# Fast and accurate solution for the SCUC problem in large-scale power systems using adapted binary programing and enhanced dual neural network

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Received 28 September 2013; received in revised form 5 November 2013

**Abstract**

This paper presents a novel hybrid method for solving the security constrained unit commitment (SCUC) problem. The proposed formulation requires much less computation time in comparison with other methods while assuring the accuracy of the results. Furthermore, the framework provided here allows including an accurate description of warmth-dependent startup costs, valve point effects, multiple fuel costs, forbidden zones of operation, and AC load flow bounds. To solve the nonconvex problem, an adapted binary programming method and enhanced dual neural network model are utilized as optimization tools, and a procedure for AC power flow modelling is developed for including contingency/security issues, as new contributions to earlier studies. Unlike classical SCUC methods, the proposed method allows to simultaneously solve the unit commitment problem and comply with the network limits. In addition to conventional test systems, a real-world large-scale power system with 493 units has been used to fully validate the effectiveness of the novel hybrid method proposed.


*Keywords:* AC power flow, Binary programming, Dual neural network, Security constrained unit commitment.

## 1. Introduction

The security constrained unit commitment (SCUC) provides a safeguarded and economic generation scheduling program on an hourly basis. Decomposition of very complex SCUC problems is an acceptable simplification technique to separate the problem into: master problem, unit commitment (UC), and some sub-problems to examine the security of the system.

In the majority of previous works, benders decomposition (BD) has been implemented to simplify the complexities of the SCUC problem (e.g. [1-5]). In these works, BD has been utilized to decompose SCUC problems into master and sub-problems.

Dynamic programming (DP) and Lagrangian relaxation (LR) were also utilized for solving the UC part, while some other techniques like linear programming (LP) were used to satisfy sub-problems. However, on the one hand, DP is not a suitable method to solve large-scale power systems [6]. On the other hand, due to unacceptable relaxations for the discrete variables, LR is not a reliable technique to acquire feasible solutions [1, 7].

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In addition to classical methods, several artificial intelligence ones have been utilized to solve UC problem, such as: simulated annealing [8], genetic algorithm (GA) [9], interior point method [10], etc. However, those methods usually need a significant computational time for large-scale power systems [11].

Based on this, other methods were applied in earlier works [12-15]. In [12], the SCUC problem has been divided into the UC and the optimal power flow (OPF) problems, using a GA to solve each problem separately. In [13], a combined method based on BD and enhanced evolutionary algorithm has been proposed to decrease the computation time. In [14], a solution method has been presented based on the combination of BD and the outer approximation technique. In [15], an adaptive hybrid stochastic search technique has been described, consisting of an adaptive binary particle swarm optimization (ABPSO) and an adaptive real coded genetic algorithm (ARCGA).

In [16], a SCUC model has been presented to include integer variables at the second stage. In this paper, an extended BD with linear feasibility and optimality cuts has been proposed to solve the mixed-integer programming at both stages. In [17], a hybridization of BD and outer approximation (OA) methods has been proposed.

The overwhelming majority of the previous methods have some intrinsic nature limitations (e.g. unreliable performance of GA and excessive decomposition of the problem for BD) [6]. On this basis, a method was presented in [18] based on an enhanced harmony search technique (EHS) for solving the UC problem, and an analytical nonlinear programming optimization approach was proposed for dealing with the security constrained economic dispatch (SCED). Although the accuracy achieved in the results of the mentioned reference is appropriate, the considerable computation time and indeterminism of solutions present serious disadvantages. Consequently, the solutions obtained from the mentioned method are not unique in different runs.

According to the importance of solving the SCUC in daily energy markets, some worthwhile studies have been presented to decrease the computation time of the problem. In [7], a fast SCUC method has been presented for large-scale power systems. In the mentioned reference, reducing the number of integer variables has been accomplished by applying infeasible criteria of SCUC solution. Since elimination of inactive constraints can accelerate the SCUC problem solving, identification of the constraints has been studied in some references. In [19], an analytical approach has been suggested to quickly identify inactive security constraints in the problem. Moreover, in [20], a systematic method based on branch-and-bound (BB) has been presented to construct feasible solutions in LR framework of the SCUC problem.

However, many practical features were ignored in the previous methods, such as multiple fuel costs (MFCs), prohibited operating zones (POZs), valve point effects (VPEs) and AC load flow limits.

Due to complexity of the SCUC problem, in most solution methods the UC problem and the network security issue are solved separately. Nonetheless, LP [21], semi-definite programming (SDP) [6] and modified BB incorporated with quadratic programming (MBB-QP) [22] have been developed for a unified solution. In those works there is no need to divide the SCUC problem into sub-problems. Although unified methods were able to obtain more accurate solutions than decomposition-based methods, they needed some simplifications and their computations times were usually high.

The fast and accurate problem solving still represents nowadays an important challenge for the conventional optimization methods. Previous works can be categorized into two major approaches to optimize the SCUC problem as a large-scale mixed integer nonlinear programming. The first approach is based on the decomposition of the SCUC problem into UC and SCED, in order to decrease the size of the problem. The second approach is based on the unified solution of the SCUC problem, using hybrid evolutionary algorithms. In [23], a comprehensive comparison has been accomplished between these two approaches to solve SCUC problem.

In this paper another approach is proposed, based on the decomposition of the SCUC problem into Quadratic Programing (QP) and Binary Programing (BP) problems. This type of decomposition is much faster than previous unified methods, being also more accurate than traditional decomposition methods that may lead to cutting off feasible or optimal solutions. It should be noted that, unlike traditional SCUC algorithms that first solve the UC problem and then check the grid constraints to satisfy the network flow limits, in this paper both steps are conducted simultaneously.

It should be noted that, although many works have utilized NN for UC, no previous reference has ever applied NN models to solve the much more complex problem, SCUC, so this powerful modelling tool has always been neglected in previous works. Because of high computational cost of NN to solve mixed-integer problems [11], this method is not appropriate to solve directly large-scale SCUC problems.

However, the valuable features of high parallelism, speed of computation and adaptability of NNs can be indeed utilized to assist to solve SCUC problems. Hence, in this paper, the NN model is successfully applied to solve the QP problem with equality and two-sided inequality restrictions. In order to solve the QP problem, NN models provide several advantages in comparison with traditional methods. They offer the parallelizable property, being able to easily overcome large-scale problems. Also, because of the global convergence property, the solution of NNs is convergent to the optimal solution without depending on input changes [24].

Although a few reports have applied BB as a traditional method for BP to solve UC problems or to eliminate the inactive constraints [20, 25], it has been rarely used for SCUC solutions. Also, computational result of the BB technique (e.g. CPLEX) is unstable [25]. Moreover, according to the nature of the binary tree, BP is known for being time-consuming.

On this basis, according to the features of the SCUC problem, this paper presents an adapted BP to overcome the instability problem and obtain better results.

The novel hybrid method proposed in this paper for solving the SCUC problem is based on the combination of adapted binary programming (ABP) with enhanced dual neural network (EDNN). Its effectiveness is assessed comparatively to several previous methods. By using the proposed method, the computation time is kept low and the accuracy of the solution is guaranteed. Therefore, this method is able to become a perfect alternative to conventional decomposition based methods (e.g. BD), even in handling stochastic SCUC problems. Three test systems have been selected to evaluate and demonstrate the proficiency of the proposed method.

Regarding contingency/security issues in solving SCUC problems, one of the most effective models on both accuracy and computation time is the power flow (PF) model. The power-flow calculation methods for solving the SCUC can be categorized into three approaches [26]: first linearized DC equations for the both of normal and contingency, second AC model for normal situation and DC equations for contingency, and third AC equations for the both of normal and contingency. However, all the mentioned approaches have some disadvantages.

In this paper, an AC-PF procedure is presented towards SCUC solution. The proposed method is more accurate than DC-SCUC methods and takes less computation time. The proposed method obviates the disadvantages of current methods, being able to be used for solving the large-scale power systems in real-time with higher accuracy. The method takes into account the contingency and network security concerns. Also, due to consideration of reactive power and voltage constraints, the method is more practical than DC-SCUC methods. Moreover, the framework provided here allows including an accurate description of warmth dependent startup costs (WDSCs), MFCs, ramp rates, minimum up and downtime restrictions, POZs and VPEs.

The remainder of this paper is partitioned as follows: Section 2 describes the problem formulation. Optimization methods are discussed in Section 3. Section 4 is devoted to the numerical studies. Finally, Section 5 concludes this paper.

## 2. Problem Formulation

SCUC involves deciding about commitment state and generation of all units to satisfy security and network constraints during a certain period. The objective is to optimize the scheduling program in a way that the total operation costs are able to be minimized while satisfying the operational limits and security constraints.

**2.1. Objective function**

The objective function of SCUC problem includes fuels, startup and shutdown costs of generating units', thus it can be expressed as [27]:

$$Min \ \{\sum_{t=1}^{T}\sum_{i=1}^{N} FC_{i,t} * u_{i,t} + \sum_{i=1}^{N} SUC_i + \sum_{i=1}^{N} SDC_i \} \tag{1}$$

The fuel cost is principally described as a quadratic equation. In addition, many units might be supplied by more than one type of fuel. On this basis, the objective function formulation is modified using piecewise functions. Therefore, this formulation is able to consider the effect of various fuel types. In addition, the VPEs are usually modelled using an absolute part of a sinusoidal function. This expression of VPEs produces non-convex ripples in the cost curve.

Therefore, in this paper an alternative expression is applied and the previously mentioned term is replaced by related quadratic terms. Fitting error is less than 1e-5, as presented in [22].

Fuel cost considering VPEs can be expressed as:

$$\begin{aligned} FC_{i,t} = {} & a_{i\,f} P_{i,t}^2 + b_{i\,f} P_{i,t} + c_{i\,f} \\ & + \alpha_{i\,f} \{P_{i,t}^q - P_{i\,f}^{\min} - (q-1)\pi / m_{i\,f}\}^2 \\ & + \beta_{i\,f} \{P_{i,t}^q - P_{i\,f}^{\min} - (q-1)\pi / m_{i\,f}\} + \gamma_{i\,f} \\ & , \ q \in (1,2,\ldots,\lfloor m_{i\,f} (P_{i\,f}^{\max} - P_{i\,f}^{\min}) / \pi \rfloor) \end{aligned} \tag{2}$$

A linearized expression of startup cost has been applied in this paper to model the warmth-dependency of each generating unit. The number of statements of the warmth-dependency depends on the considered warmth conditions. On this basis, the linearized WDSC can be described as follows [22]:

$$SUC_i = \sum_{t=1}^{T} \left\{ \begin{matrix} \lambda_{i,s}^{up} * y_{i,t} + (\lambda_{i,s+1}^{up} - \lambda_{i,s}^{up}) * SSU_{i,t}^{s+1} \\ +(\lambda_{i,s+2}^{up} - \lambda_{i,s+1}^{up}) * SSU_{i,t}^{s+2} + \ldots \end{matrix} \right\} \tag{3}$$

**2.2. Operational constraints**

In this paper, in addition to common operational constraints [22] (e.g. power balance, unit output, minimum up and down time and spinning reserve capacity), ramp rates and POZs have been considered. The unit ramp-up and ramp-down constraints have been formulated as follows:

$$u_{i,t} * u_{i,t-1} * (P_{i,t} - P_{i,t-1}) \le RU_i \tag{4}$$

$$u_{i,t} * u_{i,t-1} * (P_{i,t-1} - P_{i,t}) \le RD_i \tag{5}$$

In the operation, units' output should avoid the POZs. The mentioned limits are expressed as below:

$$P_{i,j}^{LB} * u_{i,t} \leq P_{i,t} * u_{i,t} \leq P_{i,j}^{UB} * u_{i,t} \tag{6}$$

### 2.3. PF calculations

PF solutions for the SCUC problem can be categorized into normal and contingency cases. Three different methodologies have been reported to model PF in SCUC studies [26]:

- The first methodology utilizes linearized DC equations, considering loss compensation in normal and contingency cases. In the traditional DC equations, 1/X is applied for branch impedance and the grid losses are estimated. Although the computation time is acceptable, the accuracy of results is deeply affected.
- The second methodology uses AC model for normal situation, and DC equation (e.g. PTDF) for contingencies. The accuracy of this methodology is still not suitable, because the buses voltage after a contingency might deviate considerably in comparison with normal situation.
- The third methodology utilizes AC model for both normal and contingency cases, which implies additional complexities in the solution process. On this basis, the solution speed and convergence ability are exponentially decreased. Therefore, heuristic-based techniques are usually required [6, 13, 15]. If calculation of voltages and reactive flows are important in contingencies, there is no alternative to consider AC contingencies.

Due to the limitations of the previously mentioned methodologies, none of them is appropriate for solving SCUC problems in a fast way or for handling real-world power systems. Hence, there is a need to develop a new PF algorithm to solve the SCUC problem, which should be simultaneously fast and accurate.

In the methodology proposed in this paper, the sequential PF solving (i.e. the solving technique that needs iterations to find the solution such as Newton-Raphson) has been eliminated, thus it takes less computation time than the previously mentioned AC-PF methodologies. Moreover, the reactive power and voltage deviations, which are mainly ignored in DC-PF equations, have been accurately modelled.

The AC-PF is based on operating points of the system and system topology. In the proposed methodology, the features of well-known Jacobian matrix have been utilized. On this basis, AC power flow is used to obtain the operating point of system affected on Jacobian matrix ($J_0$). Therefore, the operational point in the instant before the fault is considered to evaluate the Jacobian matrix in the instant after the fault. The Jacobian achieved from normal PF is used to calculate the voltages modifications ($\Delta\delta$ and $\Delta U$) in contingencies. Since the result of the PF in the normal situation is available, the linearized formulation of Jacobian matrix can be descripted as:

$$\begin{bmatrix} \Delta\delta \\ \Delta U \end{bmatrix} = [J_0]^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{7}$$

The deviation in the voltage of system buses is computed by Eq.(7), obtaining a new voltage profile. Thus, the new PFs can be achieved by the new voltage profile.

The iterative solutions of linearized formulations have been accomplished using the sensitivity properties of Newton-Raphson PF. The state vectors are regularly calculated and refreshed for small deviations of bus injections. These PFs, which are obtained from an operating point in normal situation, are utilized to calculate new PFs for contingencies. The major steps of utilizing the proposed PF calculations for SCUC solution are presented as follows:

Step 1) Form all feasible combinations of on/off units.

Step 2) Run a normal AC-PF for the each combination for each hour.

Step 3) Form the Jacobian matrix for all above combinations.

Step 4) Compute the voltages and the flow of branches for each contingency using Eq. (7).

The algorithm has no feasibility problem and it is accurate. Thus, branch PFs, bus injections and generator quantities are computed using the new voltages after contingencies. Afterwards, these quantities are compared with their respective limits.

## 3. Optimization Method

In this paper, an approach is proposed based on decomposition of the SCUC problem into QP and BP. EDNN is used to solve the QP, as a new contribution in SCUC solving. Binary variables must be checked to be 0 or 1. If after solving the QP some of the binary variables stay different from 0 or 1, the ABP method is applied to satisfy the binary constraints. Using ABP makes sure that the problem is deterministically optimized, providing a considerable advantage compared with evolutionary algorithms.

### 3.1. Enhanced Dual Neural Network Model

Various NN models have been developed to solve the QP problems [28-31]. However, according to the high complexity of the SCUC problem, especially in real-world power systems and considering AC-PF, most NN models with a complex architecture could not preserve the desired convergence and many models with one-layer structure might not be stable [24, 32]. In addition, two-sided inequality constraints should be satisfied by the NN model.

Based on this and according to the requirements of solving the SCUC problem with less computation time, the

EDNN model has been applied to strictly solve the QP problem. Eq. (1) corresponds to a general quadratic optimization problem, which can be expressed as:

$$\begin{aligned} &\text{Min } \frac{1}{2}X^{T}WX + C^{T}X \\ &\text{s.t. } AX = B, \quad \text{LB} \le EX \le \text{UB} \end{aligned} \tag{8}$$

The dual problem of Eq. (8) can be expressed as:

$$\begin{aligned} &\text{Max } -\frac{1}{2}X^{T}WX + B^{T}Y + \text{LB}^{T}V - \text{UB}^{T}W \\ &\text{s.t. } WX + C - A^{T}Y - E^{T}Z = 0 \end{aligned} \tag{9}$$

where $Y$, $V$ and $W$ are dual decision variables and $Z=V-W$.

In accordance with the Karush-Kuhn-Tucker (KKT) conditions [33], Eqs. (9) and (10) have equal solutions:

$$\begin{aligned} &WX + C - A^{T}Y - E^{T}Z = 0 \\ &AX = B \\ &EX = g(EX - Z) \end{aligned} \tag{10}$$

where $g(x)$ is defined as a piecewise function related to LB and UB.

By obtaining $X$ from the first term of Eq. (10) and substituting it into the second term, we can achieve:

$$AW^{-1}(A^{T}Y + E^{T}Z - C) = B \tag{11}$$

Since $W$ is an invertible matrix and $A$ is a full rank one, $AW^{-1}A^{T}$ will be also invertible. Therefore, $Y$ can be formulated as:

$$Y = (AW^{-1}A^{T})^{-1}(AW^{-1}C - AW^{-1}E^{T}Z + B) \tag{12}$$

On this basis and according to the projection theorem [34], the equation of the EDNN model can be presented as:

$$\begin{aligned} &E\frac{dz}{dt} = g(EH - I)z - EHz + (g-1)Es \\ &x = Hz + s \end{aligned} \tag{13}$$

where $H = W^{-1}E^{T} - W^{-1}A^{T}(AW^{-1}A^{T})^{-1}AW^{-1}E^{T}$ and $s = W^{-1}(A^{T}(AW^{-1}A^{T})^{-1}(AW^{-1}C + B) - C)$.

The block diagram of EDNN is presented in Fig. 1, where $e$ and $h$ are respectively the arrays of $E$ and $H$. The number of neurons of the one-layer network model is equivalent to the number of inequality restrictions. The state trajectories of EDNN indicate that the model converges to the global optimum solution from different initial states. Convergence analysis is presented in Section 3.2.

"See Fig. 1 at the end of the manuscript".

The EDNN model is able to lessen the architectural complexity while preserving appropriate convergence properties. Computational complexity is indeed a significant criterion of measuring the performance of NN models. In the EDNN model there is one neuron for each inequality constraint, while in the basic dual NN there is one neuron for each inequality and equality constraint. It should be noted that many nonlinear and non-convex features of the power system, such as VPEs, can be formulated and solved by a series of quadratic optimization problems, as presented in [22]. Those features are also taken into account in this paper.

**3.2. Convergence analysis of EDNN**

In order to investigate the effectiveness of EDNN, the convergence property has been studied. On this basis, the association of equilibrium point with the optimal solution has been analysed. A NN model is convergent if beginning from any states, the trend will converge to a specific equilibrium point. In order to study the convergence property of EDNN, KKT conditions for convex optimization [33] have been utilized.

*Theorem:* $x^* = Hz^* + s$ is the optimal solution of the QP problem of Eq. (8), if $z^*$ is an equilibrium point of Eq. (13).

*Proof:* Since $z^*$ is an equilibrium point of Eq. (13) we have $g(EHz^* + Es - z^*) - (EHz^* + Es) = 0$

Using $x^* = Hz^* + s$ , we have

$$g(Ex^* - z^*) - Ex^* = 0 \tag{14}$$

Defining $y^* = Gz^* + r$ , $G = (AW^{-1}A^T)^{-1}(AW^{-1}E^T)$ and $r = (AW^{-1}A^T)^{-1}(AW^{-1}C + B)$ become:

$$\begin{aligned} x^* &= Hz^* + s \\ &= W^{-1}(A^T(Gz^* + r) + E^T z^* - C) \\ &= W^{-1}(A^T y^* + E^T z^* - C) \end{aligned} \tag{15}$$

Therefore, we have:

$$Wx^* + C - A^T y^* - E^T z^* = 0 \tag{16}$$

Substituting $G$ and $r$ into the definition of $y^*$, $y^* = (AW^{-1}A^T)^{-1}[(AW^{-1}E^T)z^* + AW^{-1}C + B]$, then $AW^{-1}(A^T y^* + E^T z^* - C) = B$

According to Eq. (15), we have:

$$Ax^* = B \tag{17}$$

Eqs. (14), (16), and (17) form the KKT conditions. Therefore, $x^* = Hz^* + s$ is the optimal solution of the QP problem of Eq. (8). On this basis, the proposed EDNN is exactly convergent to the global optimal solution of Eq. (8). Indeed, the proposed EDNN is as accurate as exact methods to solve QP problems, whereas it has a considerably smaller amount of computation time.

### 3.3. Proposed hybrid method

The SCUC problem, using the combination of ABP with EDNN, consists of several stages that are shown in Fig. 2.

"See Fig. 2 at the end of the manuscript".

As it can be seen, at first all essential information for the SCUC problem should be imported. Then, the methodology proposed in Section 2 is used to obtain AC-PF equations for considering the network limits (in pre- and post-contingency).

For this purpose, according to the three steps of PF calculation mentioned in Section 2.4, a base case AC-PF is implemented for each unit commitment state and for each hour studied. After obtaining the Jacobian matrices for the base cases, the linearized AC-PF equations (for post-contingency) are placed with the other linearized constraints of the SCUC problem. In order to solve the QP, it is supposed that all binary variables are non-binary constrained between 0 and 1. Therefore the problem is transformed to a QP. Then, the QP is solved using EDNN as explained in Section 3.1. Afterwards, each binary variable is audited to be zero or one. If after implementing the EDNN these variables stay different from zero or one, the ABP method is utilized to satisfy the binary constraints.

In original BP approaches to solve UC problem, the binary variables of an hour are checked and their new assignments are applied. After that, the binary variables of next hour are checked and so on. Therefore, a loop of times must be utilized to check all binary variables independent of other hours. On this basis, the effect of new assigning of a binary variable of an hour on binary variables of other hours is not considered.

In order to overcome the disadvantage and augment the performance of the proposed hybrid method, some crucial modifications have been accomplished. On this basis, the loop of times is not applied and the variables of all hours are simultaneously considered. Moreover, all binary variables are arranged based on the greater distance of the margins. In other words, after obtaining the binary variables using the EDNN, differences between them and the bounds (0 and 1) are calculated. The variables with higher differences are placed in the higher rank. Thus, the variables should be arranged using the Binary Sorting Index (BSI), given below:

$$BSI = \begin{cases} X & , \; 0 \le X \le 0.5 \\ 1 - X & , \; 0.5 < X \le 1 \end{cases} \tag{18}$$

BSI has been defined as above because in this modeling the bounds of each binary variable are restricted to zero and one. Accordingly, each commitment variable is never out of the above mentioned bounds. In addition, whatever variable is farther from the bounds will be placed at the top of the arrangement list. This calculation and variables placing is repeated after each divergence of EDNN.

Two other modifications are also applied in the proposed hybrid method, which are advantageous for the convergence progress. Instead of setting the variables to zero or one randomly, the variables are assigned to the value nearest to the bound. Moreover, ramp rate limits Eqs. (4) and (5) are not considered in the EDNN model, but if the model is convergent they will be checked in each iteration.

If the constraints are not satisfied, the assigned value to the related variable should be changed. There are two reasons for separating the ramp rate constraints from the other equations. First, checking the equations in QP generally wastes too much computation time. Second, removing the loop of times and considering all the variables together cause Eqs. (4) and (5) to become nonlinear.

## 4. Numerical Studies

In order to thoroughly evaluate the proposed hybrid method for solving the SCUC problem, two conventional case studies are considered involving a 6-bus system with three generators [6] and the 118-bus test system with 54 thermal units [35]. A real-world large-scale power system with 493 units is also considered, based on the Iranian system [36]. The achieved results and computation times are compared with all previously published methods [5, 6, 15, 18, 22].

For the sake of a fair comparison, the same basic platform (PC having an Intel Pentium 4 2.0 GHz processor with 2 GB of RAM) is initially used. Moreover, in order to compare the obtained results with those of other methods reported in the literature, a uniform manner has been accomplished to adjust the CPU times of all the methods under comparison [37]. On this basis, the normalized CPU time has been utilized as Eq. (19):

$$\text{Normalized CPU time (p.u)} = \frac{\text{given CPU speed (GHz)}}{2.0\ \text{(GHz)}} \times \frac{\text{given CPU time (s)}}{\text{obtained CPU time from the proposed ABP-EDNN method (s)}} \tag{19}$$

Afterwards, a more advanced platform (64-bit Workstation having two Xeon E5-2687W 8C 3.10 GHz processors with 256 GB of RAM) is also considered for the Iranian power system.

### 4.1. 6-bus test system with 3 units

At first, the 6-bus system (that includes 3 units, 5 lines, 2 transformers and 3 buses) is used to compare the effectiveness of the SCUC method with the results of previous publications [6, 15, 18, 22]. The information of the system has been described in [6].

In Table 1, the achieved results have been compared with SDP [6], ABPSO-ARCGA [15], EHS [18] and

MBB-QP [22]. It should be noted that none of those other methods has considered VPEs, MFCs and POZs constraints. Thus, for the sake of a fair comparison, only similar features to [6, 15, 18, 22] have been considered in this first case study.

"See Table 1 at the end of the manuscript".

As shown in Table 1, the results of the proposed ABP-EDNN method are better than the results of previous methods (SDP, ABPSO-ARCGA and MBB-QP), except EHS. Although in this case the results obtained are between the average and worst results obtained with EHS, the computation time is 4.3 times less. Moreover, it should be noted that the basic platform used here for running the proposed method is weaker than the one used for EHS (64-bit computer with 16 GB of RAM and Intel Core i7 CPU). The advantages of using the proposed ABP-EDNN method are more salient as the size of the system increases, to be subsequently demonstrated in the next two case studies.

**4.2. 118-bus test system with 54 units**

The second case study is implemented on the 118-bus system (that includes 54 units, 186 branches, 9 transformers and 91 buses) [35]. The performance of the proposed method is tested again against the results of previous publications [5, 15, 18, 22].

In Table 2, the achieved results have been compared with BD [5], ABPSO-ARCGA [15], EHS [18] and MBB-QP [22]. Again, for the sake of a fair comparison, VPEs, MFCs and POZs constraints have not been considered.

"See Table 2 at the end of the manuscript".

As shown in Table 2, the results of the proposed ABP-EDNN method are better than the results of previous methods (BD, ABPSO-ARCGA and MBB-QP), being very close to the best result ever achieved with EHS. At the same time, the computation time is 16.9 times less comparatively to using EHS, which is a major improvement in spite of a weaker (basic) platform. That is, for large SCUC test cases the proposed ABP-EDNN method provides a similar accuracy to the best that is possible to obtain with EHS, but much faster. This fact can make a huge difference in a real-time decision making framework. The proposed ABP-EDNN is indeed effective to solve practical and real-world SCUC problems.

With the purpose of further investigating the performance of the proposed ABP-EDNN method, VPEs, MFCs and POZs constraints have now been considered, showing the results in Table 3.

"See Table 3 at the end of the manuscript".

As can be seen in Table 3, because of considering the VPEs, the fuel cost function of the generating units and consequently the total cost has significantly increased. It should be mentioned that although considering the

VPEs, MFCs and POZs creates a more realistic SCUC, it significantly complicates the solution, imposing discontinuity of the solution space, non-convexity, non-linearity and non-smoothness. Nevertheless, the proposed ABP-EDNN method transcends all above complications and obtains appropriate outcomes. As Table 3 clearly shows, in addition to the smallest computation time, the accuracy attained is far better.

**4.3. Iranian power system with 493 units**

The last case study is the large-scale power system of Iran that includes 493 thermal units, 936 lines and transformers, 377 buses and 36,712 MW peak load (in August 2009) [36].

In Table 4, the achieved results have been reported and compared with MBB-QP [22]. The computation time is again lower with the proposed ABP-EDNN method.

Using the more advanced platform previously described, instead of a basic one, an even with all the constraints (VPEs, MFCs and POZs) included that imply nonlinearity and non-convexity features, the computation time corresponds to just about two and a half minutes, which for a real system of that magnitude may be considered practically negligible.

Hence, the results confirm that the proposed ABP-EDNN method is especially suited for handling real-world large-scale power systems, providing both accurate and fast solutions.

"See Table 4 at the end of the manuscript".

**5. Conclusion**

A novel hybrid method based on decomposition of the SCUC problem into QP and BP problems has been proposed. Moreover, a new algorithm has been applied to model AC-PF in SCUC. The numerical studies showed that the results of the proposed ABP-EDNN method are better than the results of BD, SDP, ABPSO-ARCGA and MBB-QP methods. However, the calculation time of BD is better than the proposed method. In addition, the proposed method obtained the very close results to the best results ever achieved with EHS, while the computation speed is far higher. Furthermore, the proposed ABP-EDNN method involving AC-PF algorithm provides excellent results and computation times in practical size systems, considering practical operational constraints include VPEs, MFCs and POZs. Hence, the proposed method represents a valuable alternative for solving real-world large-scale SCUC problems in real-time market operation.

**Nomenclature**

$a_{if}$, $b_{if}$, $c_{if}$ units' cost function factors

| | |
|---|---|
| $B$ | total number of binary variables |
| $BSI$ | index for arranging the binary variables |
| $f$ | index for fuel type |
| $FC_{i,t}$ | fuel cost |
| $i$ | generation units' index |
| $j$ | forbidden operating zones index |
| $m_{i,f}$ | coefficient of the sinusoidal VPE |
| $N$ | total number of units |
| $P_{i,t}$ | active generation output |
| $P_{i,t}^{q}$ | active generation output of q-th segment |
| $P_{i,j}^{LB}$ , $P_{i,j}^{UB}$ | boundaries of POZ j |
| $P_{i,f}^{\min}$ , $P_{i,f}^{\max}$ | boundaries of generation output with fuel type f |
| $q$ | index for cuts of generation cost |
| $Q$ | reactive generation |
| $RU_i$ , $RD_i$ | constraints of ramp-up and down rates, respectively |
| $s$ | index for warmth-state of startup |
| $SI$ | index for arranging the variables |
| $SSU_{i,t}^{s}$ | binary variable equivalent to one, if the unit commits in the warmth-state s at time t |
| $SUC_i$ , $SDC_i$ | unit i startup and shutdown costs, respectively |
| $t$ | index for time period |
| $T$ | time interval |
| $u_{i,t}$ | commitment of unit i |
| $U$ | voltage magnitude |
| $V$ | total number of variables |
| $x$ | index for variables |
| $X$ | amount of variable x |
| $y_{i,t}$ | binary variable equivalent to one, if the unit commits at time t |

$\alpha_{i\,f}$ , $\beta_{i\,f}$ , $\gamma_{i\,f}$ coefficients of quadratic VPE

$\lambda_{i,s}^{up}$ startup cost in the warmth-state s

$\delta$ voltage angle

**Acknowledgements**

This work was supported by FEDER funds (European Union) through COMPETE and by Portuguese funds through FCT, under Projects FCOMP-01-0124-FEDER-014887 (PTDC/EEA-EEL/110102/2009), FCOMP-01-0124-FEDER-020282 (PTDC/EEA-EEL/118519/2010) and PEst-OE/EEI/LA0021/2013. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048.

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**Figure captions**

**Fig. 1.** Block diagram of the enhanced dual neural network

**Fig. 2.** Flowchart of SCUC using ABP-EDNN hybrid method

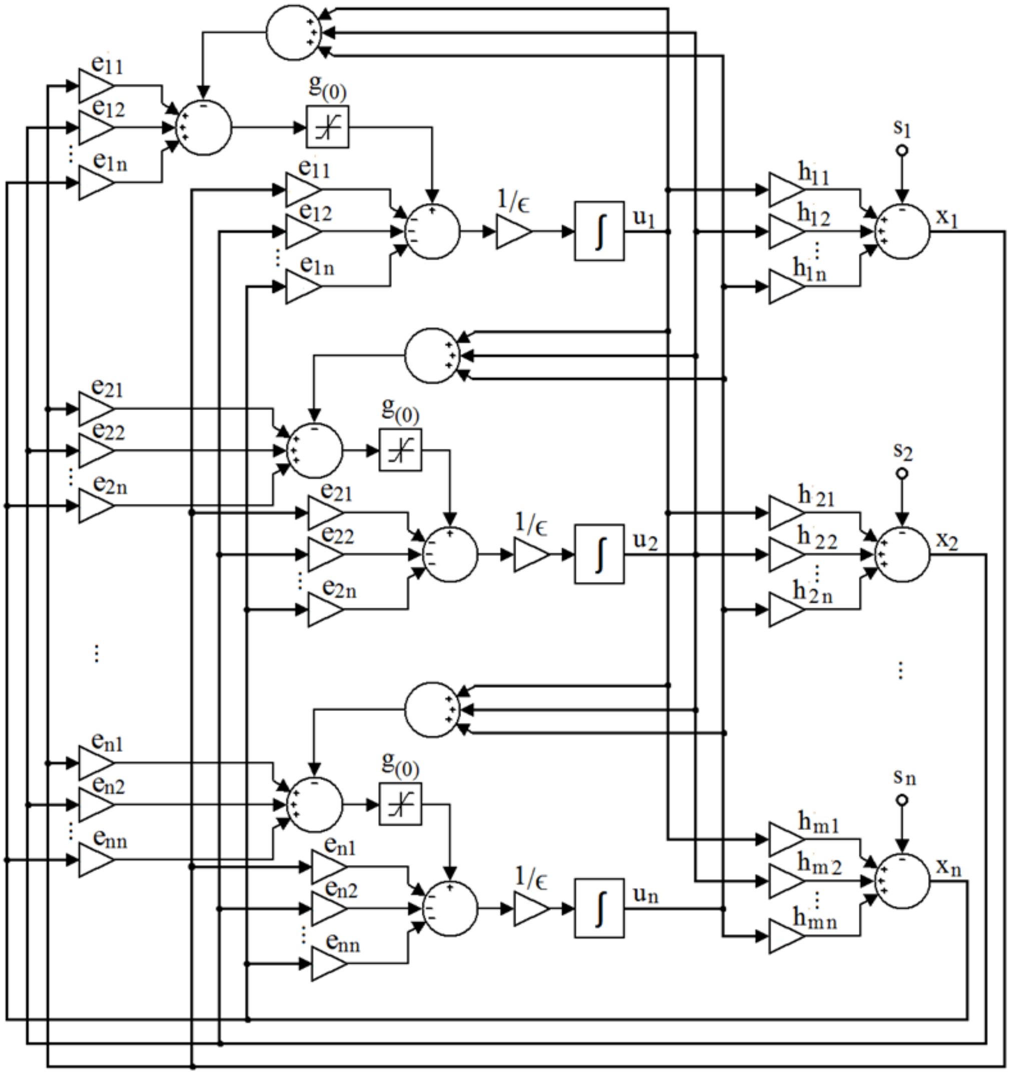
**Table captions**

**Table 1.** The achieved SCUC outcomes for the 6-bus case study

**Table 2.** The achieved SCUC outcomes for the 118-bus case study

**Table 3.** The achieved SCUC outcomes for the 118-bus case study considering VPEs, MFCs and POZs constraints

**Table 4.** The achieved SCUC outcomes for the Iranian 493-unit system

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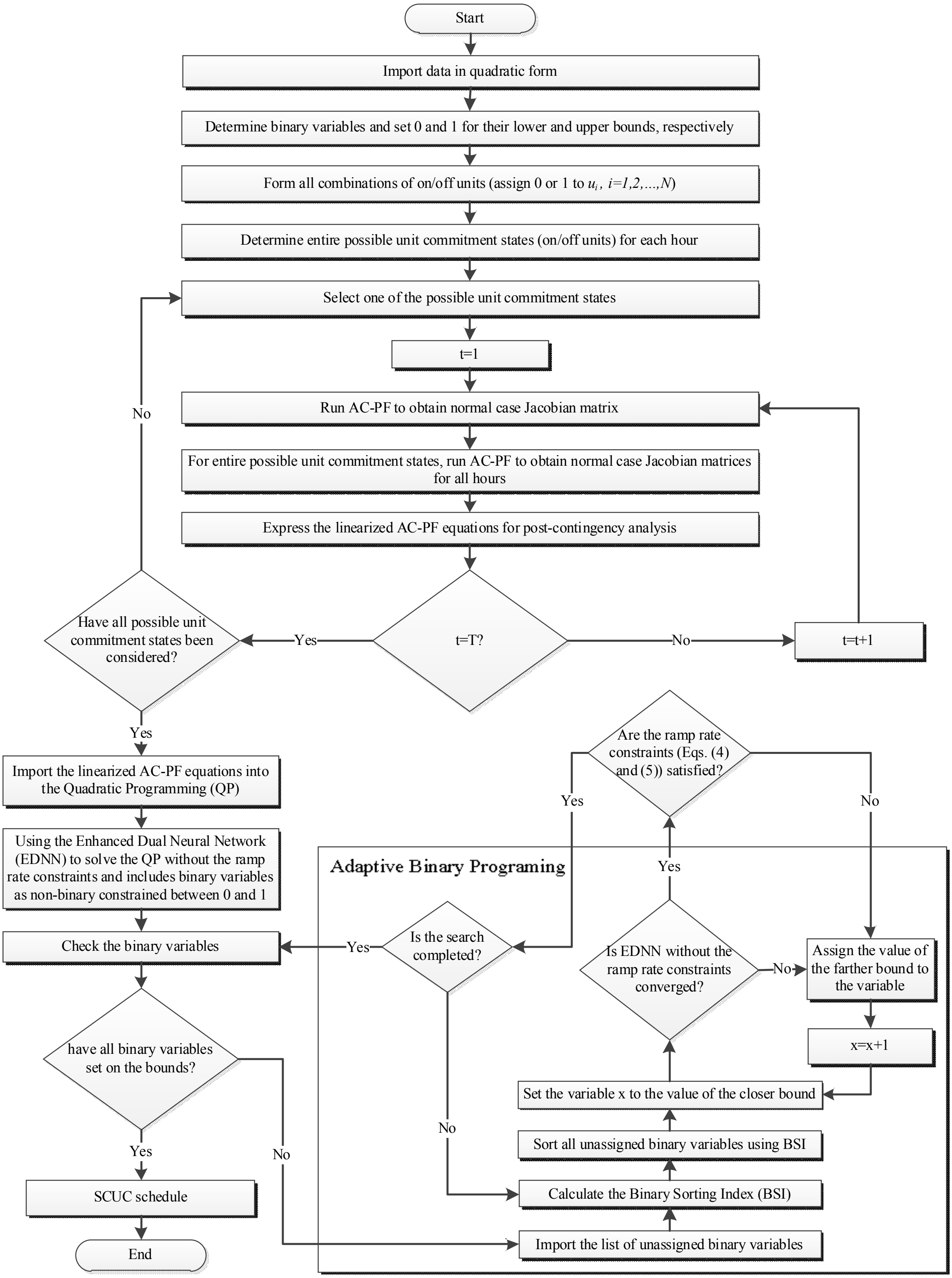


**Fig. 2.** Flowchart of SCUC using ABP-EDNN hybrid method

**Table 1**

The achieved SCUC outcomes for the 6-bus case study

| Method | | Total cost ($) | Computation time (s) | Normalized CPU time (p.u) |
|---|---|---|---|---|
| SDP [6] | | 84268.79 | N/A | N/A |
| ABPSO-ARCGA [15] | | 84243.46 | 157 | 6.19 |
| MBB-QP [22] | | 84242.93 | 34 | 1.26 |
| EHS [18] | Best result | 82805.85 | 116 | 7.30 |
| | Average result | 83044.94 | | |
| | Worst result | 83455.53 | | |
| Proposed ABP-EDNN | | 83429.22 | 27 | 1.0 |

**Table 2**

The achieved SCUC outcomes for the 118-bus case study

| Method | | Total cost ($) | Computation time (s) | Normalized CPU time (p.u) |
|---|---|---|---|---|
| BD [5] | | 851274.38 | 100 | 0.64 |
| ABPSO-ARCGA [15] | | 850843.63 | 3144 | 23.75 |
| MBB-QP [22] | | 849042.93 | 198 | 1.40 |
| EHS [18] | Best result | 848363.97 | 2388 | 28.79 |
| | Average result | 850741.76 | | |
| | Worst result | 854247.35 | | |
| Proposed ABP-EDNN | | 848605.41 | 141 | 1.0 |

**Table 3**

The achieved SCUC outcomes for the 118-bus case study considering VPEs, MFCs and POZs constraints

| Method | Total cost ($) | Computation time (s) | Normalized CPU time (p.u) |
|---|---|---|---|
| ABPSO-ARCGA [15] | 1,089,845.65 | 3152 | 19.86 |
| MBB-QP [22] | 1,084,371.31 | 208 | 1.23 |
| Proposed ABP-EDNN | 1,066,739.12 | 169 | 1.0 |

**Table 4**

The achieved SCUC outcomes for the Iranian 493-unit system

| Method | Platform | Computation time (s) | | Normalized CPU time (p.u) |
|---|---|---|---|---|
| | | SCUC | SCUC considering VPEs, MFCs and POZs constraints | SCUC |
| MBB-QP [22] | Basic | 3480 | Not presented | 1.44 |
| Proposed | Basic | 2413 | 2944 | 1.0 |
| ABP-EDNN | Advanced | 108 | 142 | - |