A VDS-NSGA-II algorithm for multiyear multiobjective dynamic generation and transmission expansion planning

Ali Esmaeel Nezhad [1*], Mohammad Sadegh Javadi [2], Alberto Borghetti [1],
Morteza Taherkhani [3], Alireza Heidari[4] and João P. S. Catalão [2,5]

[1] Department of Electrical, Electronic, and Information Engineering, University of Bologna, Bologna, Italy
[2] Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), Porto, Portugal
[3] Department of Electrical Engineering, West Tehran Branch, Islamic Azad University, Tehran, Iran
[4] School of Electrical Engineering and Telecommunications (EE&T), The University of New South Wales (UNSW), Sydney NSW 2052, Australia
[5] Faculty of Engineering of the University of Porto, (FEUP), Porto, Portugal

Abstract– The chapter develops a dynamic bi-objective model for the generation expansion planning together with the transmission system expansion planning. A virtual database supported non-dominated sorting genetic algorithm, known as "VDS-NSGA-II", is designed to tackle the multi-year multi-objective dynamic generation and transmission expansion planning (MMDGTEP) framework. The MMDGTEP is formulated as a bi-objective optimization problem in this chapter, while the objective functions are defined as total cost minimization and also minimizing the expected energy not supplied (EENS) at the hierarchy level II, known as $EENS_{HL\text{-}II}$. The first objective function is comprised of the investment and operating costs. The proposed hybrid model is decomposed into two programming problems: master problem and slave problem. In the first level, i.e. the master level, a virtual mapping procedure is incorporated in the VDS-NSGA-II to evaluate the contrast of each capacity additions in the planning horizon. In the second level, i.e. the slave problem, a linear programming approach is employed to assess the objectives of the problem. The virtual database helps reduce the computational burden. By avoiding the monotonous calculation in the proposed framework, the convergence time is reduced, appropriately. After obtaining the optimal Pareto set, the VIKOR decision maker is used to pick the most desired Pareto optimal solution. The presented long-term

* Corresponding Author: ali.esmaeelnezhad@gmail.com

planning model is simulated on a test power system to verify the effectiveness and efficiency of the framework.

Keywords: Generation system expansion; dynamic long-term planning; transmission system expansion; hybrid optimization algorithm; non-dominated sorting genetic algorithm.

Nomenclature

Variables

PG	Power generated by generation units
PL	Power transmitted throughout transmission lines
PVG	Virtual power generation (curtailed load)
f	Objective function
Gn	Generation unit's decision variable
Ln	Transmission line's decision variable
Z	Transmission switching status
δ	Bus voltage angle
TOC	Total Operational cost of generation units
$EENS_{HL-II}$	Expected energy not supplied in composite the generation and transmission level

Sets

b	Index for load bus
y	Index for planning year
i	Index for generation bus
j	Index for transmission line
k	Index for candidate unit
C	Index for candidate assets
E	Index for existing assets
NB	Number of load buses
NY	Planning horizon
NCU	Number of candidate units
NCL	Number of candidate lines
NG	Number of generation buses

Parameters

d	Annual discount rate
DT	Duration of load blocks
GI	Generation unit's investment cost
TI	Transmission line's investment cost
MTGI	Minimum time required for the generation unit installation
MTTI	Minimum time required for the transmission line installation
TGC	Maximum annual budget for the generation units' investment
TGI	Total number of new generation units can be installed for each year
TTC	Maximum annual budget for the transmission lines' investment
TTI	Total number of new transmission lines can be installed for each year
Max	Upper bound for variables
Min	Lower bound for variable
PD	Demand power
OC	Operational Cost

B Susceptance matrix of power grid

17.1 Introduction

Steady-state problems of power systems are generally studied in four time horizons as real-time studies, short-term studies, mid-term studies, as well as long-term studies. In this respect, short-term and real-time horizons usually relate to the operation of electric power systems, while the mid-term horizon is usually devoted to maintenance scheduling and fuel allocation. Long-term horizon, which is usually defined from one year to 10-20 years, mainly includes the expansion planning problems, among which the three problems known as generation expansion planning or “GEP”, transmission expansion planning or “TEP”, besides the substation expansion planning or “SEP” are well-known. The power system expansion planning models can be generally tackled by using centralized models, decentralized models, or even semi-decentralized models. The modeling strategy mainly relies on the economic priorities and aspects as well as the market conditions. In this respect, Ref. [1] includes a broad review of the planning problems in the regulated environment.

The problem of power system planning is proposed and solved to decide on the capacity, type, time, and site of new assets in power systems. An optimal planning model would guarantee the desired performance of the system [2]. The methods presented so far to tackle the mentioned problem may be generally divided into two main groups. The first group is based on the mathematical optimization and includes methods such as linear programming, Lagrangian relaxation, and branch-and-bond [3–6]. The second group is comprised of heuristic methods such as genetic algorithm, known as GA and particle swarm optimization, known as “PSO” [7,8]. Ref. [9] investigates the coordination of GEP and TEP problems. Ref. [10] used a game theory based method to characterize the relationship between the generation sector investment and transmission sector investments. It is noteworthy that the capacity expansion of the system is done economically in line with the future requirements of the system, while guaranteeing the system’s desired reliability level [11–13]. In this regard, there are too many documents available thus far, investigating the system reliability at HL-II [14–16]. As the research paper in [2] emphasized, any long-term planning problem of power systems would be comprised of three main sections as follows: the input data, the modeling and computations, and results analysis. The amount of load demand, the techno-economic data of power plants, the location of assets as well as climate conditions forecasts, are categorized into input data of the problem. The second section itself includes other sub-sections as the cost due to power system operation, the cost due to the new assets’ investment, which form the planning model. Usually, tackling the mentioned problem as a coordinated expansion planning problem would face various difficulties due to the lack of enough information and solution intractability [16]. The problem is also aimed at minimizing the total cost, including the operating and investment costs, neglecting construction sites of plants, i.e. all load centers and units are placed at the same bus. However, by introducing the power system deregulation, the fundamentals of integrated planning were significantly changed. A distributed expansion planning model has been proposed in Ref. [17] where a hybrid centralized and decentralized decision maker has been used. It is noteworthy that the uncertainties due to the load demand and price have also been taken into account. A coordinated expansion planning framework has been presented in [18], taking into consideration market conditions. In this regard, different players submit their expansion plans to the planning entity, while seeking to maximize their profits. The best plan would then be selected by taking into consideration system expansion planning priorities, such as reliability constraints and stability indexes. Nevertheless, it should be noted that excessively increasing the number of players would balance the price across the power system which in turn reduces profit of the players [19]. Ref. [20] proposes an environmental-friendly technique for the composite dynamic expansion planning problem to expand the transmission and generation systems' capacity. Moreover, a clustering model based on a bi-level technique and objective-based scenario choice was proposed in Ref. [21]. The clustering variables include the variables, relating to the investment stage and power flow problem. Moreover, a k-means clustering technique was deployed in Ref. [22] within a two-stage planning model, where the clusters are the decisions of the wind power investment stage. An optimal model has been suggested in [23] to address generation companies' (GenCos') profit through bilateral as well as multilateral contracts to trade electricity and for haggling as a function of price [12]. Ref. [24] presented an optimal long-term planning model for the markets which are not fully competitive. In this regard, the equilibrium would be obtained by iteratively maximizing profit. A game theory-based dynamic multi-objective optimization framework has been developed in Ref. [25] for the distributed generation expansion planning problem, ensuring the profits of prevalent power plants within the restructured environment. A coordinated micro-grids (MGs) expansion model has been designed in Ref. [26] while addressing the impacts of wind power and storage devices.

The integrated GEP and TEP problem is solved to determine the most desired generation units and transmission lines to be installed and added to the power system over the planning horizon, generally intended to minimize the total cost and ensuring the system's reliability. The existing restructured power systems have given rise to several challenges caused by the impact of transmission systems on the reliability issues [27,28]. In this regard, concurrently solving both GEP and TEP would be a very difficult task. As a result, first the GEP problem is tackled and the units to be installed are specified. Then, the problem of TEP is solved to determine the lines to be added to the transmission system [29]. The Deterministic *N-1* and *N-2* contingency analyses are carried out and deterministic load balance constraint is considered to alleviate the computational effort of the problem [27].

Since the TEP is highly non-convex, weighted sum approaches could not ensure Pareto optimal solutions. Accordingly, this chapter shows the use of a posterior approach, named "non-dominated sorting genetic algorithm II (NSGA II)" [9] to derive the Pareto set, which effectively exploit previously provided knowledge. Afterward, the most appropriate solution is selected by using the fuzzy decision maker [30]. The presented planning framework is comprised of two stages: a master problem (MP), and a slave problem composed by two sub-problems. The MP is devoted to producing the binary decision variables by NSGA-II which show the status of candidate assets. The reliability index and the total cost of the future system are determined by applying an iterative mixed-integer linear programming (MILP) using the enumeration approach. Furthermore, a virtual database is applied along with the NSGA-II to reduce the calculation effort, significantly boosting the rate of convergence of the optimization method.

The main characteristic of this procedure is a novel point of view to the reliability-oriented integrated GEP and TEP problem. The developed framework makes the independent system operator (ISO) able to measure the composite reliability issues of the existing and future configurations of the power system.. The novelties of this chapter are listed below:

1) Developing a dynamic multi-objective optimization framework for the integrated GEP and TEP problem with the capability to be utilized by the ISO for the optimal system expansion;
2) Presenting a virtual database as an asset to boost the convergence rate of the NSGA-II by mitigating the computational effort.

3) Developing a dynamic multi-objective optimization framework for the composite GEP & TEP problem with the capability to be utilized by the ISO for the optimal system expansion.
4) Presenting a virtual database as an asset to boost the convergence speed of the NSGA-II by mitigating the computational load of the problem.

The remainder of this chapter has been prepared as follows: Section 17.2 gives a comprehensive review of the mathematical formulation of the studied problem. The fundamentals of the multi-objective optimization and the descriptions of the NSGA-II algorithm, together with the descriptions of VIKOR decision maker are given in

Sections 17.3 and 17.4. The results, obtained from simulating the proposed problem on a 6-bus test system are included in Section 17.4, and Section 17.5 draws some relevant conclusions.

17.2 Problem Formulation

The main objective of the multi-year multi-objective dynamic generation and transmission expansion planning (MMDGTEP) problem is minimizing the total cost and total expected energy not supplied (EENS) while meeting all constraints of the system. The first objective covers the cost due to the investment in new capacity additions plus the system operating cost. The second objective is introduced to minimize the composite generation and transmission risk index, i.e. the EENS at the hierarchy level II, $EENS_{HL\text{-}II}$. As mentioned in the Introduction, the MMDGTEP problem is formulated as a hybrid two-level optimization model. The MP deals with the problem of adding new capacities to the system. In other words, the assessment of first-level decision variables is done in the MP from the economic perspective. In the slave problem, the operating cost and reliability assessment of the proposed plans are evaluated. The solution obtained from the described problem specifies the capacity, the site, and the time new assets should be added to the system, i.e., new generation and transmission assets, in an economic and secure manner. In this respect, the forecasted load demand according to the predicted growth rate should be supplied and the reliability of the system should be at a desired level.

17.2.1 Master Problem

The MP's objective is set as minimizing the investment cost associated with new capacity additions in the generation and transmission sectors. The MP is modeled as (17-1), subject to the planning constraints:

$$Min\, MP = \sum_{y=1}^{NY}\sum_{i=1}^{NG}\sum_{k=1}^{NCU}\frac{GI_{kiy}(Gn_{kiy}-Gn_{ki(y-1)})}{(1+d)^{y-1}}+\sum_{y=1}^{NY}\sum_{j=1}^{NCL}\frac{TI_{jy}(Ln_{jy}-Ln_{j(y-1)})}{(1+d)^{y-1}} \tag{17-1}$$

Total cost TC comprises the investment cost plus the system operating cost. In the MP, the optimal plan would be determined, provided that the sub-problems have been optimally solved. In other words, the MP determines the investment cost while the sub-problems of the slave problem deal with the operating cost. The capital investment costs in the generation and transmission sectors in a year are constrained as (17.2)-(17.3). Besides, the predicted capacity in a year in the generation and transmission sectors is constrained as (17.4)-(17.5), and the construction time of the candidate investment in the generation and transmission sectors are applied by (17.6) and (17.7) respectively. Constraints (17.6) and (17.7) also specify that once an asset is added to the power system, its investment status remains "1" until the end of the horizon.

$$\sum_{i=1}^{NG}\sum_{k=1}^{NU}GI_{kiy}(Gn_{kiy}-Gn_{ki(y-1)})\le TGI_y \tag{17-2}$$

$$\sum_{j=1}^{NL}TI_{jy}(Ln_{jy}-Ln_{j(y-1)})\le TTI_y \tag{17-3}$$

$$\sum_{i=1}^{NG}\sum_{k=1}^{NU} PG_{ki}^{\max,C}(Gn_{kiy} - Gn_{ki(y-1)}) \le TGC_y \tag{17-4}$$

$$\sum_{j=1}^{NL} PL_{jy}^{\max,C}(Ln_{jy} - Ln_{j(y-1)}) \le TTC_y \tag{17-5}$$

$$Gn_{ki(y-1)} \le Gn_{kiy}\ ,\ Gn_{kiy} = 0\ \ if\ \ y < MTGI_{ki} \tag{17-6}$$

$$Ln_{j(y-1)} \le Ln_{jy}\ ,\ Ln_{jy} = 0\ \ if\ \ y < MTTI_{j} \tag{17-7}$$

17.2.2 Slave Problem

The slave problem includes two sub-problems: one minimizes the operating cost and the other minimizes the EENS. The objective function of the first problem is associated with the operating cost of the given plan and installed assets on the basis of the optimal power flow (OPF). An annual load duration curve (LDC) is exploited to calculate the yearly operating cost. The objective of the second sub-problem represents the reliability index of the prospective expansion plans $EENS_{HL\text{-}II}$.

The investment plan determined by the MP is given to the associated sub-problems. The investment cost of the prospective plan is integrated in the first objective while the investment plans and the status of capacity additions are assigned to the second sub-problem. The next section provides the mathematical modeling of the two sub-problems.

17.2.3 Total Cost Assessment Objective of the MMDGTEP Problem

The first sub-problem considers the operational constraints, such as the power balance at each bus and the maximum power that can be transmitted in the lines and transformers, while addressing the annual operating limitations, and finds the minimum total operation cost over the planning years by using a DC-OPF technique.

The model of the first sub-problem is:

$$Min\ f_1 = TOC$$
$$TOC = \sum_{y=1}^{NY}\sum_{b=1}^{NB}\sum_{i=1}^{NG}\sum_{k=1}^{NU}\frac{DT_{by}.OC_{kiby}.PG_{kiby}}{(1+d)^{y-1}} \quad (17\text{-}8)$$

Subject to:

$$\sum_{i=1}^{NG}\sum_{k=1}^{NEU} PG_{kiby}^{E} + \sum_{i=1}^{NG}\sum_{k=1}^{NCU} PG_{kiby}^{C} - PD_{lby} - \sum_{j=1}^{NEL} PL_{jby}^{E} - \sum_{j=1}^{NCL} PL_{jby}^{C} = 0 \quad (17\text{-}9)$$

$$0 \le PG_{kiby}^{E} \le PG_{ki}^{\max,E} IG_{kiby}^{E} \quad (17\text{-}10)$$

$$0 \le PG_{kiby}^{C} \le PG_{ki}^{\max,C} Gn_{kiy} IG_{kiby}^{C} \quad (17\text{-}11)$$

$$PL_{jby}^{E} = B_j(\delta_{mby}^{E} - \delta_{nby}^{E}) \quad (17\text{-}12)$$

$$-PL_{j}^{\max,E} \le PL_{jby}^{E} \le PL_{j}^{\max,E} \quad (17\text{-}13)$$

$$PL_{jby}^{C} - B_j(\delta_{mby}^{C} - \delta_{nby}^{C}) - M_j^{C}(1 - Ln_{jy}) \le 0 \quad (17\text{-}14)$$

$$PL_{jby}^{C} - B_j(\delta_{mby}^{C} - \delta_{nby}^{C}) + M_j^{C}(1 - Ln_{jy}) \ge 0 \quad (17\text{-}15)$$

$$-PL_{j}^{\max,C} Ln_{jy} \le PL_{jby}^{C} \le PL_{j}^{\max,C} Ln_{jy} \quad (17\text{-}16)$$

$$\delta_{ref} = 0 \quad (17\text{-}17)$$

The power balance at bus l is modeled as (17.9), in which superscript E show the existing assets and superscript C denote the candidate assets. It should be noted that the status of each candidate asset is given by the solution of the MP and the selection procedure is not done here. In this stage, the generation level of the generation units, and transmission lines flow are the decision variables. Set j is comprised of the lines which are connected to bus l and labeled by "to bus" or "from bus". The constraints represent the capacity of the existing and candidate generation units (17.10)-(17.11), the line flows of existing transmission lines (17.12)-(17.13), the line flows of candidate lines (17.14)-(17.16), and the phase angle of the slack bus (17.17).

17.2.4 $EENS_{HL-II}$ Evaluation Procedure of the MMDGTEP Problem

The annualized value of EENS at HL-I is derived utilizing the reduced scenarios as:

$$EENS_{HL-I} = \sum_{k=1}^{N} E_k . P_k \tag{17-18}$$

where the EENS at the hierarchical level I, that includes the generation sector only, is denoted by $EENS_{HL-I}$. In this regard, it is supposed that all generation units are at one bus. The probability of contingency k and the corresponding energy curtail are indicated by P_k and E_k, respectively. Moreover, the annualized value of $EENS_{HL-II}$ which is defined as the energy curtailed at each bus is obtained as [31]:

$$EENS_k = \sum_{j \in (x,y)} L_{k_j} . D_{k_j} . F_j \tag{17-19}$$

$$EENS_{HL-II} = \sum_{k=1}^{NL} EENS_k \tag{17-20}$$

The load curtailed at bus k for the sake of mitigating the overload as a result of contingency j is denoted by L_{k_j}. Besides, the duration of the curtailment and the occurrence frequency of this contingency are represented by D_{k_j} and F_j respectively. The amount of load curtailment is evaluated by incorporating a virtual generator at each load bus by using an incidence matrix based DCOPF (IM-DCOPF) method

[32,33], considering the non-interconnectivity feature of distant generation units in the case of line outages.

The second sub-problem aims at minimizing the total annual EENS of the associated prospective network:

$$Min \quad f_2 = \sum_{y=1}^{NY} EENS_{HL-II}^{y} \tag{17-21}$$

A probabilistic index using the enumeration technique along with a minimum cost evaluation model has been employed as described in the following five steps:

1. First, the multi-stage annual load model should be produced, omitting the chronology and aggregating the load states by means of the data of the hourly load. This curve would be obtained from the annual load duration curve.
2. The second step is to choose the system states at the load level utilizing the mentioned enumeration technique. Generation units are usually modeled, utilizing multi-state random variables, comprising the up, down, and derated states. On the other hand, transmission assets are modeled by means of two-state variables, comprising only the up and down states and the derated state has been neglected to more simplify the model. It is noted that transmission lines are assumed 100% reliable, which is case-dependent. The transmission system constraints must be considered as the generation capacity may be limited by the transmission system topology.
3. The solution of a cost minimization problem described in the subsequent section allocates the generation, determines the associate cost and the amount of load curtailed together with the associated cost at each bus. With respect to the fact

that the objective is to specify the amount of the load curtailed, and afterward, specify the "EENS", the identical value for the significance weighting factor of the load bus, and the identical unit generation cost are used to avoid the merit order of commitment of generation units.

4. Iteration of the second and the third steps until convergence is reached for every load level.
5. The corresponding probabilities are used to weight the obtained results for each load level to determine the annual indices of the expected cost of generation and risk.

Resuming, the conceptual model of the mentioned procedure is illustrated in Figure 17.1, that shows the master and slave problems and their associated decision variables and outputs.

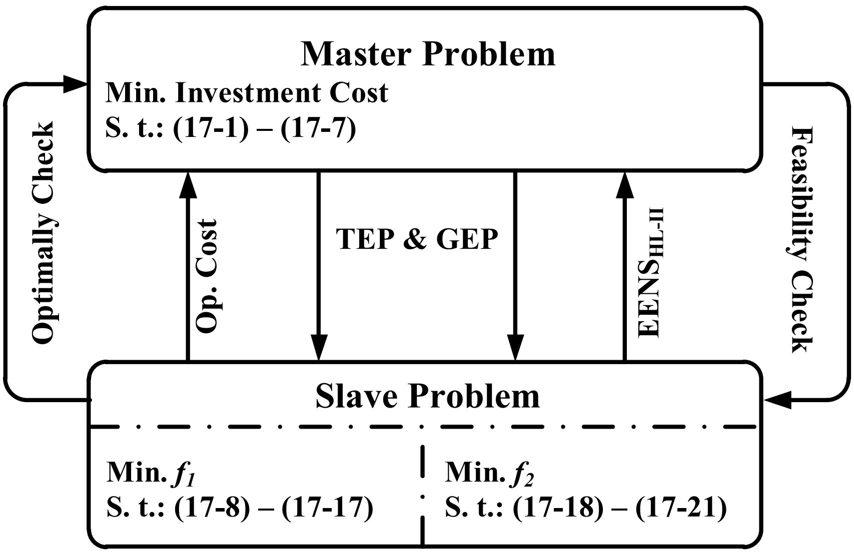

Figure 17.1 The proposed expansion planning framework.

17.3 Multi-objective Optimization Principle

In case the optimization problem is aimed at optimizing more than one objective functions with conflicting nature, multi-objective optimization tools should be used. Unlike single-objective optimization problems, solving a problem with multiple objectives would give more than one optimal solution, known as Pareto set. It is noted that all the solutions obtained are non-dominant and a better value of each objective in each Pareto optimal solution cannot be derived except at the cost of deteriorating the values of other objectives [34–36]. Expression (17.22) shows a typical multi-objective optimization problem, subject to different constraints.

$$
\begin{aligned}
&\mathit{Minimize}\, f_i(x) \quad i = 1,2,\ldots,N_{obj} \\
&\mathit{Subject\ to} \begin{cases} g_k(x) = 0 & k = 1,2,\ldots,K \\ h_l(x) \le 0 & l = 1,2,\ldots,L \end{cases}
\end{aligned}
\tag{17-22}
$$

The objective function i and a decision vector are denoted by f_i and x, respectively. It should be noted that all solutions are optimal and the most adequate solution should be specified by the planning entity taking into account the preferences of the problem. Various optimization methods have been applied to cope with the multi-objective optimization problem [36–39], among which weighted sum method, epsilon-constraint method, and goal programming transform the primary multi-objective problem into a single-objective one and then, solve the problem. The main drawback of these methods relates to generating non-optimal solutions in the Pareto set [39], while needing relatively complete information of the problem and a relatively high number of runs [32]. However, some well-established approaches are already available to solve multi-objective problems, utilizing the concept of non-dominancy with respect to all objectives [32]. NSGA-II, presented in the next section, is known as an effective algorithm, with the capability to tackle non-convex and mixed-integer problems [40].

17.4 Non-Dominated Sorting Genetic Algorithm-II

17.4.1 Computational Flow of NSGA-II

This section investigates the computational procedure of the NSGA-II together with a flowchart, showing the detail. In general, the following stages are taken by the NSGA-II [39]:

(Step 1) Initialization: first, a parent population with size N_P is randomly generated.

(Step 2) Non-dominated sorting of parent population: this stage sorts the generated population with respect to the non-domination level. In this regard, every population would be given a rank, showing its non-domination level or front number in a way that "1" shows the most desired level and "2" is the next desired one, etc. The crowding distance of populations at every non-domination level is determined and the population is put in order in a declining manner on the basis of the crowding distance.

(Step 3) Choosing tournament: two members are picked randomly and their front number and crowding distance are compared. The more desired one would be picked and copied to the mating pool.

(Step 4) Crossover and mutation: the simulated binary crossover (SBX) and polynomial mutation are adopted in the procedure described in this chapter.

(Step 5) Merging the parent and child populations with the size $2N_P$.

(Step 6) Non-dominated sorting of the merged population: the non-domination and crowding distance indices are used to sort the new merged population. In this regard, elitism would be guaranteed as all members of the two populations are used. The population of the most superior non-dominated set, shown by F_1 within the new merged population, would be highlighted among all other members. In case N_P is larger than F_1, the entire population F_1 would be selected to be used in the new population, while the other members will be selected from the next non-dominated fronts according to their ranks. Hence, F_2 would be subsequently selected and followed by the solution from F_3, etc. It is noteworthy that this process would be carried out up to the time it is not possible to accommodate any set. Assume F_l shows the last non-dominated set, after which it would not be possible to accommodate any other sets. Generally, the count of solutions within the whole sets will be greater than N_P.

(Step 7) Termination criterion: the procedure will be terminated following a given number of generations, or at the time no considerable enhancement in the solution is observed. The NSGA-II would be run for a given number of generations in this chapter. Step 8 would be taken, provided that the termination criterion is met; otherwise, a new population is copied to the parent population and the third step is processed.

(Step 8) Choose the first member of the population of the first front.

(Step 9) Termination.

The conceptual flowchart of the presented NSGA-II is depicted in Figure 17.2.

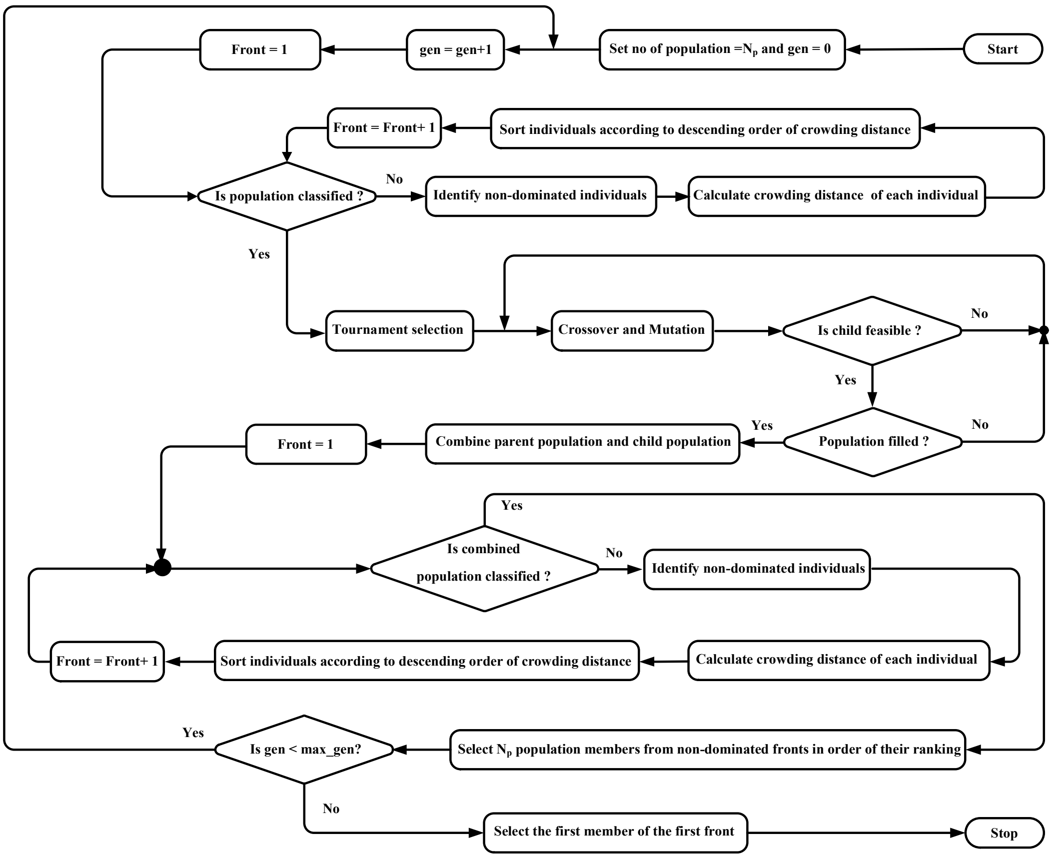

Figure 17.2 Computational flowchart of NSGA-II.

17.4.2 VDS-NSGA-II

The VDS-NSGA-II is developed and utilized in this chapter to avoid the monotonous cases in determining the reliability, which uses the enumeration technique. In this respect, the total number of cases to be used for calculating $EENS_{HLII}$ will be significantly mitigated by only accepting the cases associated with a probability greater than a predetermined threshold. It should be noted that the number of solutions that must be exploited in the enumeration technique is of very high order, particularly once a heuristic method such as NSGA-II is used. Since the total number of assets, both existing and new ones, are determined by the ISO, and EENS has been calculated for some of the cases, the database can be used to restore those states and recalculating the system risk again would be redundant. For a particular case, the EENS would not vary. Accordingly, utilizing a virtual database for the presented expansion planning problem, including binary decision variables, can substantially help enhance the search capability and search speed of the NSGA-II.

17.4.3 Methodology

This section describes the implementation of VDS-NSGA-II in the MMDGTEP problem. Since the problem of MMDGTEP is a dynamic mixed-integer programming problem of a very large size, a virtual mapping procedure, VMP, is taken into account together with the proposed VDS-NSGA-II to improve the effectiveness of aforementioned soft computing algorithm. In the proposed MMDGTEP problem, transforming the combination of candidate units’ and lines' statuses into a dummy variable for every stage of MMDGTEP allows to use the virtual database.

The three stages of the VMP are described as below.

(i) Form the prospective plan using the corresponding integer decision vector. As mentioned above, the investment status of an asset changes to "1" immediately after it is installed and remains unchanged to the end of the horizon.

(ii) Extract the annually available assets for the planning horizon.

(iii) Represent the status of each combination as a decimal number in order to submit the plan number to the associated objective functions.

Hence, a multivariable decision vector would be mapped to a single variable one for each year. The proposed VDS-NSGA-II incorporates the aforementioned VMP to manage the address cell of the virtual database in both operating cost and $EENS_{HL\text{-}II}$ objective functions. Figure 17.3 illustrates the proposed procedure.

As mentioned above, the single variable decision vector, so-called "decision address", has been considered for each year. By considering this fact that the proposed expansion planning framework is a dynamic one, decomposition of the problem into the associated planning year and considering the dynamic feature of the expansion planning accelerates the simulation process.

	Generation Expansion Planning				**Transmission Expansion Planning**			
	G.4	**G.5**	**G.6**	**G.7**	**T.8**	**T.9**	**T.10**	**T.11**
	Decision Vector							
Year	**0**	**7**	**6**	**0**	**7**	**0**	**9**	**4**
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	1
6	0	0	1	0	0	0	0	1
7	0	1	1	0	1	0	0	1
8	0	1	1	0	1	0	0	1
9	0	1	1	0	1	0	1	1
10	0	1	1	0	1	0	1	1

Figure 17.3 The Virtual Mapping Procedure Technique Adopted in VDS-NSGA-II

For example, if the commitment of transmission line "T.8" is postponed from the 7th year to the 8th one, recalculation of entire cases in the objective functions is avoided. Since the yearly calculations have been carried out in the previous stages, it is only needed to evaluate the recent 7th year plan. It means that the first six years and also last three years calculations are available from the database and only the evaluation of the recent expansion plan should be carried out. Figure 17.4 illustrates this procedure.

	Generation Expansion Planning				Transmission Expansion Planning			
	G.4	G.5	G.6	G.7	T.8	T.9	T.10	T.11
	Decision Vector							
Year	0	7	6	0	8	0	9	4
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	1
6	0	0	1	0	0	0	0	1
7	0	1	1	0	0	0	0	1
8	0	1	1	0	1	0	0	1
9	0	1	1	0	1	0	1	1
10	0	1	1	0	1	0	1	1

Figure 17.4 Illustrative framework of eliminating the repetitive calculations

The proposed virtual database in line with the virtual mapping procedure is depicted in Fig. 17.5. As it is shown in the flowchart, an annual virtual database is considered for each objective function. It means that the numbers of virtual databases are $k \times Y$, in which k and Y denote the number of objective functions and planning horizon, respectively.

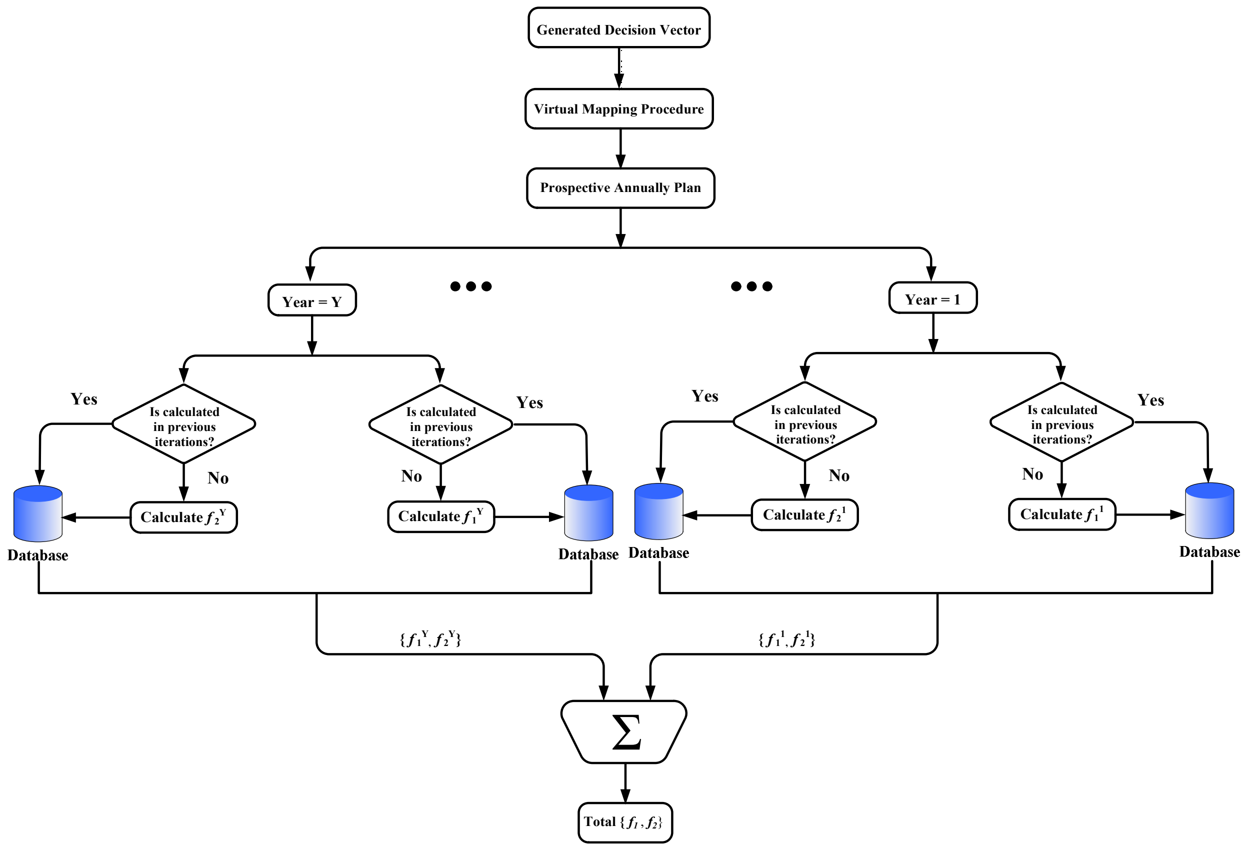

Figure 17.5 Virtual Database Implemented in NSGA-II.

17.4.4 VIKOR Decision making

The VIKOR decision maker was first developed by Oprikovic in 1998 [30] and it performs on the basis of allocating positive ideal values and negative ideal values to effectively specify the relative interval between every solution and Pareto optimal solution. Afterwards, the significance of all Pareto solutions would be specified through a ranking, indicated by x_j, where j stands for the members of Pareto set and it is up to P [42]:

1- Using f_{ij}, showing the rating functions, computing the value, pertaining to criterion i for the solution x_j. After that, the best value of the objective function, indicated by f_i^+ and the worst value of that objective function, indicated by f_i^-, would be determined by using relationships (17.23) and (17.24).

$$f_i^+ = \max\left[(f_{ij}) \mid j = 1,2,...,m\right] \tag{17.23}$$

$$f_i^- = \min\left[(f_{ij}) \mid j = 1,2,...,m\right] \tag{17.24}$$

2- Specifying the value of group utility measure, shown by S_j and the value of individual regret measure, shown by R_j by employing relationships (17.25) and (17.26).

$$S_j = \sum_{i=1}^{n} w_i \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_i^-)} \tag{17.25}$$

$$R_j = \max_i \left[w_i \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_i^-)} \right] \tag{17.26}$$

Where, w_i shows the weight of each objective so that the sum would be equal to 1 [43]. Q_j is also computed based on the relationship (17.27):

$$Q_j = w_j \left[\frac{S_j - S^+}{S^- - S^+} \right] + (1 - w_j) \left[\frac{R_j - R^+}{R^- - R^+} \right] \tag{17.27}$$

where,

$$S^+ = Min\left[(S_j) \mid j = 1,2,...,m\right] \tag{17.28}$$

$$S^- = Max\left[(S_j) \mid j = 1,2,...,m\right] \tag{17.29}$$

$$R^+ = Min\left[(R_j) \mid j = 1,2,...,m\right] \tag{17.30}$$

$$R^- = Max\left[(R_j) \mid j = 1,2,...,m\right] \tag{17.31}$$

3- Ranking the Pareto set with respect to the values of the group utility measure, the individual regret measure and also Q_j in an ascending order where the solution with the least value of Q_j would be picked as the most preferred optimal solution [44].

17.5 Simulation Results

This chapter uses a six-bus test system to evaluate the performance of the developed optimization framework to solve the MMDGTEP problem. Fig. 17.6 demonstrates the studied system, [41], which is comprised of six nodes and seven transmission lines.

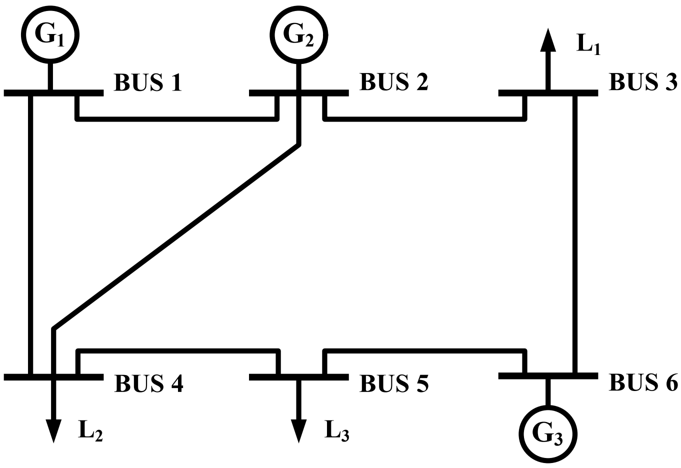

Figure 17.6 The studied six-bus system.

Table 17.1 and Table 17.2 represent the data of the studied system, including the generating units and transmission system [41]. In this regard, four candidate transmission lines and four candidate generation units will be taken into consideration. It is assumed that the time, required to construct a generation unit is three years, while a transmission line can be installed within a year. The problem is solved for a planning horizon of ten years, while Fig. 17.7 indicates the annual peak load demand. The shares of buses 3, 4, and 5 in the load demand are 40%, 30%, and 30% respectively.

The load duration of each year has been divided into four blocks as shown in Fig. 17.8 for the sake of more simplification. It should be noted that no constraint has been considered for the annual investments or the number of assets to be installed. Besides, the discount rate has been assigned to the model zero [41].

Table 17.1 Data of generation units.

Unit	G.1	G.2	G.3	G.4	G.5	G.6	G.7
Node	1	2	6	1	2	2	3
Size (MW)	100	100	50	100	80	60	20
Operating Cost ($/MWh)	Installed	Installed	Installed	200	270	250	250
Investment Cost ($/kW)	60	72	92	60	84	96	96

Table 17.2 Installed and candidate transmission lines' data [41].

Line	T.1	T.2	T.3	T.4	T.5	T.6	T.7	T.8	T.9	T.10	T.11
F_bus	1	2	1	2	4	5	3	1	2	1	5
To_bus	2	3	4	4	5	6	6	2	3	4	6
Reactance (p.u.)	0.170	0.037	0.258	0.197	0.037	0.140	0.018	0.170	0.037	0.258	0.140
Capacity (MW)	80	70	140	100	50	140	130	80	70	140	140
Investment cost ($/kW)	Installed	Installed	Installed	Installed	Installed	Installed	Installed	80	96	120	56

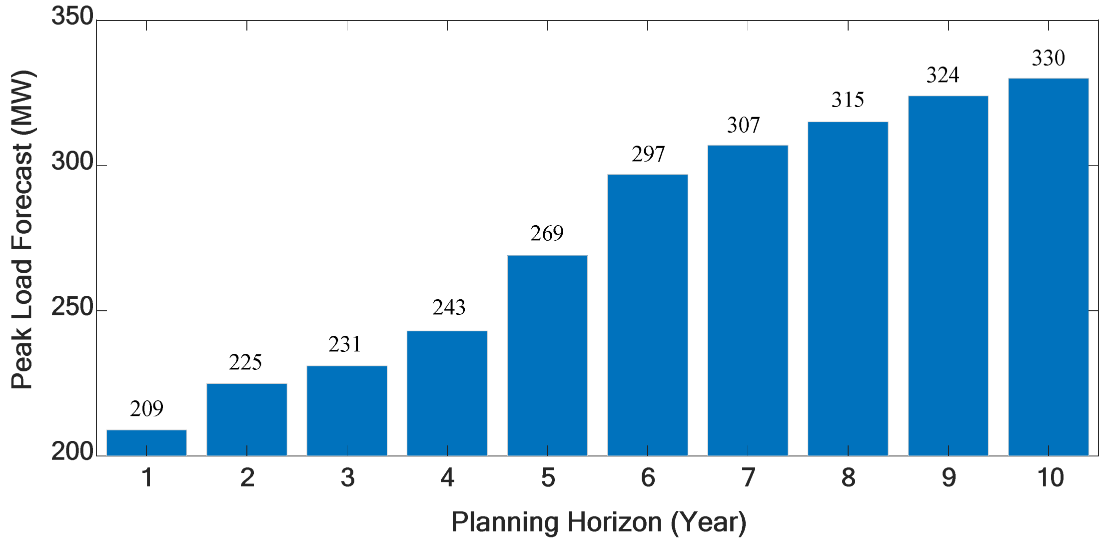

Figure 17.7 Yearly peak load forecast of six-bus test system.

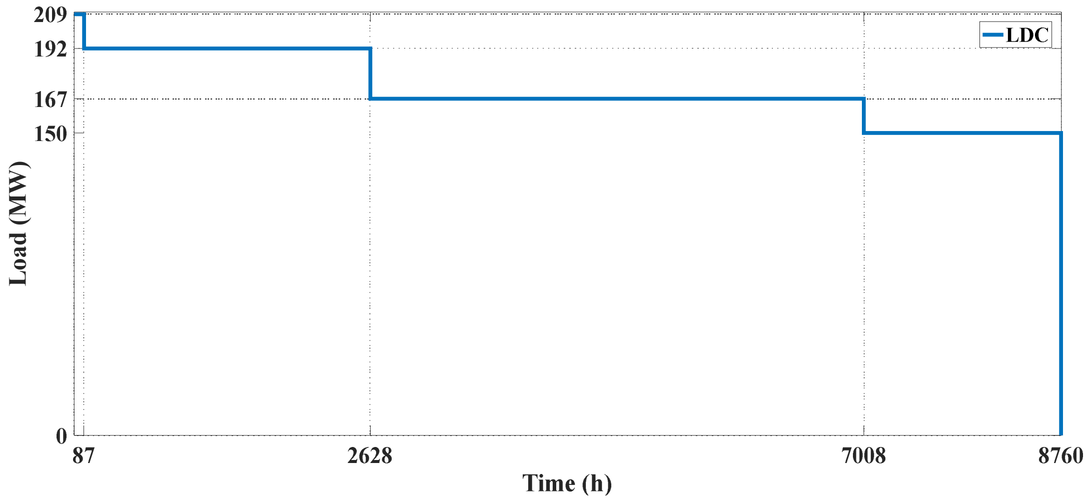

Figure 17.8 Load blocks in the first year.

The results of the MMDGTEP problem are shown in Table 17.3. All 25 reported plans are non-dominated plans of the MMDGTEP problem in the six-bus test system. The load demand during the first year of the horizon is supplied using the existing generation units and the power flow of lines is feasible. In this respect, the generation units, associated with lower costs, i.e. G.1 and G.2 are scheduled to operate at their maximum power and G.3 is supposed to meet the remaining load demand. Nonetheless, it is noted that T.2 will be congested and it prevents G.2 from operating at its rated capacity. Thus, G.3 as a more costly unit would operate at a higher level that in turn leads to an increased operating cost. Therefore, the candidate transmission line T.9 is added at the first year in all non-dominated plans, resulting in raising the transmission capacity between nodes 2 and 3. This increased transmission capacity enables G.2 to operate at a higher generation level over the following years. Consequently, the overall load will be smaller than the overall installed generation capacity over the first 4 years of the planning horizon. Taking into account the zero value of the discount rate and the minimum time to install a generation unit, a new generation unit will be added to the system in year 3. Thus, G.4 would be installed at bus 2 as higher power can be transferred by installing line T.9 in all prospective plans. These expansion plans are seen in all non-dominated plans. However, the system reliability enforces the installation of more capacity.

Table 17.3 The obtained Pareto set and VIKOR decision-maker's results.

	f_1	f_2	R	S	Q
Plan	Total Cost ($*)	$EENS_{HL\text{-}II}$ (MWh*			
P01	675147127	40.32226	0.31615	0.3668	0.40268
P02	669940319	58.05954	0.5	0.5	0.98622
P03	691339254.8	26.08278	0.20817	0.37672	0.25361
P04	685147127	27.57412	0.18401	0.33194	0.11702
P05	689565449.6	26.88526	0.19091	0.36778	0.20667
P06	689479422	27.01624	0.19007	0.3683	0.20649
P07	689388147.8	27.15902	0.18919	0.3689	0.20638
P08	689292676	27.3114	0.18826	0.36955	0.20634
P09	689194157.8	27.44924	0.1873	0.37002	0.20586
P10	**678521957.4**	**28.65292**	**0.19519**	**0.27868**	**0.017694**

P11	689567526.2	26.49862	0.19093	0.36379	0.19794
P12	691289391.6	26.4783	0.20768	0.38033	0.26078
P13	705147127	14.134794	0.34249	0.3872	0.48916
P14	706882643.4	14.127658	0.35937	0.40401	0.5528
P15	721339254.8	9.821196	0.5	0.5	0.98622
P16	715147127	11.41364	0.43976	0.45627	0.79483
P17	719565449.6	10.882058	0.48274	0.49374	0.94516
P18	719479422	11.009252	0.48191	0.49422	0.9449
P19	719388147.8	11.145816	0.48102	0.49475	0.94465
P20	719292676	11.291344	0.48009	0.49533	0.94445
P21	708521957.4	12.574452	0.37532	0.40385	0.5777
P22	719567526.2	10.497826	0.48276	0.48978	0.93649
P23	712601668.8	12.57341	0.415	0.44353	0.72766
P24	714930439.4	12.55631	0.43766	0.46601	0.81289
P25	721289391.6	10.473336	0.49951	0.50627	0.99923

* Calculated based on a 10-year horizon

The sensitivity analysis based on different values of *w* for this test system are represented in Table 17.4. Based on the reported best and worst plans and the planner's desired values for the objective functions, the final expansion plan would be extracted. For example, if the planner decides to avoid the risk, P14 is the best option. The best plans, {P1, P12, P14}, have the same transmission and generation investments, {G.4, T.8, T9, T10}. Due to zero discount rate and elimination of capacity and budget constraints, the aforementioned capacity additions would be considered the most efficient prospective projections.

Table 17.4 Sensitivity analysis results for the VIKOR decision maker

w_{cost}	w_{EENS}	Best Plan	R	S	Q
0.50	0.50	P10	0.19519	0.27868	0.017694
0.20	0.80	P21	0.15013	0.19579	0.009903
0.80	0.20	P01	0.12646	0.2075	0.006231

Implementing the virtual database in line with the NSGA-II accelerates the convergence time and mitigates the computational load, particularly in next simulation iterations. Since the number of elements in the search space is countable, the size of virtual database would be determined. By decomposing the dynamic framework to a static one in the proposed approach, the size of database reduces. Furthermore, by considering the construction time of generation units and transmission lines in the proposed decoding framework of decision vector in an annually manner, the size of virtual database is reduced. For example, as the construction time for generating units and transmission lines are considered three years and less then one year respectively, the maximum acceptable expansion plans for the first three years would be 16 ones. Thus, the size of database for the first three years is limited to 16 cells. The same analysis is carried out for the committed plans. It is noteworthy that the size of population and the upper bound of generations are assigned to the method as 5 and 100 respectively. Moreover, the probabilities associated with the crossover and mutation are considered 0.8 and 0.2 respectively.

17.6 Conclusion

This chapter has described the implementation of a virtual database together with the use of heuristic optimization algorithms within the countable searching space of a mixed-integer optimization problem. The method is useful to reduce the computational effort. In particular, the VDS-NSGA-II soft computing algorithm is implemented to tackle the MMDGTEP problem, which is a dynamic and mixed-integer optimization problem associated that includes the time-consuming procedure for the minimization of $EENS_{HL\text{-}II}$.

This chapter also highlighted the requirements of considering the two conflicting objective functions, i.e. the investment cost and the risk.

The results obtained for an illustrative case show the effectiveness and efficiency of the presented optimization framework. In this respect, the procedure provides diverse optimal expansion plans to the ISO as the decision maker. The VIKOR decision maker can be used to pick the most adequate plan.

Acknowledgement

João P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT under POCI-01-0145-FEDER-029803 (02/SAICT/2017).

References

[1] Park YM, Won JR, Park JB, Kim DG. Generation expansion planning based on an advanced evolutionary programming. IEEE Trans Power Syst 1999;14:299–305. https://doi.org/10.1109/59.744547.

[2] Mansouri SA, Javadi MS. A robust optimisation framework in composite generation and transmission expansion planning considering inherent uncertainties. J Exp Theor Artif Intell 2017;29. https://doi.org/10.1080/0952813X.2016.1259262.

[3] Akbari T, Bina MT. Approximated MILP model for AC transmission expansion planning: Global solutions versus local solutions. IET Gener Transm Distrib 2016;10:1563–9. https://doi.org/10.1049/iet-gtd.2015.0723.

[4] Binato S, Pereira MVF, Granville S. A new Benders decomposition approach to solve power transmission network design problems. IEEE Trans Power Syst 2001;16:235–40. https://doi.org/10.1109/59.918292.

[5] Garver LL. Transmission Network Estimation Using Linear Programming.

IEEE Trans Power Appar Syst 1970;PAS-89:1688–97. https://doi.org/10.1109/TPAS.1970.292825.
[6] Shrestha GB, Fonseka PAJ. Congestion-driven transmission expansion in competitive power markets. IEEE Trans Power Syst 2004;19:1658–65. https://doi.org/10.1109/TPWRS.2004.831701.
[7] Roh JH, Shahidehpour M, Fu Y. Market-based coordination of transmission and generation capacity planning. IEEE Trans Power Syst 2007;22:1406–19. https://doi.org/10.1109/TPWRS.2007.907894.
[8] Ng SKK, Zhong J, Lee CW. A game-theoretic study of the strategic interaction between generation and transmission expansion planning. 2009 IEEE/PES Power Syst. Conf. Expo. PSCE 2009, 2009. https://doi.org/10.1109/PSCE.2009.4840024.
[9] Billinton R, Allan RN. Reliability Evaluation of Power Systems. Springer US; 1996. https://doi.org/10.1007/978-1-4899-1860-4.
[10] Billinton R, Zhang W. Adequacy equivalent development of composite generation and transmission systems using a d.c. load flow. Reliab Eng Syst Saf 1999;65:295–305. https://doi.org/10.1016/S0951-8320(99)00012-5.
[11] Akhavein A, Firuzabad MF, Billinton R, Farokhzad D. Review of reduction techniques in the determination of composite system adequacy equivalents. Electr Power Syst Res 2010;80:1385–93. https://doi.org/10.1016/j.epsr.2010.06.002.
[12] Javadi MS, Saniei M, Rajabi Mashhadi H. An augmented NSGA-II technique with virtual database to solve the composite generation and transmission expansion planning problem. J Exp Theor Artif Intell 2014;26. https://doi.org/10.1080/0952813X.2013.815280.
[13] Sadegh Javadi M, Saniei M, Rajabi Mashhadi H, Gutiérrez-Alcaraz G. Multi-objective expansion planning approach: Distant wind farms and limited energy resources integration. IET Renew Power Gener 2013;7:652–68. https://doi.org/10.1049/iet-rpg.2012.0218.
[14] Mazer A. Electric Power Planning for Regulated and Deregulated Markets. Hoboken, NJ, USA: John Wiley & Sons, Inc.; 2007.

https://doi.org/10.1002/9780470130575.
[15] Motamedi A, Zareipour H, Buygi MO, Rosehart WD. A transmission planning framework considering future generation expansions in electricity markets. IEEE Trans Power Syst 2010;25:1987–95. https://doi.org/10.1109/TPWRS.2010.2046684.
[16] Wang X (Xifan), McDonald JR (James R. Modern power system planning. London ;;New York : McGraw-Hill; 1994.
[17] Botterrud A, Ilic MD, Wangensteen I. Optimal investments in power generation under centralized and decentralized decision making. IEEE Trans Power Syst 2005;20:254–63. https://doi.org/10.1109/TPWRS.2004.841217.
[18] Roh JH, Shahidehpour M, Wu L. Market-Based Generation and Transmission Planning With Uncertainties. IEEE Trans Power Syst 2009;24:1587–98. https://doi.org/10.1109/TPWRS.2009.2022982.
[19] Javadi MS, Esmaeel Nezhad A. Intelligent particle swarm optimization augmented with chaotic searching technique to integrate distant energy resources. Int Trans Electr Energy Syst 2017;27. https://doi.org/10.1002/etep.2447.
[20] Seddighi AH, Ahmadi-Javid A. Integrated multiperiod power generation and transmission expansion planning with sustainability aspects in a stochastic environment. Energy 2015;86:9–18. https://doi.org/10.1016/j.energy.2015.02.047.
[21] Sun M, Teng F, Konstantelos I, Strbac G. An objective-based scenario selection method for transmission network expansion planning with multivariate stochasticity in load and renewable energy sources. Energy 2018;145:871–85. https://doi.org/10.1016/j.energy.2017.12.154.
[22] Zolfaghari S, Akbari T. Bilevel transmission expansion planning using second-order cone programming considering wind investment. Energy 2018;154:455–65. https://doi.org/10.1016/j.energy.2018.04.136.
[23] Chen SL, Zhan TS, Tsay MT. Generation expansion planning of the utility with refined immune algorithm. Electr Power Syst Res 2006;76:251–8. https://doi.org/10.1016/j.epsr.2005.06.005.

[24] El-Khattam W, Bhattacharya K, Hegazy Y, Salama MMA. Optimal investment planning for distributed generation in a competitive electricity market. IEEE Trans Power Syst 2004;19:1674–84. https://doi.org/10.1109/TPWRS.2004.831699.

[25] Sarjiya, Budi RFS, Hadi SP. Game theory for multi-objective and multi-period framework generation expansion planning in deregulated markets. Energy 2019;174:323–30. https://doi.org/10.1016/j.energy.2019.02.105.

[26] Hemmati R, Saboori H, Siano P. Coordinated short-term scheduling and long-term expansion planning in microgrids incorporating renewable energy resources and energy storage systems. Energy 2017;134:699–708. https://doi.org/10.1016/j.energy.2017.06.081.

[27] Choi J, Tran T, El-Keib AA, Thomas R, Oh HS, Billinton R. A method for transmission system expansion planning considering probabilistic reliability criteria. IEEE Trans Power Syst 2005;20:1606–15. https://doi.org/10.1109/TPWRS.2005.852142.

[28] Multi-Objective Optimization using Evolutionary Algorithms | Wiley n.d.

[29] Nezhad AE, Ahmadi A, Javadi MS, Janghorbani M. Multi-objective decision-making framework for an electricity retailer in energy markets using lexicographic optimization and augmented epsilon-constraint. Int Trans Electr Energy Syst 2015;25. https://doi.org/10.1002/etep.2059.

[30] Opricovic S, Tzeng G-H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. Eur J Oper Res 2004;156:445–55. https://doi.org/https://doi.org/10.1016/S0377-2217(03)00020-1.

[31] Moeini-Aghtaie M, Abbaspour A, Fotuhi-Firuzabad M. Incorporating large-scale distant wind farms in probabilistic transmission expansion planning-part I: Theory and algorithm. IEEE Trans Power Syst 2012;27:1585–93. https://doi.org/10.1109/TPWRS.2011.2182363.

[32] Basu M. Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. Int J Electr Power Energy Syst 2008;30:140–9. https://doi.org/10.1016/j.ijepes.2007.06.009.

[33] Basu M. Economic environmental dispatch of hydrothermal power system. Int J

Electr Power Energy Syst 2010;32:711–20. https://doi.org/10.1016/j.ijepes.2010.01.005.

[34] Kim IY, De Weck OL. Adaptive weighted-sum method for bi-objective optimization: Pareto front generation. Struct Multidiscip Optim 2005;29:149–58. https://doi.org/10.1007/s00158-004-0465-1.

[35] Kim IY, De Weck OL. Adaptive weighted sum method for multiobjective optimization: A new method for Pareto front generation. Struct Multidiscip Optim 2006;31:105–16. https://doi.org/10.1007/s00158-005-0557-6.

[36] Jones D, Tamiz M. Advanced topics in goal programming formulation. Int. Ser. Oper. Res. Manag. Sci., vol. 141, Springer New York LLC; 2010, p. 53–75. https://doi.org/10.1007/978-1-4419-5771-9_4.

[37] Coello Coello CA, Christiansen AD. Moses: A multiobjective optimization tool for engineering design. Eng Optim 1999;31:337–68. https://doi.org/10.1080/03052159908941377.

[38] Varadarajan M, Swarup KS. Solving multi-objective optimal power flow using differential evolution. IET Gener Transm Distrib 2008;2:720–30. https://doi.org/10.1049/iet-gtd:20070457.

[39] Srinivas N, Deb K. Muiltiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. Evol Comput 1994;2:221–48. https://doi.org/10.1162/evco.1994.2.3.221.

[40] Javadi MS, Esmaeel Nezhad A. Multi-objective, multi-year dynamic generation and transmission expansion planning- renewable energy sources integration for Iran's National Power Grid. Int Trans Electr Energy Syst 2019;29. https://doi.org/10.1002/etep.2810.

[41] Khodaei A, Shahidehpour M, Kamalinia S. Transmission switching in expansion planning. IEEE Trans Power Syst 2010;25:1722–33. https://doi.org/10.1109/TPWRS.2009.2039946.

[42] Tavana M, Kiani Mavi R, Santos-Arteaga FJ, Rasti Doust E. An extended VIKOR method using stochastic data and subjective judgments. Comput Ind Eng 2016;97:240–7. https://doi.org/https://doi.org/10.1016/j.cie.2016.05.013.

[43] Kackar RN. Off-Line Quality Control, Parameter Design, and the Taguchi

Method. J Qual Technol 1985;17:176–88. https://doi.org/10.1080/00224065.1985.11978964.

[44] Sayadi MK, Heydari M, Shahanaghi K. Extension of VIKOR method for decision making problem with interval numbers. Appl Math Model 2009;33:2257–62. https://doi.org/https://doi.org/10.1016/j.apm.2008.06.002.