Application of HVDC Technology in Economic Dispatch with Renewable Energy

Benson Onyango Ojwang

Abstract – Due to need for low cost of energy, environmental concerns, security, stability and distributed generation, there has been increased use of HVDC technology in the modern power systems. This paper is concerned with the Economic Dispatch (ED) in which both HVDC and HVAC lines are considered plus increased Renewable Energy(RE) penetration. This has resulted into Multi Objective Dynamic ED (MODED) with thermal, hydro, wind, solar and combined line losses cost objectives. Improved Strength Pareto Evolution Algorithm (SPEA2) has been used in the solution process. The validation is done on IEEE 14 Bus System with high RE penetration. Hybrid of HVDC and HVAC is preferred when RE is present in ED due to their ability to reduce cost, reduced losses and improved voltage profile.

Keywords – Economic Dispatch (ED), HVAC, HVDC, HVDC Technology, Improved Strength Pareto Evolution Algorithm (SPEA2), Multi Objective Dynamic Economic Dispatch (MODED), Renewable Energy (RE).

I: INTRODUCTION

Three works have been put in place to study Economic Dispatch (ED) with HVDC technology in the recent past [1]. According to Angela, 2015 [2], the better understanding of HVDC system operation is through the study of OPF and LPF in addition to load flow analysis which helps for future expansion planning, stability studies and determining economic operation of the existing systems. Angela used Improved Genetic Algorithm (IGA) in her works. Further work by Musau et al, 2015 [3], looked into the HVAC, OPF and load flow analysis in order to analyze the transmission line losses, control of power flow and voltage stability besides the generation cost. This work used IGA method and OPF. Finally, Waswa, 2016 [4], addressed ED for a hybrid system of HVDC and HVAC. Waswa compared the HVDC cost with HVAC cost and hybrid cost. The author used PSO method on MATLAB environment. In these works, however, Renewable Energy (RE) was not included.

RE has been used with HVDC technology in two research works. According to Musau, et al, 2016 [1], Multi Objective Dynamic Economic Dispatch (MODED) with RE (Wind and Solar) and HVDC transmission lines provided a better alternative as compared to pure HVAC system. The authors formulated and considered AC and DC parameters and used probabilistic load flow (PLF) to determine the optimal cost. Further, uncertainties and variability of RE have been modelled using scenario based method (SBM). The problem was then solved using improved genetic algorithm (IGA). This work has helped to determine the total fuel cost and HVDC link parameters. Moreover, Edwin, 2016 [5], compared purely thermal generation with that of hybrid of thermal, wind and solar PV generation through HVDC transmission with line losses being considered. The author used MPSO method in MATLAB Environment. However, in all these works, none have considered the hydroelectric power as a source of RE besides failing to address the conversion losses for AC/DC from the sending end and to the receiving end. Further, an overall efficiency of the HVDC transmission with all losses and RE need to be considered. These have been seen as the weaknesses of their research works.

A: Contribution: The hydro resource and the respective constraints is introduced for the first time in the ED with HVDC and RE. A better and more accurate formulation of the line losses (HVDC and HVAC) is also given. A new approach Improved Strength Pareto Evolution Algorithm (SPEA 2) is applied in its solution.

B: Paper Organization: The rest of the paper is organized as follows: Section II presents the formulation of the problem , Section III is the review of the methods applied in ED with HVDC and the proposed method(SPEA2), Section IV is a

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presentation of the simulated results Section V gives the paper conclusion and suggestions for further works. Finally, a list of references is provided.

II: PROBLEM FORMULATION

A. *Thermal Cost Function (TCF):* The general form of single objective dynamic economic dispatch (SODED) with more accurate cubic cost function can be formulated as [1]

$$\mathrm{F}(P_{ij}) = \left\{a_{0,i} + \sum_{j=1}^{L=n} a_{ji}\, P_{t,i}^{j} + r_i\right\} + \left|e_i \sin f_i (P_i^{min} - P_i)\right| \quad (1)$$

Where $a_{0,i,}a_{j,i}, e_i$ and f_i are the cost coefficients of the i^{th} unit, $P_i^{min}$is the lower generation bound for the i^{th}unit and $r_i$is the error associated with the ith equation.

B. *Renewable Cost Functions (RCF)*

Hydroelectric Cost Function (HCF): The HCF is formulated by considering the variables of the plant (operating state and discharge of the plant), power output of the plant, the average net head of the plant, efficiency and storage capacity of the plant [7] as follows:

$$F(P_{i,k}) = \sum_{i=1}^{T}(D_{jk,i} - \sum_{k=1}^{H}(ST_{k,i}P_{k,i}))^2 \quad (2a)$$

$$P_{i,k} = 9{,}81.\, Q_{k,i}.\, H_{k,i}.\, \eta_{k,i}.\, 10^{-3} \quad (2b)$$

$$\forall k \in [1, H];\ \forall i \in [1, T] \quad (2c)$$

where $P_{i,k}$ is the hydro plant power output (MW), $ST_{k,i}$ is the operating state of hydro-plant, $D_{jk,i}$ is the total load demand without addition of other sources of RE (MW), $H_{k,i}$ is the average net head of hydroelectric plant, $Q_{k,i}$ is the discharge of hydroelectric plant, $\eta_{k,i}$ is the efficiency of the plant, k is the hydro plant index, H is the number of hydro plants, i is the time interval index (hours) and T is the total number of the time intervals.

Wind Cost Function (WCF): The operational cost objective function for wind power generation is formulated in [6] as

$$F(w_{ij}) = F_{wi}(w_{ij}) + F_{p,wi}(w_{ij,av} - w_{ij}) + F_{r,wi}(w_{ij} - w_{ij,av}) \quad (3)$$

where w_{ij} is the scheduled output of the i^{th} wind generator in the j^{th} hour, $F_{wi}(w_{ij})$ is the weighted cost function representing the cost based on wind speed profile, $F_{p,wi}(w_{ij,av} - w_{ij})$ is the penalty cost for not using all the available wind power and $F_{r,wi}(w_{ij} - w_{ij,av})$ is the penalty reserve requirement cost which is due to the fact that that actual or available power is less than the scheduled wind power.

Solar Cost Function(SCF): Similarly, the operational cost objective function for the PV power generation plant is formulated as [6]

$$F(PV_{ij}) = F(PV_{ij}) + F_{p,PVi}(PV_{ij,av} - PV_{ij}) + F_{r,PVi}(PV_{ij} - PV_{ij,av}) \quad (4)$$

$F_{PVi}(PV_{ij})$ is the weighted cost function representing cost based on solar irradiance. The other two are the respective penalty costs as in wind, equation (3).

C. *Losses Cost Function:*

HVDC Conversion *Loss Cost Function:* The problem is formulated by considering the sending end and receiving end conversion (switching) losses. Switching losses are formulated as [9]

$$P_{sw} = \frac{1}{T_{net}}\sum_{i=1}^{n} E_i \approx \frac{f_{sw}}{T_{net}}\int_{t=1}^{T}(\sum_{j=1}^{n} a_j i t^{j-1})\frac{V_{DC}}{V_{ref}}dt \quad (5)$$

where E_i is the energy for the i[th] unit, T_{net} is the time taken for the network to switch, f_{sw} is the switching frequency, V_{DC} is the DC voltage to be transmitted and V_{ref} is the reference voltage. The assumption made here in order to formulate the cost function is that the conduction losses by the semiconductors are negligible and the conversion losses at the sending end equal the conversion losses at the receiving end. Thus, $P_{convloss} = 2P_{sw}$. Hence, the HVDC loss cost function is given by

$$F(P_{L,DC}) = F(P_{convloss,ij}) = \left\{\sum_{j=1}^{m} a_{j,i}P_{convlossj,i}^{j-1} + c_j\right\} \quad (6a)$$

where c_j is the error associated with conversion.

The cost of the HVAC transmission line losses between plants are accounted with the actual fuel cost function by using a price factor g_i .This factor is defined as the ratio between the fuel cost at its maximum power output to the maximum power output. Thus, the cost function for the AC losses at a particular time becomes [1]

$$\mathrm{F}(P_{L,AC}) = \sum_{i=1}^{n} g_i(\alpha_{3,i}\, P_{t,i}^3 + \alpha_{2,i}\, P_{t,i}^2 + \alpha_{1,i}P_{t,i} + \alpha_{0,i}P_{t,i}) \quad (6b)$$

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Combined Line Loss Cost Function (CLLCF): The HVDC–HVAC losses function is formulated using equations (6a) and (6b) as:

$$F(P_{L,i}) = WF(P_{L,AC}) + (1-W)F(P_{L,DC}) \quad (7)$$

where $F(P_{L,AC})$ is the AC line loss cubic cost function, W is the weighting factor for AC and DC system losses (dependent on the number of HVDC and HVAC lines)

D. *Overall Formulation:* According to equations (1), (2a), (3), (4) and (7)

$$\text{F} = \min \left[\sum_{i=1}^{n} F(P_{i,j}) + \sum_{i=1}^{H} F(P_{i,k}) + \sum_{i=1}^{w} F(w_{j,i}) + \sum_{i=1}^{r} F(pv_{i,j}) + F(P_{L,i})\right] \quad (8)$$

Where n, H, w, and r are the number of thermal, hydroelectric, wind and solar PV units respectively.

E. Problem Constraints

(i) *Combined Constraints:* The solution of the formulated problems can be arrived at by combining the thermal, RE, losses and power demand as formulated below:

$$\sum_{i=1}^{n} P_{ij} + \sum_{i=1}^{W} Pw_{ij} + \sum_{i=1}^{S} PV_{ij} = P_{Dj}^{a} + P_{loss\ j} \quad (9a)$$

$$P_r\left[\sum_{i}^{n} P_{im} + \Omega(w_{ij} + PV_{ij})\right] \le P_{Dj}^{a} + P_{loss\ j} \le P_a \quad (9b)$$

$$P_D^a = P_D^t - (PV_{ij,av} + w_{ij,av}) \pm P_R \quad (9c)$$

$$(PV_{ij} + w_{ij})_d \le xP_D^a \quad (9d)$$

$$P_R \le (PV_{ij,av} + w_{ij,av})_g - (PV_{ij} + w_{ij})_d \quad (9e)$$

$$P_R \le y\sum_{T_a}(PV_{ij,av} + w_{ij,av})_g - (PV_{ij} + w_{ij})_d \quad (9f)$$

$$\textstyle\sum_{T_u} P_R \le \sum_{T_a} P_R \quad (9g)$$

(ii)*Renewable Energy Constraints:*

Wind

$$0 \le w_{j,i} \le w_{r,i} \quad (10a)$$

Solar

$$0 \le pv_{i,j} \le pv_{K_{t\,max}} \quad (10b)$$

Hydroelectric plant constraints

$$ST_{k,i}\cdot(P_{min,k} + {}^{RSV-}P_{k,i}) \le P_{k,i} \le ST_{k,i}\cdot(P_{max,k} - {}^{RSV+}P_{k,i}) \quad (11a)$$

$$ST_{k,i}\cdot(Q_{min,k} + {}^{RSV-}Q_{k,i}) \le Q_{k,i} \le ST_{k,i}\cdot(Q_{max,k} - {}^{RSV+}Q_{k,i}) \quad (11b)$$

Reservoir Storage Constraints

$$V_{min,k} \le V_{k,i} \le V_{max,k} \quad (12a)$$

$$V_{k,0} = V_{in,k} \quad (12b)$$

$$V_{k,T} = V_{fin,k} \quad (12c)$$

(iii) *HVAC Constraints*

$$P_j^{min} \le P_j \le P_j^{max} \quad (13a)$$

$$P_{j,i} - P_{j,i-1} \le UR_j \quad (13b)$$

$$P_{j,i-1} - P_{j,i} \le DR_j \quad (13c)$$

$$-P_l^{max} \le P_{l,j} \le P_l^{max} \quad l = 1,2,3,4,\ldots,L \quad (13d)$$

$$P^{pz,low} \le P_j \le P^{pz,high} \quad (13e)$$

(iv)*HVDC Constraints*

Converter Tap Constraints Ratio:

$$T_{min} \le T \le T_{max} \quad (14a)$$

Converter Ignition Angle Constraint:

$$a_{min} \le a \le a_{max} \quad (14b)$$

Converter Extinction Angle Constraint:

$$\gamma_{min} \le \gamma \le \gamma_{max} \quad (14c)$$

Voltage Constraint:

$$V_{DC,min} \le V_{DC} \le V_{DC,max} \quad (14d)$$

III: PROPOSED METHODOLOGY

A: Review of Methods

In the reviewed works in the introduction, the following methods have been applied to the HVDC-ED problem: Scenario Based Method (SBM), Improved Genetic Algorithm (IGA), Modified Particle Swarm Optimization (MPSO), Particle Swarm Optimization (PSO), Probabilistic Load Flow

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(PLF) and Optimal Power Flow (OPF). These methods are discussed as follows:

Scenario Based Method (SBM): This method has been used to determine the expected values of a variable y which is a function of x [1]. Scenario Based Method (SBM) describes more than one future expectation in which multiple future are realizable and desirable. Besides, SBM helps to recognize technological disruptive occurrence and effect it into long-range planning. However, this method consumes a lot of time since it requires extensive collection and interpretation of data from different sources. The method is usually applied in modelling the RE scenarios.

Improved Genetic Algorithm (IGA): This method has been used to get a set of random techno-economic solutions (small population) in [2] and [3]. The advantage of Improved Genetic Algorithm (IGA) is that it has a great convergence property based upon Penalty Function and a good capacity to solve optimization. It, however, has little extent of application since it only has powerful manner of depending on optimization problem. Therefore, it is not flexible to solve other problems.

Particle Swarm Optimization (PSO): PSO has been implemented by looking throughout the generation of the power plants P_i within the constraints [4]. This method is preferred because it is robust to control parameters and takes less computational time, thus easy to implement. However, it has slow convergence rate and convergences prematurely.

Modified Particle Swarm Optimization (MPSO): It has been used for non-smooth ED where the focus is on the treatment of the equality and the inequality constraints when revamping each individual's search strategy [5]. MPSO has a good execution in global convergence and stability. It, however, has a faster convergence rate for a multi-peak function in comparison to the next improvement. Therefore, it is a bit difficult to choose the appropriate velocity limitation between maximum and minimum extremes.

Probabilistic Load Flow (PLF): In [1], the method has been used to resolve on the HVDC, RE and other system parameters. This method avoids the complications due to computation but adds abstraction to the phenomena in study. Due to the approach given, whether numerical (like for the case of Monte Carlo method) or analytical (like the case of convolution method), the weaknesses can be pointed out. Monte Carlo method consumes a lot of time since it needs a large number of simulations whereas analytical approach has complicated mathematical computation and less accurate due to different approximation.

Optimal Power Flow (OPF): OPF has been used to give a better understanding for HVDC system operation in order to meet the demands and minimize the operating cost in [3] and [2]. The main advantage of this method is that it helps to determine the best operating levels for the electric power plants throughout a transmission network. It, however, has increasing difficulty of solving problems with increasing network size and complexity.

B: Improved Strength Pareto Evolutionary Algorithm (SPEA2).

The proposed method in this paper is the Improved Strength Pareto Evolutionary Algorithm simply known as SPEA2. It is an extension of SPEA which is an Evolutionary and a Multiple Objective Optimization Algorithm. The SPEA has an objective of locating and maintaining a front of non-dominant set of Pareto Optimal solutions. The achievement of this is realized by using the evolutionary process (which explores the search space) and a selection process. The selection process uses a combination of the level in which candidate solution is dominated and the density of the Parent front estimation as an assigned fitness. A population of candidates and an Archive of the non-dominant set are separately maintained. This provides a form of superiority (elitism) [13].

As opposed to SPEA, SPEA2 has an improved fitness assignment scheme. In this scheme, each individual is taken into account to know the number of individuals it dominates. Besides, there is incorporation of the nearest neighbor density estimation technique. This allows for the guidance of the search process to be more precise. Finally, SPEA2 employs new archive truncation methods where the preservation of boundary solutions is guaranteed. However, this algorithm only considers the minimized distance to the optimal front. In this paper, this weakness is our strength since this problem investigates also the minimum distance in which HVDC transmission is economical [13].

SPEA2 Parameters

This problem in this case involves two main objectives: minimization of the HVDC transmission distance to the optimal front, and maximization of the diversity of the generated solutions in terms of power with possible minimal fuel cost.

Population, P_t: This is a set of random solutions. SPEA2 is based on its evaluation. The starting population, P_0 represents a gene pool with randomly formed elements. The population is made of individuals.

Individuals, i: An individual represents a potential solution to the problem. In this paper, individuals are the generator outputs, P_{Gi}.

Generations: This refers to the evolution through successive iteration of generator outputs, P_{Gi}. During each generation, individuals are evaluated using fitness function.

In order to meet the total load demand against the generation limits and losses with minimized total operating cost, the fuel cost function is evaluated subject to:

Power balance equation,

$$\sum_{i=1}^{n}(P_{i,j}) + \sum_{i=1}^{m}(P_{i,k}) + \sum_{i=1}^{l}(w_{j,i}) + \sum_{i=1}^{r}(pv_{i,j}) - (P_{dem}^{a} + P_{convloss\,j,i} + P_{L,i}) = 0 \quad (15)$$

The inequality constraints,

$$P_r\left[\sum_{i=1}^{n} D_{jk,i} + \Omega\left(w_{j,i} + pv_{i,j}\right)\right] \leq P_{dem}^{a} + P_{convloss\,j,i} + P_{L,i} \leq P_a \quad (16)$$

Thus, the objective function is to provide a measure of how individual has performed in the problem domain.

Archives, A: This is a set of a non-dominated population (external set). This non-dominated set is the power load demand (the output power A) in this paper. If the non-dominated set fits exactly into the archive, then the selection is completed. Otherwise, refer to *environmental selection* part.

Fitness Assignment: Each individual *i* is taken into account to know the number of individuals it dominates or dominate it. The number of solutions dominated by each individual *i* in the population P_t and the archive *A* is assigned a strength value *S(i)* given by [13]:

$$S(i) = |\{j | j \in P_t \cup A \wedge i \succ j\}| \quad (17)$$

Where |.| is the cardinal of a set, ∪ is the multiset union and ≻ is the Pareto dominance relation.

Based on the values of *S(i)*, the individual $\boldsymbol{i}$, the raw fitness $R_f(i)$ is given by:

$$R_f(i) = \sum_{j \in P_t \cup A,\, j \succ i} S(j) \quad (18)$$

Thus, the raw fitness is determined by its dominators strengths in both P_t and *A*. Note that $R_f(i)$ is to be minimized. For $R_f(i) = 0$ then it corresponds to non-dominated individual and if $R_f(i) = high\ value$ then it implies that *i* is dominated by many individuals which in turn dominate many individuals. However, the raw fitness may fail if the domination of each other by the most individuals do not occur. This problem can be solved by the additional density information.

Density Estimation, k: This is incorporated to discriminate between individuals having identical raw fitness values. For each individual *i,* the HVDC transmission distances to all individuals, *j* in *A* and P_t are calculated and stored in the list. The list is then sorted in increasing order for the *k-th* element to give the distance sought, σ_i^k.

k is set to be the square-root of the sample size, $k = \sqrt{M + \bar{M}}$ followed by the calculation of the density *D(i)* for the corresponding *i* as:

$$D(i) = \frac{1}{\sigma_i^k + 2} \quad (19)$$

Finally, the fitness *F(i)* is then calculated as the sum of the raw fitness and the density, that is,

$$F(i) = R_f(i) + D(i) \quad (20)$$

Run Time: The density estimator, $(\mathcal{O}(N^2 logN))$ dominates the run time of fitness assignment procedure. $R_f(i)$ and *D(i)* is of complexity of $\mathcal{O}(N^2)$ with $N = M + \bar{M}$.

Mating Selection: The search of Pareto-optimal front is guided by the mating selection where the individuals for offspring production are selected by assignment of a pool of fitness values and individuals *j.* This procedure for filling the mating pool is usually randomized.

Environmental Selection: This selection decides on which individuals to keep during the process of evolution. Here deterministic selection is mostly used. In this selection, there are two cases:

When there is constant number of individuals in the archive over time. In this case, an archive A becomes the power output (load demand) as explained under archive, *A* above.

When the boundary conditions cannot be removed due to truncation method *(Archive Truncation).*

To get the *new generation (offspring or new archive)* from the individuals, *i,* and investigate the above two cases, the following equation is used:

$$New\ Archive, A_{t+1} = \{i | i \in P_t + A_t \wedge F(i) < 1\} \qquad (21)$$

When $New\ Archive, A_{t+1} = A_t = power\ output\ A$, then the environmental selection step is completed (case i).

When $New\ Archive, A_{t+1} < A_t$ (too small archive), then the best $A_t - |A_{t+1}|$ dominated individuals in the previous archive and population are copied to the new archive.

When $New\ Archive, A_{t+1} > A_t$ (too large archive), then an archive truncation procedure is invoked. This iteratively removes individuals from A_{t+1} until $New\ Archive, A_{t+1} = A_t$. This is achieved by taking the individual with minimum distance to another individual chosen at each stage. If there are several individuals with minimum distance, the tie is broken by taking the second smallest distance and so forth. The parameter mapping to the MODED problem is summarized in Table 1.0.

Table 1.0 Summary of the mapping

SPEA2 Parameter	*Mapping To The Problem*
Population, P_t (input)	RE, pure thermal energy
Individuals, i (input)	Generators (power at the sending end)
Archive, A_t (output)	Power output demand (power at the receiving end)
Crossover	Networking through injection of RE
Mutation	Networking without injection of RE
New Archive, A_{t+1}	Newly acquired generations as a result of Networking with losses incorporated
Distance sought, $\boldsymbol{\sigma_i^k}$	Transmission line length

Pseudo Code

Steps involved in solving SPEA2 process are [13] [14]:

Step 1: *Initialization*

The generation of population P_0 with size P (energy sources) and external Pareto-optimal set A_0 with size A (load demands) are done.

Step 2: *External Pareto set updating*

To get an updated set of the external Pareto optimal set, below steps are useful:

The population of the non-dominated individuals are highlighted and reproduced to the external Pareto set.

Check for the set of external Pareto and design for the non-dominated individuals.

If condition $New\ Archive, A_{t+1} < A_t$ is satisfied, then select the individuals with highest fitness values until $New\ Archive, A_{t+1} = A_t$.

If $New\ Archive, A_{t+1} > A_t$, then archive truncation is done until $New\ Archive, A_{t+1} = A_t$.

Step 3: *Fitness Assignment*

The fitness values of individuals are worked upon for both A_t and P_t as follows:

The strength value and raw fitness are calculated illustrated from equations 14 and 15 respectively.

The distance sought between individual i and j individuals in the course of A_t and P_t sets are listed. Then the list is sorted cumulatively in the range [1 k] followed by the calculation of fitness value i. See equations 16 – 18.

Step 4: *Selection*

From the two individuals selected at random basis from A_{t+1}, the best one is selected, based on their fitness values, and copied to the mating pool.

Step 5: *Crossover and Mutation*

Operations for mutation and crossover are carried out based on their probabilities for the generation of new archive.

Step 6: *Looping back*

The criteria for stopping is looked at. If satisfied then case i above under the *Environmental Selection* is implemented, else, see case ii as illustrated above.

Step 7: *Termination*

The termination criteria are looked at. If this criterion is satisfied, then the fuzzy set theory is applied to determine the best compromise solution out of A_{t+1}.

The simulation in this paper is done on MATLAB R2014a. This tool has a high-performance language for technical computation. It helps in algorithm development besides math and computation. Its environment is easy to use in programming and visualizing especially where the problem formulated and solutions are expressed in mathematical notation.

This problem is validated on 5 generators, 14 Bus IEEE System shown in Figure 1.0.

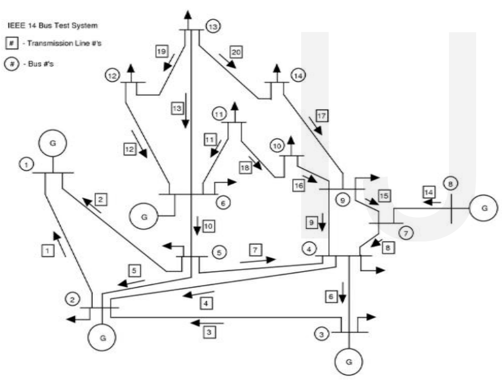

Figure 1.0 :14 Bus IEEE System

IV: RESULTS AND ANALYSIS

The optimal results have been obtained for fuel costs, HVDC line losses and voltage profile at increasing load demand. Five generators have been used. These include 2 thermal, 1 hydroelectric, 1 solar PV and 1 wind power units at the generator buses. The results for optimal generation for each has been simulated. Besides, the load demand for each bus bar for IEEE 14-Bus system has been simulated and their voltage profile plotted. The total load demand used is from 150MW to 600 MW at intervals of 50MW. To know the speed and accuracy of SPEA2, the number of iterations and runtime have been also recorded.

The following three cases have been considered:

Case 1: Economic Dispatch for HVAC with Losses (Base Scenario)

Case 2: Economic Dispatch for HVAC & HVDC with Losses

Case 3: Economic Dispatch for HVAC & HVDC with Losses and RE

A: Fuel Cost

With smaller loads (under generation), say 150MW, the fuel cost of HVDC with RE is seen to be the highest followed by that of purely thermal generations. This is because at low power generation, the fuel cost cumulatively for RE generations becomes much more expensive since each generator incurs some costs. The trend is seen to be changing with increase in load demand and generations. The rate of fuel cost for thermal generation increases with increase in demand followed by that of HVDC then HVDC with RE. This is due to the fact that thermal fuels are the most expensive of all (Hydro, PV and Wind generators). However, at a demand of 600MW (over generation), the fuel cost for HVDC is the highest. At this load, there is overheating of the converters, thus a lot of energy is used for cooling of the heat sinks.

Table 2.0 Fuel Cost with Changing Demand ($/h)

Power Demand(MW)	Fuel Cost ($/h)		
	Case 1	Case 2	Case 3
150	889.704	862.443	943.155
200	1115.38	1069.4	1051.08
250	1377.12	1311.13	1116.91
300	1676.38	1588.78	1263.45
350	2014.75	1903.67	1353
400	2394.09	2256.92	1474.71
450	2817.07	2650.02	1610.06
500	3286.23	3084.22	1759.63
550	3554.13	3407.77	1923.79
600	3657.22	3908.38	2050.48

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A bar graph of fuel cost versus the demand is as shown in Figure 2.0. Further, some extra cost is incurred for the excess fuel used to produce this cooling energy. This does not happen with HVDC with RE since all the load burdens are shared by the different fuel generators. It can therefore be concluded that for ED with HVDC and HVAC, the power demand should be relatively higher and the use of RE should be encouraged. Thus, Case 3 is the best system for minimized fuel cost.

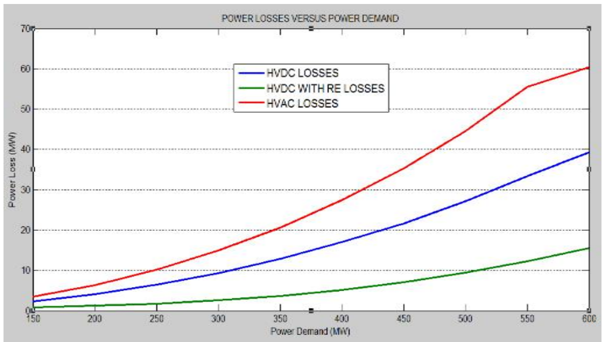

Figure 2.0: Fuel Cost for Versus Power Demand

B: Line Losses

The power losses for the three cases were compared by Figure 3.0. From the figure, it is clear that there is greatest power loss with HVAC transmission and least in HVDC with RE. The losses are almost linearly related. The margin of losses in HVDC with RE transmission is seen to be averagely 78% of the losses in purely HVAC transmission, that is, $P_{loss,HVDC\ with\ RE} \cong 0.22 P_{loss,HVAC}$. Besides, the margin of losses in HVDC is seen to be averagely 63% of that of HVAC, that is, $P_{loss,HVDC} \cong 0.37 P_{loss,HVAC}$. In addition to this, the margin of power loss in HVDC and HVDC with RE is seen to about 35% at initial stages and decreases up to about 20%. Thus, by average, $P_{loss,HVDC\ with\ RE} \cong 0.75 P_{loss,HVDC}$. The behavior of these transmission systems is due to the transmission line impedances (R, L and c). DC links have much more resistance for active power transfer and reduced reactive power due to DC frequency (almost zero). In AC link, the reactive power is consumed as a result of oscillations (50Hz or 60Hz frequencies). These complex power leads to high transmission power losses. From these analysis, it can be concluded that the best power transmission system is the HVDC with RE transmission. This system is the most efficient of all.

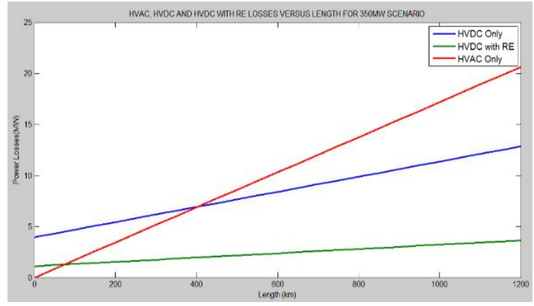

Figure 3.0: Comparison of Power Losses for Three Cases

The power losses for the 3 Cases considered versus the HVDC and HVAC transmission line length for 350MW demand is as shown in Figure 4.0.

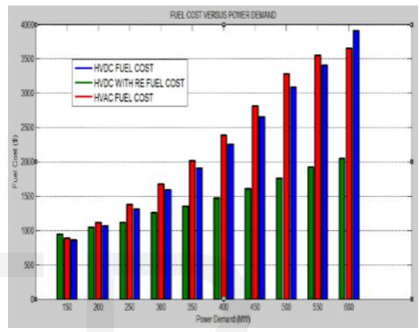

Figure 4.0: Line Losses versus Transmission Line Lengths for 350MW

At initial distances, it evident that the power losses are least in HVAC transmission and the most in HVDC transmissions. This is due to conversion losses from HVAC to HVDC which pure HVAC does not undergo. From the Figure, the losses were read as 1.11486MW and 3.94848MW for HVDC with RE and HVDC transmission systems respectively. This tallies to 0.318% and 1.128% of the power demand which is 350MW for the two systems respectively. The optimum power loss between Case 1 and Case 3 is 1.288MW at a distance of 75km from generation plant and that of HVAC transmission system and HVDC transmission system is 6.935MW at a distance of 405km. It can therefore be concluded that HVDC transmission system is better over longer distances while HVAC transmission should be only applied over shorter distances. Thus, generation should be in HVAC then conversion to HVDC followed by transmission in HVDC and distribution in AC. Further, the use of RE should be encouraged.

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This will lead to the minimum power losses and greater efficiency and stability of the system.

C: Power Demand at Each Bus

The power demand at each bus bar is as shown in Figure 5.0. From the figure,the demand is greatest at bus bar 3. This can be heavy industrial area. The power demand is also seen to be smallest at bus bar 11 and 12. This can be domestic areas.

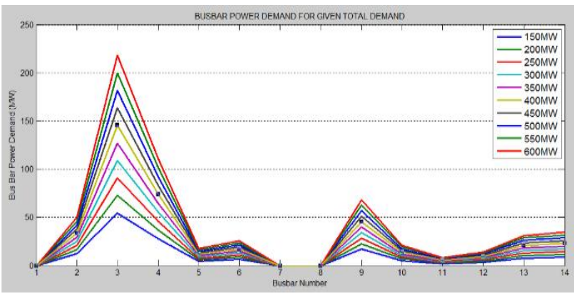

Figure 5.0: Power Demand at Each Bus Bar for Different Total Load Demand

The power demand is relatively higher at bus bar 9. This can be light industrial areas. However, there is no power demand in bus bars 1, 7 and 8 since there is no demand at these bus bars. Besides, as the power demand increases, there is linear increment of power demand at each bus bar as seen in the graph 4 profile.

D.Voltage Profile

The voltage profile for the bus bars is as shown in Figure 6.0. The voltage profile improved with HVDC technology.

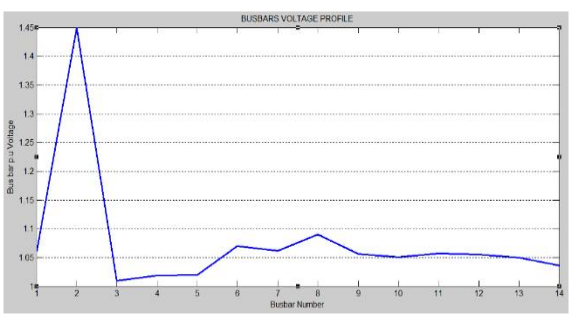

Figure 5.0: Bus bars Voltage Profile

V: CONCLUSION

It can be concluded that for the best transmission system, in regard to the power losses and fuel cost, Case 3 is preferred. The power should be generated in HVAC, transmitted in HVDC over long distances and distributed in AC over short distances. This gives the best ED for power transmission system. Conclusively, ED for HVAC & HVDC and RE (Case 3) is the best among the three cases addressed in this paper. HVDC with RE transmission has been found to be decreasing power losses and total fuel costs while meeting load demands. With this in mind, this system has the ability to control power flow and maintain voltage stability; thus, making the whole system to be more reliable and efficient. The SPEA2 algorithm has been implemented in MATLAB 2014a and it could be concluded that SPEA2 has a good runtime and a few iterations. Thus, with this method, the system results have been proved to be more accurate and efficient. However, at the extreme ends of the demands, the iterations are maximum which makes the convergence time to be lengthy thus creating a big error as seen in the 600MW demand.

Further, research has to be done on ED with HVDC lines. There is need to study the power losses due to effects of transmission line bundles for specific material(s) (i.e ACSR lines) in both HVAC and HVDC and how they affect the fuel cost. Considering the power losses due to cooling of converter systems and the plant and how these affect the fuel cost is also a viable option. Further, it is paramount to clearly study the effects of using RE during the peak and off peak and how can these fluctuations be addressed for the best minimum fuel costs of the system. Incorporating the Economic Dispatch for Monopolar, Bipolar and Homopolar HVDC Links with Line and Conversion Losses with RE (hydro, solar, PV and biomass) is also an interesting case. Lastly, introduction environmental effects function to the problem with tradeoff is the more practical scenario which can be investigated.

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