1}	$location_1$	X_S (pu)	n_{CF2}	$location_2$	α_P (rad)	n_{CF3}	$location_3$	α_U (rad), V_U (pu)	n_{CF4}	$location_4$	Q_V (MVar)
EP	1	Line 24-25	0.017	1	Line 1-2	0.058	1	Line 2-6	2.579, 0.068	1	Bus 21	8.174
TS	1	Line 15-23	0.023	1	Line 2-4	0.010	1	Line 10-21	0.724, 0.038	1	Bus 25	0.474
TS/SA	1	Line 8-28	0.051	1	Line 1-2	0.019	1	Line 2-4	2.014, 0.051	1	Bus 28	1.968
IEP	0	-	-	1	Line 6-9	0.092	1	Line 9-10	1.458, 0.041	1	Bus 25	0.287
HEA	0	-	-	1	Line 6-8	0.013	1	Line 6-7	1.737, 0.059	1	Bus 24	6.353

Table 4.7 TTC Results and CPU Times on the Modified IEEE 30-bus System

Method	Bilateral Transaction with FACTS					Multilateral Transaction with FACTS				
	TTC			Standard Deviation	CPU Time (min)	TTC			Standard Deviation	CPU Time (min)
	Best	Average	Worst			Best	Average	Worst		
EP	30.86	27.14	22.91	3.08	1.13	90.51	84.33	75.41	4.87	2.00
TS	29.34	27.15	22.93	2.81	1.17	101.14	86.25	76.96	8.99	1.85
TS/SA	31.02	26.87	22.95	2.57	0.91	103.96	97.33	81.04	7.55	1.55
IEP	39.54	32.23	26.12	5.40	1.52	104.10	93.32	73.72	9.76	2.88
HEA	43.65	34.05	26.50	5.38	1.51	111.92	102.56	88.78	5.58	2.72

C. Optimal placement of FACTS controllers with three different objective functions

In this case study, two transactions including a bilateral transaction from bus 1 to 21 and a multilateral transaction from area 1 to 2 with three different objective functions: i) maximize TTC, ii) minimize power loss, and iii) simultaneously maximize TTC and minimize loss, are considered.

For bilateral transaction from bus 1 to 21 without FACTS controllers in Table 4.8, base case load at bus 21 is 17.50 MW. To maximize TTC using HEA method, TTC value is 40.447 MW without violating system constraints, which is 1.29%, 0.84%, 0.31%, and 0.58% more than those from EP, TS, TS/SA, and IEP methods, respectively. To minimize system power loss without curtailing the existing generations and loads, only generator bus voltages are optimized using HEA, TTC value and power loss are 17.50 MW and 2.045 MW, which are similar to those of the other methods. To simultaneously maximize TTC and minimize loss using HEA, TTC is 40.449 MW, which is 0.85%, 0.55%, 0.38%, and 0.58% more than those from EP, TS, TS/SA, and IEP, respectively.

HEA has optimally placed each type of FACTS controllers to simultaneously maximize TTC and minimize loss. The TTC is 154.061 MW without violating system limits, which is increased by 280.88% compared to that without FACTS controllers. In addition, the TTC value is 22.25%, 21.54%, 20.91%, and 15.04% higher than those from EP, TS, TS/SA, and IEP methods, respectively. For either TTC maximization or loss minimization only, optimally placed OPF with FACTS controllers by HEA could also significantly enhance the TTC value and reduce system power loss far more than OPF without FACTS controllers.

For multilateral transaction from area 1 to 2 without FACTS controllers in Table 4.9, base case load at area 2 is 56.20 MW. To simultaneously maximize TTC and minimize loss using HEA method, TTC value is 125.930 MW, which is 0.21%, 0.12%, 0.10%, and 0.17% higher than those from EP, TS, TS/SA, and IEP methods, respectively. For either TTC maximization or loss minimization only, HEA approach can also effectively re-dispatch real power generations except slack bus in a source area, increment of real power loads in a sink area, and optimal setting of generation bus voltages.

HEA has optimally placed each type of FACTS controllers with maximum allowable one component for each type of FACTS controllers to simultaneously maximize TTC and minimize loss. The TTC is 191.379 MW, which is increased by 51.97% compared to that without FACTS controllers. In addition, the TTC value is 40.68%, 20.60%, 18.40%, and 15.61% higher than those from EP, TS, TS/SA, and IEP methods, respectively. The optimal placements of multi-type FACTS controllers of the power transaction are shown in Table 4.10.

Table 4.8 Test Results With Bilateral Transaction on the Modified IEEE 30-bus System

Method	Without FACTS controllers						With FACTS controllers					
	Maximize TTC		Minimize Loss		Max.TTC & Min.Loss		Maximize TTC		Minimize Loss		Max.TTC & Min.Loss	
	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss
EP	39.932	4.594	17.500	2.045	40.110	4.613	125.531	3.921	17.500	1.296	126.021	3.914
TS	40.111	4.634	17.500	2.045	40.229	4.688	126.274	3.725	17.500	1.281	126.755	3.793
TS/SA	40.322	4.785	17.500	2.045	40.297	4.686	127.113	3.880	17.500	1.258	127.415	3.715
IEP	40.213	4.655	17.500	2.045	40.217	4.659	128.675	3.176	17.500	1.154	133.919	2.827
HEA	40.447	4.734	17.500	2.045	40.449	4.732	147.322	4.152	17.500	1.096	154.061	3.607

Table 4.9 Test Results with Multilateral Transaction on the Modified IEEE 30-bus System

Method	Without FACTS controllers						With FACTS controllers					
	Maximize TTC		Minimize Loss		Max.TTC & Min.Loss		Maximize TTC		Minimize Loss		Max.TTC & Min.Loss	
	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss	TTC	Loss
EP	124.994	6.421	56.200	2.029	125.663	6.035	133.694	6.001	56.200	1.144	136.040	3.980
TS	125.553	6.140	56.200	2.029	125.781	5.916	157.054	6.438	56.200	1.105	157.389	6.449
TS/SA	125.808	6.287	56.200	2.029	125.806	5.793	158.482	6.465	56.200	1.101	161.642	6.971
IEP	125.451	6.248	56.200	2.029	125.716	5.967	158.904	7.057	56.200	0.998	165.545	6.351
HEA	125.629	6.043	56.200	2.029	125.930	5.738	185.095	7.426	56.200	0.968	191.379	7.474

Table 4.10 Optimal Placement of FACTS controllers of Multilateral Transaction on the Modified IEEE-30 bus System
(Simultaneously Maximize TTC and Minimize Loss)

Method	Location	TCSC Parameter	Location	TCPS Parameter	Location	UPFC Parameter	Location	SVC Parameter
EP	Line 12-16	$X_S=0.0044$ p.u.	Line 2-6	$\alpha_p=0.0016$ rad	Line 6-8	$V_U=0.0247$ p.u. $\alpha_U=1.1091$ rad	Bus 16	$Q_V=1.504$ MAVr
TS	Line 14-15	$X_S=0.0017$ p.u.	Line 12-14	$\alpha_p=0.0236$ rad	Line 12-15	$V_U=0.0489$ p.u. $\alpha_U=0.9440$ rad	Bus 17	$Q_V=2.360$ MAVr
TS/SA	Line 12-15	$X_S=0.0173$ p.u.	Line 6-8	$\alpha_p=0.0585$ rad	Line 2-6	$V_U=0.0391$ p.u. $\alpha_U=0.8280$ rad	Bus 17	$Q_V=4.011$ MAVr
IEP	Line 27-30	$X_S=0.0274$ p.u.	Line 9-10	$\alpha_p=0.0198$ rad	Line 10-17	$V_U=0.0568$ p.u. $\alpha_U=0.4461$ rad	Bus 14	$Q_V=3.118$ MAVr
HEA	Line 12-15	$X_S=0.0118$ p.u.	Line 10-20	$\alpha_p=0.0463$ rad	Line 10-17	$V_U=0.0677$ p.u. $\alpha_U=0.6103$ rad	Bus 8	$Q_V=7.786$ MAVr

Table 4.10 TTC Results and CPU Times of Multilateral Transaction on the Modified IEEE 30-bus System
(Simultaneously Maximize TTC and Minimize Loss)

Method	Without FACTS controllers					With FACTS controllers				
	Best	TTC (MW) Average	Worst	Standard Deviation	CPU Time (min.)	Best	TTC (MW) Average	Worst	Standard Deviation	CPU Time (min.)
EP	125.663	124.205	121.891	1.48	0.71	136.040	129.790	121.937	5.46	3.11
TS	125.781	125.339	124.796	0.31	0.62	157.389	142.263	125.554	12.68	2.58
TS/SA	125.781	125.339	124.796	0.31	0.62	157.389	142.263	125.554	12.68	2.58
IEP	125.716	125.349	124.840	0.32	0.77	165.545	142.758	130.716	10.55	4.26
HEA	125.930	125.351	124.923	0.31	0.75	191.379	170.497	156.352	9.83	4.17

To compare the convergence characteristic, IEP and HEA approaches utilize a probabilistic updating strategy based on annealing schedule of SA, resulting in more generations required and slower convergence characteristic than EP, TS, and TS/SA methods. In addition, the convergence speed of HEA is improved by introducing a flexible memory of search history of TS to prevent cycling and to avoid entrapment in local optima compared to IEP algorithm.

Comparisons of TTC results and CPU times evaluated by EP, TS, TS/SA, IEP, and HEA methods from 20 runs are shown in Table 4.11. The proposed HEA method can obtain better results on the best, average, and the worst TTC values than those from the other optimization methods because HEA approach uses the selection mechanism with a probabilistic updating strategy based on TS and SA algorithms to avoid dependency on fitness function and to escape from the entrapment in local optimal solutions. Furthermore, the variation of the HEA best solution is smaller as evidenced by a smaller standard deviation, leading to a more stable HEA algorithm.

4.5.2 The modified IEEE 24-bus RTS

The modified IEEE 24-bus RTS in Figure 4.9 is partitioned into three areas. A multilateral transaction from area 1 to 2 with contingency constraints is considered. Only the outage of the largest generator in each area and the outage of tie lines are included in the contingency list. For the transaction with optimally placed FACTS controllers using HEA method, normal case TTC value is 906.03 MW, which is increased by 26.70% compared to that without FACTS controllers shown in Table 4.12.

Considering the pre-specified contingency constraints, contingency TTC value using HEA is 814.69 MW without violating network constraints, which is increased by 30.10% compared to that without FACTS controllers. The critical contingency case is the interconnected line 19-20 outage between those two areas. In addition, the TTC value is decreased by 12.46% compared to that without contingency constraints. It is evident that neglecting the effects of contingency constraints on TTC evaluation will inevitably lead to insecure system operation.

To meet the specific reliability criterion, which is $LOLE < 2.4$ hour/year, area 1 needs to import 60 MW and 40 MW from area 2 and 3, respectively. CBM for the critical contingency case is 60 MW. Therefore, ATC value using HEA method is 754.69 MW, which is 20.87%, 22.78%, 13.48%, and 4.43% higher than those from EP, TS, TS/SA, and IEP, respectively. Test results indicate that HEA can effectively re-dispatch real power generations except slack bus in the source area, increase real power loads in the sink area, and optimally set of generation bus voltages. Table 4.13 shows the optimal placement of FACTS controllers of the contingency TTC values.

Test results indicate that single-population search of EP, TS, and TS/SA is less effective than multi-population search of IEP and HEA methods. Even though the HEA requires slightly higher computing time, for planning horizon, the quality of solutions is far more important. In addition, the elapsed time can be further reduced by dividing into multiple subsolutions using more than 2 CPUs.

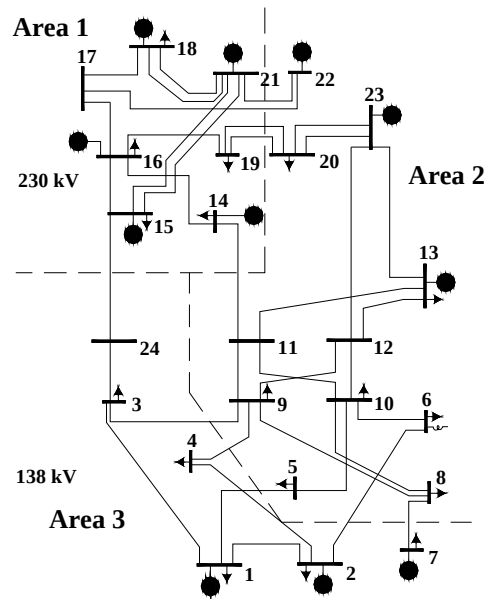


Figure 4.9 Diagram of the modified IEEE 24-bus RTS.

Table 4.12 ATC Values of Multilateral Transaction on the Modified IEEE 24-bus RTS

Case	TTC level (MW) without FACTS controllers					TTC level (MW) with FACTS controllers				
	EP	TS	TS/SA	IEP	HEA	EP	TS	TS/SA	IEP	HEA
Normal	706.44	708.39	708.82	711.90	715.33	794.18	788.84	803.24	905.24	906.03
Largest gen. in area 1 outage	707.58	701.93	711.76	708.77	711.57	781.33	833.64	752.83	883.60	974.04
Largest gen. in area 2 outage	710.76	710.86	714.91	711.98	714.31	739.02	715.19	748.41	826.32	835.38
Line 21-22 outage	705.07	706.43	706.52	712.24	705.07	784.12	833.43	838.15	915.83	965.51
Line 17-22 outage	712.05	705.18	708.83	713.34	713.53	809.09	791.53	803.96	914.19	916.15
Line 19-20 outage	679.50	688.83	691.56	697.95	700.09	721.88	720.96	725.06	782.65	814.69
Line 14-11 outage	623.99	622.76	624.19	624.12	626.18	684.39	674.66	765.89	859.61	913.47
Contingency TTC Value (MW)	623.99	622.76	624.19	624.12	626.18	684.39	674.66	725.06	782.65	814.69
ATC Value (MW)	563.99	562.76	564.19	564.12	566.18	624.39	614.66	665.06	722.65	754.69

Table 4.13 Optimal Placement of FACTS controllers of Multilateral Transaction on the Modified IEEE 24-bus RTS

Method	TCSC			TCPS			UPFC			SVC		
	n_{CF1}	$location_1$	X_S (pu)	n_{CF2}	$location_2$	α_P (rad)	n_{CF3}	$location_3$	α_U (rad), V_U (pu)	n_{CF4}	$location_4$	Q_V (MVar)
EP	1	Line 15-24	0.007	1	Line 14-16	0.075	1	Line 12-13	-0.619, 0.001	1	Bus 22	9.160
TS	1	Line 10-12	0.021	1	Line 15-21	0.021	1	Line 15-24	0.377, 0.028	1	Bus 15	3.873
TS/SA	1	Line 16-17	0.013	1	Line 8-10	0.025	1	Line 12-13	-1.339, 0.012	1	Bus 5	1.382
IEP	1	Line 18-21	0.005	1	Line 6-10	0.006	1	Line 16-17	1.900, 0.046	1	Bus 1	6.332
HEA	1	Line 7-8	0.021	1	Line 15-24	0.016	1	Line 15-16	0.610, 0.017	1	Bus 5	5.332

4.5.3 The modified IEEE 118-bus system

The modified IEEE 118-bus system consists of 54 generator buses and 186 branches. The system is partitioned into 9 areas as shown in Figure 4.10. The system data are modified as follows: Real power generation upper limit at bus 69 is 1,000 MW. Reactive power generation upper limit at bus 34, 70, and 103 is 80 MVar. Reactive power generation lower limit at bus 19, 32, 34, 102, and 105 is -22 MVar. Thermal limit at line 65-66 is 300 MVA. A multilateral transaction from area 6 to 3 with contingency constraints is considered. Only the outage of the largest generators in each area and the outage of tie lines are included in the contingency list. Base case load at area 6 is 406.00 MW and system real power loss is 132.863 MW.

Base case TTC without FACTS controllers using HEA method is 710.57 MW. Considering the pre-specified contingency constraints as shown in Table 4.14, contingency TTC value using HEA approach is 461.03 MW without violating network constraints, which is 4.89%, 5.25%, 0.91%, and 0.57% higher than those from EP, TS, TS/SA, and IEP, respectively. In addition, the TTC value is decreased by 35.12% compared to that without contingency constraints. The critical contingency case is the interconnected line 42-49 between those two areas outage. It is evident that neglecting the effects of contingency constraints on TTC evaluation will inevitably lead to insecure system operation.

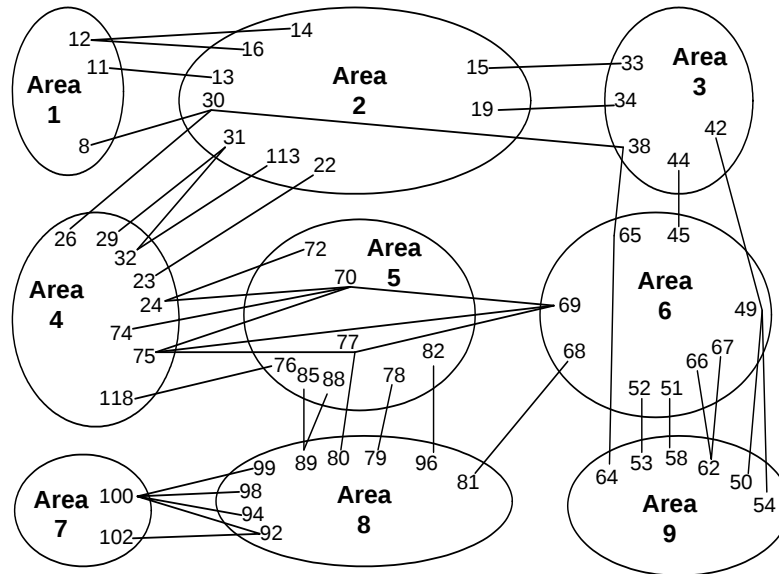


Figure 4.10 Control areas of the modified IEEE 118-bus system.

Table 4.14 TTC Level and Contingency TTC Values of Multilateral Transaction on the Modified IEEE 118-bus System

Case	TTC level (MW) without FACTS controllers					TTC level (MW) with FACTS controllers				
	EP	TS	TS/SA	IEP	HEA	EP	TS	TS/SA	IEP	HEA
Normal	701.61	703.68	706.17	707.27	710.57	706.81	718.21	721.27	720.01	725.17
Largest gen. in area 6 outage	656.24	663.68	673.95	669.84	677.84	674.11	687.29	687.29	690.45	695.08
Largest gen. in area 3 outage	694.29	694.98	703.40	706.12	708.50	708.67	705.20	712.88	723.36	733.64
Line 38-65 outage	481.08	483.31	483.38	483.68	487.13	486.75	484.96	487.94	498.87	513.62
Line 42-49 outage	439.55	438.05	456.87	458.40	461.03	481.07	475.87	497.45	493.48	520.76
Line 44-45 outage	664.59	651.42	655.80	661.85	666.56	671.73	661.08	668.70	683.75	688.79
Contingency TTC Value	439.55	438.05	456.87	458.40	461.03	481.07	475.87	487.94	493.48	513.62

Table 4.15 Optimal Placement of Multi-Type FACTS controllers of Contingency TTC Value With FACTS controllers on the Modified IEEE 118-bus System

Method	TCSC		TCPS		UPFC		SVC	
	Location	Parameter	Location	Parameter	Location	Parameter	Location	Parameter
EP	Line 23-24	$X_S=0.0266$ p.u.	Line 34-43	$\alpha_p=0.0415$ rad	Line 37-39	$V_U=0.0340$ p.u., $\alpha_U=1.1032$ rad	Bus 18	$Q_V=4.745$ MAVr
TS	Line 8-30	$X_S=0.0485$ p.u.	Line 90-91	$\alpha_p=0.0240$ rad	Line 37-39	$V_U=0.0461$ p.u., $\alpha_U=1.3518$ rad	Bus 42	$Q_V=4.276$ MAVr
TS/SA	Line 19-20	$X_S=0.0102$ p.u.	Line 66-67	$\alpha_p=0.0302$ rad	Line 83-85	$V_U=0.0101$ p.u., $\alpha_U=1.2415$ rad	Bus 88	$Q_V=2.931$ MAVr
IEP	Line 51-52	$X_S=0.0495$ p.u.	Line 99-100	$\alpha_p=0.0385$ rad	Line 37-39	$V_U=0.0473$ p.u., $\alpha_U=1.4463$ rad	Bus 97	$Q_V=2.307$ MAVr
HEA	Line 30-38	$X_S=0.0535$ p.u.	Line 39-40	$\alpha_p=0.0607$ rad	Line 42-49	$V_U=0.0084$ p.u., $\alpha_U=1.4457$ rad	Bus 84	$Q_V=2.819$ MAVr

Table 4.16 TTC Results and CPU Times of Multilateral Transaction Without Contingency Constraints on the Modified IEEE 118-bus System

Method	Without FACTS controllers					With FACTS controllers				
	TTC (MW)		Standard Deviation	CPU Time (min.)		TTC (MW)		Standard Deviation	CPU Time (min.)	
	Best	Average				Best	Average			
EP	701.61	699.48	697.71	1.97	3.47	706.81	704.11	699.75	2.69	7.99
TS	703.68	691.67	676.98	14.60	3.45	718.21	708.80	698.97	3.58	9.82
TS/SA	706.17	697.64	688.95	7.71	2.74	721.27	713.66	709.13	10.15	8.25
IEP	707.27	700.34	695.27	6.22	6.97	720.01	706.47	698.58	11.78	16.32
HEA	710.57	706.03	700.76	3.92	6.83	725.17	716.61	710.50	7.64	12.63

HEA has optimally placed each type of FACTS controllers to simultaneously maximize TTC and minimize loss. Base case TTC with optimally placed FACTS controllers is 725.17 MW, which is increased by 2.05% compared to that without FACTS controllers. Considering contingency constraints, contingency TTC value using HEA is 513.62 MW, which is increased by 11.41% compared to that without FACTS controllers. The critical contingency case is the interconnected line 38-65 outage between those two areas. In addition, the TTC value is 6.77%, 7.93%, 5.26%, and 4.08% higher than those from EP, TS, TS/SA, and IEP, respectively. Table 4.15 shows the optimal placement of multi-type FACTS controllers of the contingency TTC values.

Test results in Table 4.16 indicate that single-population search of EP, TS, and TS/SA is less effective than multi-population search of IEP and HEA methods. Even though the HEA approach requires slightly higher computing time, for planning horizon, the quality of solutions is far more important. In addition, the elapsed time can be further reduced by dividing into multiple subsolutions using more than 2 CPUs.

4.5.4 The modified Thai power 160-bus system

A modified practical Thai power 160-bus system shown in Figure 4.11 is the reduced network of the Thai power system considering only 500 kV, 230 kV and 115 kV transmission systems. The lower voltage transmission systems are considered as lumped loads. The system consists of 42 generating plants, 82 load buses, and 185 branches. A multilateral transaction from area 6 to 7 without contingency constraints is considered. To meet the specific reliability criterion, which is $LOLE < 2.4$ hour/year, area 6 needs to import 30 MW from area 7. Therefore, CBM of the transaction is 30 MW.

For the transaction without FACTS controllers, base case load at area 7 is 56.20 MW. In Table 4.17, to simultaneously maximize ATC and minimize loss using HEA method, ATC value is 360.45 MW, which is 24.03%, 25.11%, 0.50%, and 0.34% higher than those from EP, TS, TS/SA, and IEP methods, respectively.

The HEA approach has optimally placed multi-type FACTS controllers with maximum allowable one and two components for each type. Using HEA method, the ATC value with maximum allowable two components for each type of FACTS is 448.34 MW, which is increased by 24.38% compared to that without FACTS controllers. In addition, the ATC value is 14.29%, 14.05%, 5.90%, and 5.69% higher than those from EP, TS, TS/SA, and IEP methods, respectively. The optimal placements of FACTS controllers are shown in Table 4.18. Test results in Table 4.19 indicate that HEA is far more effective to search for the best, average, and worst solutions compared to the others methods.

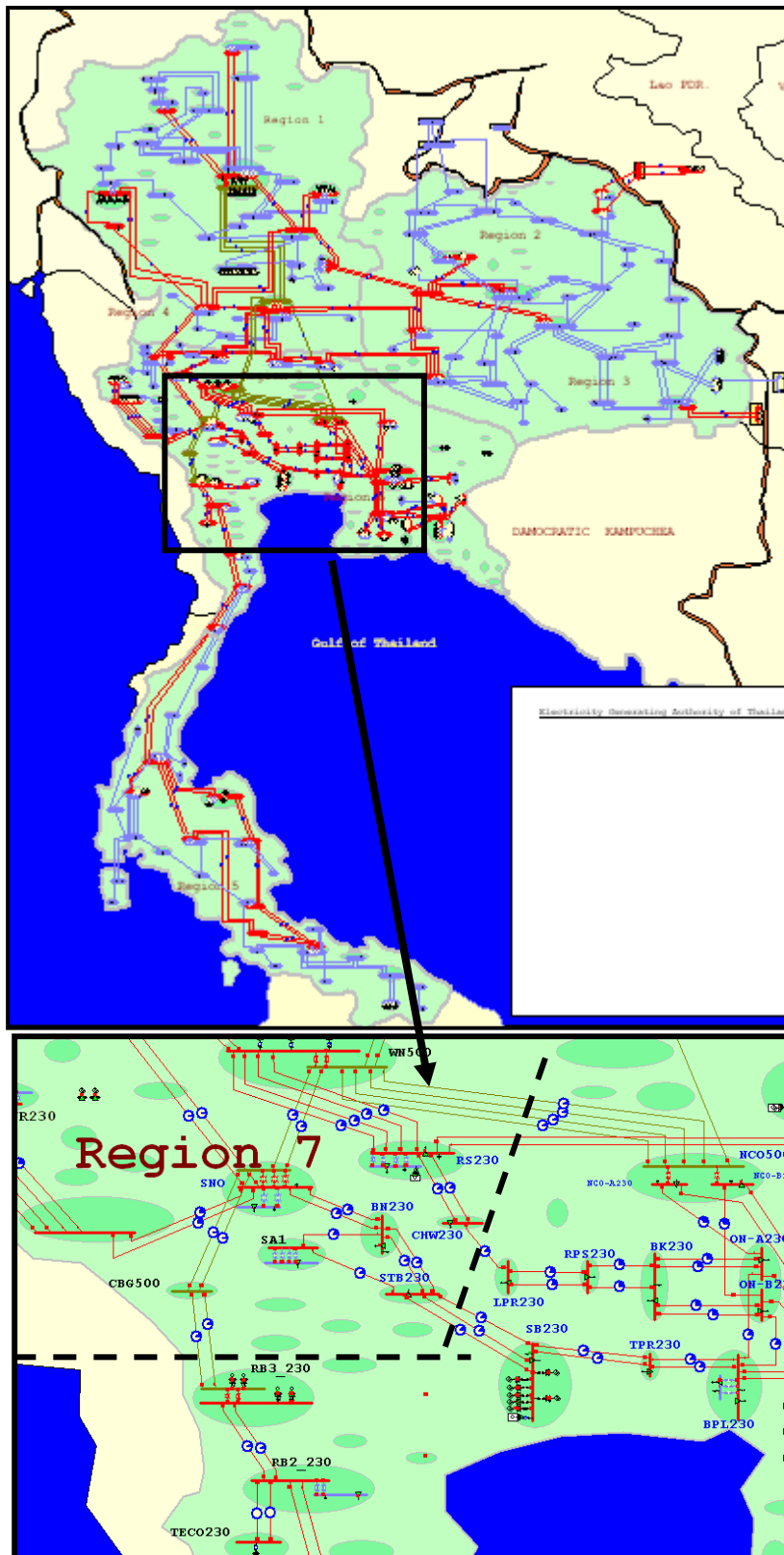


Figure 4.11. Diagram of the modified Thai power 160-bus system.

Table 4.17 ATC Values of the Modified Thai Power 160-bus System

Method	ATC values (MW) without FACTS	ATC values (MW) with maximum allowable $n_{CFK}=1$ for each type of FACTS	ATC values (MW) with maximum allowable $n_{CFK}=2$ for each type of FACTS
EP	273.85	348.98	384.25
TS	269.93	324.29	385.33
TS/SA	358.64	383.01	421.87
IEP	359.21	400.86	422.83
HEA	360.45	433.02	448.34

Table 4.18 Optimal Placement of FACTS controllers With Maximum Allowable $n_{CFK}=2$ for Each Type of FACTS of Multilateral Transaction on the Modified Thai Power 160-bus System

Method	TCSC			TCPS			UPFC			SVC			
	n_{CF1}	$location_1$	X_S (pu)	n_{CF2}	$location_2$	α_P (rad)	n_{CF3}	$location_3$	α_U (rad)	V_U (pu)	n_{CF4}	$location_4$	Q_V (MVar)
EP	1	Line 47-14	0.009	1	Line 150-82	0.059	0	-	-	-	2	Bus 55 Bus 64	1.214 2.562
TS	1	Line 75-49	0.060	1	Line 55-29	0.004	2	Line 81-87 Line 71-82	1.989 1.995	0.058 0.064	1	Bus 63	9.321
TS/SA	1	Line 75-124	0.088	1	Line 86-134	0.052	1	Line 88-136	0.223	0.067	2	Bus 100 Bus 124	4.394 2.687
IEP	1	Line 100-147	0.051	1	Line 82-90	0.098	0	-	-	-	2	Bus 74 Bus 94	5.761 1.126
HEA	1	Line 159-40	0.005	2	Line 52-85 Line 67-68	0.068 0.003	1	Line 79-148	1.156	0.100	1	Bus 96	3.309

Table 4.19 ATC Results and CPU Times of Multilateral Transaction on the Modified Thai Power 160-bus System

Method	With maximum allowable n_{CFK} =2 for each type of FACTS				
	ATC (MW)			Standard	CPU Time
	Best	Average	Worst	Deviation	(min.)
EP	384.255	371.609	357.711	14.28	15.09
TS	385.332	382.274	368.666	12.36	14.29
TS/SA	421.867	399.174	373.091	24.56	12.87
IEP	422.829	400.625	373.864	26.11	28.76
HEA	448.343	424.603	389.605	25.73	27.01

4.6 Conclusion

In this chapter, the HEA approach could efficiently and effectively determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize system power losses of power transactions in deregulated power systems, resulting in higher ATC values than those from EP, TS, hybrid TS/SA, and IEP algorithms. In addition, test results indicate that optimally placed OPF with multi-type FACTS controllers by the HEA approach could enhance the ATC values far more than OPF without FACTS controllers, under normal and contingency conditions.

Chapter 5

Conclusion

In this research, the proposed HEA approach is effectively implemented to determine ATC values of power transfers between different control areas constrained by load flow equations and system operating limits, resulting in higher ATC values than those from EP, TS, hybrid TS/SA, and IEP methods. It is indicated that the HEA can effectively re-dispatch real power generations except slack bus in a source area, increment of real power loads in a sink area and optimal setting of generation bus voltages, leading to an efficient utilization of the existing power systems. This is because the mechanisms of hybrid's components prevent the cycling movement, can jump from local optima, and make good decision movement. Moreover, the algorithm can consider additional voltage and angle stability limits, resulting in a higher trading level of energy transactions in secured power systems.

FACTS controllers are integrated in electrical power systems to provide direct control of power flow over designated transmission routes, and to increase the power transfer capability of transmission networks. However, the extent of these benefits depends upon where these devices are placed and how they are controlled in the systems. When multi-type FACTS controllers are considered in OPF-based ATC determination, the problem is extended to the optimal placement of multi-type FACTS problem, which is a MINLP problem with continuous and discrete variables. The combined objective function including ATC maximization and system real power loss minimization is considered in the new problem formulation.

The HEA approach could efficiently and effectively determine the optimal placement of multi-type FACTS controllers to simultaneously maximize ATC and minimize system power loss of power transactions in deregulated power systems, resulting in higher ATC values than those from EP, TS, hybrid TS/SA, and IEP algorithms. In addition, test results on the modified IEEE 24-bus, 30-bus, 118-bus, and Thai power 160-bus systems indicate that optimally placed OPF with multi-type FACTS controllers by the HEA approach could enhance the ATC values far more than OPF without FACTS controllers, under normal and contingency conditions, leading to a higher trading level of energy transactions in a normal secured system.

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Research Output

ผลลัพธ์ที่ได้จากโครงการวิจัย

ได้ดำเนินการส่งบทความ เพื่อตีพิมพ์ลงในวารสารวิชาการนานาชาติ International Journal of Energy Optimization and Engineering (IJE OE) ที่มีขั้นตอนการตรวจสอบต้นฉบับ (peer review) จากคณะกรรมการผู้ทรงคุณวุฒิ ซึ่งหลังจากที่ได้แก้ไขบทความตามข้อเสนอแนะของคณะกรรมการผู้ทรงคุณวุฒิแล้วเสร็จ มีผลการพิจารณา ได้รับการตอบรับเพื่อตีพิมพ์บทความลงในวารสารดังกล่าว โดยมีผู้วิจัยเป็นชื่อแรกในบทความ และได้ประกาศเกียรติคุณของนักวิจัยที่ปรึกษา รวมถึงสำนักงานกองทุนสนับสนุนการวิจัย (สกว.) และมหาวิทยาลัยเชียงใหม่ไว้ในบทความ ดังแสดงใน Appendix

Jirapong, P. (*in press*). FACTS devices allocation for power transfer capability enhancement and power system losses reduction. *International Journal of Energy Optimization and Engineering*.

การนำผลงานวิจัยไปใช้ประโยชน์

เพื่อเป็นการขยายผลการวิจัย และนำผลการศึกษาที่ได้ไปประยุกต์ใช้ให้เกิดประโยชน์มากยิ่งขึ้น ในระหว่างที่ดำเนินการวิจัย ผู้วิจัยได้มีการเชื่อมโยงกับนักวิจัยทั้งภายในและต่างประเทศโดยการแลกเปลี่ยนข้อมูลการวิจัย และการนำเสนอผลงานวิจัย รวมถึงมีการขยายขอบเขตงานวิจัยเพื่อเชื่อมโยงกับ สำนักงานนโยบายและแผนพลังงาน

กระทรวงพลังงาน ในการพัฒนานักวิจัยรุ่นใหม่ ในระดับบัณฑิตศึกษา ทั้งระดับปริญญาโท และปริญญาเอก โดยมีผลการศึกษาและงานวิจัยที่ได้นำเสนอต่อที่ประชุมวิชาการระดับนานาชาติ รวมถึงบทความตีพิมพ์เผยแพร่ในวารสารการประชุมวิชาการระดับนานาชาติ จำนวนทั้งสิ้น 5 บทความ ตลอดช่วงเวลาที่ผู้ดำเนินการวิจัยได้รับการสนับสนุนจาก สำนักงานกองทุนสนับสนุนการวิจัย สำนักงานคณะกรรมการการอุดมศึกษา และ มหาวิทยาลัยเชียงใหม่ ดังมีรายละเอียดแสดงใน Appendix ซึ่งประกอบด้วยผลงานตีพิมพ์เผยแพร่ ดังนี้

ชื่อเรื่อง : Power Transfer Capability Enhancement with Optimal
Number of FACTS Controllers Using Hybrid TSSA
ชื่อผู้แต่ง : Suppakarn Chansareewittaya and **Peerapol Jirapong**
การประชุมวิชาการ : IEEE SoutheastCon 2012
วันที่ : 15 – 18 March 2012
สถานที่ : Wyndham Orlando Resort Hotel, Orlando, Florida, USA
ฐานข้อมูลอ้างอิง : IEEE *Xplore*

ชื่อเรื่อง : Power Transfer Capability Enhancement with Optimal
Maximum Number of FACTS Controllers Using Evolutionary
Programming
ชื่อผู้แต่ง : Suppakarn Chansareewittaya and **Peerapol Jirapong**
การประชุมวิชาการ : The 37th Annual Conference of the IEEE Industrial
Electronics Society (IECON 2011)
วันที่ : 7 – 10 November, 2011
สถานที่ : Crown Conference Centre, Melbourne, AUSTRALIA
ฐานข้อมูลอ้างอิง : IEEE *Xplore*

ชื่อเรื่อง : Optimal Capacitor Allocation for Power Transfer Capability and Power Loss Improvements in Power Transmission Systems Using Evolutionary Programming

ชื่อผู้แต่ง : Phattarakrit Srisathian and **Peerapol Jirapong**

การประชุมวิชาการ : The 8th International Conference of Electrical Engineering / Electronics, Computer, Telecommunications and Information Technology Association (ECTI-CON 2011)

วันที่ : 17 – 19 May 2011

สถานที่ : Pullman Raja Orchid, Khon Kaen, THAILAND

ฐานข้อมูลอ้างอิง : IEEE *Xplore*

ชื่อเรื่อง : Power Transfer Capability Enhancement with Multi-Type FACTS Controllers Using Particle Swarm Optimization

ชื่อผู้แต่ง : Suppakarn Chansareewittaya and **Peerapol Jirapong**

การประชุมวิชาการ : The International Technical Conference of IEEE Region 10 (TENCON 2010)

วันที่ : 21 – 24 November, 2010

สถานที่ : Fukuoka International Convention Center, Fukuoka, JAPAN

ฐานข้อมูลอ้างอิง : IEEE *Xplore*, ISI Proceedings, EI Compendex

ชื่อเรื่อง : Optimal Choice and Allocation of Distributed Generations Using Evolutionary Programming

ชื่อผู้แต่ง : Rungmanee Jomthong and **Peerapol Jirapong**

การประชุมวิชาการ : The 4th IASTED Asian Conference on Power and Energy Systems (IASTED AsiaPES 2010)

วันที่ : 24 – 26 November 2010

สถานที่ : Novotel Phuket Resort, Phuket, THAILAND

ฐานข้อมูลอ้างอิง : Cambridge Scientific Abstracts, Conference Proceedings Citation Index, EI Compendex, FIZ Karlsruhe, INSPEC

นอกจากนี้ยังได้มีการนำข้อมูลจากการศึกษา และผลงานวิจัยไปใช้เป็นส่วนหนึ่งของการเรียน-การสอน ในกระบวนวิชา EE252723 Computational Techniques in Power System Analysis และ EE252724 Electrical Energy Technology ในระดับบัณฑิตยศึกษาของ คณะวิศวกรรมศาสตร์ มหาวิทยาลัยเชียงใหม่ อีกด้วย

การเชื่อมโยงทางวิชาการกับนักวิชาการอื่น ๆ ทั้งในและต่างประเทศ

ในระหว่างที่ดำเนินการศึกษาวิจัย ได้มีการเชื่อมโยงทางวิชาการกับนักวิชาการท่านอื่น ๆ ดังนี้

- การติดต่อเพื่อขอรับและแลกเปลี่ยนข้อมูลระบบไฟฟ้ากำลัง กับหน่วยงานของการไฟฟ้าที่เกี่ยวข้อง และนักวิชาการท่านอื่น ๆ
- เข้าร่วมงานประชุมทางวิชาการเรื่อง Thailand Smart Grid Smart Utility 2010 ซึ่งจัดขึ้นที่โรงแรม รามา การ์ดैन, กรุงเทพฯ ในระหว่างวันที่ 24 – 25 พฤศจิกายน 2553 เพื่อพบปะและแลกเปลี่ยนความรู้กับนักวิชาการท่านอื่น ๆ
- เข้าร่วมงานสัมมนา การผลักดันผลงานวิจัยสู่การนำไปใช้ประโยชน์ ซึ่งจัดขึ้นที่ ห้องอาวุธ ศรีสุกรี มหาวิทยาลัยเชียงใหม่ ในวันที่ 18 พฤษภาคม 2554
- เข้าร่วมการประชุมวิชาการระดับนานาชาติ เพื่อนำเสนอผลงานและแลกเปลี่ยนความรู้กับนักวิชาการท่านอื่น ๆ จากทั้งในและต่างประเทศ ในช่วงปี พ.ศ. 2553 - 2555

Appendix

Manuscript Acceptance

Requesting Revisions from Author

Final Manuscript

Reprints from Proceedings

IEEE SoutheastCon 2012, USA

The 37th Annual Conference of the IEEE Industrial Electronics Society
(IECON 2011), AUSTRALIA

The 8th International Conference of Electrical Engineering / Electronics,
Computer, Telecommunications and Information Technology
Association (ECTI-CON 2011), THAILAND

The International Technical Conference of IEEE Region 10
(TENCON 2010), JAPAN

The 4th IASTED Asian Conference on Power and Energy Systems
(IASTED AsiaPES 2010), THAILAND

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Subject: Manuscript Number: IJE0E 43 - MANUSCRIPT ACCEPTANCE
From: "EIC IJE0E" <eic.ijeoe@gmail.com>
Date: Tue, June 19, 2012 9:05 pm
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Cc: "EIC IJE0E" <eic.ijeoe@gmail.com>
Priority: Normal
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*MANUSCRIPT ACCEPTANCE *

* *

Dear Professor Jirapong:

We are pleased to inform you that your manuscript IJE0E-00043,* *entitled FACTS Devices Allocation for Power Transfer Capability Enhancement and Power System Losses Reduction has been accepted for publication in an upcoming issue of the International Journal of Energy Optimization and Engineering.

Please also note that we have attached a "Library Recommendation Form" which we would encourage you to use in order to recommend this journal to your institution's librarian.

Thank you for your contribution to this journal. We are pleased to be able to work with you toward your goal of publication. Two complimentary copies of the journal issue containing your manuscript will be sent to you upon publication. If you have any questions, please feel free to contact us.

Sincerely,

P. Vasant, Ph.D

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****REQUESTING REVISIONS FROM AUTHOR****

Dear Professor Peerapol Jirapong;

The review of your manuscript IJEOE-00043, entitled FACTS Devices Allocation for Power Transfer Capability Enhancement and Power System Losses Reduction*, *has been completed. Although our reviewers find the topic to be important, they believe that the coverage should be strengthened before the manuscript can be accepted for publication in the International Journal of Energy Optimization and Engineering.

We have included all pertinent comments provided by the reviewers for your use, including the Associate Editor's report. Please study the comments carefully and incorporate the changes into your revised version. Once you have completed the revisions, please forward

*1) An electronic copy of your updated manuscript in MS WORD file and *

* *

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FACTS Devices Allocation for Power Transfer Capability Enhancement and Power System Losses Reduction

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ABSTRACT

In this paper, a hybrid evolutionary algorithm (HEA) is proposed to determine the optimal placement of multi-type flexible AC transmission system (FACTS) devices to simultaneously maximize the total transfer capability (TTC) and minimize the system real power loss of power transfers in deregulated power systems. Multi-objective optimal power flow (OPF) with FACTS devices including TTC, power losses, and penalty functions is used to evaluate the feasible maximum TTC value and minimum power loss within real and reactive power generation limits, thermal limits, voltage limits, stability limits, and FACTS devices operation limits. Test results on the modified IEEE 30-bus system indicate that optimally placed OPF with FACTS by the HEA approach could enhance TTC far more than those from evolutionary programming (EP), tabu search (TS), hybrid tabu search and simulated annealing (TS/SA), and improved evolutionary programming (IEP) algorithms, leading to much efficient utilization of the existing transmission systems.

Keywords: total transfer capability; flexible AC transmission system; hybrid evolutionary algorithm; optimal power flow; evolutionary optimization

INTRODUCTION

In competitive electric power markets, electric utilities have to operate closer to their limits, causing unpredictable line loading, voltage variations, and stability problems. Flexible AC transmission system (FACTS) devices are used to provide direct control of power flows over designated transmission routes and increase power transfer capability of the transmission networks, resulting in a lower system loss, stability enhancement, operating cost reduction, and fulfilled contractual requirements (Hingorani & Gyugyi, 1999). The extent of these benefits depends upon where these devices are placed and how they are controlled in the systems, which in turn requires efficient methodologies to solve the optimal FACTS placement problems. This is an important aspect in the context of growing energy demand and the emergence of energy trading markets.

Available transfer capability is a measure of the transfer capability remaining in a physical transmission network for further commercial activity over and above already committed uses (Maliszewski, Rozier & Cummings, 1996). Electrical power transfer capability calculation is required for each control area and posted on a public communication system for open-access of a transmission network to deliver electric energy (Withnell, Leahy & Coleman, 1996). Mathematically, available transfer capability is defined as the total transfer capability (TTC) less the transmission reliability margin, less the sum of existing

transmission commitments and the capacity benefit margin. TTC is defined as the amount of electric power that can be transferred over the transmission network in a reliable manner while meeting all of a specific set of defined pre- and post-contingency system conditions (Maliszewski, Rozier & Cummings, 1996). Transmission reliability margin and capacity benefit margin are two transmission margins considering the inherent reliability and uncertainty in the transmission system.

Accurate determination of TTC is essential to maximize utilization of the existing transmission network while maintaining system security. Underestimated TTC may lead to under-utilization of transmission system, while overestimated TTC could lower system reliability. Wide varieties of mathematical methods such as: 1) linear method based on linear incremental DC load flow approximation considering only thermal limits (Ejebe, Waight, Nieto & Tinney, 2000), 2) continuation power flow based on the continuation method to trace load flow solution curve through the maximum loading point (Ejebe *et al.*, 1998), 3) repetitive power flow based on repeated load flow calculations to establish the maximum transfer capability (Gravener & Nwankpa, 1999), and 4) a bifurcation approach for assessing dynamic TTC considering transient stability limits (Kumar, Srivastava & Singh, 2004) have been developed for TTC computations. In addition, optimal power flow (OPF) based methods, which can be implemented by traditional optimization techniques have been proposed to calculate TTC with various degrees of success (Ou & Singh, 2002; Shaaban, Li, Yan, Ni & Wu, 2003).

These methods require convexity of objective function to obtain the optimal solution. However, the OPF problem is generally nonlinear and nonconvex optimization problem and, as a result, many local solutions may exist especially in power systems with embedded FACTS devices (Wong, Yuryevich & Li, 2003). FACTS parameters are additional control variables that cannot be effectively solved by conventional optimization methods because these parameters will change the admittance matrix. Therefore, conventional techniques may converge to local optimal solutions or diverge altogether (Lai, 1998).

In recent years, power transfer capability enhancement (Ou & Singh, 2001; Xiao, Song, Liu & Sun, 2003) and power losses reduction (Chung & Shaoyun, 1998) using multi-type FACTS devices are significant because of competition enhancement and efficient existing transmission system utilization. Sensitivity index approaches have been commonly used to determine suitable locations of FACTS devices for maximizing TTC (Verma, Singh & Gupta, 2001) or minimizing power losses (Preedavichit & Srivastava, 1998). However, these methods may not lead to the optimal solution because of dependency to system topology and loading conditions.

With the advent of evolutionary computation, genetic algorithm combined with continuation power flow method is used to determine the optimal placement of thyristor-controlled series capacitor (TCSC) for maximizing TTC (Feng & Shrestha, 2001). Genetic algorithm is used to search for the optimal location and parameter of TCSC while continuation power flow is used to evaluate the TTC value with the optimally placed TCSC subject to thermal and voltage limits. For the optimal placement of multi-type FACTS devices, floating point genetic algorithm is used to simultaneously search for locations, types, and parameters of TCSC, static var compensator (SVC), thyristor-controlled phase shifter (TCPS), and thyristor-controlled voltage regulator (Gerbex, Cherkaoui & Germond, 2001). The optimization strategy based on repetitive power flow method is performed to determine the maximum system loadability subject to thermal and voltage limits. However, using continuation and repetitive power flow methods may lead to a conservative TTC value because these methods do not result in the optimal generation, loading, and generator bus voltages. Furthermore, optimally placed OPF with FACTS problem is generally a combinatorial optimization problem (Cai, Erlich & Stamtis, 2004), which may not be

effectively solved by either conventional methods or a single evolutionary computation technique.

In this paper, a new hybrid evolutionary algorithm (HEA) is proposed to determine the optimal placement of multi-type FACTS devices to simultaneously maximize TTC and minimize power losses of power transactions between different control areas without violating system constraints. The proposed algorithm is tested on the modified IEEE 30-bus system. Test results are compared with those from evolutionary programming (Wong, Yuryevich & Li, 2003), tabu search (Abido, 2002), hybrid tabu search and simulated annealing (Ongsakul & Bhasaputra, 2002), and improved EP (Jirapong & Ongsakul, 2009) algorithms.

PROBLEM FORMULATION

Multi-objective OPF with FACTS devices including TTC, system real power losses, and penalty functions in (1) is used to evaluate the feasible TTC value that can be transferred from a specific set of generators in a source area to loads in a sink area within real and reactive power generation limits, thermal limits, voltage limits, steady-state stability limits, and FACTS devices operation limits. Real and reactive power balance equations with the expression of FACTS devices parameters are shown in (2) and (3), respectively. Four types of FACTS devices are included: SVC, TCSC, TCPS, and unified power flow controller (UPFC). TCSC is modeled by the adjustable series reactance. TCPS and UPFC are modeled using the injected power model (Ongsakul & Bhasaputra, 2002). SVC is modeled as shunt-connected static var generator or absorber.

$$\text{Maximize} \quad F = \sum_{i=1}^{ND-SNK} P_{Di} - \sum_{i=1}^N (P_{Gi} - P_{Di}) - PF \quad (1)$$

Subject to

$$P_{Gi} - P_{Di} + \sum_{k=1}^{m(i)} P_{Pi}(\alpha_{Pk}) + \sum_{k=1}^{n(i)} P_{Ui}(V_{Uk}, \alpha_{Uk}) - \sum_{j=1}^N V_i V_j Y_{ij}(X_S) \cos(\theta_{ij}(X_S) - \delta_i + \delta_j) = 0 \quad (2)$$

$$Q_{Gi} - Q_{Di} + \sum_{k=1}^{m(i)} Q_{Pi}(\alpha_{Pk}) + \sum_{k=1}^{n(i)} Q_{Ui}(V_{Uk}, \alpha_{Uk}) + Q_{Vi} + \sum_{j=1}^N V_i V_j Y_{ij}(X_S) \sin(\theta_{ij}(X_S) - \delta_i + \delta_j) = 0 \quad (3)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (4)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (5)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (6)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (7)$$

$$VCPI_i \leq 1 \quad \forall i \in N \quad (8)$$

$$|\delta_{ij}| \leq \delta_{ij}^{\text{crit}} \quad \forall i \in NL \quad (9)$$

$$X_{Si}^{\min} \leq X_{Si} \leq X_{Si}^{\max} \quad (10)$$

$$\alpha_{Pi}^{\min} \leq \alpha_{Pi} \leq \alpha_{Pi}^{\max} \quad (11)$$

$$V_{Ui}^{\min} \leq V_{Ui} \leq V_{Ui}^{\max} \quad (12)$$

$$\alpha_{Ui}^{\min} \leq \alpha_{Ui} \leq \alpha_{Ui}^{\max} \quad (13)$$

$$Q_{Vi}^{\min} \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (14)$$

Where

F	multi-objective function,
PF	penalty function,

Input Variables

$P_{Gi}^{\min}, P_{Gi}^{\max}$	lower and upper limits of real power generation at bus i (kW),
$Q_{Gi}^{\min}, Q_{Gi}^{\max}$	lower and upper limits of reactive power generation at bus i (kVAr),
$V_i^{\min}, V_i^{\max}$	lower and upper limits of voltage magnitude at bus i (pu),
$S_{Li}^{\max}$	i th line or transformer loading limit (kVA),
$\delta_{ij}^{\text{crit}}$	critical angle difference between bus i and j (degree),
$X_{Si}^{\min}, X_{Si}^{\max}$	lower and upper limits of TCSC at line i (pu),
$\alpha_{Pi}^{\min}, \alpha_{Pi}^{\max}$	lower and upper limits of TCPS at line i (rad),
$V_{Ui}^{\min}, V_{Ui}^{\max}$	lower and upper voltage limits of UPFC at line i (pu),
$\alpha_{Ui}^{\min}, \alpha_{Ui}^{\max}$	lower and upper angle limits of UPFC at line i (rad),
$Q_{Vi}^{\min}, Q_{Vi}^{\max}$	lower and upper limits of SVC at bus i (kVAr),
N, NL	number of buses and branches,
NG	number of generator buses,
ND_SNK	number of load buses in a sink area,

State Variables

V_i, V_j	voltage magnitudes at bus i and j (pu),
δ_i, δ_j	voltage angles of bus i and j (degree),
P_{G1}, Q_{G1}	real and reactive power generations at slack bus (kW),

Output Variables

P_{Gi}, Q_{Gi}	real and reactive power generations at bus i (kW),
P_{Di}, Q_{Di}	real and reactive loads at bus i (kW),
$P_{Pi}(\alpha_{Pk})$	injected real power of TCPS at bus i (kW),
$Q_{Pi}(\alpha_{Pk})$	injected reactive power of TCPS at bus i (kVAr),
$P_{Ui}(V_{Uk}, \alpha_{Uk})$	injected real power of UPFC at bus i (kW),
$Q_{Ui}(V_{Uk}, \alpha_{Uk})$	injected reactive power of UPFC at bus (kVAr),
$Y_{ij}(X_S)$	magnitude of ij th element in bus admittance matrix with TCSC included (pu),
$\theta_{ij}(X_S)$	angle of the ij th element in bus admittance matrix with TCSC included (rad),
$m(i)$	number of injected power from TCPS at bus i ,
$n(i)$	number of injected power from UPFC at bus i ,
$ S_{Li} $	i th line or transformer loading (kVA),
$VCPI_i$	voltage collapse proximity indicator at bus i ,
$ \delta_{ij} $	angle difference between bus i and j (degree),
X_{Si}	reactance of TCSC at line i (pu),
α_{Pi}	phase shift angle of TCPS at line i (rad),
V_{Ui}, α_{Ui}	voltage magnitude (pu) and angle (rad) of UPFC at line i , and
Q_{Vi}	injected reactive power of SVC at bus i (kVAr).

Voltage collapse proximity indicator is used to directly determine voltage collapse conditions within voltage stability limits. A procedure for calculating the indicator can be found in (Han, Zheng, Tian & Hou, 2009). Angle stability constraints considered can be either static or dynamic (Canizares, 2000; Yuan, Kubokawa, Nagata & Sasaki, 2003). This

paper considers only static angle stability constraint. Critical angle displacement is used as a criterion to determine angle stability limit. For a reasonable level of typical heavy line loading situations, it is assumed that the angle difference between bus i and j across a transmission line is kept within a critical angle difference which is 44° as recommended in (He, Kolluri, Mandal Galvan, 2004). Voltage and angle stability limits are treated as OPF variables in (8) and (9), respectively. During the optimization, inequality constraints are enforced using a penalty function in (15).

$$PF = k_p h(P_{G1}) + k_q \sum_{i=1}^{NG} h(Q_{Gi}) + k_v \sum_{i=1}^N h(V_i) + k_s \sum_{i=1}^{NL} h(|S_{Li}|) + k_d \sum_{p=1}^{NL} h(|\delta_{ij,p}|) \quad (15)$$

$$h(x) = \begin{cases} (x - x^{\max})^2 & \text{if } x > x^{\max} \\ (x^{\min} - x)^2 & \text{if } x < x^{\min} \\ 0 & \text{if } x^{\min} \leq x \leq x^{\max} \end{cases} \quad (16)$$

Where

k_p	penalty coefficient for real power generation at slack bus,
k_q	penalty coefficient for reactive power generation of all PV buses and slack bus,
k_v	penalty coefficient for bus voltage magnitude,
k_s	penalty coefficient for line loading,
k_d	penalty coefficient for angle difference, and
$x^{\min}, x^{\max}$	lower and upper limits of variable x .

Two types of transactions (Kumar, Srivastava & Singh, 2004) are considered:

Bilateral transaction: A bilateral transaction is made directly between a seller and a buyer. The seller injects a certain amount of power at one generator bus and the buyer receives this power at the other load bus. Mathematically, each bilateral transaction satisfies the power balance relationship in (17).

$$P_{Gi} - P_{Dj} = 0 \quad (17)$$

Multilateral Transaction: A multilateral transaction trading among several parties is arranged by a scheduling coordinator. Mathematically, a multilateral transaction involving several sellers and buyers can be expressed in (18).

$$\sum_{i \in S} P_{Gi} - \sum_{j \in B} P_{Dj} = 0 \quad (18)$$

Where

P_{Gi}	real power generation at bus i in a source area (kW),
P_{Dj}	real power load at bus j in a sink area (kW),
S	set of sellers who sell the power to buyers,
B	set of buyers who buy the power from sellers.

Considering base case configuration, let TTC_0 be the maximum amount of power

transfer without contingency constraints. Similarly, let TTC_k be the maximum amount of power transfer under the contingency k . Therefore, a feasible contingency TTC value is given in (19). The limiting condition on some portions of the systems can shift among thermal, voltage, and voltage and angle stability limits as the network operating conditions change over time, which is illustrated in Figure 1. TTC must be evaluated from the most restrictive of these limitations.

$$TTC = \text{Min}\{TTC_0, TTC_1, \dots, TTC_k\} \quad (19)$$

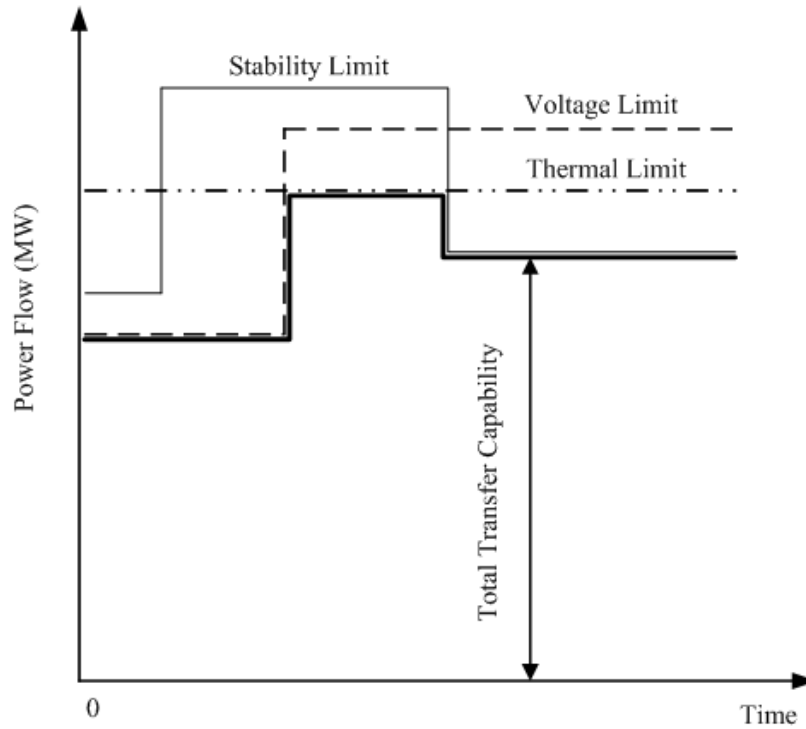


Figure 1. Limits to TTC

COMPUTATIONAL INTELLIGENCE

Computational intelligence is a set of nature-inspired computational methodologies and approaches to address complex problems to which traditional methodologies are ineffective or infeasible. The main advantage of using intelligence search lies in the gain of flexibility and adaptability to the task at hand, in combination with robust performance and global search characteristics. The majority of current implementations of computational intelligence algorithms descend from three strongly related but independently developed approaches: evolutionary programming, tabu search, and simulated annealing.

Evolutionary Programming

Evolutionary programming (EP) is originally developed as a stochastic optimization method in the area of evolutionary computation, which uses the mechanics of evolution to produce optimal solutions to a given problem. The EP algorithm starts with random generation of initial individuals in a population and then the mutation and selection are preceded until the best individual, which has the highest fitness, is found (Ongsakul and Jirapong, 2004).

Tabu Search

Tabu search (TS) is a higher level heuristic algorithm called metaheuristic for solving combinatorial optimization problems (Abido, 2002). It is an iterative improvement procedure that starts from any initial solution and attempts to determine a better solution. Opposite to randomizing approaches such as simulated annealing where randomness is widely used, TS is characterized by its ability to avoid the entrapment in local optimal solution and prevent cycling by using flexible memory of search history (Kamboj and Sengupta, 2009). TS uses a local or neighborhood search procedure to iteratively move from one potential solution to an improved solution, until some stopping criterion has been satisfied.

Simulated Annealing

Simulated annealing (SA) is a generic probabilistic metaheuristic based on the annealing process in the statistical mechanics for solving optimization problems. The SA strategy starts with a high temperature giving a high probability to accept non-improving movements. The temperature and probability levels diminish as long as the algorithm advances to the optimal solution. Therefore, SA has the ability to escape from local minima by accepting non-improving energy solutions during the first and medium stages of the algorithm (Sepulveda and Lazo, 2003). The main drawback of SA procedure is that the annealing procedure is very time consuming.

Several computational intelligence techniques have evolved in the last decades that facilitate solving many optimization problems that are previously difficult or impossible to solve. Recently, new evolutionary computation and heuristic techniques have been combined among themselves and with other traditional approaches to solve complicated optimization problems. Principles of some hybrid algorithms are summarized in the following section.

Hybrid Tabu Search and Simulated Annealing

A hybrid tabu search and simulated annealing (TS/SA) approach is a hybrid algorithm of TS and SA by using TS as the main algorithm (Bhasaputra and Ongsakul, 2006). The perturbation of the TS/SA imitates from SA algorithm and the aspiration criterion is adapted by using probabilistic acceptance criterion of SA instead of aspiration level of TS. The cooling schedule of SA is also applied in the perturbation.

Improved Evolutionary Programming

An improved evolutionary programming (IEP) is a hybrid algorithm of EP and SA by using EP as the main algorithm (Jirapong and Ongsakul, 2009). IEP balances the explosion by dividing the population into subpopulations. Multiple mutation operators are employed to enhance the search diversity. The selection mechanism with probabilistic updating strategy based on annealing schedule of SA is utilized to avoid being trapped in local optimum. Reassignment strategy for individuals is designed for every subpopulation to fuse information and enhance population diversity.

HYBRID EVOLUTIONARY ALGORITHM

To improve the robustness of conventional evolutionary computation and metaheuristic techniques (Back, Hammel & Schwefel, 1997; Bansal, Bhatti & Kothari, 2003), a new hybrid evolutionary algorithm (HEA) approach integrating EP, TS, and SA algorithms is proposed. The HEA has special features and merits described as follows:

- 1) Multiple population search with various mutation operators is designed to enhance search diversity and improve population update, providing higher quality of solutions than those from single population search.
- 2) Reassignment strategy is carried out to fuse and exchange the search information of all subpopulations so that premature convergence caused by consistency of individuals in a single population will be alleviated.
- 3) Selection with a probabilistic updating strategy based on TS and annealing schedule of SA is applied to avoid dependency on fitness function and to avoid being trapped in local optimal solutions.
- 4) The algorithm can easily facilitate parallel implementation on parallel computers to reduce the elapsed time without sacrificing the quality of solution.

The HEA is used to simultaneously search for real power generations in a source area excluding slack bus, generation bus voltages, real power loads in a sink area, and optimal placement of multi-type FACTS devices for determining the feasible TTC value. A flowchart of the HEA approach is shown in Figure 2, which can be explained as follows:

Representation of Solution

Each individual consists of OPF control variables coded by real number. The whole population P is divided into M subpopulations according to the number of mutation operators used. The p th individual in a population is represented by a trial vector in (20). There are four types of FACTS devices with allowable maximum n_{CFk} component for each type, which is assigned as input data. The placement configuration is represented by three parameters: n_{CFk} , $location_k$, and $parameter_k$ given in (21). For FACTS type $k \in \{1,2,3,4\}$ representing placement configuration of TCSC, TCPS, UPFC and SVC, respectively, the number of FACTS component type k , $n_{CFk} = \{0,1,...,n\}$. More specifically, there is either no FACTS type k if $n_{CFk}=0$ or a number of FACTS type k if $n_{CFk} \neq 0$. Therefore, number of FACTS components, locations, and parameters of each type of FACTS devices are simultaneously searched by the HEA. Note the searched locations and parameters of FACTS type k is valid only when $n_{CFk} \neq 0$.

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}, Loc_k] \quad (20)$$

$$Loc_k = [n_{CFk}, location_k, parameter_k] \quad (21)$$

Where

S_p	trial solution vector of the p th individual,
V_{Gi}	voltage magnitude of generator at bus i including slack bus,
Loc_k	allocation vector of FACTS device type k ,
n_{CFk}	number of FACTS components, $n_{CFk} = \{0,1,...,n\}$,
$location_k$	line or bus location of FACTS type k , and
$parameter_k$	parameter settings of FACTS type k .

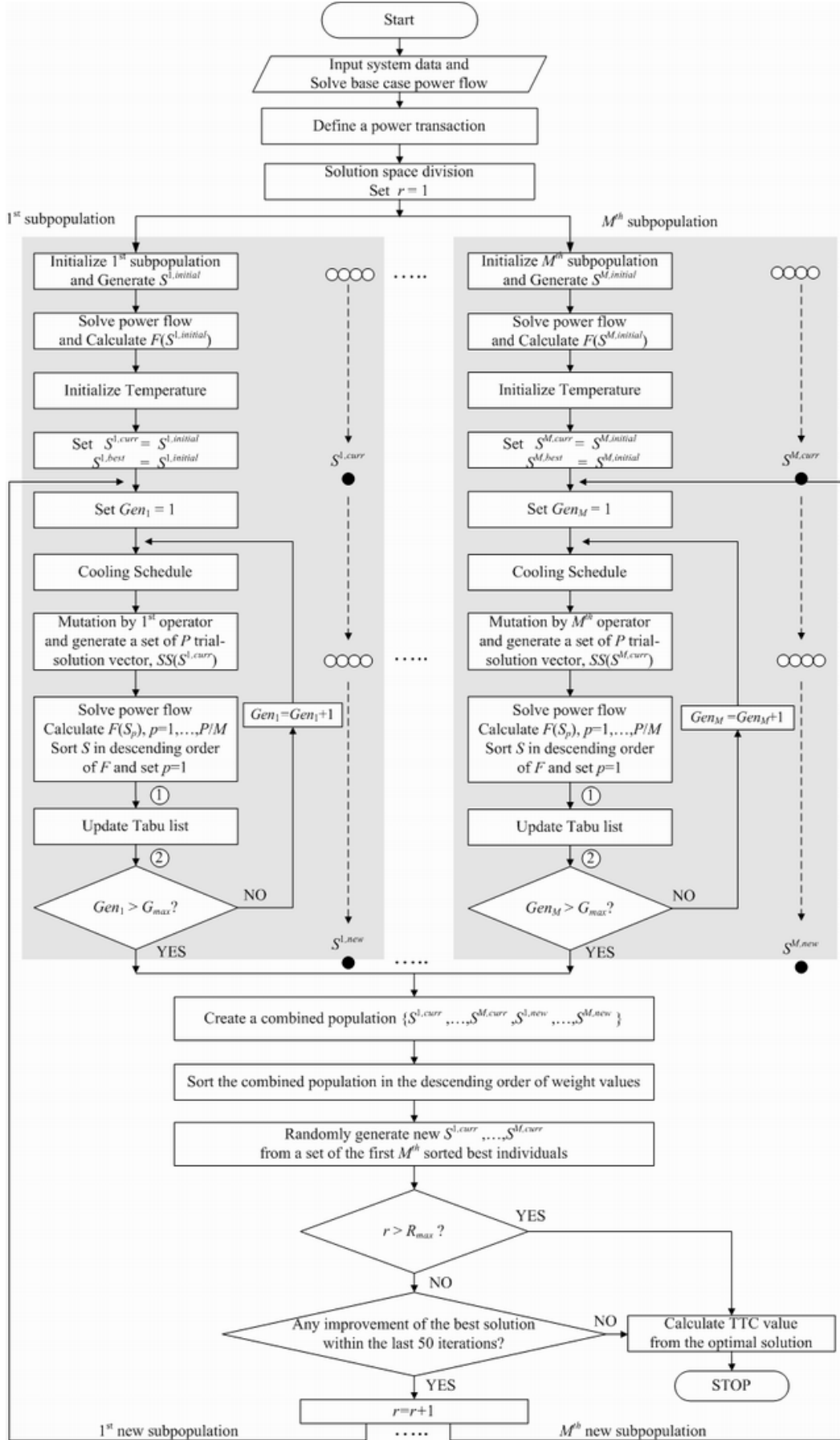


Figure 2. A flowchart of the HEA approach

Initialization

Each element of the trial vector is initialized randomly within its search space using uniform random number in (22).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \quad (22)$$

Where

x_i i th element of the individual in a population,
 $x_i^{\min}, x_i^{\max}$ lower and upper limits of the i th element of the individual, and
 u uniform random number in the interval [0,1].

Power Flow Solution

During iterations, a full AC Newton-Raphson power flow analysis is used to check the feasibility of each individual solution.

Fitness Function

The extended objective function in (1) is taken as the fitness function of the HEA approach.

Cooling Schedule Procedure

The initial temperature of each subpopulation is determined in (23). The temperature is cooled down by the temperature annealing function in (24).

$$T_{0,m} = -(F_m^{\max} - F_m^{\min}) / \ln p_r \quad (23)$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \quad (24)$$

Where

$T_{0,m}$ initial temperature of the m th subpopulation,
 $F_m^{\min}, F_m^{\max}$ objective value of the worst and the best individuals in the m th subpopulation,
 p_r probability of accepting the worst individual with respect to the best individual,
 $T_{r,m}$ annealing temperature of the m th subpopulation after the r th reassignment,
 λ rate of cooling, and
 r iteration counter of reassignment strategy.

Mutation

In different subpopulations, different mutation operators are used to create new offspring subpopulation so that many hybrid operators are applied to enhance the search diversity. Two mutation operators including Gaussian and Cauchy are applied. Each element of the offspring is calculated in (25).

$$x'_{k,i} = x_{k,i} + \sigma_{k,i} \cdot \xi_m \quad (25)$$

$$\sigma_{k,i} = T_{r,m} \cdot a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \quad (26)$$

Where

$x'_{k,i}$ i th element of the k th offspring individual,
 $x_{k,i}$ i th element of the k th parent individual,
 $\sigma_{k,i}$ mutation step size for the i th element of the k th individual,

ξ_m	mutation operator of the m th subpopulation e.g. $N(0,1)$, $C(0,1)$, etc.,
$N(0,1)$	Gaussian random number with mean 0 and standard deviation 1,
$C(0,1)$	Cauchy random number,
a	positive number slightly less than one,
$x_i^{\max}, x_i^{\min}$	subinterval's or interval's upper and lower limits of the i th element of the individual.

Tabu List

Tabu list is a finite length one-in one-out first-in first-out structure, which records a set of current best solutions visited. A new trial vector is placed on top of the list and the oldest trial vector is taken out of the list.

Aspiration Criterion

The aspiration criterion in (27) adopts a probabilistic acceptance criterion of SA. When the probabilistic acceptance criterion is higher than a uniform randomly generated variable in the interval $[0,1]$, the tabu restriction is overruled.

$$p_{k,m} = 1 / (1 + \exp(-\Delta / T_{r,m})) \quad (27)$$

Where

$p_{k,m}$	probabilistic acceptance criterion of the k th offspring individual within the m th subpopulation, and
Δ	difference of objective values between the k th offspring individual and its corresponding parent individual, i.e. the k th parent individual.

Reassignment Strategy

Tournament scheme is used to select new current parent population from the combined population of current parent ($S^{1,curr}, \dots, S^{M,curr}$) and new offspring ($S^{1,new}, \dots, S^{M,new}$) individuals of all subpopulations. Each individual in the combined population is assigned a weight value according to the competition in (28).

$$w_k = \sum_{t=1}^{N_t} \begin{cases} 1 & \text{if } F_k > F_r \\ 0 & \text{otherwise} \end{cases} \quad (28)$$

Where

w_k	weight value of k th individual in combined population,
F_k	fitness value of k th individual in combined population,
F_r	fitness value of r th opponent randomly selected from the combined population based on $r = \lfloor 2 \cdot M \cdot u + 1 \rfloor$, and
N_t	number of competitors.

After sorting the combined population of $2M$ individuals in the descending order of weight values, each new current parent solution individual of all subpopulations will be randomly selected from a set of the first M th sorted best solution individuals.

Termination Criteria

There are three termination criteria in the proposed HEA approach. The first termination criterion is set as the maximum number of generations of each subpopulation and the second termination criterion is the number of reassignment required. The algorithm will be stopped if

there is no improvement of the best fitness within 50 generations as the third termination criterion.

CASE STUDY AND TEST RESULTS

The modified IEEE 30-bus system is used to demonstrate the optimal placement of multi-type FACTS devices using the HEA approach. The HEA is implemented using MATLAB version 6.5 on an AMD Athlon64 X2 3600+ computer with 1.0 GB memory. Parameter settings of the proposed algorithm suggested in (Lai, 1998) are utilized. Test results from HEA are compared to those from EP (Wong, Yuryevich & Li, 2003), TS (Abido, 2002), hybrid TS/SA (Ongsakul & Bhasaputra, 2002), and IEP (Jirapong & Ongsakul, 2009) methods. The reactance limit of TCSC in p.u. is $0 \leq X_{si} \leq 60\%$ of line reactance; phase shifting angle limit of TCPS is $-\pi/4 \leq \alpha_{pi} \leq \pi/4$ radian; voltage limit of UPFC is $0 \leq V_{ui} \leq 0.1$ p.u.; angle limit of UPFC is $-\pi \leq \alpha_{ui} \leq \pi$ radian; and reactive power injection limit of SVC is $-10 \leq Q_{vi} \leq 10$ MVar. Loads are modeled as constant power factor loads.

The modified IEEE 30-bus system in Figure 3 is partitioned into three areas with two generators in each area (Zimmerman, Sanchez & Gan, 2007). Two transactions including a bilateral transaction from bus 2 to 21 and a multilateral transaction from area 1 to 3 are considered.

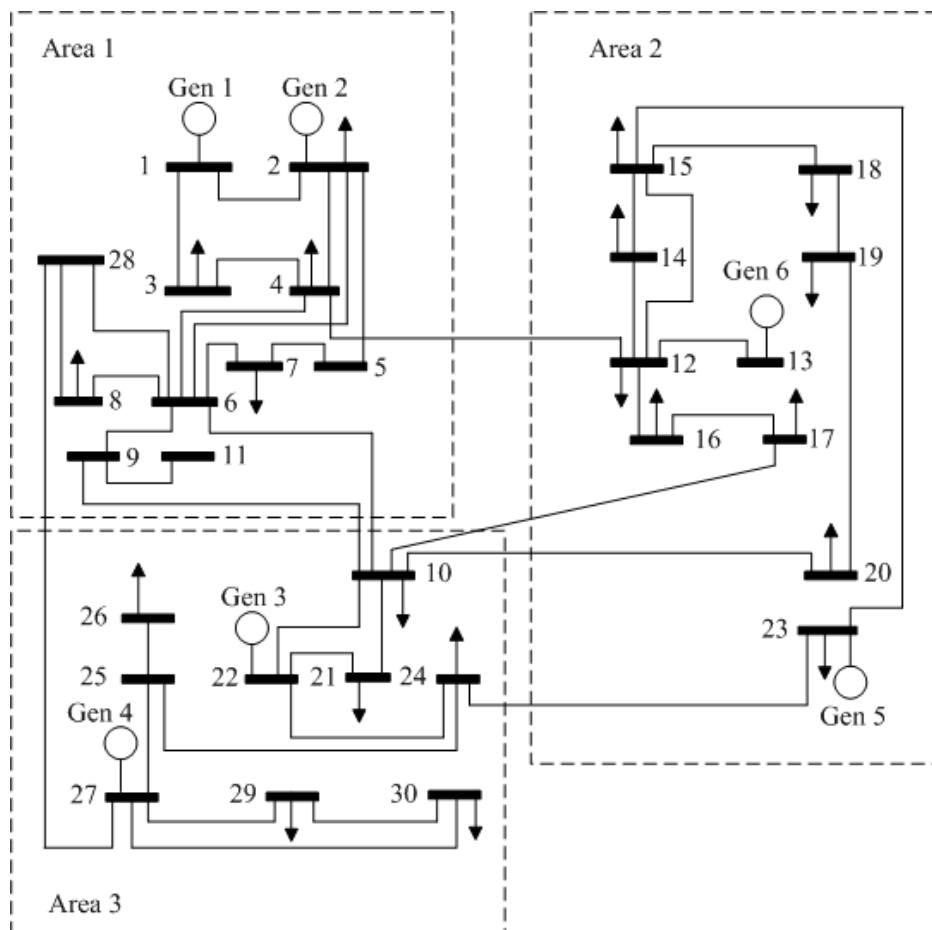


Figure 3. Diagram of the modified IEEE 30-bus system

Bilateral Transaction

For the bilateral transaction with optimally placed FACTS devices using HEA method, TTC value is 43.65 MW without violating system constraints, which is increased by 89.62% compared to that without FACTS devices shown in Table 1. In addition, the TTC value is 41.45%, 51.04%, 40.72%, and 10.39% more than those from EP, TS, TS/SA, and IEP methods, respectively.

Table 1. TTC values on the modified IEEE 30-bus system

Method	Bilateral Transaction				Multilateral Transaction			
	Without FACTS		With FACTS		Without FACTS		With FACTS	
	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)	TTC (MW)	Loss (MW)
EP	23.02	2.63	30.86	2.67	79.48	4.03	90.51	4.98
TS	23.02	2.63	28.90	2.78	78.84	4.23	101.14	5.71
TS/SA	23.02	2.63	31.02	2.89	79.44	3.97	103.96	5.79
IEP	23.02	2.63	39.54	1.89	79.45	3.99	104.10	4.17
HEA	23.02	2.63	43.65	2.15	79.61	3.98	111.92	5.85

Multilateral Transaction

For the multilateral transaction with optimally placed FACTS devices using HEA method, TTC value is 111.92 MW, which is increased by 40.59% compared to that without FACTS devices. In addition, the TTC value is 23.65%, 10.66%, 7.66%, and 7.51% more than those from EP, TS, TS/SA, and IEP, respectively. The optimal placements of FACTS devices are shown in Table 2.

Table 2. Optimal placement of FACTS devices of multilateral transaction

Method	TCSC			TCPS			UPFC			SVC		
	n_{CF1}	$location_1$	X_S (pu)	n_{CF2}	$location_2$	α_p (rad)	n_{CF3}	$location_3$	α_{ij} (rad), V_U (pu)	n_{CF4}	$location_4$	Q_V (MVar)
EP	1	Line No. 24-25	0.017	1	Line No. 1-2	0.058	1	Line No. 2-6	2.579, 0.068	1	Bus No. 21	8.174
TS	1	Line No. 15-23	0.023	1	Line No. 2-4	0.010	1	Line No. 10-21	0.724, 0.038	1	Bus No. 25	0.474
TS/SA	1	Line No. 8-28	0.051	1	Line No. 1-2	0.019	1	Line No. 2-4	2.014, 0.051	1	Bus No. 28	1.968
IEP	0	-	-	1	Line No. 6-9	0.092	1	Line No. 9-10	1.458, 0.041	1	Bus No. 25	0.287
HEA	0	-	-	1	Line No. 6-8	0.013	1	Line No. 6-7	1.737, 0.059	1	Bus No. 24	6.353

Comparisons of TTC results and average CPU times from 20 runs are shown in Table 3. The reported CPU time is the total computation time of HEA approach from starting to ending including the Newton-Raphson power flow of all individuals. The HEA can obtain better results on the best, average, and the worst TTC values than those from the other methods. Furthermore, the variation of the HEA best solution is smaller as evidenced by a smaller standard deviation, leading to a more stable HEA approach. To compare the convergence characteristic, IEP and HEA utilize a probabilistic updating strategy based on annealing schedule of SA, resulting in more generations required and slower convergence characteristic than EP, TS, and TS/SA methods as shown in Figure 4.

Table 3. Optimal TTC values with FACTS devices and CPU times

Method	Bilateral Transaction with FACTS					Multilateral Transaction with FACTS				
	TTC			Standard Deviation	CPU Time (min)	TTC			Standard Deviation	CPU Time (min)
	Best	Average	Worst			Best	Average	Worst		
EP	30.86	27.14	22.91	3.08	1.13	90.51	84.33	75.41	4.87	2.00
TS	29.34	27.15	22.93	2.81	1.17	101.14	86.25	76.96	8.99	1.85
TS/SA	31.02	26.87	22.95	2.57	0.91	103.96	97.33	81.04	7.55	1.55
IEP	39.54	32.23	26.12	5.40	1.52	104.10	93.32	73.72	9.76	2.88
HEA	43.65	34.05	26.50	5.38	1.51	111.92	102.56	88.78	5.58	2.72

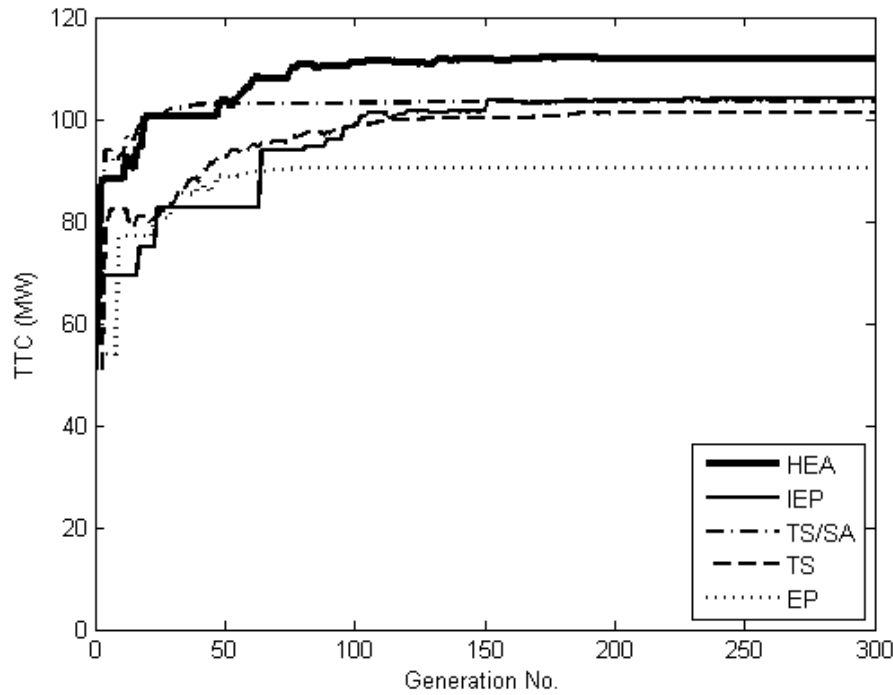


Figure 4. Convergence characteristic of solutions

CONCLUSION

The proposed HEA method could efficiently and effectively determine the optimal placement of multi-type FACTS devices to simultaneously maximize TTC and minimize system power losses of power transactions in deregulated power systems, resulting in higher TTC values than those from EP, TS, hybrid TS/SA, and IEP algorithms. In addition, test results indicate that optimally placed OPF with multiple and multi-type FACTS devices by the HEA approach could enhance the TTC values far more than OPF without FACTS devices, leading to a higher trading level of energy transactions in a normal secured system.

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Total Transfer Capability Enhancement with Optimal Number of FACTS Controllers Using Hybrid TSSA

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Abstract— In this paper, hybrid tabu search and simulated annealing (TSSA) with search space managing methods are proposed to determine the optimal number and allocation of FACTS controllers to enhance power transfer capability of power transactions between generators and loads in power systems. Particular optimal allocation includes optimal locations and parameter settings. Two types of FACTS controllers including thyristor-controlled series capacitor (TCSC) and static var compensator (SVC) are used individually. The objective function is formulated as maximizing total transfer capability (TTC) and minimizing power losses. Power transfer capability determinations are calculated based on the optimal power flow (OPF) technique. Split and non-split search space managing methods are used to improve the solution searching capability. Test results on IEEE 118-bus system and the practical Electricity Generating Authority of Thailand (EGAT) 58-bus system show that the proposed hybrid TSSA with optimal number of FACTS criteria and the split search space managing method give higher TTC and less number of FACTS controllers than those from evolutionary programming (EP) and non-split search space method.

Keywords—component; Evolutionary Computing, Tabu Search, Simulated Annealing, Flexible AC Transmission System, Load Flow

I. INTRODUCTION

Demands for electrical energy increase every year, so the installation of new power plants, distributed generations, and expanding transmission lines may respond to these increasing demands. However, these utilities have some disadvantages such as the pollution control, the high cost of installations and operations, and the land acquisitions. In the other hand, using Flexible AC Transmission System (FACTS) controllers provide advantages such as none pollution, less cost of installations and operations, and providing flexible control of the existing transmission system.

FACTS controllers are power electronics based system and other static equipment that have the capability of controlling various electrical parameters in transmission networks. These parameters can be adjusted to provide adaptability conditions of transmission network. There are many types of FACTS controllers such as thyristor-controlled series capacitor (TCSC), static var compensator (SVC), thyristor controlled phase shifting transformer (TCPST), and unified power flow controller (UPFC) [1]. These FACTS controllers have been

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proved that they can be used to enhance system controllability resulting in total transfer capability (TTC) enhancement and minimizing power losses in transmission networks [2].

TTC is defined as an amount of electric power that can be transferred over the interconnected transmission network in a reliable manner while meeting all of a set of defined pre and post-contingency system conditions [3]. TTC can be calculated by several power flow solution methods such as linear ATC (LATC) method [4], continuation power flow (CPF) method [5], repetitive power flow (RPF) method [6], and optimal power flow (OPF) based methods [7].

The maximum performance of using FACTS controllers to increase TTC and minimize losses should be obtained by choosing the optimal types, numbers, parameter settings, and locations in transmission systems. Modern heuristics optimization techniques such as genetic algorithm (GA), evolutionary programming (EP), particle swarm optimization (PSO), tabu search (TS), and simulated annealing (SA) are successfully implemented to solve complicated optimization problems efficiently and effectively [8]. The optimal allocation of four types of FACTS controllers including TCSC, SVC, TCPST, and UPFC using GA are presented in [9]. Simulation results validate the efficiency of this approach in minimizing the overall system cost function, including generation costs, and investment costs of FACTS controllers. In [10], the optimal allocations of four types of FACTS controllers are determined by EP. Test results indicate that optimally placed OPF with FACTS controllers by EP can enhance the TTC more than OPF without FACTS controllers. In [11], PSO is used to determine type, locations, and parameter of multi-type FACTS controllers to achieve maximum benefit to cost ratio of TTC enhancement and total FACTS installation cost. Three types of FACTS controller including SVC, TCSC, and UPFC are used. Test results indicate that optimally placed OPF with FACTS controllers using PSO enhance higher power transfer capability than those from EP. Moreover, PSO gives higher benefit to cost ratio and faster convergence than EP for all transfer areas. In [12], GA is used to determine locations, numbers, and operating points of static synchronous compensator (STATCOM) and static synchronous series compensator (SSSC) in steady state simulation by two steps method. The optimal points and numbers of FACTS controllers could serve minimum fuel cost and active power losses.

However, the conventional heuristic methods have some limitations such as the almost used control variables have chances to define to the local values which give the almost local answer values and lots of CPU times consuming are used. In this paper, the hybrid TSSA is used. The aims of merging TS and SA are to solve these limitations. The proposed hybrid TSSA is used with optimal number of FACTS controller algorithm. Determination of the optimal numbers, locations, and parameter settings of TCSC and SVC, to conduct power transfer capability enhancement and minimize power losses are also investigated. The IEEE 118-bus system and practical Thailand 58-bus system from Electricity Generating Authority of Thailand (EGAT) are used as the test systems.

II. PROBLEM FORMULATION

To determine the optimal number and allocation of FACTS controllers for TTC enhancement and power losses reduction, the objective function is formulated as maximization of TTC and minimization of power losses represent by (1). Power transfer capability can be defined as TTC value, which is the power that can be transferred from generators in source buses to load buses in power systems subject to real and reactive power generations limits, voltage limits, line flow limits, and FACTS controllers operating limits. The sum of real power loads in the load buses at the maximum power transfer is defined as the TTC value. Two types of FACTS controllers including TCSC and SVC are used. These FACTS controllers are represented by the static model [13], [14].

$$\max F = \sum_{i=1}^{ND_BUS} P_{Di} - \sum_{i=1}^{NL} P_{Li} \quad (1)$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij}(X_S) \cos(\theta_{ij}(X_S) - \delta_i + \delta_j) = 0 \quad (2)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^N V_i V_j Y_{ij}(X_S) \sin(\theta_{ij}(X_S) - \delta_i + \delta_j) = 0 \quad (3)$$

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (4)$$

$$Q_{Gi} - Q_{Di} + Q_{Vi} + \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (5)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (6)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (7)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (8)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (9)$$

$$0 \leq X_{Si} \leq X_{Si}^{\max} \quad (10)$$

$$0 \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (11)$$

where

P_{Di}	real power loads in the i th bus,
P_{Li}	losses in line flows at i th line,
ND_BUS	number of load buses,
NL	number of lines,
P_{Gi}	real power generation at i th bus,
N	total number of buses,
V_i	voltage magnitude at i th bus,
V_j	voltage magnitude at j th bus,
$Y_{ij}(X_S)$	magnitude of the element in ij th bus admittance matrix with TCSC included,
$\theta_{ij}(X_S)$	angle of the element in ij th bus admittance matrix with TCSC included,
δ_i	voltage angles of i th bus,
δ_j	voltage angles of j th bus,
Q_{Gi}	reactive power generation at i th bus,
Q_{Di}	reactive power load at i th bus,
θ_{ij}	angle of the element in ij th bus admittance matrix,
Q_{Vi}	fixed injected reactive power of SVC at i th bus,
$ S_{Li} $	i th line or transformer loading,
X_{Si}	vector of reactance of TCSC at i th line,
NG	number of generators,
$P_{Gi}^{\min}, P_{Gi}^{\max}$	lower and upper limit of real power generation at i th bus,
$Q_{Gi}^{\min}, Q_{Gi}^{\max}$	lower and upper limit of reactive power generation at i th bus,
$V_i^{\min}, V_i^{\max}$	lower and upper limit of voltage magnitude at i th bus,
$S_{Li}^{\max}$	i th line or transformer loading limit,
$X_{Si}^{\max}$	upper limits of reactance of TCSC at i th line, and
$Q_{Vi}^{\max}$	upper limit of injected reactive power of SVC at i th bus

III. PROPOSED ALGORITHM

A. Hybrid Tabu Search and Simulated Annealing

Hybrid TSSA is proposed in [15] which is an integrated approach between TS and SA by using TS as a main algorithm [16]. The trial generated neighborhood solution of SA is presented for generating neighborhood for TS. In addition, the probabilistic acceptance criterion of SA is used [17]. The general flowchart of hybrid TSSA is shown in Fig. 1. The main components of the algorithm are briefly explained as follows.

1) Representation of Solution:

Each individual of trial neighborhood solution vectors in a population composes of OPF control variables, which are coded by real number. The k th individual in a population is represented by a trial solution vector as (12).

$$V_k = [P_{Gi}, V_{Gi}, P_{Di}, NFS_i, Loc_i, FS_i] \quad (12)$$

where

- P_{Gi} real power generation at i th bus of generator bus excluding slack bus,
- V_{Gi} voltage magnitude of generator bus at i th bus including slack bus,
- P_{Di} real power load bus at i th bus of load bus,
- NFS_i i th FACTS controllers,
- Loc_i locations of i th FACTS controllers, and
- FS_i parameter of i th TCSC or the parameter of i th SVC.

2) Initialization:

The initial population of trial neighborhood solution vectors is initialized randomly by using (13).

$$x_i = x_i^{\min} + u(x_i^{\max} - x_i^{\min}) \quad (13)$$

where

- x_i value of the i th element,
- $x_i^{\min}, x_i^{\max}$ lower and upper limits of the i th element, and
- u uniform random in the interval $[0,1]$.

3) Power flow solution:

During iterations, a power flow is performed for each individual to evaluate objective function. A full Newton-Raphson (NR) power flow analysis is used.

4) Fitness function:

The fitness function of the individual k can be computed by using (14).

$$f_k = Kf * F \quad (14)$$

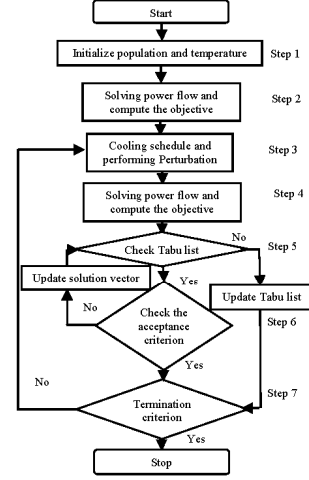


Figure 1. Flow chart of hybrid TSSA.

where

- f_k fitness function of k th individual, and
- Kf arbitrary constant, define as 1.

5) Perturbation:

The trial neighborhood solution vectors are generated by perturbing the initial solution vector based on the uniform probability distribution function. In addition, the upper limits of FACTS parameters are used to limit the ranges of perturbation. A trial neighborhood solution vector is randomly generated by:

$$S_T^{(k,m)} = S_T^{(k,0)} + (T_k * [U] * F_U) \quad (15)$$

$$T_k = r^{(k-1)} * T_1 \quad (16)$$

where

- T_1 initial temperature equals to 0.2,
- T_k temperature at iteration k th,
- k iteration counter,
- r reducing rate equals to 0.9,
- $S_T^{(k,m)}$ trial m neighborhood solution vector at iteration k th,
- $S_T^{(k,0)}$ initial solution vector at iteration k th,
- $[U]$ diagonal matrix of uniform randomly generated number between 0 and 1, and
- F_U upper limit vector of FACTS controller parameter.

6) *Acceptance Criterion:*

The probabilistic acceptance criterion of SA is used instead of aspiration level (AL) of TS. The acceptance criterion is designed for decision movement of the current neighborhood solution, which is in tabu list (TL). The probabilistic acceptance criterion is given as follow:

$$p^k = \frac{1}{1 + \exp(\Delta / T_k)} \quad (17)$$

where

p^k probabilistic acceptance criteria of current neighborhood solution vector at iteration k th,

Δ difference between the objective function of the current neighborhood solution vector in the second set $\{SS_T^{(k,m)}\}$ and the best solution vector reached or $(F(S_C^k) - F_B)$,

$(F(S_C^k))$ objective function of solution vector S_C^k ,

S_C^k current neighborhood solution vector at iteration k , and

F_B best objective function.

7) *Termination criteria:*

If the maximum generation number is reached, the iteration process is terminated. Otherwise, the perturbation and acceptance criterion will be reiterated until the criterion is satisfied. Evolutionary Programming

B. *Evolutionary Programming*

The EP algorithm starts with random generation of initial individuals in a population and then mutation [18]. The processes after mutation are competition and selection. The main components of the algorithm are briefly explained as follows.

1) *Representation of Solution:*

Each individual in a population composes of OPF control variables, which are coded by real number. The k th individual in a population is represented by a trial solution vector as (12).

2) *Initialization:*

The initial population is initialized randomly using sets of uniform random number distribution ranging over the limitation of each control variable as (13).

3) *Power flow solution:*

During iterations, a power flow is performed for each individual to evaluate objective function. A full Newton-Raphson (NR) power flow analysis is used.

4) *Fitness function:*

The fitness function of the individual k th can be computed by using (14).

5) *Mutation:*

A new population is generated by using gaussian mutation operator.

6) *Selection:*

The selection technique utilized is a tournament scheme.

7) *Termination criteria:*

If the maximum generation number is reached, the iteration process is terminated. Otherwise, the number and selection process will be reiterated until the criterion is satisfied.

C. *Optimal number of FACTS controllers*

The algorithm of optimal number of FACTS controllers shown in Fig. 2. The following index is calculating using optimal value of objective function by using (18) and (19).

$$INC_i = \frac{\Delta Z_i}{\Delta Z_{i-1}} \quad (18)$$

$$|\Delta Z_i| = |Z_i - Z_{i-1}| \quad (19)$$

where

INC_i index to check out the increasing number of FACTS controller, subscript i denotes the number of FACTS controller,

Z_i, Z_{i-1} optimal value of the objective function when applying i th and $i-1$ th FACTS controller, and

$\Delta Z_i, \Delta Z_{i-1}$ variation of the objective value when the number of FACTS controller is increased from $i-1$ to i . This is increased when INC_i is greater than INC_{i-1} and INC_i is greater than $BestINC$ value, and

$BestINC$ maximum value of INC .

The numbers of FACTS controller will be increased and continue evaluating objective value until the stopping criteria is reach.

D. *Search space managing method*

There are two methods used to manage search space of FACTS controller operating point. The first method is generally used with the default minimum and maximum operating point of FACTS controllers.

The second method is used to split the search space of operating point of FACTS controllers into n search spaces depended on the number of FACTS controllers. If the number of FACTS controller equals one, minimum and maximum values of operating point are used by the initial value. If number of FACTS controllers is greater than one, the search space will be split.

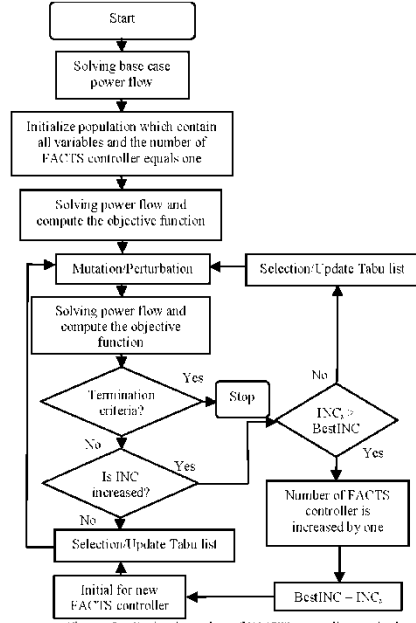


Figure 2. Optimal number of FACTS controller method.

IV. CASE STUDY AND EXPERIMENTAL RESULT

The IEEE 118-bus and Thailand 58-bus systems are used to demonstrate the placement of FACTS controllers with optimal number of FACTS controllers and search space managing methods. Base case TTC is calculated by using OPF. Maximum TTC are calculated with EP and hybrid TSSA. The reactance limits of TCSC in pu. is $0 \leq X_{ST} \leq 0.1$, reactive power injection limit is $0 \leq Q_{T3} \leq 10$ Mvar. The population size of EP and hybrid TSSA are set to 30. The maximum iteration number is set to 400. In all optimization problems, several

cases in terms of using of FACTS controllers are considered with TCSC and SVC individually.

A. The IEEE 118-bus system

The IEEE 118-bus system consisting of 54 generating plants, 64 load buses, and 186 lines shown in Fig. 3 is used as a test system. The system data can be found in [19]. Bus 69 is set as swing bus which is framed in Fig. 3. Base case TTC of IEEE 118-bus system equals 1433.00 MW.

In Table I, EP and hybrid TSSA with the split search space managing method tend to give higher TTC than these results from non-split managing method. Furthermore, the hybrid TSSA gives higher TTC than EP. The best, the average, and the worst TTC values obtained from TCSC placement by using hybrid TSSA with split search space managing method are 2975.37 MW, 2708.51 MW, and 2590.86 MW, respectively. For SVC placement, the best, the average, and the worst TTC value are 2996.34 MW, 2815.47 MW, and 2589.63 MW, respectively. The results show that the optimal number and the optimal allocation of SVC by using hybrid TSSA with the split search space managing method gives higher TTC than TCSC. The optimal number and the allocation of all FACTS controllers are represented in Table II.

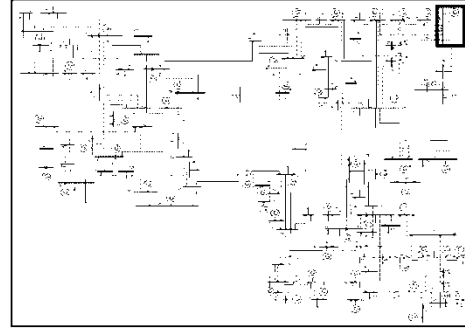


Figure 3. Diagram of the IEEE 118-bus system.

TABLE I. TTC RESULTS FROM EACH FACTS CONTROLLERS AND CPU TIME FROM TWO METHODS USING EP/HYBRID TSSA ON IEEE 118-BUS SYSTEM

TTC (MW)	EP				Hybrid TSSA			
	with TCSC		with SVC		with TCSC		with SVC	
	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method
Best	2922.30	2938.60	2918.05	2965.43	2945.59	2975.37	2937.64	2996.34
Average	2567.66	2589.09	2621.23	2637.92	2590.12	2708.51	2804.93	2815.47
Worst	2420.24	2405.41	2405.23	2432.38	2522.23	2590.86	2566.27	2589.63
Standard deviation	123.70	146.96	121.34	144.04	130.69	151.15	134.34	152.78
Average CPU Time (min)	40.29	40.28	40.27	40.27	30.12	30.11	30.11	30.11

TABLE II. OPTIMAL NUMBER AND PARAMETER SETTING OF EACH FACTS CONTROLLER ON IEEE 118-BUS SYSTEM

Method	EP				Hybrid TSSA			
Type of FACTS Controller	TCSC		SVC		TCSC		SVC	
Search space managing	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method
Number of FACTS Controllers	4	2	3	2	2	2	2	2
Location /Parameter of FACTS Controller	Line 1-2 /0.0217 (pu)	Line 53-54 /0.00657 (pu)	Bus 115 /3.475 (Mvar)	Bus 2 /2.197 (Mvar)	Line 12-16 /0.0333 (pu)	Line 15-19 /0.0188 (pu)	Bus 10 /8.677 (Mvar)	Bus 21 /7.005 (Mvar)
	Line 4-5 /0.0399 (pu)	Line 96-97 /0.0405 (pu)	Bus 98 /6.944 (Mvar)	Bus 27 /6.903 (Mvar)	Line 18-19 /0.0847 (pu)	Line 24-43 /0.0893 (pu)	Bus 79 /4.646 (Mvar)	Bus 113 /4.019 (Mvar)
	Line 34-43 /0.0731 (pu)	-	Bus 36 /6.403 (Mvar)	-	-	-	-	-
	Line 48-49 /0.0487 (pu)	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-

B. Thailand 58-bus system

In this case study, a reduced practical test system from EGAT 230 kV and 500 kV network is used as another test system. For day-load case, the EGAT 58-bus system consisting of 17 generating plants, 41 load buses, and 77 lines as shown in Fig. 4 is used [20]. Bus 1 is set as swing bus which is framed in Fig. 4. Base case TTC of the system equals 10261.50 MW.

In Table III, higher TTC values are obtained from EP and hybrid TSSA with split search space managing method than from the non-split search space managing method with TCSC and SVC placement by individually. For TCSC placement by using hybrid TSSA with split search space managing method gives the best, the average, and the worst TTC values are 16305.98 MW, 15868.52 MW, and 15318.64 MW, respectively. For SVC placement by using hybrid TSSA with TCSC and SVC placement by individually. For TCSC placement by using hybrid TSSA with split search space managing method gives the best, the average, and the worst TTC values are 16305.98 MW, 15868.52 MW, and 15318.64 MW, respectively. The results show that the optimal number and the optimal allocation of SVC by using TSSA with the split search space managing method gives

higher TTC than TCSC. The optimal number and allocation of all FACTS controllers are showed in Table IV.

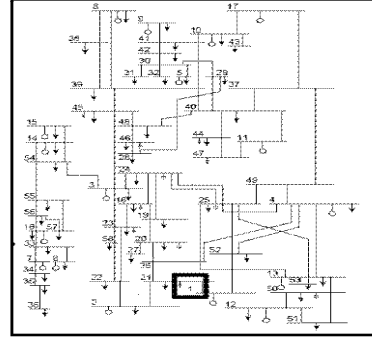


Figure 4. Diagram of the EGAT 58-bus system

TABLE III. TTC RESULTS FROM EACH FACTS CONTROLLERS AND CPU TIME FROM TWO METHODS USING EP/HYBRID TS/SA ON EGAT 58-BUS SYSTEM

TTC (MW)	EP				Hybrid TS/SA			
	with TCSC		with SVC		with TCSC		with SVC	
	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method
Best	15114.72	15541.64	15123.27	15380.40	16201.02	16305.98	16212.78	16521.14
Average	14185.15	14745.44	14597.84	14674.74	15866.17	15868.52	15736.11	15559.92
Worst	13911.46	14086.68	14326.79	14701.50	15267.12	15318.64	15155.45	15402.91
Standard deviation	422.14	389.91	309.21	317.11	427.85	390.07	312.34	322.81
Average CPU Time (min)	33.28	33.27	33.28	33.28	19.38	19.37	19.37	19.37

TABLE IV. OPTIMAL NUMBER AND PARAMETER SETTING OF EACH FACTS CONTROLLER ON EGAT 58-BUS SYSTEM

Method	EP				Hybrid TS/SA			
Type of FACTS Controller	TCSC		SVC		TCSC (pu)		SVC (Mvar)	
Search space managing	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method	Non-split search space method	Split search space method
Number of FACTS Controller	3	2	3	3	2	2	2	2
Location /Parameter of FACTS Controller	Line 9-10 /0.0241 (pu)	Line 41-42 /0.0073 (pu)	Bus 38 /2.159 (Mvar)	Bus 8 /1.545 (Mvar)	Line 9-10 /0.0531 (pu)	Line 3-4 /0.0082 (pu)	Bus 3 /9.871 (Mvar)	Bus 3 /2.815 (Mvar)
	Line 4-11 /0.0494 (pu)	Line 29-31 /0.0596 (pu)	Bus 21 /3.157 (Mvar)	Bus 12 /5.203 (Mvar)	Line 29-31 /0.0284 (pu)	Line 51-52 /0.0701 (pu)	Bus 20 /2.213 (Mvar)	Bus 46 /5.504 (Mvar)
	Line 43-44 /0.0212 (pu)	-	Bus 8 /6.279 (Mvar)	Bus 18 /6.931 (Mvar)	-	-	-	-

V. CONCLUSION

In this paper, proposed hybrid TSSA is used with the optimal number of FACTS controllers' algorithm and search space managing methods comparing to EP. The results indicate that optimal number of FACTS controllers, split search space managing methods, and hybrid TSSA with FACTS controllers can enhance TTC from base case. Higher TTC is also obtained within less average CPU time by the hybrid TSSA than by EP with both non-split and split search space managing method. The optimal number method can be used to reduce CPU time, compared to the increasing number of FACTS controller step by step. In addition, the overall number of FACTS controllers from the split search space managing method is less than non-split search space managing method. Therefore, the installation of FACTS controllers with optimal number and optimal allocation are beneficial for the further expansion plans.

ACKNOWLEDGMENT

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Power Transfer Capability Enhancement with Optimal Maximum Number of FACTS Controllers Using Evolutionary Programming

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Abstract—In this paper, evolutionary programming (EP) with optimal maximum number of FACTS controller and search space managing methods are proposed to determine the optimal allocation of FACTS controllers to enhance power transfer capability of power transactions between generators and load buses. Particular optimal allocation includes optimal locations and parameter settings. Two types of FACTS controllers including thyristor-controlled series capacitor (TCSC) and static var compensator (SVC) are used individually in this study. The objective function is formulated as maximizing total transfer capability (TTC) and minimizing power losses. Power transfer capability determinations are calculated based on the optimal power flow (OPF) technique. Split and non-split search space managing methods are used. Test results on IEEE 118-bus system and the practical Electricity Generating Authority of Thailand (EGAT) 58-bus system showed that EP with optimal maximum number of FACTS and the proposed split search space managing method gave higher TTC and less maximum number of FACTS controllers than those from non-split method. Therefore, the installation of FACTS controllers with optimal maximum number and optimal allocation are beneficial for the further expansion plans.

I. INTRODUCTION

Demands for electrical energy increase every year, so the installation of new power plants or distributed generations may respond this increasing demand. Compared to Flexible AC Transmission System (FACTS), these constructions have some disadvantages such as the pollution control, the cost of operation, and the land acquisitions. In the other hand, using FACTS controllers provide advantages for transmission system because FACTS controllers require non-discriminatory open access of transmission resources.

FACTS controllers are power electronics based system and other static equipment that have the capability of controlling various electrical parameters in transmission networks. These parameters can be adjusted to provide adaptability conditions of transmission network. There are many types of FACTS controllers such as thyristor-controlled series capacitor (TCSC) and static var compensator (SVC) [1]. TCSC is connected in series with the line conductor to compensate the inductive reactance of the line while SVC serves generated or absorbed reactive power for transmission networks. These FACTS controllers, therefore, give benefits in increasing system transmission capability and power flow control flexibility [2]. Moreover, it has been proved that TCSC and SVC can be used to enhance system controllability

resulting in total transfer capability (TTC) enhancement and minimizing power losses in transmission networks [3].

TTC is defined as an amount of electric power that can be transferred over the interconnected transmission network in a reliable manner while meeting all of a set of pre-defined and post-contingency system conditions [4]. TTC can be calculated by several power flow solution methods such as 1) linear ATC (LATC) method [5], 2) continuation power flow (CPF) method [6], 3) repetitive power flow (RPF) method [7], and 4) optimal power flow (OPF) based methods [8].

The maximum performance of using FACTS controllers to increase TTC and minimize losses should be obtained by choosing the types, numbers, parameter settings, and locations in the transmission systems. The modern heuristics optimization techniques such as genetic algorithm (GA), evolutionary programming (EP), and particle swarm optimization (PSO) are successfully implemented to solve complex problems efficiently and effectively [9]. The optimal choices and allocation of four types of FACTS controllers are defined in [10]. Simulation results validate the efficiency of this new approach in minimizing the overall system cost function, including generation costs, and investment costs of the FACTS controllers. In [11], EP is used to determine the optimal allocation of four types of FACTS controllers. Test results indicated that optimally placed OPF with FACTS controllers by EP can enhance the TTC more than OPF without FACTS controllers. PSO is also used to optimize location and parameters of FACTS controllers to achieve minimum cost of installation of FACTS controllers and improve system load ability [12]. Numbers of FACTS controllers are increased manually and the results from the study showed that both unified power flow controller (UPFC) and TCSC yield maximum system load ability. UPFC gives high cost of installation in IEEE 6, 30, and 118-bus test systems but TCSC gives minimum cost in TNEB 69-bus practical test system. In [13], GA is used to determine locations, numbers, and operating points of FACTS controllers. Static synchronous compensator (STATCOM) and static synchronous series compensator (SSSC) are used in steady state simulation by two steps method. The optimal points and numbers of FACTS controllers could serve minimum fuel cost and active power losses.

In this paper, EP and proposed algorithm are used to determine the optimal maximum numbers, locations, and parameter settings of two types of FACTS controllers to conduct power transfer capability enhancement and minimizing power losses. The IEEE 118-bus system and practical Thailand 58-bus system from Electricity Generating Authority of Thailand (EGAT) are used as the test systems.

II. PROBLEM FORMULATION

Power transfer capability is marked as TTC value, which is the power that can be transferred from all generators in source buses to all load buses in transmission system subjected to real and reactive power generations limits, voltage limits, line flow limits, and FACTS controllers operation limits. Two types of FACTS controllers including TCSC and SVC are used. These FACTS controllers are represented by the static model [14]. TCSC and SVC are modeled by the adjustable series reactances and the injected power model, respectively. The sum of real power loads in the load buses at the maximum power transfer is defined as the TTC value. In all optimization problems, several cases in terms of using of FACTS controllers are considered with TCSC and SVC individually [15].

The objective function of OPF with FACTS controllers is represented by (1):

$$\max F = \left[\sum_{i=1}^{ND_BUS} (P_{Di} - P_{Di}^{base}) \right] - \sum_{i=1}^{NL} (P_{Li} - P_{Li}^{base}) - h(x_i) \quad (1)$$

$$h(x_i) = \begin{cases} (x_i - x_i^{\max})^2 & \text{if } x_i > x_i^{\max} \\ (x_i^{\min} - x_i)^2 & \text{if } x_i < x_i^{\min} \\ 0 & \text{if } x_i^{\min} \leq x_i \leq x_i^{\max} \end{cases} \quad (2)$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \cos(\theta_{ij}(X_{si}) - \delta_i + \delta_j) = 0 \quad (3)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \sin(\theta_{ij}(X_{si}) - \delta_i + \delta_j) = 0 \quad (4)$$

$$P_{Gi} - P_{Di} - \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} + \sum_{i=1}^N Q_{Vi} - \sum_{j=1}^N V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (6)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (7)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (8)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (9)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (10)$$

$$0 \leq X_{Si} \leq X_{Si}^{\max} \quad (11)$$

$$0 \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (12)$$

where

P_{Di}	real power loads in the i th bus,
P_{Di}^{base}	base case real power loads in the i th load bus,
P_{Li}	the losses in line flows at i th line,
P_{Li}^{base}	the base case losses in line flows at i th line,
ND_BUS	number of load buses,
NL	number of lines,
$h(x_i)$	penalty function of variable i th x ,
P_{Gi}	real power generation at i th bus,
N	total number of buses,
V_i	voltage magnitude at i th bus,
V_j	voltage magnitude at j th bus,
$Y_{ij}(X_s)$	magnitude of the element in ij th bus admittance matrix with TCSC included,
$\theta_{ij}(X_s)$	angle of the element in ij th bus admittance matrix with TCSC included,
δ_i	voltage angles of i th bus,
δ_j	voltage angles of j th bus,
Q_{Gi}	reactive power generation at i th bus,
Q_{Di}	reactive power load at i th bus,
θ_{ij}	angle of the element in ij th bus admittance matrix,
Q_{Vi}	fixed injected reactive power of SVC at i th bus,
$ S_{Li} $	i th line or transformer loading,
X_{Si}	vector of reactance of TCSC at i th line,
NG	number of generators,
$P_{Gi}^{\min}, P_{Gi}^{\max}$	lower and upper limit of real power generation at i th bus,
$Q_{Gi}^{\min}, Q_{Gi}^{\max}$	lower and upper limit of reactive power generation at i th bus,
$V_i^{\min}, V_i^{\max}$	lower and upper limit of voltage magnitude at i th bus,
$S_{Li}^{\max}$	i th line or transformer loading limit,
$X_{Si}^{\max}$	upper limits of reactance of TCSC at i th line, and
$Q_{Vi}^{\max}$	upper limit of injected reactive power of SVC at i th bus.

III. PROPOSED ALGORITHM

A. Evolutionary Programming

The EP algorithm [16] starts with random generation of initial individuals in a population and then mutation. The processes after mutation are competition and selection. The best individual taken by the highest fitness value is found. The main components of the algorithm are briefly explained as follows.

1. Representation of Solution

Each individual in a population composes of OPF control variables, which are coded by real number. The k th individual in a population is represented by a trial solution vector as (13).

$$V_k^T = [P_{Gi}, V_{Gi}, P_{Di}, Loc_i, FS_i] \quad (13)$$

where

P_{Gi}	real power generation at i th bus of generator bus excluding slack bus,
V_{Gi}	voltage magnitude of generator bus at i th bus including slack bus,
P_{Di}	real power load bus at i th bus of load bus,
Loc_i	locations of i th FACTS controllers, and
FS_i	parameter of i th TCSC or the parameter of i th SVC.

2. Initialization

The initial population is initialized randomly using sets of uniform random number distribution ranging over the limitation of each control variable as (14).

$$x_i = x_i^{\min} + u(x_i^{\max} - x_i^{\min}) \quad (14)$$

where

x_i	value of the i th element,
$x_i^{\min}, x_i^{\max}$	lower and upper limits of the i th element, and
u	uniform random in the interval [0,1].

3. Power flow solution

During iterations, a power flow is performed for each individual to evaluate objective function. A full Newton-Raphson (NR) power flow analysis is used.

4. Fitness function

The fitness function of the individual k can be computed by using (15).

$$f_k = Kf * F \quad (15)$$

where

f_k	fitness function of k th individual, and
Kf	arbitrary constant, defined as 1.

5. Mutation

A new population is generated by using Gaussian mutation operator. Each element of the new trial solution vector k , V'_k is computed by using (16) and (17).

$$x'_{k,i} = x_{k,i} + N(0, \sigma_{k,i}^2) \quad (16)$$

$$\sigma_{k,i} = (x_i^{\max} - x_i^{\min}) \left(\frac{f_{\max} - f_k}{f_{\max}} + a^g \right) \quad (17)$$

where

$x'_{k,i}$	value of the i th element of the k th offspring individual,
$x_{k,i}$	value of the i th element of k th parent individual,
$N(0, \sigma_{k,i}^2)$	Gaussian random number with a mean of zero and standard deviation of $\sigma_{k,i}$,
$x_i^{\min}, x_i^{\max}$	lower and upper limits of the i th element,
f_k	fitness value of the k th individual,
$f_{\max}$	maximum fitness of the parent population,
a	positive constant slightly less than one, and
g	generation counter.

6. Selection

The selection technique utilized is a tournament scheme, which can be computed from (18) and (19).

$$w_t = \begin{cases} 1 & \text{if } f_k > f_r \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

$$s_k = \sum_{t=1}^N w_t \quad (19)$$

where

w_t	weight value of each opponent,
f_k	fitness value of the k th individual,
f_r	fitness of the r th opponent randomly selected from the combined population based on $r = \lfloor 2 * P * u + 1 \rfloor$,
u	uniform random in the interval [0,1],
P	population size,
s_k	total score of each k th individual, and
Nt	number of the opponents.

7. Termination criteria

If the maximum generation number is reached, the iteration process is terminated. Otherwise, the number and selection process will be reiterated until the criterion is satisfied.

B. Optimal maximum number of FACTS controllers

The proposed algorithm shown in Fig. 1 is started for one FACTS controller and having found the optimal solution. Evaluation is continued by adding one of FACTS controller. The number of controller is increased one by one and the following index is calculating using optimal value of objective function by using (20) and (21).

$$INC_i = \frac{\Delta Z_i}{\Delta Z_{i-1}} \quad (20)$$

$$|\Delta Z_i| = |Z_i - Z_{i-1}| \quad (21)$$

where
 INC_i

index to check out the increasing number of FACTS controller, subscript i denotes the number of FACTS controller, Z_i optimal value of the objective function when applying i th FACTS controller, and $\Delta Z_i, \Delta Z_{i-1}$ variation of the objective value when the number of FACTS controller is increased from $i-1$ to i . This is increased when INC_i is greater than INC_{i-1} and INC_i is greater than $BestINC$ value, and maximum value of INC .

$BestINC$

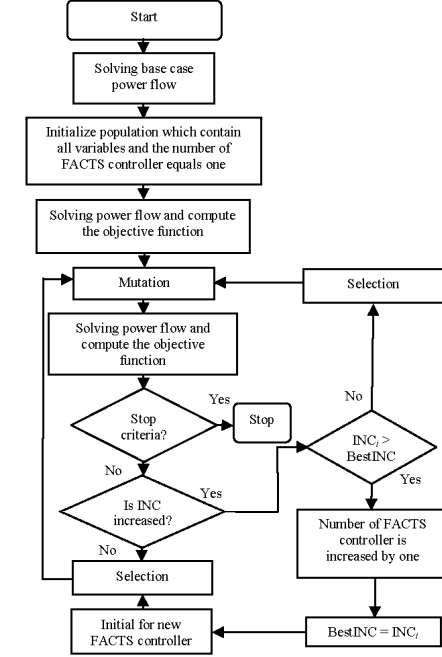


Fig. 1. Flow chart of proposed algorithm.

The numbers of FACTS controller will be increased and continue evaluating objective value until the stopping criteria is reach.

C. Search space managing method

There are two methods used to manage search space of FACTS controller operating point. The first method is generally used with the default minimum and maximum operating point of FACTS controllers. The second method is used to split the search space of operating point of FACTS controllers into n search spaces depended on the number of FACTS controllers. If the number of FACTS controller equals one, minimum and maximum values of operating point are used by the initial value. If number of FACTS controllers is greater than one, the search space will be split by the methods shown in Fig. 2 and Fig. 3.

IV. CASE STUDY AND EXPERIMENTAL RESULT

The IEEE 118-bus and Thailand 58-bus systems are used to demonstrate the maximum optimal number and placement of FACTS controllers for simultaneously maximizing TTC and minimizing power loss. Base case TTC is calculated by using OPF with EP.

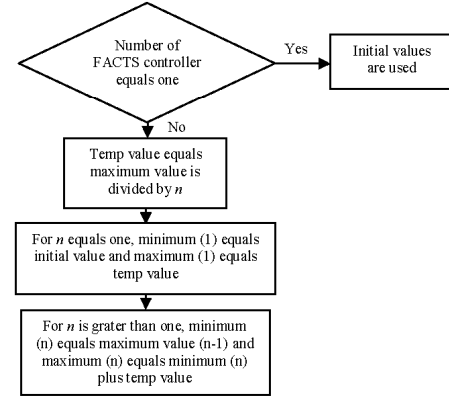


Fig. 2. Flow chart of splitting search space.

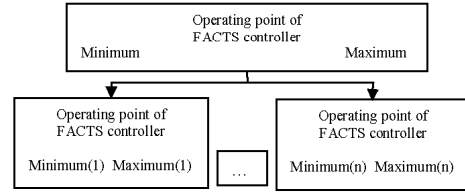


Fig. 3. Diagram of splitting of search space method.

The reactance limits of TCSC in pu. is $0 \leq X_{si} \leq 0.1$ and reactive power injection limit is $0 \leq Q_{vi} \leq 10$ Mvar. The population size of EP is set to 30. The maximum iteration number is set to 400. All test systems are evaluated 20 runs with each type of FACTS controller.

A. The IEEE 118-bus system

The IEEE 118-bus system consisting of 54 generating plants, 64 load buses, and 186 lines shown in Fig. 4 is used as a test system. The system data can be found in [17]. Bus 69 is set as swing bus which is framed in Fig. 4. Base case TTC of IEEE 118-bus system equals 1433.00 MW.

In Table I, the split search space managing method tends to give higher TTC than the non-split managing method. The best and the average TTC values obtained from TCSC placement are 2938.60 MW, and 2589.09 MW, respectively. For SVC placement, the best, the average, and the worst TTC value are 2965.43 MW, 2637.92 MW, and 2432.38 MW, respectively. The results showed that the optimal number and the optimal allocation of SVC with the split search space managing method give higher TTC than TCSC. The optimal number and the allocation of all FACTS controllers are represented in Table II.

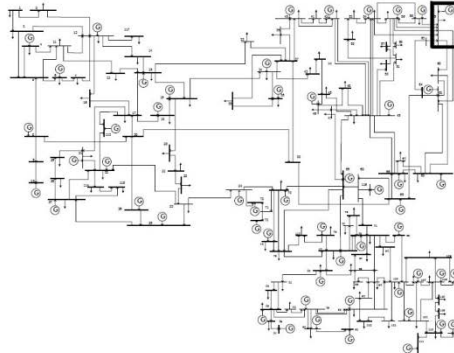


FIG. 4. DIAGRAM OF THE IEEE 118-BUS SYSTEM.

TABLE I
TTC RESULTS FROM EACH FACTS CONTROLLERS AND CPU TIME FROM TWO METHODS ON IEEE 118-BUS SYSTEM

TTC (MW)	TCSC		SVC	
	1 st method	2 nd method	1 st method	2 nd method
Best	2922.30	2938.60	2918.05	2965.43
Average	2567.66	2589.09	2621.23	2637.92
Worst	2420.24	2405.41	2405.23	2432.38
Standard deviation	123.70	146.96	121.34	144.04
Average CPU Time (min)	40.29	40.28	40.27	40.27

TABLE II
OPTIMAL NUMBER AND PARAMETER SETTING OF EACH FACTS CONTROLLER ON IEEE 118-BUS SYSTEM

	TCSC (pu)		SVC (Mvar)	
	1 st method	2 nd method	1 st method	2 nd method
Number of FACTS Controller	4	2	3	2
Location /Parameter	Line 1-2 /0.0217	Line 53-54 /0.00657	Bus 115 /3.475	Bus 2 /2.197
	Line 4-5 /0.0399	Line 96-97 /0.0405	Bus 98 /6.944	Bus 27 /6.903
	Line 34-43 /0.0731		Bus 36 /6.403	
	Line 48-49 /0.0487			

The overall results from IEEE 118-bus system showed that the optimal maximum number of SVC with the split search space managing method give higher TTC than the TCSC placement. Moreover, the averages CPU time obtained from both search managing methods used are not different.

B. Thailand 58-bus system

In this case study, a reduced practical test system from EGAT 230 kV and 500 kV network is used as another test system. For day-load case, the EGAT 58-bus system consisting of 17 generating plants, 41 load buses, and 77 lines as shown in Fig. 5 is used [18]. Bus 1 is set as swing bus which is framed in Fig. 5. Base case TTC of the system equals 10261.50 MW.

In Table III, higher TTC values is obtained from split search space managing method than from the non-split search space managing method using TCSC and SVC placement by individually. For TCSC placement, the best, the average, and the worst TTC values are 15541.642 MW, 14745.439 MW, and 14086.684 MW, respectively. For SVC placement, the best, the average, and the worst TTC values are 15380.40 MW, 14674.74 MW, and 14101.50 MW, respectively. The results showed that the optimal number and the optimal allocation of TCSC with the split search space managing method give higher TTC than SVC. The optimal number and allocation of all FACTS controllers are showed in Table IV.

TABLE III
TTC RESULTS FROM EACH FACTS CONTROLLERS AND CPU TIME FROM TWO METHODS ON EGAT 58-BUS SYSTEM

TTC (MW)	TCSC		SVC	
	1 st method	2 nd method	1 st method	2 nd method
Best	15114.72	15541.64	15123.27	15380.40
Average	14185.15	14745.44	14597.84	14674.74
Worst	13911.46	14086.68	14326.79	14101.50
Standard deviation	422.14	369.91	309.21	317.11
Average CPU Time (min)	33.28	33.27	33.28	33.28

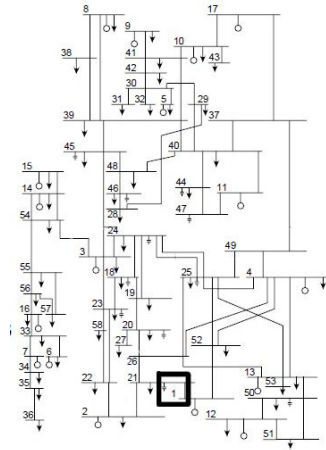


FIG. 5. DIAGRAM OF THE EGAT 58-BUS SYSTEM

TABLE IV
OPTIMAL NUMBER AND PARAMETER SETTING OF EACH FACTS
CONTROLLER ON EGAT 58-BUS SYSTEM

	TCSC (pu)		SVC (Mvar)	
	1 st method	2 nd method	1 st method	2 nd method
Number of FACTS Controller	3	2	3	3
Location /Parameter	Line 9-10 /0.0241	Line 41-42 /0.0073	Bus 38 /2.159	Bus 8 /1.545
	Line 4-11 /0.0494	Line 29-31 /0.0596	Bus 21 /3.157	Bus 12 /5.203
	Line 43-44 /0.0212		Bus 8 /6.279	Bus 18 /6.931

The results from the EGAT 58-bus system indicated that the optimal maximum number of TCSC with the split search space managing method give higher TTC than SVC.

V. CONCLUSION

In this paper, the optimal maximum number of FACTS controllers and search space managing methods are proposed. The optimal maximum number method can be used to reduce CPU time compared to the increasing number of FACTS controller step by step. The split search space managing method divides search space into sub spaces which reduces the interval of operating point of FACTS controller. This method results in the effectiveness to improve the searching for optimal operating points of FACTS controllers. The overall results from both systems indicate that the proposed algorithm and split search space managing method with FACTS controllers can enhance TTC from base case and give higher TTC than non-split search space managing method. In addition, the overall number of FACTS controllers from the split search space managing method is less than non-split search space managing method.

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ชื่อเรื่อง : Optimal Capacitor Allocation for Power Transfer Capability and Power Loss Improvements in Power Transmission Systems Using Evolutionary Programming

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Optimal Capacitor Allocation for Power Transfer Capability and Power Loss Improvements in Power Transmission Systems Using Evolutionary Programming

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Abstract—Capacitor allocation in power transmission systems have been considered to improve voltage profile and reduce power loss. An evolutionary programming (EP) is a computationally efficient methodology for the optimal capacitor allocation in power transmission network. The method is chosen due to its robustness and its ability to handle many practical constraints, explore all possible solutions, and find optimal solution within reasonable time. This method is proposed to determine the optimal allocation of capacitor for maximizing the total transfer capability (TTC) and minimize power loss by focusing on cost of capacitors and max TTC in systems.

Index Terms—capacitor placement, evolutionary programming, loss minimization, optimization method, optimal power flow.

I. INTRODUCTION

Capacitors have been commonly used to provide reactive power compensation in transmission systems. They minimize power losses and maintain voltage profile within the acceptable limits. In addition, they could be used to enhance power transfer capability.

Optimal capacitor allocation is very much linked to the placement of capacitors in transmission systems which are essentially determination of the location, size, number and type of capacitors to be placed in the systems. The capacitor placement problem is a well-researched topic and has been addressed by many authors in the past. All the either approaches differ from each other by way of their problem formulation and the problem solution methods employed. In most of these approaches, the objective function is considered as an unconstrained maximization of savings due to energy loss reduction and peak power loss reduction against the capacitor cost. Others have formulated the problem with some variations of the above objective function. There have been analytical approaches [1]-[4], numerical programming methods [5]-[7], and artificial intelligence(AI)-based techniques [8]-[12] devised to solve this capacitor problem. These study cases developed a procedure for optimizing the net monetary saving associated with the reduction of power loss by placing fixed and switched capacitors.

Evolutionary programming (EP) is a computational optimization method, which uses the mechanic of evolution to

find the optimal solution of complex optimization problems [13]. It works by evolving a population of candidate toward the solutions through the use of the mutation operator and selection scheme. This algorithm can move over hills and across valleys to discover an optimal point. Because of this, EP is more robust than the existing direct search method. In this paper, the EP algorithm is proposed to determine the optimal allocation of capacitors. EP simultaneously searches for capacitor locations, size, numbers and determine maximum total transfer capability (TTC) value.

II. CAPACITOR ALLOCATION PROBLEM FORMULATION

Capacitor allocation is formulated as the optimal power flow (OPF). OPF is a static, nonlinear optimization problem, which calculates a set of optimum variables from the network state, load data and system parameters. Optimal values are computed in order to achieve a certain goal such as number, size, and cost or power loss minimization subject to equality and inequality constraints. The OPF problem can be represented as (1)

$$\begin{aligned} \max \quad & f(x, u) \\ \text{s.t} \quad & g(x, u) = 0 \\ & h(x, u) \leq 0 \end{aligned} \quad (1)$$

Where, f is the objective function that typically includes number, size, and cost in transmission systems. $g(x, u)$ represents the load flow equations and $h(x, u)$ represents transmission line limits and other security limits. The vector of dependent and control variables are denoted by x and u respectively

OPF with capacitor is used to evaluate the feasible TTC value of power transactions. TTC is a terminology that is used to define the amount of electric power that can be transferred over the interconnected transmission systems in a reliable manner [14]. There is a possibility to minimize the loss associated with the reactive power flow through the branches.

The objective function in (2) is to minimize cost, loss and maximize the power that can be transferred from a specific set of generators in a source area to loads in a sink area, subject to

real and reactive power generation limits, voltage limits, line flow limits, and capacitors limits. The systems constraints are shown in (7) - (13).

The mathematical models of capacitors are used to perform the steady-state studies. Therefore, capacitors are modeled using the injected power model [15].

$$\text{Maximize } F = \frac{B}{C} \quad (2)$$

$$B = K \times \sum_{j=1}^N [TD_j \times (TTC_{TDj} - Loss_{TDj})] \quad (3)$$

$$C = \sum_{i=1}^{Nc} (C_{ins,i} + C_{kVAR,i}) \quad (4)$$

$$TTC = \sum_{i=1}^N \sum_{j=1}^{SNK} P_{Di} \quad (5)$$

$$Loss = \sum_{i=1}^{Nl} P_{loss,i} \quad (6)$$

subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^n V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (7)$$

$$Q_{Gi} - Q_{Di} + Q_{Vi} - \sum_{j=1}^n V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (8)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (9)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (10)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (11)$$

$$Q_{Vi}^{\min} \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (12)$$

$$S_i \leq S_i^{\max} \quad \forall i \in N_l \quad (13)$$

Where, F is objective function. B is benefit of energy transfer. C is sum of capacitor cost. TTC is a power transactions between source and sink areas (kW). $Loss$ is power loss in system (kW). N_{SNK} is a number of load buses in sink area. TD_j is a j^{th} of time duration (hr/year). K is a cost per power loss (Baht/kWhr). P_{loss} is a power loss in system. N is the number of load buses. Nc is the number of capacitor banks. NG is the number of generators. N_l is the number of branches. C_{ins} is an installation and maintenance cost of capacitor bank in (Baht). C_{kVAR} is a cost of capacitor bank in (Baht/kVAR). n is the total number of load buses. i, j represents bus number. V_i, V_j are voltage magnitudes at bus i and j . P_{Gi}, Q_{Gi} are real and reactive power generations at bus i . P_{Di}, Q_{Di} are real and reactive loads at bus i . Q_{Vi} is an injected reactive power of capacitor at bus i . δ_i, δ_j are voltage angles of bus i and j . θ_{ij} is an angle of the ij^{th} element in bus admittance matrix. Y_{ij} is a bus admittance matrix element. S_i is the apparent power flow in line. $V_i^{\min}, V_i^{\max}, P_{Gi}^{\min}, P_{Gi}^{\max}, Q_{Gi}^{\min}, Q_{Gi}^{\max}, Q_{Vi}^{\min}, Q_{Vi}^{\max}, S_i^{\max}$ are the lower and upper limits of the corresponding variables respectively.

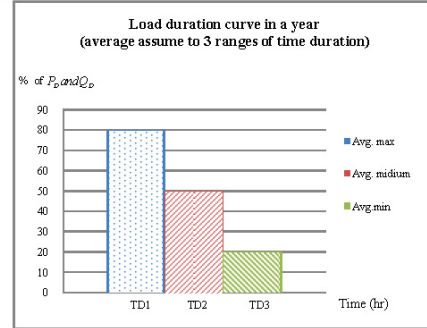


Fig. 1 Load duration curve in a year

Calculation is performed using 1-year-operating-time data of daily load curve. The applied of load duration curve aims to find the best solution for fixed capacitors and maximize power transfer capacity.

1-year-operating-time data are divided into 3 durations as Fig. 1. Each has its own average P_{Di} and Q_{Di} value. By the way, load duration curve can be calculated every minute or second. Calculation chart is shown in Fig. 2.

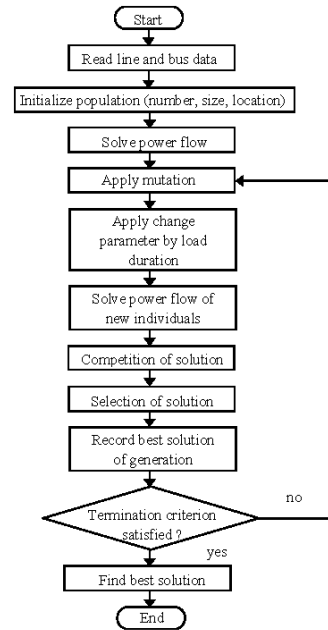


Fig. 2 Program flow chart

III. EVOLUTIONARY PROGRAMMING

EP algorithm starts with random generation of initial individuals in a population then mutation and selection are preceded until the best individual reached. It is a kind of an optimization algorithm. The main components of the algorithm are explained as follows.

A. Representation of Solution

Each individual in a population composes of OPF control variables, which are coded by real number. The k^{th} individual in a population is represented by a trial solution vector as (14).

$$V_k^T = [P_{Gi}, P_{Di}, n, Loc_i, Q_{Vi}] \quad (14)$$

Where, P_{Gi} is the real power generation at bus i in source area excluding slack bus. P_{Di} is the real power load at bus i in sink area. n is number of capacitor installed. Loc_i is bus number of capacitor bank. Q_{Vi} is the parameter of capacitor bank.

B. Initialization

The initial population is initialized randomly using sets of uniform random number distribution ranging over the feasible limits of each control variable as (15).

$$x_i = x_i^{\min} + u(x_i^{\max} - x_i^{\min}) \quad (15)$$

Where, x_i is the i^{th} element of the individual in a population. $x_i^{\min}$ and $x_i^{\max}$ are the lower and upper limits of the i^{th} element of the individual. u is a uniform random number in the interval $[0,1]$.

C. Power Flow Solution

During iterations, a power flow is performed for each individual to compute its state variables. A full AC Newton-Raphson (NS) power flow analysis is used.

D. Fitness Function

The fitness of the k^{th} individual can be calculated by using (16).

$$f_k = K_f * F \quad (16)$$

Where, f_k is the fitness of the k^{th} individual. K_f is an arbitrary constant, and F is the objective function. The generalized objective function in equation (2) is taken as fitness function of the algorithm ($K_f = 1$).

E. Mutation

A new population is generated by using the Gaussian mutation operator. Each element of the k^{th} new trial solution vector is computed by using (17) and (18).

$$x'_{k,i} = x_{k,i} + N(0, \sigma_{k,i}^2) \quad (17)$$

$$\sigma_{k,i} = (x_i^{\max} - x_i^{\min}) \left(\frac{f_{\max} - f_k}{f_{\max}} + \alpha^g \right) \quad (18)$$

Where, $x'_{k,i}$ is the value of the i^{th} element of the k^{th} offspring individual. $x_{k,i}$ is the value of the i^{th} element of the k^{th} parent individual. $N(0, \sigma_{k,i}^2)$ is a Gaussian random number with a mean of zero and standard deviation of $\sigma_{k,i}$. $x_i^{\min}$ and $x_i^{\max}$ are the lower and upper limits of the i^{th} element of the k^{th} parent individual. $f_{\max}$ is the maximum fitness of the

parent population. α is a positive number constant slightly less than one and g is the iteration counter.

F. Selection

The selection technique utilized is a tournament scheme, which can be expressed as (19) and (20).

$$w_t = \begin{cases} 1 & \text{if } f_k > f_r \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

$$S_k = \sum_{t=1}^{Nt} w_t \quad (20)$$

Where, f_k is the fitness of the k^{th} individual in the combined population. f_r is the fitness of the r^{th} opponent randomly selected from the combined population based on $r = [2 * P * u + 1]. [x]$ is the greatest integer less than or equal to x . u is a uniform random number in the interval $[0,1]$ and P is the population size.

G. Termination Criterion

If the maximum generation number is reached, the iteration process is terminated. Otherwise, the mutation and selection process will be reiterated until the criterion is satisfied.

IV. CASE STUDY AND RESULT

A modified IEEE 30-bus system, shown in Fig. 3, is used as a test system. Bus and line data can be found in [16]. In the IEEE 30-bus, the reactive power injection limit of capacitor is $0 \leq Q_{Vi} \leq 11.2$ MVar [17]. The result of calculation is shown in Table I, Table II, and Table III.

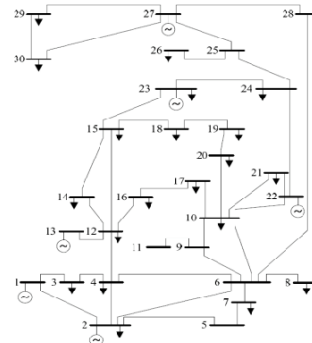


Fig. 3 Diagram of the IEEE 30-bus system

TABLE I
TTC RESULTS, LOSS AND CPU TIMES WITHOUT CAP

Without Cap.	TTC(MW)	Loss(MW)	Loss Cost (MBaht/Yr)
Best	137.10	5.16	113.07
Average	129.11	4.21	92.13
Worst	118.96	3.33	72.81
Standard deviation	5.52	0.45	9.77
Average CPU time (min)	1.83		

TABLE II
TTC RESULTS, LOSS AND CPU TIME WITH CAP

With Cap.	TTC (MW)	Loss (MW)	Loss Cost (MBaht/Tr.)	Install cost (MBaht)
Best	148.72	5.84	127.96	2.60
Average	133.52	4.49	98.23	2.26
Worst	120.31	3.76	82.24	1.61
Standard deviation	7.45	0.61	13.38	1.60
Average CPU time (min)	2.46			

TABLE III
CAPACITOR LOCATION AND SIZE

Install Capacitor at bus No.	Size of the Capacitor (MVar)
8	1.88
17	2.60
20	0.82
21	1.20

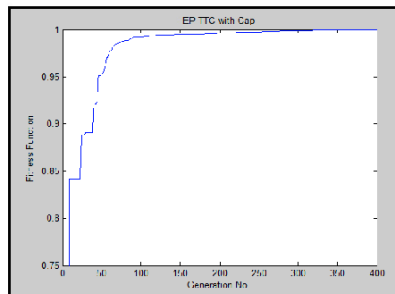


Fig. 4 Convergence characteristic of the fitness of the EP method.

All of the results calculate of 20 iterations, the results indicate that optimally placed OPF with capacitors can enhance TTC values of the system far more than OPF without capacitors. Focusing on the best result of condition cases, TTC without capacitor is 137.10 MW while loss is 5.16 MW which differs 131.94 MW. TTC with capacitor is 148.72 MW while loss is 5.84 MW which differs 142.88 MW. Result shows TTC with capacitor is 8.29% better than without capacitor. The fitness value at different generations is shown in Fig. 4; there is no much improvement in the fitness value from generation 150-250, which means the calculated solution is the optimum value that fulfills all the constraints.

In this paper, it has been shown that placing the optimal values of capacitors at proper locations in the system results in a very good power transfer capability and extends the reduction of power losses for more transfer power into system which in turn contribute to the total costs. The optimal solution improves the overall efficiency of power transfer systems.

V. CONCLUSION

EP method has been used to find the optimal allocation of capacitors in the power transmission systems. EP can properly and effectively determine optimal locations and sizes of capacitor. It is implemented to minimize cost of installation and less loss cost. Test results from the test system indicate that optimally placed OPF with capacitor by EP could enhance the TTC value far more than OPF without capacitor.

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ชื่อเรื่อง : Power Transfer Capability Enhancement with Multi-Type FACTS
Controllers Using Particle Swarm Optimization

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Power Transfer Capability Enhancement with Multitype FACTS Controllers Using Particle Swarm Optimization

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Abstract— In this paper, particle swarm optimization (PSO) is proposed to determine the optimal allocation of multitype FACTS controllers to enhance power transfer capability of power transactions between source and sink areas in power systems. The particularly optimal allocation includes optimal types, locations, and parameter settings. Three types of FACTS controllers including unified power flow controller (UPFC), thyristor-controlled series capacitor (TCSC), and static var compensator (SVC) are used in this study. The objective function is formulated as maximizing the benefit to cost ratio. The benefits mean increasing total transfer capability (TTC) with deducting system losses while the cost are the investment of FACTS controllers installation. Power transfer capability determinations are calculated based on optimal power flow (OPF) technique. Test results on the modified IEEE 30-bus system from PSO are compared with those from evolutionary programming (EP). The results show that PSO can be used to determine the optimal allocation of multitype FACTS controllers. The optimally placed OPF with FACTS controllers using PSO enhance higher power transfer capability than those from EP. Moreover, PSO gives higher benefit to cost ratio and faster convergence than EP for all transfer areas. Therefore, this installation is worthwhile and beneficial for the decision making of investment costs and further expansion plans.

Keywords—particle swarm optimization; FACTS controller; optimal allocation; power transfer capability

I. INTRODUCTION

The demands for electrical power energy have increased every year, so the installation of new power plants or transmission networks can help these requirements. However, there are some problems with these constructions, for examples, environment and pollution control, the cost of installation, and the land acquisition. The alternative solutions to respond these increasing demands are to improve the efficiency of power transfer capability in the power system using Flexible AC Transmission System (FACTS) [1]. The advantages of FACTS include less pollution, more acceptable of people who lived in the installed area, and less cost of installation. In addition, FACTS controllers' parameters can be adjusted to provide adaptability for the future planning of the transmission network.

FACTS controllers are power electronics based system and other static equipment that regulate control of one or more AC transmission system parameters. There are many types of FACTS controllers such as unified power flow controller (UPFC), thyristor-controlled series capacitor (TCSC), and static var compensator (SVC) [2]. It has been proved that these FACTS controllers can be used to increase power transfer capability and enhance system controllability resulting in minimizing power losses in transmission network [3].

Total transfer capability (TTC) is defined as an amount of electric power that can be transferred over the interconnected transmission network in a reliable manner while meeting all of a set of defined pre- and post-contingency system conditions [4]. TTC can be calculated by several power flow solution methods such as 1) linear ATC (LATIC) method [5], 2) continuation power flow (CPF) method [6], 3) repetitive power flow (RPF) method [7], and 4) optimal power flow (OPF) based methods [8].

The maximum performance of using FACTS controllers to increase TTC and minimize system losses should be obtained by choosing the suitable types, locations, and parameter settings. In [9], Evolutionary Programming (EP) is used to determine the optimal allocation of four types of FACTS controllers. Test results indicated that optimally placed OPF with FACTS controllers by EP can enhance the TTC more than OPF without FACTS controllers. In [10], OPF using Genetic Algorithm (GA) is used to considered the optimal allocations of SVC. Test results showed that the purpose method can be used to minimize the overall cost function, including generation costs of power plants and investment costs. In [11], both GA and Particle Swarm Optimization (PSO) are used to optimize the parameters of TCSC. However, there are more advantageous performances of the PSO than that of GA. PSO seems to arrive at its final parameter values in fewer generations than GA. PSO gives a better balanced mechanism and better adaptation to the global and local exploration abilities. Furthermore, it can be applied to solve various optimization problems in electrical power system such as power system stability enhancement [12] and capacitor placement problems [13].

In this paper, PSO is used to determine the optimal locations, types, and parameter settings of multitype FACTS controllers, leading to power transfer capability enhancement and power losses reduction with less installation cost. The modified IEEE 30-bus system is used as the test system.

II. PROBLEM FORMULATION

Power transfer capability is defined as TTC value, which is the power that can be transferred from the set of generators in a source area to loads in a sink area subjected to real and reactive power generation limits, voltage limits, line flow limits, and FACTS controllers operation limits. Three types of FACTS controllers are included: UPFC, TCSC, and SVC. These FACTS controllers are represented by the static model [14]. UPFC and SVC are modeled using the injected power model while TCSC is modeled by the adjustable series reactances. The sum of real power loads in the sink area at the maximum power transaction is defined as the TTC value.

The objective function of OPF with multitype FACTS controllers is represented by (1):

$$\text{Maximize } F = \frac{B}{C} \quad (1)$$

$$B = \Delta TTC = \left[\sum_{i=1}^{ND_SNK} (P_{Di} - P_{Di}^{base}) - \sum_{i=1}^{NL} (P_{Li} - P_{Li}^{base}) \right] - h(x_i) \quad (2)$$

$$C = C_{UPFC} + C_{TCSC} + C_{SVC} \quad (3)$$

$$C_{UPFC} = 0.0003S^2 - 0.2691S + 188.22$$

$$C_{TCSC} = 0.0015S^2 - 0.7130S + 153.75 \quad (4)$$

$$C_{SVC} = 0.0003S^2 - 0.3051S + 127.38$$

$$h(x_i) = \begin{cases} (x_i - x_i^{\max})^2 & \text{if } x_i > x_i^{\max} \\ (x_i^{\min} - x_i)^2 & \text{if } x_i < x_i^{\min} \\ 0 & \text{if } x_i^{\min} \leq x_i \leq x_i^{\max} \end{cases} \quad (5)$$

Subject to

$$P_{Gi} - P_{Di} + \sum_{k=1}^{n(i)} P_{Ui}(V_{Uk}, \alpha_{Uk}) - \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \cos(\theta_{ij}(X_s) - \delta_i + \delta_j) = 0 \quad (6)$$

$$Q_{Gi} - Q_{Di} + \sum_{k=1}^{n(i)} Q_{Ui}(V_{Uk}, \alpha_{Uk}) + Q_{Vi} + \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \sin(\theta_{ij}(X_s) - \delta_i + \delta_j) = 0 \quad (7)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad \forall i \in NG \quad (8)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad \forall i \in NG \quad (9)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \in N \quad (10)$$

$$|S_{Li}| \leq S_{Li}^{\max} \quad \forall i \in NL \quad (11)$$

$$0 \leq X_{Si} \leq X_{Si}^{\max} \quad (12)$$

$$0 \leq V_{Ui} \leq V_{Ui}^{\max} \quad (13)$$

$$-\pi \leq \alpha_{Ui} \leq \pi \quad (14)$$

$$Q_{Vi}^{\min} \leq Q_{Vi} \leq Q_{Vi}^{\max} \quad (15)$$

where

- P_{Di} : real power loads in the sink area,
- P_{Di}^{base} : base case real power loads in the sink area,
- P_{Li} : the losses in line flows,
- P_{Li}^{base} : the base case losses in line flows,
- ND_SNK : number of load buses in sink area,
- NL : number of branches,
- $h(x_i)$: penalty function of variable x_i ,
- S : operating range of the FACTS controllers in Mvar,
- P_{Gi} : real power generation at bus i ,
- $P_{Ui}(V_{Uk}, \alpha_{Uk})$: injected real powers of UPFC at bus i ,
- V_i : voltage magnitude at bus i ,
- V_j : voltage magnitude at bus j ,
- $Y_{ij}(X_s)$: magnitude of the ij th element in bus admittance matrix with TCSC included,
- $\theta_{ij}(X_s)$: angle of the ij th element in bus admittance matrix with TCSC included,
- δ_i : voltage angles of bus i ,
- δ_j : voltage angles of bus j ,
- Q_{Gi} : reactive power generation at bus i
- Q_{Di} : reactive power load at bus i
- $Q_{Ui}(V_{Uk}, \alpha_{Uk})$: injected reactive powers of UPFC at bus i ,
- Q_{Vi} : fixed injected reactive power of SVC at bus i ,
- X_{Si} : vector of reactance of TCSC at line i ,

$|S_{Li}|$: i th line or transformer loading,
 N : total number of buses,
 NG : number of generators,
 $P_{Gi}^{\min}, P_{Gi}^{\max}$: lower and upper limit of real power generation at bus i ,
 $Q_{Gi}^{\min}, Q_{Gi}^{\max}$: lower and upper limit of reactive power generation at bus i ,
 $V_i^{\min}, V_i^{\max}$: lower and upper limit of voltage magnitude at bus i ,
 $S_{Li}^{\max}$: i th line or transformer loading limit,
 $X_{Si}^{\max}$: upper limits of reactance of TCSC at line i ,
 $V_{Ui}^{\min}, V_{Ui}^{\max}$: lower and upper limit of voltage magnitude of UPFC at line i ,
 $\alpha_{Ui}^{\min}, \alpha_{Ui}^{\max}$: lower and upper limit of voltage angle of UPFC at line i , and
 $Q_{Vi}^{\min}, Q_{Vi}^{\max}$: lower and upper limit of injected reactive power of SVC at bus i ,

III. PARTICLE SWARM OPTIMIZATION

A. Overview of Particle Swarm Optimization

PSO is developed by Eberhart and Kenedy in 1995 [16]. It is a form of swarm intelligence in which the behavior of a biological social system like a flock of birds or a school of fish is simulated. The PSO provides a population-based search procedure in which individuals called particles change their position. The position of each particle is represented in X-Y plane with its position. Each particle physically moves to the new position using velocity according to its own experience, called $Pbest$, and according to the experience of a neighboring particle, called $Gbest$, which made use of the best position encountered by itself and its neighbor.

The modification of searching point is showed in Fig. 1 and it can be represented by the concept of velocity. Velocity of each particle can be modified by (16):

$$v_i^{k+1} = w \times v_i^k + c_1 \times rand_1 \times (p_{besti} - s_i^k) + c_2 \times rand_2 \times (g_{best} - s_i^k) \quad (16)$$

where

v_i^k : velocity of particle i at iterations,
 w : weight function,
 c_1 and c_2 : weighting coefficients both equal to 2,
 $rand_1$ and $rand_2$: random number between 0 and 1,

s_i^k : current positions of particle i at iteration k ,
 p_{besti} : best position of particle i th up to the current iteration, and
 g_{best} : best overall position found by the particles up to the current iteration.

Weight function is given by (17):

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (17)$$

where

$w_{\max}$: initial weight equal to 0.9,
 $w_{\min}$: final weight equal to 0.4,
 $iter_{\max}$: maximum iteration number, and
 $iter$: current iteration number.

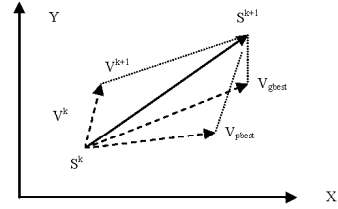


Figure 1. Concept of searching point by PSO

The first term of (16) is the previous velocity of the particle. The second and third terms are utilized to change the velocity of the particle. Without the second and third terms, the particle will keep on "searching" in the same direction until it hits the boundary. On the other hand, without first term, the velocity of the "searching" particle is only determined by using its current position and its best positions in history.

The new position can be modified by (18):

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (18)$$

The general flowchart of PSO is shown in Fig. 2, which can be described as follows.

Step 1: Generation of initial condition of each particle. Initial searching points (s_i^0) and velocities (v_i^0) of each particle are usually random within the allowable range. The current searching point is set to $Pbest$ for each particle. The best evaluated value of $Pbest$ is set to $Gbest$, and the best value is stored.

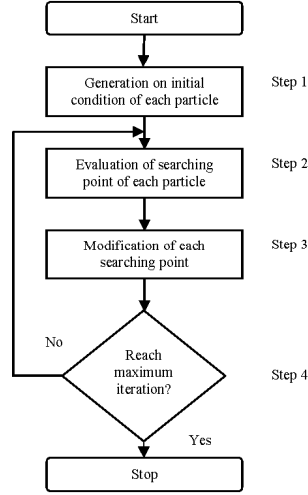


Figure 2. A general flowchart of PSO

Step 2: Evaluation of searching point of each particle. The objective function value is calculated for each particle. If the value is better than the current $Pbest$ of the particle, the $Pbest$ value is replaced by the current value. If the best value of $Pbest$ is better than the current $Gbest$, $Gbest$ is replaced by the best value and the best value is stored.

Step 3: Modification of each search point. The current searching point of each particle is changed using (16), (17), and (18).

Step 4: Checking the exit condition. The current iteration number reaches the pre-determined maximum iteration number, then exits. Otherwise the process proceeds to step 2.

B. Optimal Power Flow with FACTS controllers by Particle Swarm Optimization

PSO is used to determine the optimal allocation of multitype FACTS controllers to maximize the objective function. The proposed method is shown in Fig. 3, which can be described as follows.

Step 1: Solving base case power flow. This step solves base case power flow between selection source and sink areas. A full ac Newton-Raphson (NR) power flow analysis is used.

Step 2: Initialize particles contain all variables. The i th particle in a population is represented by a trial solution vector as (19)

$$V_i^T = [P_{G_i}, V_{G_i}, P_{D_i}, Loc_i, X_{D_i}, V_{U_i}, \alpha_{U_i}, Q_{D_i}] \quad (19)$$

$$Loc_i = [Loc_{i1}, Loc_{i2}, Loc_{i3}] \quad (20)$$

where

V_{G_i} : voltage magnitude at bus i in source area excluding slack bus, and

Loc_i : location vector of FACTS controllers type i , where $i = 1, 2$, and 3 , representing the line location of TCSC and UPFC, and bus location of SVC, respectively

Step 3: Solving power flow. This step solves power flow between selection source and sink areas. A full ac Newton-Raphson (NR) power flow analysis is used by including FACTS controllers static model and compute the objective function. Then keep V_i^T of the best objective value as $Pbest$ and $Gbest$. The fitness values are evaluated by using (21):

$$f_i = K_f \times F \quad (21)$$

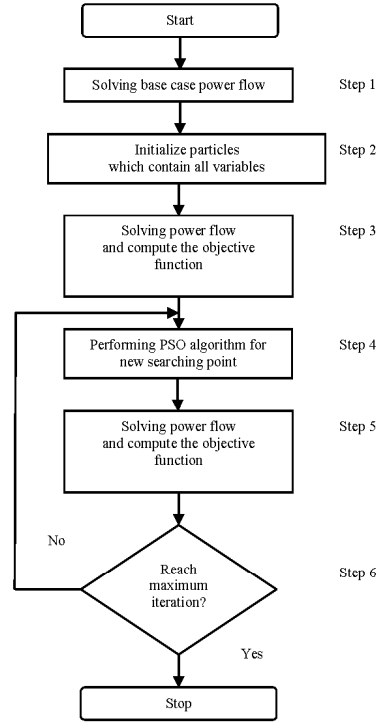


Figure 3. Flow chart of the propose algorithm

Where f_i is the fitness of the i th particle. K_f is an arbitrary constant and F is the objective function.

Step 4: Performing PSO algorithm for new searching point. All variables in (19) are modified to new searching point using (16), (17), and (18).

Step 5: Solving power flow. This step solves power flow between selection source and sink areas. A full ac Newton-Raphson (NR) power flow analysis is used by including FACTS controllers static model and compute the objective function. Then keep the V_i^T of best objective value as P_{best} . If new objective value is better than the previous value then V_i^T is stored as G_{best} . The fitness values are evaluated, too.

Step 6: Repeat Step 4-5. Until a stopping criterion is satisfied or the maximum number of iterations is reached.

IV. CASE STUDY AND EXPERIMENTAL RESULT

The modified IEEE 30-bus system in Fig. 4 is used as a test system. Bus and line data can be found in [17]. The system has three areas with two generators in each area. Transactions between different control areas are studies. In the simulations, one component of FACTS controllers for each type are used, voltage and angle limits of UPFC are $0 \leq V_{r_i} \leq 0.1$ pu, and $-\pi \leq \alpha_{r_i} \leq \pi$ radian, respectively. The reactance limit of TCSC is $0 \leq X_{si} \leq 0.1$ pu. The reactive power injection of SVC is $0 \leq Q_{r_i} \leq 10$ Mvar. Test result from PSO are compared with the results from OPF with EP.

The number of particle of PSO and population size of EP are set to 30. The max iteration number is set to 400. There are six power transaction from source to sink areas including from area 1 to 2, from 1 to 3, from 2 to 1, from 2 to 3, from 3 to 1, and from 3 to 2. Table I showed the benefit to cost ratio and the average CPU time of PSO and EP which can be calculated from (1).

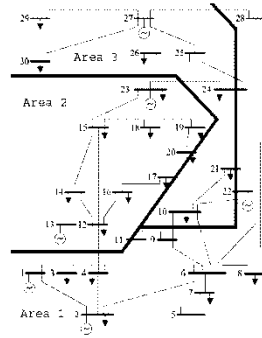


Figure 4. Diagram of the modified IEEE 30-bus system

TABLE I. OBJECTIVE VALUE FROM DIFFERENT POWER TRANSACTION

	Transfer Area	Case					
		From 1 to 2	From 1 to 3	From 2 to 1	From 2 to 3	From 3 to 1	From 3 to 2
EP Method	Worst	0.085	0.111	0.092	0.111	0.084	0.071
	Best	0.118	0.153	0.131	0.175	0.135	0.094
	Average	0.099	0.122	0.111	0.137	0.116	0.084
	Standard deviation	0.009	0.012	0.012	0.022	0.016	0.007
	Average CPU time (min)	2.72	3.63	4.60	2.11	2.47	2.13
PSO Method	Worst	0.122	0.147	0.284	0.158	0.199	0.158
	Best	0.204	0.171	0.577	0.236	0.320	0.178
	Average	0.155	0.158	0.352	0.189	0.249	0.167
	Standard deviation	0.030	0.009	0.085	0.026	0.045	0.006
	Average CPU time (min)	1.89	1.86	1.90	1.92	1.90	1.89

From Table I, PSO gives higher the best benefit to cost ratio than EP in all transfer areas which are 42.15%, 10.52%, 77.29%, 25.84%, 57.81%, and 47.19%, respectively. All of the worst, the best, and average objective values from PSO are also better than EP. In addition, the average CPU time of PSO for all transfer areas are less than EP.

Table II showed the best overall of TTC, losses, Mvar of each FACTS controller, and total cost of installation which obtained by PSO and EP. For all transfer areas, PSO gives higher TTC values than those from EP. Lower total cost of FACTS controllers obtained by PSO in half of transfer areas (between from-to area 1-2, 1-3, and 2-1). Therefore, the overall benefit to cost ratio are mostly obtained by PSO.

The best optimal allocation of FACTS controllers from EP and PSO is shown in Table III. The overall results indicate that PSO can determine higher benefit to cost ratio than EP. Furthermore, PSO gives faster convergence characteristics of the fitness value than EP which is shown in Fig. 5.

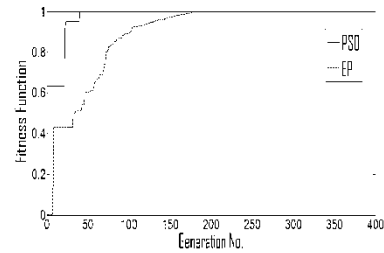


Figure 5. The convergence characteristic of the fitness of PSO and EP

TABLE II. RESULTS FROM THE MODIFIED IEEE 30-BUS SYSTEM

Transfer		EP Method						PSO Method					
From Area	To Area	TTC (MW)	Losses (MW)	UPFC (Mvar)	TCSC (Mvar)	SVC (Mvar)	Total Cost (US\$/Kvar)	TTC (MW)	Losses (MW)	UPFC (Mvar)	TCSC (Mvar)	SVC (Mvar)	Total Cost (US\$/Kvar)
1	2	103.101	5.965	136.652	9.100	3.466	430.761	142.726	8.343	155.077	13.067	4.650	424.360
1	3	127.711	5.225	49.559	13.200	2.538	446.828	141.088	10.151	2.965	-	5.853	313.029
2	1	147.062	3.546	-	2.000	3.376	278.684	235.003	6.370	77.396	-	-	169.190
2	3	132.040	4.442	104.819	32.085	2.980	421.730	172.942	13.092	70.943	0.044	4.350	441.387
3	1	151.046	4.018	-	29.713	1.455	260.825	239.426	6.692	18.965	7.500	-	331.711
3	2	96.390	4.723	-	7.6	-	148.418	137.444	11.443	75.374	30.000	5.670	429.011

TABLE III. PARAMETER OF FACTS CONTROLLERS

Transfer		EP Method						PSO Method					
From Area	To Area	UPFC			TCSC			UPFC			TCSC		
		α_{ij}	V_{ij}	Line	X_i	Line	Bus	α_{ij}	V_{ij}	Line	X_i	Line	Bus
1	2	0.3839	0.0801	9-10	0.0201	4-12	3.4660	8	0.5230	0.0420	6-8	0.0301	10-17
1	3	2.0640	0.0529	9-10	0.0175	10-21	2.5380	28	1.0300	0.0122	5-7	-	5.8530
2	1	-	-	-	0.0416	10-22	3.3760	18	-2.0954	0.0553	6-8	-	-
2	3	0.3795	0.0306	6-8	0.0360	12-15	2.9800	20	0.2388	0.0933	16-17	0.0443	10-21
3	1	-	-	-	0.0768	5-7	1.4550	30	1.2545	0.0788	6-8	0.0775	12-13
3	2	-	-	-	0.0642	9-10	-	-	0.7158	0.6530	10-21	0.0955	8-28

V. CONCLUSION

In this paper, PSO is used to determine the optimal allocations of multitype FACTS controllers. Test results from the test system indicate that optimally placing OPF with FACTS controllers by PSO can effectively and successfully enhance the power transfer capability compared to those from EP. Furthermore, PSO gives higher benefit to cost ratio, faster convergence, and less CPU time than EP for all transfer areas. Therefore, the installation of FACTS controllers with optimal allocation using PSO are worthwhile and beneficial for the decision making of investment costs and further expansion plans.

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ชื่อเรื่อง : Optimal Choice and Allocation of Distributed Generations Using
Evolutionary Programming

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OPTIMAL CHOICE AND ALLOCATION OF DISTRIBUTED GENERATIONS USING EVOLUTIONARY PROGRAMMING

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ABSTRACT

In this paper, evolutionary programming (EP) is proposed to determine the optimal choice and allocation of multi-type distributed generations (DG) to enhance power transfer capability and minimize system power losses of power transactions between source and sink areas in power systems. The optimal allocation includes the optimal type, size, and location. Two types of DG including photovoltaic (PV) and wind turbine (WT) are used in this study. The objective function is formulated as maximizing the benefit to cost ratio. The benefit means increasing in total transfer capability (TTC) with deducting system losses while the costs are the investment and operating costs of the selected DG units. Power transfer capability determinations are calculated based on the optimal power flow (OPF) technique. Test results on the modified IEEE 30-bus system show that the proposed EP can determine the optimal choice and allocation of DG to achieve the best TTC in the power system with the highest benefit to cost ratio.

KEY WORDS

Distributed power generations, evolutionary programming, optimal power flow, and optimal allocation

1. Introduction

Distributed generation (DG) is an electric power generation unit connected directly to distribution networks or on the customer site [1]. The technologies adopted in DG comprise small gas turbines, micro-turbines, fuel cells, wind, and solar energy, [2] etc. In power systems, DG can provide benefits for the consumers as well as for the utilities, especially in sites where central generations are impracticable or where there are deficiencies in the transmission systems [3]. The optimal allocated DG units can be used to enhance power transfer capability, reduce power system losses, improve voltage profile, increase system reliability, reduce pollute of emission, [4] etc.

Even though DG units have many benefits when they are placed in power systems, the installation of DG units at non-optimal places can result in an increase in

system losses, implying in an increase in costs and, therefore, having an effect opposite to the desired [5]-[6]. Since cost is an important role, the planner's idea goal will regard to the optimal solution that gives minimizing overall cost within technical constraints [7]-[8]. Therefore, the problem of selection of the best places for installation and the preferable size of the DG units in large power systems is of great importance. However, the optimal choice and allocation of DG is a complex combinatorial optimization problem.

There are many studies focus on selection of the optimally placed DG units in power systems. In [9], genetic algorithm (GA) has been proposed to determine the optimal DG location. Sizing of the selected DG unit has been done by optimal power flow (OPF). In [10], an optimal proposed approach (OPA) is presented to determine both optimal sitting and sizing of DG with multi-system constraints to obtain a single or multi-objectives considering composite technical and economic benefit using GA. The linear programming (LP) is used not only to confirm the optimization results obtained by GA but also to investigate the influences of varying ratings and locations of DG. Recently, metaheuristics optimization techniques are used to obtain the optimal placements and sizes of DG to minimize cost in distribution utility when DG is presented [11]. However, these methods cannot simultaneously determine the optimal type, size, and location of DG units in the same time. Therefore, the use of an optimization method capable of indicating the best solution for a given power system can be very useful for the system planning engineer when dealing with the increase of DG units [12]-[13].

At present, evolutionary programming (EP) [14]-[15] has been suggested to overcome the above-mentioned difficulties of conventional methods. In this paper, EP is used to simultaneously determine the optimal type, size, and location of multi-type DG to enhance power transfer capability and minimize power losses with less installation cost of power transactions in power systems. Photovoltaic (PV) and wind turbine (WT) are used in the study. The objective function is formulated as maximizing the benefit to cost ratio. The modified IEEE 30-bus system is used as the test system.

2. Problem Formulation

2.1 Objective Function

The OPF-based objective function with multi-type DG including total transfer capability (TTC), system real power losses, and DG installation costs in (1) is used to evaluate the feasible TTC value that can be transferred from a specific set of generators in a source area to loads in a sink area within real and reactive power generation limits, thermal limits, voltage limits, and DG operation limits. Two types of DG are included: photovoltaic (PV) and wind turbine (WT). They are represented by the static model [16].

$$\text{Maximize } F = \frac{B}{TC} \quad (1)$$

Where

F : objective function,
 B : benefit from installation of DG units, and
 TC : total costs of DG installation.

The benefit means increasing in TTC with deducting system losses as shown in (2). The sum of real power loads in the sink area at the maximum power transaction in each case is defined as the TTC value.

$$\begin{aligned} B &= TTC - Loss \\ &= \sum_{i=1}^{ND_SNK} (P_{Di} - P_{Di}^{base}) - \sum_{i=1}^{NL} (P_{Li} - P_{Li}^{base}) \end{aligned} \quad (2)$$

Where

TTC : total transfer capability,
 $Loss$: system real power loss,
 P_{Di} : real power load in sink area at bus i th,
 P_{Di}^{base} : base case real power load in sink area at bus i th,
 P_{Li} : losses in the line flows at line i th,
 P_{Li}^{base} : base case losses in the line flows at line i th,
 NL : number of branches, and
 ND_SNK : number of load bus in sink area.

The total cost (TC) is the cost function of investment and operating costs of DG, which can be calculated in (3) [16]. The technical and economic data of DG technologies are shown in Table 1 [16].

$$\begin{aligned} TC &= \sum_{i=1}^{ND_SNK} \sum_{j \in Tech} CPV_1 \cdot IC_j \cdot P_{DG,ij} \\ &+ \sum_{i=1}^{ND_SNK} \sum_{j \in Tech} CPV_2 \cdot OC_j \cdot P_{DG,ij} \cdot a_j \cdot 8,746 \end{aligned} \quad (3)$$

Where

CPV_1 : cumulative present values related to fix cost,

Table 1
Technical and economic data of DG technologies

Type	IC (\$/MW-year)	OC (\$/MWh)	Commercial size (KW)	Plant factor (%)
PV	618,000	0.0	100	25
WT	206,000	10.9	200, 300	20

CPV_2 : cumulative present values related to variable cost,

j : DG technologies used in the study,

IC_j : investment cost of DG type j th,

OC_j : operating cost of DG type j th,

$P_{DG,i}$: injected real power of DG at bus i th.

$P_{DG,ij}$: capacity of the DG type j at bus i th,

a_j : plant factor of DG unit type j .

2.2 System Constraints

- **Voltage Profile:** The voltage of all buses should be within the limits in (4) allowed by regulation.

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (4)$$

Where

V_i : voltage magnitude at bus i th,

$V_i^{\min}$: lower limit of voltage magnitude at bus i th, and

$V_i^{\max}$: upper limit of voltage magnitude at bus i th.

- **Feeder Transmission Capacity Constraint:** Power flow through any feeder must comply with the thermal capacity limit in (5).

$$|S_{Li}| \leq S_{Li}^{\max} \quad (5)$$

Where

$|S_{Li}|$: line loading at line i th, and

$S_{Li}^{\max}$: line loading limit at line i th.

- **Maximum Installed Capacity:** The power generated by DG must be less than or equal to maximum installed capacity of DG units at each bus. This value is considered to be 8 MW according to the voltage limits at 22 KV, in order to apply with Provincial Electricity Authority (PEA) in Thailand.

$$P_{DG,i} \leq P_{DG}^{\max} \quad (6)$$

Where

$P_{DG,i}$: injected real power of DG at bus i th, and

$P_{DG}^{\max}$: maximum install capacity of DG unit.

- **Power Balance Constraint:** The total power generation of any generator buses and DG units must be enough for the total load demand and the total power losses, which can be determined in (7) and (8).

$$P_{Gi} - P_{Di} + P_{DG,i} = 0 \quad (7)$$

$$\sum_{N_g} P_g + \sum_{i=1}^{N_{DG}} P_{DG,i} = P_D + P_L \quad (8)$$

Where

P_{Gi} : real power generation at bus i th,

P_{Di} : real power load in sink area at bus i th,

$P_{DG,i}$: real power generation from DG at bus i th,

$\sum_{N_g} P_g$: total power generation in the system,

P_D : total load demand in the system,

P_L : total active power loss, and

N_{DG} : total number of DG units.

3. Evolutionary Programming

3.1 Evolutionary Programming

EP is an optimization technique that searches for the optimal solution by evolving a population of candidate solution, starts with random generation of initial individual. Then, the mutation and selection are preceded until the best individual is found. The structure of EP algorithm is shown in Figure 1 [17]. The major steps of the algorithm are explained as follows.

3.1.1 Initialization

The initial population consists of individuals and it is created randomly. It is generated within a feasible range of each control variable in (9).

$$x_i = x_i^{\min} + \mu (x_i^{\max} - x_i^{\min}) \quad (9)$$

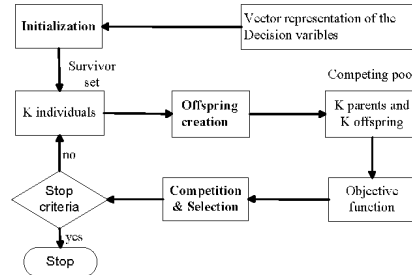


Figure 1. Structure of the evolutionary programming

Where

x_i : i th element of the individual in a population,

$x_i^{\min}$: lower limit of the i th element of the individual,

$x_i^{\max}$: upper limit of the i th element of the individual, and

μ : uniform random number in the interval $[0,1]$.

3.1.2 Mutation

Each individual is mutated to generate a new population which is an offspring vector. The new population is generated by the Gaussian random variable. The K parents create K offspring, result from this step is $2K$ individual. Each element is computed in (10) and (11).

$$x_{k,j}' = x_{k,j} + N(0, \sigma_{k,j}^2) \quad (10)$$

$$\sigma_{k,j} = (x_i^{\max} - x_i^{\min}) \left(\frac{f_{\max} - f_k}{f_{\max}} + a^g \right) \quad (11)$$

Where

$x_{k,j}'$: j th element of the k th offspring individual,

$x_{k,j}$: j th element of the k th parent individual,

$N(0, \sigma_{k,j}^2)$: Gaussian random number with mean 0

and standard deviation of $\sigma_{k,j}$,

$\sigma_{k,j}$: standard deviation,

$x_i^{\min}$: lower limits of the i th element of the K th parent individual,

$x_i^{\max}$: upper limits of the i th element of the K th parent individual,

f_k : fitness of the K th individual,

$f_{\max}$: maximum fitness of the parent population,

a : a positive number constant slightly less than one,

g : iteration counter.

3.1.3 Competition

Each individual in the combined population has to compete with some other individuals to get chance to be transcribed to the next generation. The best K individuals with maximum fitness values are retained to be parents of the next generation. A weight value is assigned to the individual according to the competition in (12) and (13).

$$w_i = \sum_{t=1}^{N_t} w_t \quad (12)$$

$$w_i = \begin{cases} 1 & \text{if } f_k > f_r \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

Where

- w_t : weight value of K th individual in combined population,
- f_k : fitness value of K th individual in combined population,
- f_r : fitness value of R th opponent randomly selected from the combined population, and
- N_t : number of competitors.

3.1.4 Termination criterion

The termination criterion is set as the maximum number of generations.

3.2 Algorithm of EP-based OPF

The EP-based OPF is used to simultaneously search for real power generations in a source area excluding slack bus, generation bus voltages, real power loads in a sink area, and optimal placement of multi-type DG for determining the feasible TTC value. A flowchart of the proposed approach is shown in Figure 2, which can be explained as follows.

- **Step 1.** Prepare bus data and line data.
- **Step 2.** Assume population size (*popsiz*) and the maximum number of generation (*maxgen*).
- **Step 3.** Set valid number of population counter to zero (*poptmp* = 0).
- **Step 4.** Each of OPF control variables of an individual is initialized randomly using a trial solution vector as (14).

$$V_k^T = [P_{G_i}, V_{G_i}, P_{D_i}, Loc_i] \quad (14)$$

Where

- P_{G_i} : real power generation at bus i th in the source area excluding slack bus,
- V_{G_i} : voltage magnitude of generator at bus i th including the slack bus,
- P_{D_i} : real power load at bus i th in the sink area, and
- Loc_i : type and location of DG: Loc_1 and Loc_2 is bus number of PV and WT.
- **Step 5.** Run power flow using the Newton-Raphson method (NR) to calculate power flow in each transmission line of the system.
- **Step 6.** Check the system constraints, voltage profile, feeder transmission capacity, maximum install capacity, and power balance equations.
- **Step 7.** If all the constraints are satisfied, increment *poptmp* by 1. If *poptmp* less than or equal to *popsiz* go to step 4, otherwise go to next step.

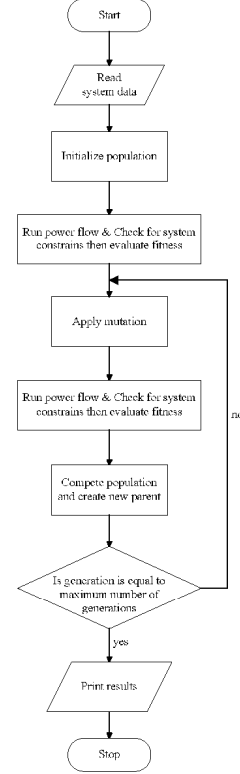


Figure 2. Flowchart of EP-based OPF

- **Step 8.** Calculate fitness function of an individual candidate in the population. The fitness function of each individual is defined in (15).

$$f_k = K_f \times F \quad (15)$$

Where

- f_k : fitness value of the K th individual,
- K_f : an arbitrary constant, and
- F : objective function.
- **Step 9.** Find and store maximum fitness of all valid individual parents and corresponding generation pattern.
- **Step 10.** Set generation count, *gencount*=1.
- **Step 11.** A new population is produced from the existing population through the mutation operator ($x'_{k,j}$), which is computed by (10) and (11).

- **Step 12.** Check the $x_{k,i}$ in (10). It should be between lower and upper limit. If individual is not in range, this will be rejected.
- **Step 13.** Run power flow using the NR method for each set of new OPF variables satisfying constraint of step 12.
- **Step 14.** Check system constraints as mentioned in step 6. If all the constraints are satisfied, the individual of the new population becomes valid otherwise it becomes invalid.
- **Step 15.** Find the maximum fitness among all valid individuals. If it is more than f_{max} , store this fitness in f_{max} and also store corresponding OPF variables.
- **Step 16.** Increase the $gencount$ by 1. If it is less than or equal to $maxgen$, select the best individuals for the next population and go to step 11 otherwise go to next step.
- **Step 17.** Find the optimal solution among all population groups.

4. Case Study and Simulation Results

The modified IEEE 30-bus system is used to demonstrate the optimal choice and allocation of multi-type DG units using the EP approach. The test system in Figure 3 from [18] is partitioned into three areas with two generators in each area, bus data and line data from [19]. Six transactions between area 1, 2 and 3 are considered. The EP parameters used in the study are shown in Table 2.

In the simulations, the maximum install capacity of DG unit of PV and WT are 8.0 MW. The numbers of each DG are imposed according with the power generation in the system, quantity of each DG type up to three devices. The EP is implemented using MATLAB version 6.5 on an AMD Athlon X2 250 computer with 2.0 GB memory.

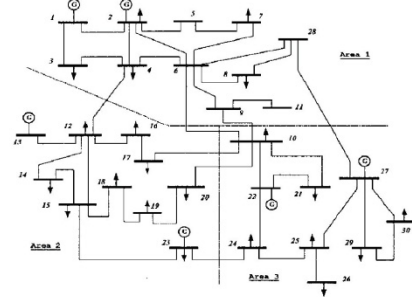


Figure 3. Diagram of the modified IEEE 30-bus system

Table 2
Parameter setting of EP

EP parameter	Value
Population size: $popsize$	20
Maximum generation: $maxgen$	400
Constant value: a	0.90
Number of competitors: N_i	15
An arbitrary constant: K_f	1

Table 3
The transaction results when each DG type = 1.

Transfer		Base case	With DG multi-type=1			Photovoltaic		Wind Turbine	
From Area	To Area	TTC (MW)	TTC (MW)	Total cost (\$)	Objective function	Bus no.	Size (MW)	Bus no.	Size (MW)
1	2	84.500	130.925	164,485.26	0.268	6	6.247	25	6.708
1	3	56.200	70.811	6,875.57	1.971	26	2.486	24	0.280
2	1	48.500	70.218	6,331.88	3.224	18	5.880	22	0.258
2	3	56.200	75.519	32,534.76	0.566	16	7.803	27	1.327
3	1	48.500	67.681	109,343.54	0.162	25	7.425	11	4.459
3	2	84.500	108.297	30,214.62	0.754	9	5.858	17	1.232

Table 4
The transaction results when each DG type = 2.

Transfer		Base case	With DG multi-type =2				Photovoltaic		Wind Turbine	
From Area	To Area	TTC (MW)	TTC (MW)	Total cost (\$)	Objective function	Bus no.	Size (MW)	Bus no.	Size (MW)	
1	2	84.500	133.818	50,304.94	0.947	N1=23 N2=26	5.440 7.692	N1=20 N2=12	0.535 0.982	
1	3	56.200	106.996	45,868.26	1.031	N1=22 N2=5	3.489 2.495	N1=25 N2=23	0.815 0.241	
2	1	48.500	82.547	221,698.00	0.145	N1=19 N2=29	5.495 5.406	N1=29 N2=28	3.007 3.028	
2	3	56.200	102.072	137,905.80	0.316	N1=19 N2=12	7.964 0.502	N1=8 N2=1	0.493 4.638	
3	1	48.500	70.452	46,495.52	0.438	N1=27 N2=15	3.215 5.289	N1=14 N2=9	0.305 1.287	
3	2	84.500	113.905	27,660.03	1.018	N1=2 N2=5	1.303 6.255	N1=7 N2=23	0.423 0.283	

Table 5
The transaction results from area 1 to area 2 and each DG type = 2.

Test no.	Base case	With DG					Photovoltaic		Wind Turbine		CPU time (min)
	TTC (MW)	TTC (MW)	P _{loss} (MW)	Total cost (\$)	Objective function	P _{DG} (MW)	Bus no.	Size (MW)	Bus no.	Size (MW)	
1	84.50	138.407	4.372	125,084.27	0.415	12.170	N1=24 N2=21	5.457 1.891	N1=13 N2=6	0.279 4.544	1.60
2	84.50	133.818	4.088	50,304.94	0.947	14.649	N1=23 N2=26	5.440 7.692	N1=20 N2=12	0.535 0.982	2.65
3	84.50	98.796	2.179	153,469.65	0.095	15.770	N1=13 N2=22	3.609 7.181	N1=10 N2=11	1.279 3.701	1.69
4	84.50	119.260	3.844	172,770.14	0.186	11.897	N1=13 N2=6	4.368 0.601	N1=14 N2=20	0.119 6.808	1.62
5	84.50	126.240	3.814	177,019.93	0.228	12.877	N1=11 N2=21	1.564 7.115	N1=3 N2=13	3.022 1.177	1.66
6	84.50	131.632	4.095	130,481.87	0.348	9.999	N1=15 N2=5	0.031 6.117	N1=21 N2=23	1.472 2.378	1.77

Table 6
The transaction results when each DG type = 3.

Transfer		Base case	With DG multi-type =3			Photovoltaic		Wind Turbine	
From Area	To Area	TTC (MW)	TTC (MW)	Total cost (\$)	Objective function	Bus no.	Size (MW)	Bus no.	Size (MW)
1	2	84.500	170.685	279,431.60	0.293	N1=12 N2=9 N3=29	6.077 5.562 0.147	N1=17 N2=18 N3=15	0.093 5.520 0.076
1	3	56.200	168.168	393,287.49	0.207	N1=6 N2=8 N3=9	4.040 5.760 6.949	N1=19 N2=22 N3=3	5.296 0.018 0.116
2	1	48.500	98.273	78,911.71	0.587	N1=17 N2=30 N3=8	5.012 4.156 1.250	N1=10 N2=1 N3=30	0.116 0.760 1.350
2	3	56.200	110.985	124,347.30	0.421	N1=20 N2=9 N3=12	7.684 7.149 6.088	N1=26 N2=10 N3=23	0.331 0.833 2.412
3	1	48.500	82.035	171,206.40	0.181	N1=14 N2=30 N3=26	3.642 6.154 2.958	N1=17 N2=18 N3=10	0.229 1.257 3.782
3	2	84.500	162.576	203,685.50	0.369	N1=28 N2=21 N3=15	2.515 1.667 5.526	N1=30 N2=25 N3=16	0.731 2.725 0.664

Six transactions between area 1, 2, and 3 are shown in Table 3. In each case, the total number of DG unit is set as one device for each DG type. The maximum TTC improvement is the power transaction from area 1 to 2. The additional 46.425 MW is increased in this transaction. The real power from PV unit installed at bus 6 is 6.247 MW and the real power from WT unit installed at bus 25 is 6.708 MW. The minimum TTC improvement is the transaction from area 1 to 3. The additional capacity of 14.611 MW is increased in this transaction. The real power from PV at bus 26 is 2.486 MW and the real power from WT at bus 24 is 0.280 MW.

Table 4 shows the six power transactions with the quantity of each DG type is two devices. The maximum TTC improvement is the power transaction from area 1 to 3. The additional 50.746 MW is increased in this transaction, which is the additional of 90.38%. The real powers from PV installed at bus 22 and 5 are 3.489 MW and 2.495 MW, respectively and the real powers from WT installed at bus 25 and 23 are 0.815 MW and 0.241 MW, respectively. For the other transactions, the maximum TTC improvement of the transaction [1-2, 2-1, 2-3, 3-1, 3-

2] is [58.36%, 70.20%, 81.62%, 45.26%, 34.80%], respectively.

In addition, total real power loss is increased when DG placed in the system. Loss in each simulation is shown in Table 5. Table 5 shows the power transaction from area 1 to area 2 when quantity of DG unit is set as two devices. The additional power from the test number one is increased from 84.500 MW to 138.407 MW. Total real power loss is 4.372 MW when real power from DG is 12.170 MW. The real powers from PV are [5.457, 1.891] MW at bus [24, 21] and the real powers from WT are [0.279, 4.544] MW at bus [13, 6] respectively. Even though, the transaction number one has the maximum TTC, the installation cost of DG increase as TTC. Then, the optimal allocation is considered from objective function. The best objective function value from Table 5 is 0.947 which come from the test number two. The injected power is increased from 84.500 MW to 138.407 MW. Total real power loss in sink area is 4.088 MW and real power from DG is 14.649 MW. The real powers from PV at bus [23, 26] are [5.440, 6.692] MW and the real powers from WT at bus [20, 12] are [0.535, 0.982] MW, respectively.

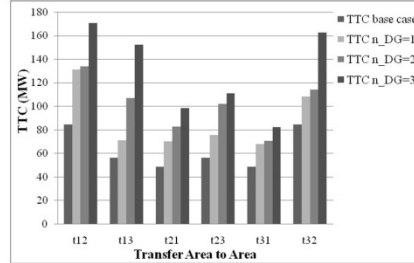


Figure 4. TTC result with different number of DG units

Table 6 shows the six transactions which the quantity of each DG type is three devices. The maximum TTC improvement is the power transferred from area 1 to 3. The additional power in this transaction is 111.968 MW. The real powers from PV at bus [6, 8, 9] are [4.040, 5.760, 6.949] MW and the real powers from WT at bus [14, 30, 26] are [5.296, 0.018, 0.116] MW, respectively

Figure 4 shows graph that compare results from base case until total number of each DG type is three devices. When number of DG is increased, the real power in the test system is more transferred. From the results, the transaction from area 1 to area 2 has the most TTC while the transaction from area 3 to area 2 has nearby TTC value in the transaction 1 to 2. Figure 5 shows the rapid convergence characteristic of fitness of EP method.

5. Conclusion

In this paper, the proposed EP is implemented to determine the optimal choice and allocation of multi-type DG units to enhance power transfer capability of power transfers between different control areas in power systems constrained by real and reactive power generation limits, thermal limits, voltage limits, and DG operation limits. The OPF-based objective function with multi-type DG is formulated as maximizing the benefit to cost ratio. The benefit means increasing in TTC with deducting system losses while the costs are the investment and operating costs of DG.

Test results on the modified IEEE 30-bus system show that the EP approach can simultaneously determine the optimal type, size, and location of photovoltaic and wind turbine DG units to maximize TTC and minimize power losses with the lowest cost. In addition, the test results indicate that optimally placed OPF with multi-type DG units by the EP approach could enhance the TTC value far more than OPF without DG, leading to a higher trading level of energy transactions in a normal secured system.

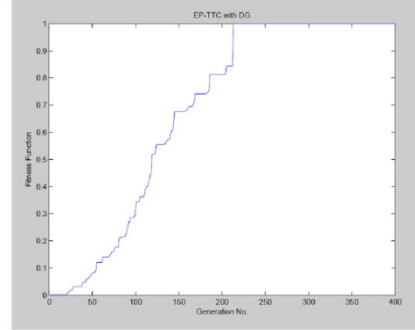


Figure 5. The convergence characteristic of the EP approach

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