

Hybrid Dynamic-Evolutionary Programming for Multi-Objective Long-Term Malaysia Generation Mix

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Abstract

A Hybrid Dynamic-Evolutionary Programming (HDPEP) is proposed to find an optimal solution for multi-objective power generation mix model. The present contribution is intended to develop a method to facilitate simultaneous modelling of multi-objective optimization considering the cost of power generation, carbon emission and power system reliability. The study introduces the implementation of Evolutionary Programming (EP) via weighted sum method (WSM) approach within the HDPEP framework to optimize the weighted coefficient in providing accurate decision for generation mix planning. The EP-WSM reduces 'discrimination' when choosing the weight values of each objective function. The proposed HDPEP were compared with non-optimal weighted approach. Results show that the HDPEP model provides a better performance in providing the lowest Multi-Objectives Index (MOI) in solving multi-objective power generation mix problem.

Keywords: Multi-objective optimization, generation mix, evolutionary programming, dynamic programming, weighted sum method.

1. Introduction

Sustainable power generation mix planning are designed to meet various objectives and involve analyzing and managing various information such as economy, environment, technology, risk, reliability and society (Sadeghi, Rashidinejad, & Abdollahi, 2016). In practice, power generation mix planning comprises of decision-making problems to simultaneously achieve some objectives such as minimizing risk, maximizing system reliability and minimizing costs (Pereira & Saraiva, 2013). To serve such purpose, multi-objective optimization (MOO) has been widely used in energy resource allocation, energy planning and electric utility applications. Traditionally, the generation mix problem was solved at least cost such as reported by many researchers in the literature (Afful-Dadzie, Afful-Dadzie, Iddrisu, & Banuro, 2017; Aliyu, Ramli, & Saleh, 2013; Dehghan, Amjady, & Kazemi, 2014; Georgiou, 2016; Ghaderi, Parsa Moghaddam, & Sheikh-El-Eslami, 2014; Hemmati, Hooshmand, & Khodabakhshian, 2013; M. Jadidoleslam, Bijami, Amiri, Ebrahimi, & Askari, 2012; Morteza Jadidoleslam & Ebrahimi, 2015; Khodaei & Shahidehpour, 2013; Koltsaklis, Dagoumas, Kopanos, Pistikopoulos, & Georgiadis, 2014; Mohd Shokri, Dahlan, & Ahmad, 2015; Pereira & Saraiva, 2013; Pineda, Morales, Ding, & Stergaard, 2014; Venkatachary, Prasad, & Samikannu, 2017; Yoza, Yona, Senju, & Funabashi, 2014).

However, given the adverse impact of electricity generation on environment and the demand from consumers to have a reliable system, the lowest cost objective alone is no longer appropriate. In this case, Multi-Objectives Optimization (MOO) has been introduced to solve power generation mix problem integrating various decision techniques to trade-off between the conflicting objectives. Moreover, the mathematical model becomes more realistic if distinct evaluation aspects are explicitly considered by

giving them an explicit role as objective functions rather than aggregating them in a single economic indicator objective function.

Numerous studies have modelled generation mix planning as MOO problems considering trade-offs between economic and environmental impact for sustainable energy planning as presented in (Habib & Chungpaibulpatana, 2014; Leibowicz & Larsen, 2013; Majewski, Wirtz, Lampe, & Bardow, 2017; Majidi, Nojavan, & Zare, 2017; Mohd Shokri & Dahlan, 2014; Nazemi, Ghaderi, Moghadam, & Farsaei, 2016; Priya & Bandyopadhyay, 2017; Promjiraprawat & Limmeechokchai, 2013; Zhu, Luo, Zhang, & Chen, 2017) (Mohd Shokri & Dahlan, 2014). On the other hand, works in (Abon, Dahlan, & Mat Yassin, 2015; Aghaei, Akbari, Roosta, & Baharvandi, 2013b; Mohd Shokri, Dahlan, & Mohamad, 2017; Mutalib et al., 2014) consider cost, environment and reliability as the objectives. The multi-objectives generation mix models have shown a better performance than the single objective model in term of its ability to: 1) identify many alternative solutions and 2) provide more realistic results (Abon, Dahlan, & Mat Yassin, 2015).

List of Symbols, Set and Constants

i	state optimization
t	time interval (year) index considered in the time horizon
T	a lifetime of the new plant (optimization horizon)
TC	the total cost of generation mix over the simulation horizon [\$]
$PC_{all,t}$	total production cost of all the generating units in the system at year t [\$]
IC_t	the total investment cost of the new investments at year t [\$]
X_t	cumulative capacity vector in year t [MW]
U_t	capacity addition vector in year t [MW]
$FOM_{all,t}$	total fixed O&M cost of all the generating units at year t [\$]
$VOM_{all,t}$	total variable O&M cost of all the generating units at year t [\$]
CC_t	total carbon emission cost of coal and combined cycle technologies at year t [\$]
MCB_j	the marginal cost of generating unit j
$P_{j,s}$	the power produced by generating unit j at segment s [MW]
TCO_2	total carbon emission of generation mix over the simulation

	horizon [tc]
CI	Amount of CO ₂ generated by coal and combined cycle technologies in time period t [ton/MW]
C_j	actual capacity for unit j [MW]
Ca	capacity outage [MW]
Pd	load demand [MW]
d	duration for each segment [hours]
f	the actual value of the objective function
f_{min}	the minimum value of objective function
f_{max}	maximum value of the objective function
f_{norm}	Normalized objective function
Kt	capacity retirement[MW]
Xt	generation capacity[MW]
R	reserve margin
R^{min}	minimum reserve requirement each year
R^{max}	maximum reserve requirement each year

Various generation mix models have been proposed in the literature for solving MOO by integrating different decision techniques such as weighted sum method (WSM)(Mohd Shokri et al., 2017), analytical hierarchy process (AHP)(Mavalizadeh & Ahmadi, 2014; Zhu et al., 2017), fuzzy set theory (A.R. Abbasi & Seifi, 2014; Ali Reza Abbasi & Seifi, 2014; Javadi, Mashhadi, Saniei, & Gutiérrez-Alcaraz, 2013; Majidi, Nojavan, Esfetanaj, Najafi-Ghalelou, & Zare, 2017), normal boundary intersection(NBI) (Aghaei et al., 2013b; Gitizadeh, Kaji, & Aghaei, 2013), graphical illustration using trade-offs curve, (Mohd Shokri & Dahlan, 2014; Zhang, Mclellan, Tezuka, & Ishihara, 2013) and fractional programming, (Chen, Huang, & Fan, 2015). In MOO, different methods are often used to generate a set of efficient solutions from which the decision maker can choose. Each of the methods discussed above has advantages and disadvantages and many of them can be adapted for specific problems. However, there is still no general 'best' method that can be used to solve MOO problems.

In general, WSM-decision technique is simple to implement but the results obtained are highly dependent on the weights used, which must be specified before the optimization process begins. Several researchers use WSM as a base technique to solve MOO by manually varying the weight, then combine it with other decision techniques. Authors in (Aghaei, Akbari, Roosta, & Baharvandi, 2013a; Majidi, Nojavan, Esfetanaj, et al., 2017) solve the multi-objective functions using WSM approach and select the best solution by employing fuzzy satisfying approach. Authors in (Cacchiani & D'ambrosio, 2016) solve multiple objective problems using branch-and-bound algorithm, which integrate the WSM and the ϵ -constraint approaches.

This paper proposes Hybrid Dynamic-Evolutionary Programming (HDPEP) technique to improved MOO for power generation mix problem. The role of Dynamic Programming (DP) is to find the optimal long-term multi-objectives generation mix which simultaneously optimize cost, carbon emission and the loss of load expectation (LOLE). On the other hand, EP is implemented via WSM approach within the HDPEP framework to find the optimal weighted coefficient by minimizing a weighted sum called multi-objective index (MOI). The weighted coefficient attributes to the importance of the objective function in power generation mix planning. The proposed technique is compared with non-optimal WSM.

Our motivation is to develop specific conditions for the weighted coefficients. The goal is to improve the WSM decision technique. Contribution of this study is to develop HDPEP multi-objective decision technique that optimize weighted coefficient for WSM approach of MOO problem. Solving the HDPEP multi-objective generation mix reduces 'discrimination' when choosing the weight values. This proposed technique combines mathematical and intelligence approach that will overall improve the MOO-based generation mix.

The paper is organized as follows. Section 2 presents the overview of HDPEP in multi-objective power generation mix model. Section 3 describes problem formulation of DP multi-objective. Section 4 presents the implementation of EP algorithm via WSM

approach. The computational results and discussion are described in section 5. Finally, we draw some conclusions in Section 6.

2. Overview of Hybrid DP-EP Multi Objectives Generation Mix Model

Error! Reference source not found. represents the overview framework of hybrid DP-EP (HDPEP) multi-objectives generation mix model. The required input data for solving the generation mix problem are load growth and characteristics of new and existing units such as operation and investment cost, emission rate and forced outage rate.

In DP-generation mix model, there is N unit of candidate plants can be selected

yearly in stage t for T years. State consists of existing units plus the new units each year. At stage 1, the feasible states are built by the combination of 2^N . Path is the selected new generations each year from stage 1 to T . DP will save the combinations' transition path (e.g. a_{ij}^1, a_{ij}^{T-1}) of the lowest MOI with an optimal weight

coefficient for each year until the end year of the planning. Then, it traces back from the saved feasible path to find the lowest MOI path as the multi-objective generation mix problem solution.

We model the MOO to get a set of MOI that represent the state of the process in each year. WSM-decision making is used within the MOO in the generation mix problem. The MOI was defined by transforming the multi-objective into a single objective function. The optimal weighted coefficient is determined for each objective by implementing EP optimization technique via the WSM approach. Detail description on EP-WSM will be discussed in the next section.

3. Mathematical Model

3.1 Multiple Objective functions

Multi-objective model is developed by minimizing the MOI combining three objective functions. The objective functions are: 1) economic, 2) environmental and 3) reliability of the system. In the following, a detailed description of objective and constraints of the gen mix problem is presented.

3.1.1 Economic objective

The economic objective is developed to minimize the total cost of generation expansion over the planning horizon as shown in equation 1. This objective function includes the production cost for all generating units, investment cost for new generation units, fixed and variable operation and maintenance cost for all generating units and carbon emission cost of coal and gas technologies.

$$f_1 : \text{Minimize } TC = \sum_{t=1}^T \left\{ \begin{array}{l} PC_{all}(X_t)_t + IC(U_t)_t + \\ FOM_{all}(X_t)_t + VOM_{all}(X_t)_t \\ + CC_t \end{array} \right\} \quad (1)$$

Economic dispatch (equation 2) is modelled in the DP-based generation mix to determine the power dispatch by the generating unit in the system and production cost of each unit. This is a short-term determination of the optimal output of a number of electricity generation facilities to meet the system load at the lowest possible cost.

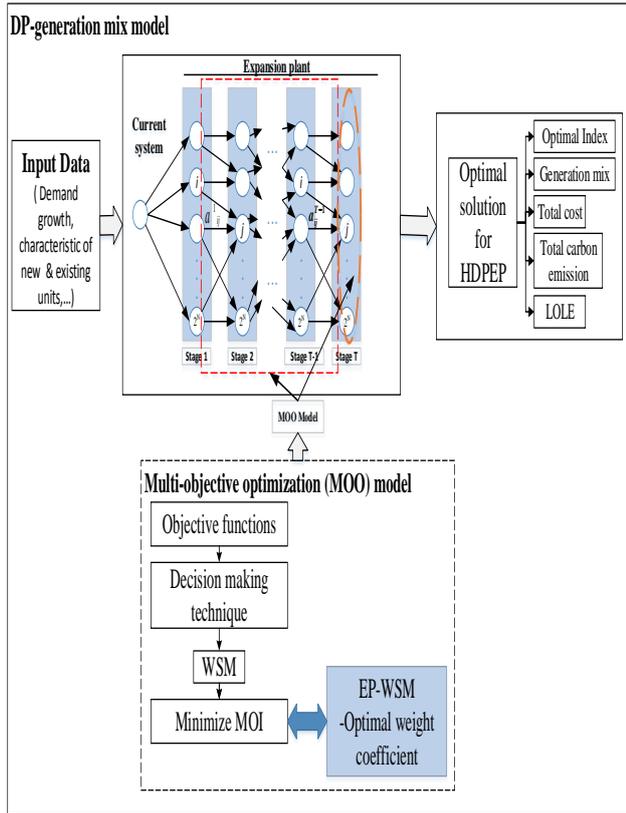


Fig. 1: Framework hybrid DP-EP (HDPEP) multi-objective generation mix model

$$PC_j = \min \left\{ \sum_{s=1}^S \sum_{i=1}^I (MCB_j P_{i,s} d_s) \right\} \quad (2)$$

3.1.2 Environmental objective

This objective function is to minimize the total carbon emission. It is determined based on the carbon content of the fossil-fuel generating unit.

$$f_2 : \text{Minimize } TCO_2 = \sum_{t=1}^T \{CI(X_t)_t\} \quad (3)$$

3.1.3 Reliability objective

In power supply industry, generator outage occurs due to planned maintenance or mechanical failure that may leave the system with insufficient generating capacity to meet load demand. The loss of load probability (LOLP) and loss of load expectation (LOLE) of the system are given by the following equation:

$$f_3 : \text{Minimize } LOLE = \sum_{t=1}^T d.LOLP \quad (4)$$

$$LOLP = \sum_{s=1}^S \sum_{j=1}^j P_j ((C_j - Ca(j)) < P_d) \quad (5)$$

3.1.4 Combine objective function

In the mathematical term, a general MOO problem is given as follows:

$$\min f(x) = \{f_1(x), \dots, f_k(x)\}^T \quad (6)$$

where x is the decision variable of the problem, at $k \geq 2$. To solve the MOO problem, the WSM is used in this study. The MOO is first determined by normalizing the objective function for each stage. All columns represent a set of feasible

states for the objective functions which is formulated as:

$$f_j = \begin{bmatrix} f_{1,1}(x) & \cdots & f_{k,1}(x) \\ \vdots & \ddots & \vdots \\ f_{1,j}(x) & \cdots & f_{k,j}(x) \end{bmatrix} \quad (7)$$

where $f_{k,j}$ are the feasible states for the k -th objective function and j -th state. Each individual objective has different units and scales; therefore, the objective is formulated as normalized values of these three objective cases. The normalized index of the multi-objective function is given by the following equation:

$$f_{norm} = \frac{f - f_{min}}{f_{max} - f_{min}} \quad (8)$$

The normalized objective function, f_{norm} are scaled between zero and one. For each of the three case objectives, a minimum and maximum value, f_{min} and f_{max} are determined. The new normalized objective function form defined as below:

$$f_{norm} = \begin{bmatrix} f_{n1,1}(x) & \cdots & f_{nk,1}(x) \\ \vdots & \ddots & \vdots \\ f_{n1,j}(x) & \cdots & f_{nk,j}(x) \end{bmatrix} \quad (9)$$

The least MOI normalized is equal to the summation of three normalized objective functions multiplied by a weighted coefficient. The MOI is given by the following equation:

$$f_T(x) = \min \sum_{i=1}^k w_i f_i \quad (10)$$

where w_i is weighted coefficient for the objective function k , f_i is the normalized objective function for objective function k . The $f_T(x)$ is summation of weighted coefficient multiplied by the normalized objective function.

3.2 Constraints

The MOO is to minimize the MOI subject to a set of constraints as follows.

3.2.1 Cumulative generation constraints

The cumulative generation capacity at year t is equal to the capacity of the previous year, plus the new capacity built at year t , minus the capacity retirement happening at year t .

$$X_t = X_{t-1} + U_t - K_t, \forall t \in T \quad (11)$$

3.2.2 Reserve margin limit

Reserve margin lies between the minimum and maximum reserve, the installed capacity to be within the minimum and maximum reserve requirements allowed in the system.

$$R^{\min} \leq R(X_t) \leq R^{\max}, \forall t \in T \quad (12)$$

3.2.3 Generation capacity

Generation capacity larger than demand capacity plus some reserve margin

$$X_t > Pd + R(X_t), \forall t \in T \quad (13)$$

3.2.4 Capacity addition constraints

The capacity addition in each year is subjected to investment availability in year t .

$$U_t \leq C_t, \forall t \in T \tag{14}$$

3.2.5 Non-negativity constraints

$$X_t, U_t, K_t \geq 0, \forall t \in T \tag{15}$$

3.2.6 Weighted coefficient constraints

There are two constraints considered in WSM; 1) total weighted coefficient must equal to 1 and 2) weighted coefficient must be larger than zero. These constraints are shown in the following:

$$\sum_{i=1}^k w_i = 1 \tag{16}$$

$$w_i > 0 \tag{17}$$

In the most cases involve weights of objective function, setting one or more of the weights to zero can result in weak Pareto optimality (Marler & Arora, 2004). The relative value of the weights reflects the relative importance of the objectives. Each set is then used to form an independent weighted sum function with a unique set of the weighted coefficient, and in this way, the number of original objective functions is reduced.

4. EP-WSM

Figure 3 shows the EP-WSM flowchart within the HDPEP. EP is implemented via WSM approach to find the optimal weighted coefficient w_i of each objective function $f_i(x)$ by minimizing the MOI. This minimization is an approach to trade-offs the objective functions that combine the total cost, carbon emission and reliability of the system.

A flowchart for the EP-WSM optimization is illustrated in **Error! Reference source not found.** In the first stage, the HDPEP along with the EP optimization is evaluated using a set of normalized objective function f_{n1} , f_{n2} and f_{n3} with several test functions (5, 10, 20, 30, 64 options). In this experiment, we simulated 5 evaluations with 1,000 iterations to ensure the consistency of the weighted coefficient of MOI minimization. In practice, the EP optimization is implemented as follow: first, the initialization part. A random number were generated to represent the weighted coefficient. Initially a series of random number, w_i is generated using a uniform distribution number, where;

$$w_i = \{w_{i,1}, w_{i,2}, \dots, w_{i,p}\}^T \tag{18}$$

where i is variable number that is weighted coefficient number, p is the population size from a set of random distributions with constraints considered are as in equation (16) and (17). The random number represents the new weighted coefficient, which functioned as the control variables. The number of variables depends on the number of objective functions are considered. The random numbers generated during initialization are called as initial population. Normally 20 populations are required during initialization process.

The second step is fitness calculation. The fitness is MOI as presented in equation (10). In the third step, mutation is performed on the random number, w_i to produce offspring. The mutation process is computed based on the following equation:

$$w_{i+m,j} = w_{i,j} + N[0, \beta(w_{jmax} - w_{jmin}) (\frac{ft_i}{ft_{max}})]; \quad j = 1,2,3.. \tag{19}$$

Where:

- $w_{i+m,j}$ = mutated parents (offspring)
- $w_{i,j}$ = parents
- N = Gaussian random variable with mean, μ and variance, γ^2
- β = mutation scale, $0 < \beta < 1$
- w_{jmax} = maximum random number for every variable
- w_{jmin} = minimum random number for every variable
- ft_i = fitness for the i^{th} random number
- ft_{max} = maximum fitness

The fifth step is selection process. In this process, the offspring produced from the mutation process is combined with the parents to identify the candidates that can be transcribed into the next evaluation. The combined population equal to matrix size $[2n \times m]$, where n is the number of rows or number of population, while m is the number of variables.

There are two ways to implement the process namely pair-wise comparison and priority ranking. In this study, the priority ranking technique was selected (to solve the MOI / for the tournament selection). In the priority ranking approach, the populations are sorted in ascending order according to their fitness values. The first half of the populations are transcribed to the next iteration evaluation. Pair-wise selection technique can also be used as an alternative selection technique.

The pair-wise comparison selection technique was found less accurate in the literature (Talib, Musirin, & Kalil, 2007) due to its randomized criteria, therefore is not considered in this study.

Finally, is the convergence test. The stopping criterion determines the convergence of the optimization process to achieve the optimal solution. The convergence criterion is set using the following equation:

$$ft_{max} - ft_{min} \leq 0.0001 \tag{20}$$

If the criterion is not met, the entire process will be repeated. Then, the optimally weighted coefficient for each state.

5. Numerical Results

The HDPEP power generation mix model has been tested on Malaysia's Power System. The planning period was set for eighteen years. The candidates' technology for additional capacity are coal, gas, hydro and RE. The more detail data input can be found in (Mohd Shokri, Dahlan, & Mohamad, 2017). The proposed HDPEP MOO model has been implemented in Matlab programming software. The computer model is HP Pavilions slimline 400 PC series.

The ranking of technology according to economic, environmental and reliability objectives are shown in **Error! Reference source not found.** The optimal power generation mix is to minimize the MOI. The result of proposed HDPEP model that optimized the weighted coefficient at minimum MOI is presented. The result of the proposed model is compared with two DP models: 1) classical WSM approach named Dynamic Programming Non-Preference Method (DPNPM), and 2) Dynamic Programming Preference Method (DPPM). In DPNPM, it is assumed that the objective functions have similar weight, which is set at 0.33 for each objective. On the other hand, in DPPM, it is assumed that the economic cost objective has more weight than environmental and reliability objective. The weigh coefficient for economic cost, environmental and reliability objective are set to 0.5, 0.25 respectively.

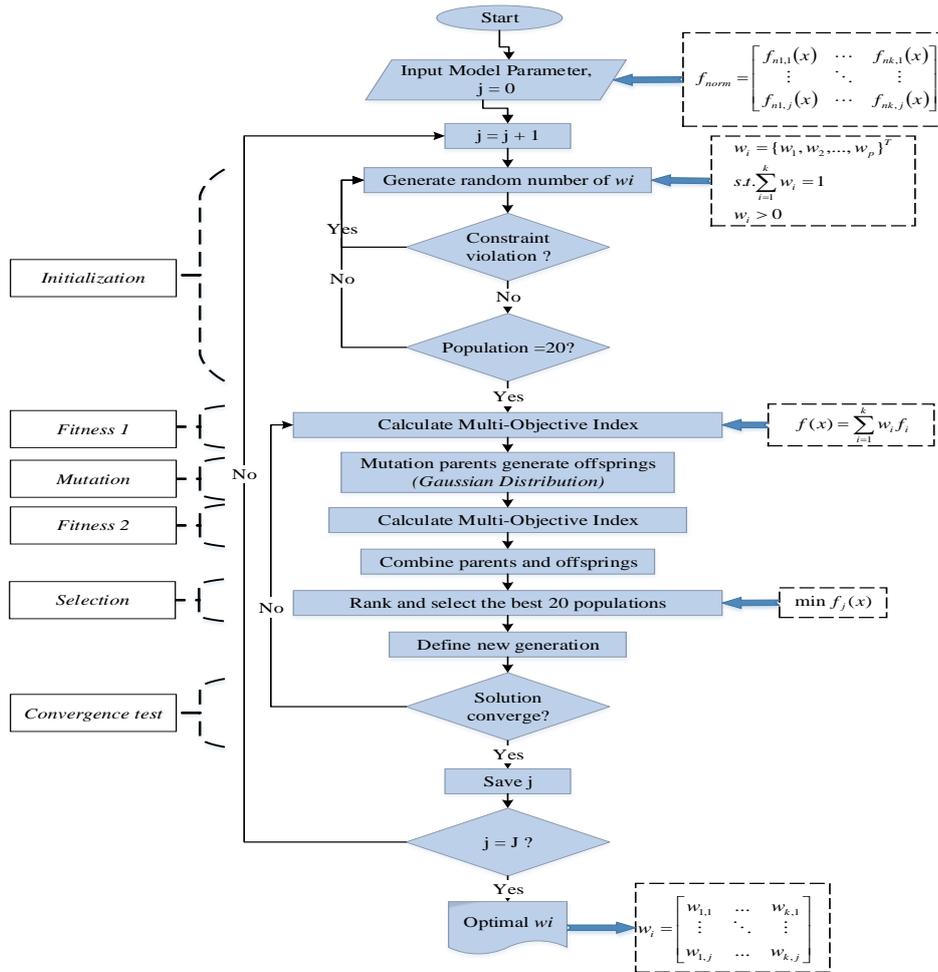


Fig. 2: EP implementation on the optimally weighted coefficient WSM framework

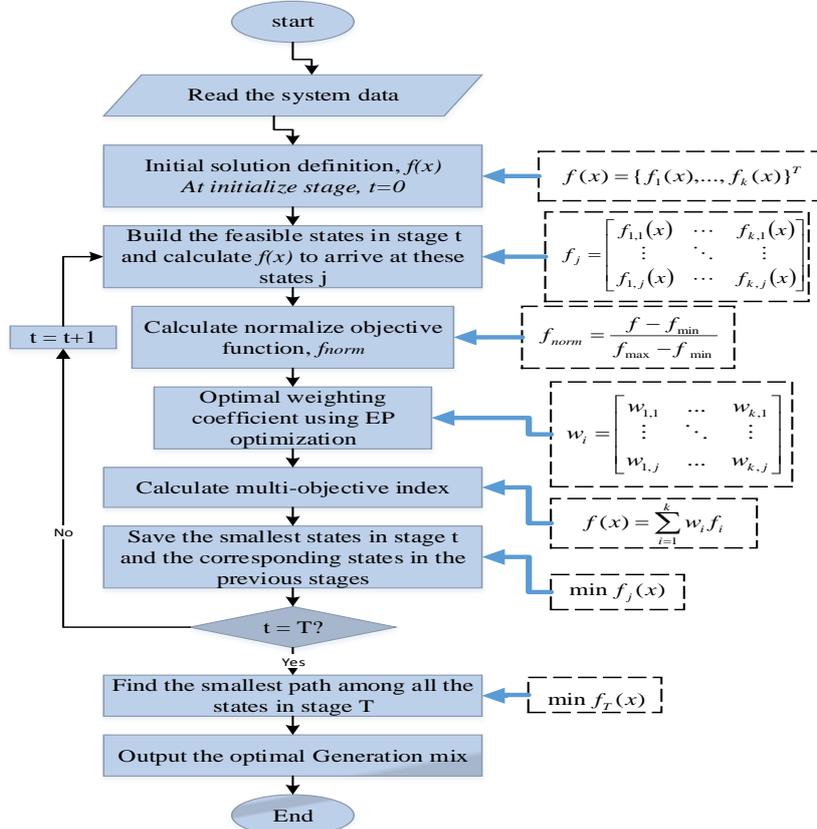


Fig. 3: Flowchart of proposed HDPEP decision-making technique

* EP implement in DP-based generation mix

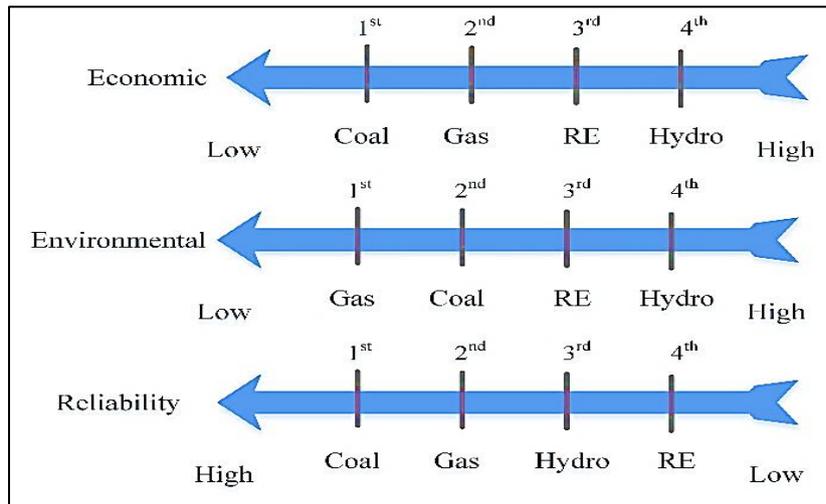


Fig. 4: Ranking of technologies according to economic, environmental and reliability objectives

5.1 Multi-objective optimization

Table 1 shows the initial value of the randomized weighted coefficient for 20 populations. Each weight is higher than zero and sum of three weight is equal to one. The optimally weighted coefficient, normalized objective functions and MOI for each option are given in

Table 2. From the results, S25 is the optimal option that give the lowest MOI of 0.0903 with optimal weighted coefficient of $w_1 = 0.19$, $w_2 = 0.02$ and $w_3 = 0.79$. The optimum option is used to trace back the combinations' transition path of each state-stage. The set of options represents a group of different options to generation mix problem.

Table 3 presents the optimum weight coefficient of option S_{25} for the path transition at each state-stage. The weighted coefficient for each objective (w_1, w_2, w_3) affects DP evaluation of the candidate technologies. The three-dimensional (3D) trade-offs plot between the three objectives cases is shown graphically in Fig. The points represent the feasible options at year 18.

There are 64 alternative solutions found by HDPEP that met all the constraints set in the multi-objectives generation mix model. The optimal generation mix is option S_{25} as circled in Figure 5 and highlighted in Table 2.

Table 1: EP Initialization

Count	w_1	w_2	w_3
1	0.48	0.07	0.45
2	0.52	0.41	0.07
3	0.37	0.25	0.38
4	0.02	0.6	0.38
5	0.38	0.42	0.2
6	0.49	0.04	0.47
7	0.33	0.08	0.59
8	0.18	0.68	0.14
9	0.02	0.28	0.7
10	0.44	0.49	0.07
11	0.19	0.02	0.79
12	0.06	0.12	0.82
13	0.42	0.4	0.18
14	0.17	0.17	0.66
15	0.36	0.5	0.14
16	0.2	0.25	0.55
17	0.56	0.41	0.03
18	0.35	0.32	0.33
19	0.29	0.44	0.27
20	0.04	0.29	0.67

Table 2: Option results of multi-objective index by hybrid EP-DP method

Options (S_j)	Weighted Coefficient			Normalized Values of Objectives			MOI
	w_1	w_2	w_3	f_1	f_2	f_3	
S_1	0.70	0.1	0.29	0.3111	0.5764	0.5993	0.5440
S_2	0.49	0.04	0.47	0.0834	0.8647	0.2368	0.2201
S_3	0.49	0.04	0.47	0.1008	0.7212	0.1618	0.1613
S_4	0.49	0.04	0.47	0.1561	0.9039	0.2367	0.2347
S_5	0.49	0.04	0.47	0.0722	0.7211	0.1840	0.1734
S_6	0.19	0.02	0.79	0.3247	0.5114	0.2008	0.2305
S_7	0.19	0.02	0.79	0.1661	0.7729	0.1835	0.1919
S_8	0.19	0.02	0.79	0.2929	0.8280	0.1838	0.2173
S_9	0.56	0.41	0.03	0.0013	0.6964	0.6557	0.5321
S_{10}	0.49	0.04	0.47	0.1538	0.8641	0.2368	0.2335
S_{11}	0.49	0.04	0.47	0.0000	0.7766	0.3291	0.2755
S_{12}	0.19	0.02	0.79	0.2892	0.7576	0.1583	0.1951
S_{13}	0.49	0.04	0.47	0.0068	0.6405	0.3017	0.2524

S ₁₄	0.18	0.68	0.14	0.3878	0.2984	0.5176	0.4885
S ₁₅	0.06	0.12	0.82	0.4890	0.5709	0.0060	0.1090
S ₁₆	0.18	0.68	0.14	0.4797	0.3379	0.5177	0.5068
S ₁₇	0.02	0.60	0.38	0.6937	0.3002	0.4081	0.4601
S ₁₈	0.19	0.02	0.79	0.3712	0.7529	0.3514	0.3631
S ₁₉	0.49	0.04	0.47	0.2362	1.0000	0.3766	0.3623
S ₂₀	0.19	0.02	0.79	0.4398	0.7921	0.3513	0.3768
S ₂₁	0.19	0.02	0.79	0.3490	0.5966	0.2915	0.3084
S ₂₂	0.19	0.02	0.79	0.4413	0.6513	0.2920	0.3274
S ₂₃	0.19	0.02	0.79	0.4327	0.5666	0.0064	0.0985
S ₂₄	0.19	0.02	0.79	0.5111	0.6908	0.2915	0.3411
S ₂₅	0.19	0.02	0.79	0.3222	0.6034	0.0216	0.0903
S ₂₆	0.19	0.02	0.79	0.3972	0.7267	0.3450	0.3624
S ₂₇	0.19	0.02	0.79	0.3692	0.4822	0.1685	0.2128
S ₂₈	0.06	0.12	0.82	0.5025	0.6404	0.0000	0.1082
S ₂₉	0.19	0.02	0.79	0.3898	0.5960	0.2898	0.3148
S ₃₀	0.19	0.02	0.79	0.4830	0.6509	0.2903	0.3340
S ₃₁	0.18	0.68	0.14	0.7517	0.2893	0.5992	0.6218
S ₃₂	0.19	0.02	0.79	0.5532	0.6905	0.2898	0.3477
S ₃₃	0.18	0.68	0.14	0.5320	0.3007	0.6185	0.5956
S ₃₄	0.49	0.04	0.47	0.0989	0.8591	0.2368	0.2229
S ₃₅	0.56	0.41	0.03	0.1332	0.8241	0.7671	0.6477
S ₃₆	0.49	0.04	0.47	0.2347	0.8789	0.7659	0.6671
S ₃₇	0.56	0.41	0.03	0.1959	0.4855	0.6924	0.5938
S ₃₈	0.56	0.41	0.03	0.2950	0.5401	0.6920	0.6134
S ₃₉	0.56	0.41	0.03	0.4945	0.5304	0.5790	0.5619
S ₄₀	0.56	0.41	0.03	0.3695	0.5795	0.6924	0.6286
S ₄₁	0.49	0.04	0.47	0.1706	0.5965	0.4451	0.3959
S ₄₂	0.49	0.04	0.47	0.2686	0.6508	0.4452	0.4156
S ₄₃	0.49	0.04	0.47	0.2400	0.6352	0.4451	0.4098
S ₄₄	0.49	0.04	0.47	0.3428	0.6903	0.4451	0.4304
S ₄₅	0.49	0.04	0.47	0.2329	0.5955	0.4470	0.4092
S ₄₆	0.49	0.04	0.47	0.3329	0.6502	0.4471	0.4294
S ₄₇	0.19	0.02	0.79	0.3906	0.4863	0.1740	0.2213
S ₄₈	0.49	0.04	0.47	0.4080	0.6898	0.4470	0.4443
S ₄₉	0.18	0.68	0.14	0.9029	0.0000	1.0000	0.9614
S ₅₀	0.49	0.04	0.47	0.4896	0.6485	0.6051	0.5839
S ₅₁	0.56	0.41	0.03	0.4521	0.6278	0.6056	0.5767
S ₅₂	0.49	0.04	0.47	0.5553	0.6828	0.6056	0.5974
S ₅₃	0.06	0.12	0.82	0.5430	0.3864	0.3109	0.3564
S ₅₄	0.06	0.12	0.82	0.6432	0.4412	0.3109	0.3765
S ₅₅	0.56	0.41	0.03	0.5253	0.5258	0.5790	0.5676
S ₅₆	0.02	0.60	0.38	1.0000	0.3849	0.4146	0.5251
S ₅₇	0.56	0.41	0.03	0.4096	0.5627	0.5993	0.5624
S ₅₈	0.49	0.04	0.47	0.5090	0.6173	0.5996	0.5826
S ₅₉	0.06	0.12	0.82	0.8293	0.4573	0.2218	0.3419
S ₆₀	0.49	0.04	0.47	0.5842	0.6568	0.5993	0.5974
S ₆₁	0.18	0.68	0.14	0.7800	0.2289	0.9746	0.9226
S ₆₂	0.06	0.12	0.82	0.6866	0.4408	0.3079	0.3824
S ₆₃	0.18	0.68	0.14	0.8522	0.2682	0.9746	0.9371
S ₆₄	0.06	0.12	0.82	0.6497	0.6563	0.6043	0.6138

Table 3: Optimum weight coefficient of option S₂₅ for path transition at each state-stage

Path	w ₁	w ₂	w ₃
a _{1,2}	0.48	0.07	0.45
a _{2,3}	0.52	0.41	0.07
a _{3,4}	0.37	0.25	0.38
a _{4,5}	0.02	0.6	0.38
a _{5,6}	0.38	0.42	0.2
a _{6,7}	0.49	0.04	0.47
a _{7,8}	0.33	0.08	0.59
a _{8,9}	0.18	0.68	0.14
a _{9,10}	0.02	0.28	0.7
a _{10,11}	0.44	0.49	0.07
a _{11,12}	0.19	0.02	0.79
a _{12,13}	0.06	0.12	0.82
a _{13,14}	0.42	0.4	0.18
a _{14,15}	0.17	0.17	0.66
a _{15,16}	0.36	0.5	0.14
a _{16,17}	0.2	0.25	0.55
a _{17,18}	0.56	0.41	0.03

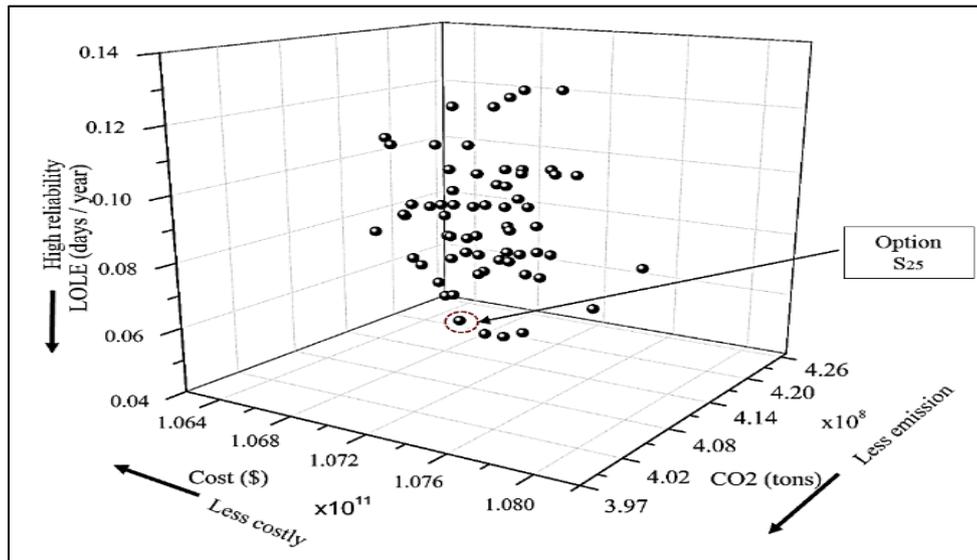


Fig. 5: Trade-offs between the three-objective cases

5.2 Generation mix optimization

Fig shows the new generation installed capacity and scheduled retired capacity each year by HDPEP multi-objectives. It is interesting to note that at optimum weight, with higher weight for reliability objective, gas technology has been chosen as the favourable technology throughout the years.

Fig. 6: Number of newly introduced technologies by hybrid DP-EP multi-objective

shows the resulting generation mix evolution over the planning period. Apparently, the gas and hydro technologies are selected extensively by the proposed model in the case where the weighted coefficient is optimized. Oil technology is retired in year 13 and been replaced by Hydro and RE. The optimum generation mix at the end of the planning period is 45.11% from gas, 35.34% from coal, 9.82% from RE and 9.73% from hydro.

Table 4 shows the comparison of proposed HDPEP model with other two DP models namely DPNPM and DPPM in term of MOI, installed capacity for each technology, total cost, total CO₂ and LOLE.

Results show that, the proposed HDPEP model produces the lowest MOI, i.e. 0.0903, followed by DPPM with 0.2378 and DPNPM with 0.4171. The highest installed capacity by technology in generation mix by HDPEP in year 18 is contributed by gas with 13,910 MW followed by coal with 10,900 MW, RE with 3,029 MW and hydro with 3,000 MW. The installed capacity from gas, hydro and RE technologies by HDPEP model are found higher than the mix provided by DPNPM and DPPM. These technologies significantly reduce the amounts of coal. The optimum total cost, carbon emission and LOLE over the 18 years planning period simulated by the proposed HDPEP is \$106.84 billion, 415 million tCO₂, and 0.0496 days per year respectively.

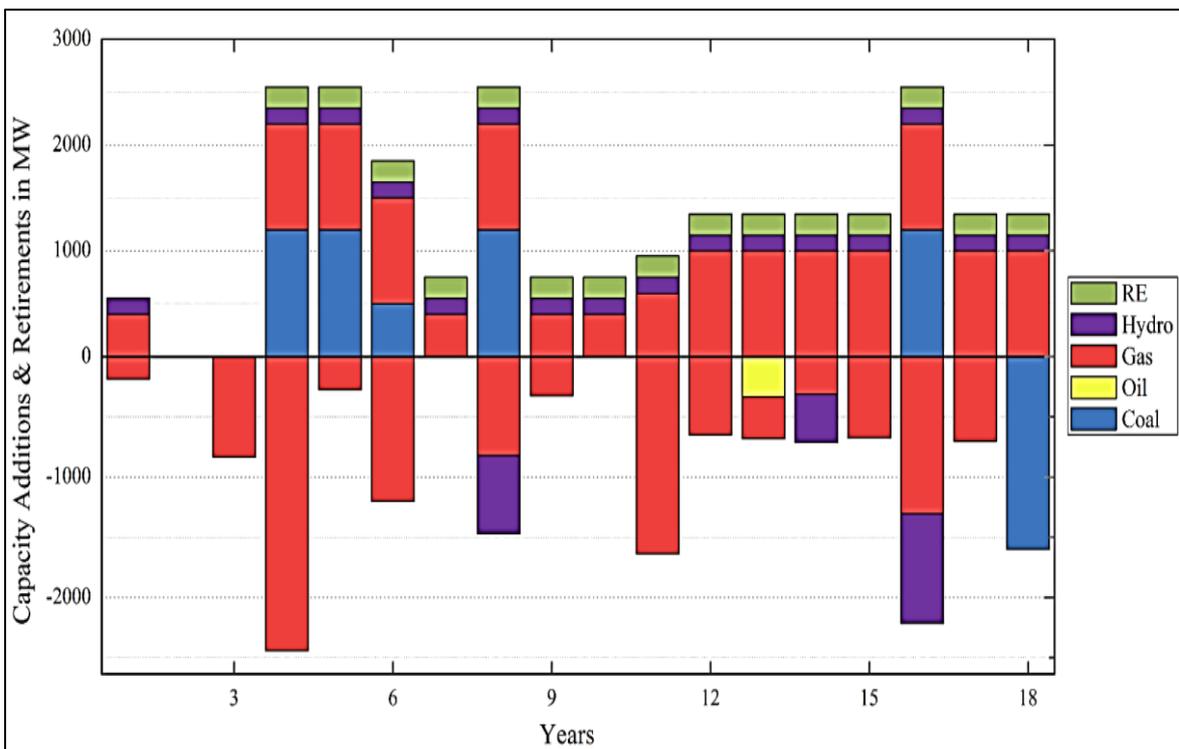


Fig. 6: Number of newly introduced technologies by hybrid DP-EP multi-objective

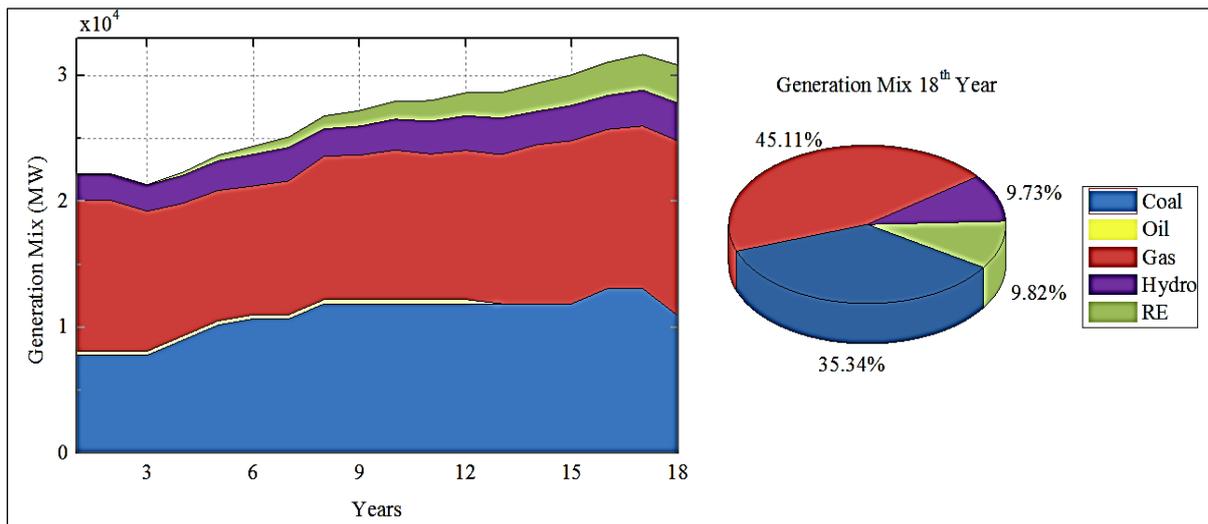


Fig. 7: Evolution of generation mix by HDPEP for 18-year planning period and percentage generation mix at year 18

Table 4: Optimum multi-objective index, installed capacity, total cost, total CO₂ and LOLE for proposed HDPEP model and two DP model

Solution Method	Normalize Index	Coal (MW)	Gas (MW)	Hydro (MW)	RE (MW)	Total Cost (\$)	Total Carbon Emission (tc)	LOLE (days/year)
DPNPM	0.4171	15,200	12,710	2,101	1,030	104,032,930,775.29	447,424,628.73	0.0031
DPPM	0.2378	15,901	12,710	1,201	1,229	102,572,822,242.93	454,874,577.62	0.0080
HDPEP	0.0903	10,900	13,910	3,000	3,029	106,837,117,927.57	415,171,586.03	0.0496

6. Conclusion

This paper presents the development of a new efficient HDPEP method as an alternative method to solve multi-objectives generation mix problem. The result shows that Malaysia optimum generation mix at year 18 is 45.11% from gas, 35.34% from coal, 9.82% from RE and 9.73% from hydro. The proposed HDPEP multi-objectives yields a better solution in term of providing the lowest multi objective index (MOI) as compared to the non-optimal WSM DP model.

The proposed HDPEP multi-objectives model could be further extended too their heuristic technique for a better multi-objectives performance hence accurate generation mix.

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