Application of genetic algorithm in electrical system optimization for offshore wind farms

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***Abstract*—Genetic Algorithm (GA) has been widely used in solving optimization problem in different areas. This paper illustrates the application of GA in the electrical system design for offshore wind farms, where the main components of a wind farm and key technical specifications are used as input parameters and the electrical system design of the wind farm is to be optimized regarding both the production cost and the system reliability.**

***Index Terms*—Optimization, Offshore Wind Farm, Genetic Algorithm, Wind Farm Planning**

I. Introduction

R Renewable energy, especially the wind power will be one of the main energy sources of the future. In order to reduce the cost, the turbines are placed in wind farms and the recent trend is offshore wind farms. However, the costs of offshore wind farms (OWF) are higher than onshore farms (normally 30%-60% more than equivalent onshore farms). Studies have found that the major cost difference between onshore and offshore wind farm is the cost of foundations and the grid connection. Also maintenance will be more costly. Different wind farm configurations may lead to different energy production cost. Reference [1] investigated layouts of various large-scale wind parks (using both AC and DC). An inventory of electrical systems in wind turbines has been made in [2]. Especially, the different ways of transmission the wind power to shore were discussed in [2]. In addition, wind farm design studies have been present in several papers, for instance [3] [4] [5] [6]. The cost for an offshore wind farm is affected by transmission length, transmission voltage, rated power, average wind speed, wind turbine type and the topology of wind farm network. All these factors are interacting and constrained by external conditions. Such complex problem has many variables to be considered. The search space for an optimum solution may therefore contain many sub-optimal points and as the dimensions of the problem increase, finding the global optimum becomes difficult. Due to the difficulties of analytical method to solve such a complicated optimization problem, the Genetic Algorithm (GA) is selected as the approach.

The GA is a good method to solve optimization problems, which is based on natural evolution. It consists of a population of bit strings transformed by three genetic operators: selection, crossover and mutation. Each string (chromosome) represents a possible solution for the problem being optimized and each bit (or group of bits), represents a value for a variable of the problem (gene). These solutions are classified by an evaluation function, giving better values, or fitness, to better solutions. The theory of GA has been systematically presented in [7] and [8]. An application of GA in distribution network planning has been presented in [9]. This paper shows the application of GA in the electrical system optimization for OWF.

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II. Optimization Model

A. Optimization model

The objective of this paper is to find the optimum system design with minimum Levelized Production Costs (LPC) and required reliability. Such a design should also be feasible in practice. That means the connection of components should be meaningful as an electrical system. The optimization can be described as:

Minimize $$OBJ = LPC + \beta \bullet R_{sys} \quad (1)$$

Subject to $$V_{low} \le V_i \le V_{up} \quad (2)$$

$$S_{branch} \le S_{\max} \quad (3)$$

$$P_{WT} = P(v) \quad (4)$$

$$f(V, \theta, P, Q) = 0 \quad (5)$$

Where LPC is the Levelized Production Cost

β is the penalty coefficient related to reliability

R_s is the reliability of the wind farm

V_i is the voltage magnitude of bus i

V_{low}, V_{up} are the required voltage range

S_{branch} is the apparent power of a branch

S_{max} is the power limit of a branch

v is the wind speed

P_{WT} is the power output of WT at wind speed v

$f(x)$ is the load flow equation within the wind farm

B. Levelized Production Costs

The LPC formula takes the capital costs, the maintenance costs and the energy production into account. The LPC is formulated as follows **Error! Reference source not found.**[1]:

$$LPC = [\frac{C_0 r(1+r)^N}{(1+r)^N - 1} + OAM] \frac{1}{P_{mean,out} T} \frac{100}{100 - PR} \quad (6)$$

where

C_0 is the initial capital investment.

r is the economic factor regarding bank interest (i) and also the inflation rate (v):

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$$r = \frac{1+i}{1+v} - 1$$

N is the economic lifetime (normally 20years).

OAM is the operation and maintenance cost per year.

$P_{mean,out}$ is the mean output power of the wind farm excluding losses.

T is the he hours per year (= 8760).

PR is the profit in %.

The OAM is composed of operation costs (an approximate percentage value) and maintenance costs. The maintenance is composed of preventive maintenance and corrective maintenance. The corrective maintenance cost is related to the failure rate and repair cost of a component.

C. *Reliability Evaluation*

The reliability index R_s, which represents the probability of at least certain percent of wind power will be lost due to possible failures of any component, is obtained using the method proposed in [10]. The Generation Ratio (GR) is defined in [10] to represent the ratio between the output power of a wind farm and the power generation from all WT. The wind speed is divided into 16 states with different probability of occurrence. Each component in a wind farm is assumed either in service or out of service (denoted by states 'up' and 'down' respectively). The wind speed state together with the state for each component represents a wind farm state. Such a state is associated with a value of GR, which is less than 1 due to the failure of some components and also the losses. All the possible wind farm states form the state apace, which is numbered in total as 6*2^N (N is the number of components). A criterion GR is defined to distinguish an acceptable wind farm state from unacceptable states. Then the state space can be divided into two sets by comparing the GR with the criteria GR:

- Set {A}: the GR • the criteria GR
- Set {B}: the GR < the criteria GR

Then the R_s = Probability of set {B}.

Due to the large number of wind farms states, it is not practical to check GR for each state. Several methods have been proposed in [10] to reduce the calculation time and then to obtain a relative accurate results.

D. *Optimization Structure*

The Genetic Algorithm is employed to optimize the electrical system of offshore wind farms. The main structure of this work is shown in Fig. 3.

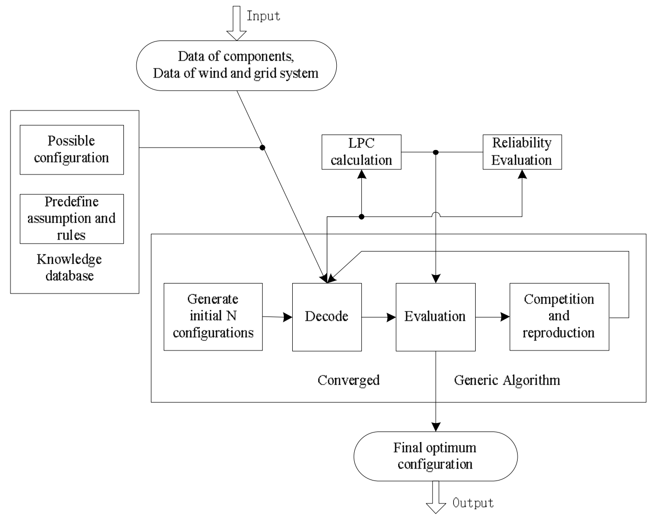

Fig. 3. The main structure of the optimization platform.

The main parts of the platform are explained as follows.

1) *Input data*

- Data of components: All the possible components shall be included, such as different type of sea cables, different type of transformers etc. For each component, the related parameters are required, such as the rated voltage, the cost, the failure rate and average repair duration per failure etc.
- Data of wind and grid system (to which the wind farm is connected): the voltage level of the grid system, the capacity of the farm, the distance to shore etc. The optimization will be based on these input data.

2) *Predefined assumptions and rules*

From other research and experience up to now, some assumption will be made to simplify the complexity. Following assumptions are made in this work:

- All the components have only one failure mode.
- The failure rate and repair duration of each component is not varying along with the time and they are given for different wind speed.
- The geographic location of the start point and the end point of the transmission cables are given and will not change with different electrical designs.
- The straight-line distance between WT is adopted for the calculation of cable length.
- The power flow of each cable is checked against its power limit in any cases (including different wind speed, different operation condition). The overloaded cables will be tripped out from the system automatically.

3) *Possible configuration*

The object of this work is to find the optimal configuration of an offshore wind farm. Based on present experience and knowledge, certain kinds of sub-configurations are present internally (details can be found in the database design in this report).

4) *Genetic algorithm*

The genetic algorithm approach to optimize an offshore wind farm is drawn under the following general lines:

- A set of variables is chosen to represent a system design. These variables are encoded into a chromosome.
- A genetic algorithm is applied to a family of solutions,

giving birth to new generations.

- Each solution in the new generation is evaluated through a fitness function, which considers both the LPC and the reliability.

III. Implementation of GA

As mentioned above, GA is composed of populations of strings, or chromosomes, and three evolutionary operators: selection, crossover, and mutation [8]. The chromosomes may be binary coded. Each chromosome is an encoding of a solution to the problem at hand, and each individual has an associated fitness that depends on the application. A highly fit population is evolved through several generations by selecting two individuals, crossing the two individuals, and mutating characters in the resulting individuals with a given mutation probability. In a GA having overlapping generations, only a fraction of the individuals is replaced in each generation. As involved in the optimization procedure, the encoding of chromosomes, the computation of fitness, the methods for the three evolutionary operators, and the techniques of overlapping generations will be clarified in details as follows.

A. *Optimization Variables*

The variable represents either a choice or a number. All these variables together compose a solution of system designs. All these variables could precisely specify the configuration of the wind farm, the topology of the network, the voltage level and the selection of each component etc.

B. *Coding of variables*

There are two methods to code the optimization variable: one uses binary string which is the traditional method, the other one uses floating-point variables. In this paper, the binary coding is selected because the optimization variables are all discrete values (such as voltage levels) or indexed options (such as the topology of networks which is selected from given candidates). For the binary string coding method, each optimization variable is represented by several binary bits (i.e. the gene of a chromosome). All the genes are arranged from left to right in the chromosome. In this paper, the total number of bits and also the location of each gene in a chromosome are configurable for a specific application. For a typical offshore wind farm, the length of the chromosome is 94 binary bits. There are 2^{94} possible solutions in theory. However, the actual feasible solutions are much less than that due to the correlation among those variables.

The binary strings processed in GA cannot be used to calculate the LPC and reliability directly. They must be decoded back to network descriptions, which clearly show the topology and component parameters etc (as shown in Fig. 9). The rule Check module is used to check the feasibility of a design. A design might be adjusted to be feasible or discarded if it fails in the check anyway.

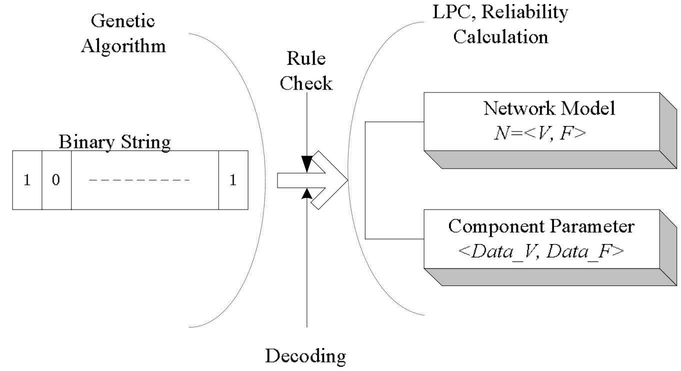

Fig. 9.Description of decoding module

C. *Initial population*

The initial population could be obtained randomly. For the OES-OWF application, each variable (represented by a gene) has its own valid range. Therefore, the random value for the initial population should be generated in the gene level in order to check the value range of each variable.

As the diversity of the initial population is helpful for avoiding the premature (i.e. stagnating at local optima) problem of GA, a Diversity Check method is proposed in this paper. This method ensures the diversity of some user defined important genes. The important genes represent the key characteristic of a design, such as the WT clustering topology. Using the Diversity Check, each important gene has nearly equal number of individuals with different values of this gene, although these individuals are still generated randomly. For example, the population size is 30 and one important gene has 5 possible values. Then the initial population will have 6 individuals for each possible value of this gene.

D. *Selection operator*

Some chromosomes will be selected to produce the next generation (these chromosomes are called a mating population). Generally, the better chromosome is more likely to be selected. In this paper, the Niching Method with Restricted Tournament Selection is employed.

Niching methods have been developed to reduce the effect of genetic drift resulting from the selection operator in SGA. They maintain population diversity and permit the GA to investigate many peaks in parallel. On the other hand, they prevent the GA from being trapped in local optima of the search space [11]. The crowding method is the most attractive niching method as it requires no information about the search space and can be applied to various problems without restriction. Crowding methods insert new elements in the population by replacing similar elements. There are three kinds of crowding methods: Standard Crowding [12], Deterministic Crowding [13] and Restricted Tournament Crowding (RTS). RTS adapts standard tournament selection for multimodal optimization [14]. RTS has less replacement errors compared to Standard Crowding and smaller complexity order compared to Deterministic Crowding.

E. *Crossover operator*

Crossover is a genetic operator that combines (mates) two chromosomes (parents) to produce a new chromosome (offspring). The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of the parents. Crossover occurs during evolution according to a user-definable crossover probability (denoted as P_c). The Uniform Crossover allows the parent chromosomes to be mixed at the gene level rather than the segment level (as with one and two point crossover). This additional flexibility outweighs the disadvantage of destroying building blocks. Therefore, the Uniform Crossover operators will be adopted for the wind farm optimization in this paper.

F. Mutation operator

Mutation is a genetic operator that alters one ore more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. With these new gene values, the genetic algorithm may be able to arrive at better solution than was previously possible. Mutation is an important part of the genetic search as it helps to prevent the population from stagnating at any local optima. Mutation occurs during evolution according to a user-definable mutation probability (denoted as P_m). This probability should usually be set fairly low (such as 0.01). If it is set to high, the search will turn into a primitive random search. In this paper, the *Non-Uniform method* [15] will be used as the mutation operator, which decreases P_m by a small step along with the generations.

G. Stop criteria

Termination is the criterion by which the genetic algorithm decides whether to continue searching or stop the search. The following stop criteria specified in Chapter 2 will be used in OES-OWF platform:

- Generation number - The evolution stops when the user-specified max number of evolutions $N_{GA}^{\max}$ have been run.
- Fitness convergence – The average fitness is smoothed by two filters with different length L_{f_l} and L_{f_s} and then two smoothed values are obtained which are denoted by $FIT_{min,l}$ and $FIT_{min,s}$. The iteration stops when the following condition is satisfied:

$$(FIT_{AVG,l} - FIT_{AVG,s}) \big/ FIT_{AVG,s} \le \varepsilon_{fit} \qquad ()$$

Where ε_{fit} is the threshold for the fitness convergence check.

$FIT_{AVG,l}$, $FIT_{AVG,s}$ are smoothed average fitness with long and short filter respectively.

- Population convergence - The evolution stops when the following condition is satisfied:

$$(FIT_{AVG} - FIT_{\min}) \big/ FIT_{\min} \le \varepsilon_{pop} \qquad ()$$

Where FIT_{AVG} *is* the average fitness value cross the population

FIT_{min} is the best fitness value cross the population

ε_{pop} is the threshold for the population convergence check.

- Best Individual Convergence – A simple termination criterion which stops the evolution when the same best individual has remained for user defined number of generations (denoted by N_ε).
- Variation Convergence - A new terminal method proposed in this paper that stops the evolution when no more new chromosome could be found. All the chromosomes which have been processed already have been stored in a table. A child will be discarded if it is already in the table, and the crossover and mutation operator will be repeated until a new chromosome is found. If a user defined number of cycles (denoted by R_N) have been run without finding any new one, the evolution will be stopped.

Therefore, all the stop criteria, including both the conventional criteria such as Generation Number, Population convergence, Gene Convergence and the two new criteria, are checked for each generation to see if it is time to stop the iteration.

H. Rule check

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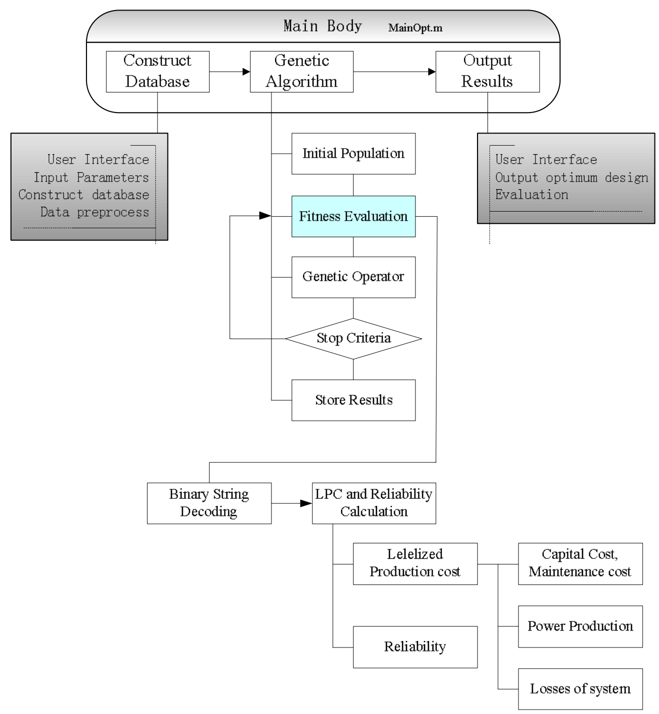
I. Functional structure

The whole functional structure of the optimization platform is shown in :::



IV. Application Example

A. Description of the wind farm

A real offshore wind farm in UK is taken as an example to illustrate the optimization platform of this paper. This wind farm is composed of 60 WT and the distance to shore is 6 km. Additional 5.6 km land cable is required before going to PCC. The geographical location of each WT is determined by the wind direction and seabed condition so it is fixed during the optimization. The possible WT could be 3 MW, 3.6 MW, 4.5 MW and 5 MW variable speed turbines. The voltage level of the PCC is either 132 kV or 400 kV.

The costs for cables include the cost for buying the cables and also the cost for installation. One horizontal directional drilling is assumed for each SCC and no other onshore drilling work. The cost for offshore platform is estimated using existing projects and it is affected by the capacity of the platform. The availability of WT is the value claimed by manufactures with certain amount of maintenance cost. These datasheet of all the components that might be used in this project are obtained under the help of Elsam Engineering A/S (Denmark).

The optimization platform specified in this paper has been applied to this wind farm project. The network design and component selection are optimized in terms of both LPC and reliability.

B. Parameters used in GA

Some essential parameters of GA are listed in Table II.

TABLE II
ESSENTIAL PARAMETERS USED IN GA

Parameter	Symbol	Value
Population size	N	50
Maximum number of Generation	$N_{GA}^{\max}$	200
Probability of crossover	P_c	0.8
Initial probability of mutation	P_m^0	0.1
The max probability of mutation	$P_m^{\max}$	0.005
Penalty coefficient	β	2
Length of longer filter	$L_{f\text{-}l}$	20
Length of short filter	$L_{f\text{-}s}$	5
Threshold for fitness convergence	ε_{fit}	1%
Threshold for population convergence	E_{pop}	0.5%
Number of best individual convergence	N_ε	100
Number of variation convergence	R_N	1000

C. Optimization results

The GA platform specified in Section II an III has been applied to this wind farm project to find the optimal electrical system design. The GA converged with the termination criterion – Population convergence after 85 generations. The iteration track is shown in Fig. 10.

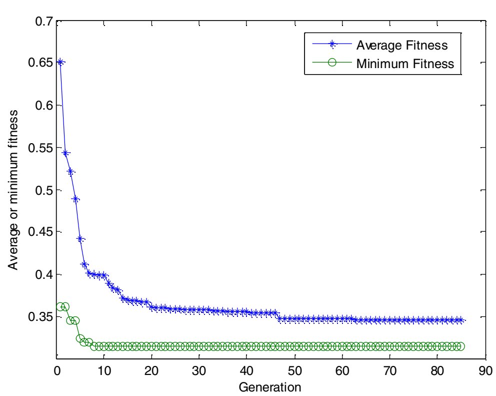


Fig. 10.GA Search procedure: the fitness values along with generations

It took 4.8 hours using a 1.8 GHz computer to get the final results. The key parameters of the optimal design obtained using the GA platform is listed in Table III.

The single line diagram of the optimal design is shown in Fig. 11.

TABLE III
DETAILS OF THE PTIMAL DESIGN FOR INVESTIGATED WIND FARM

Optimization variables	Optimal values
Selection of wind turbine	*4.5 MW*
Type of clustering	String clustering without redudancy
Number of clusters	*6*
Number of group(s)	*1*
Integration system	STST
Transmission system	*AC, 1 SCC*
Voltage level	*34 kV / 220 kV / 400 kV*
Selection of ICC	*34 kV, 3*95 / 3*300 / 3*800mm²*
Selection of SCC – offshore	*250 kV, 3*630 mm²*
-- onshore	*250 kV, 1*800 mm²*
Selection of offshore transformer	*1 offshore platform, 300 MVA, 224/34 kV*
Selection of onshore transformer	*1 substation, 300 MVA, 400/224 kV (with tap change)*

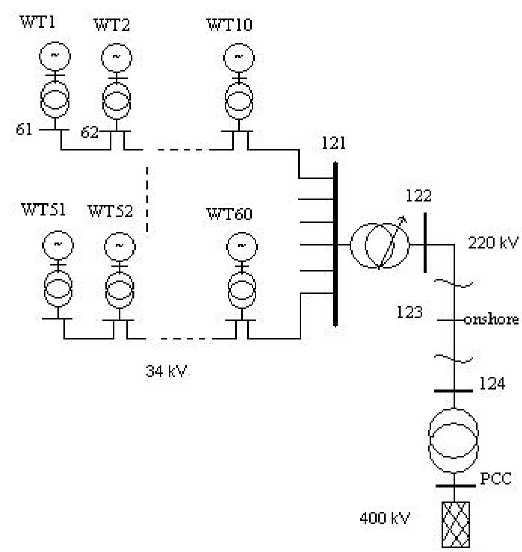


Fig. 11.The optimal design obtained using GA method

The tap change of 220/34 kV transformer is used to raise the voltage of transmission system to 224 kV at full load conditions in order to avoid overload of transmission cables. The LPC of this design is 0.2218 DKK/kWH and its reliability is estimated as 90.7%. The total power losses with respect to the wind speed are shown in Fig. 12 and the mean power loss percentage is 3.01%.

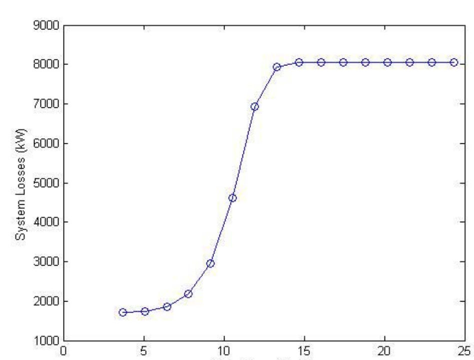


Fig. 12.The total power losses of the optimal design

The voltage profiles of bus 61, 121, 122 and 124 are shown in Fig. 13, which are all within 95% ~ 105% range.

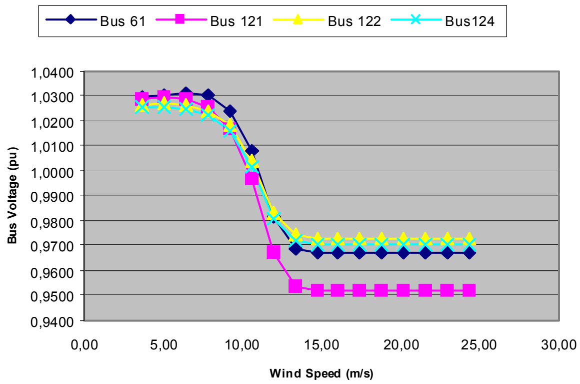


Fig. 13.The voltage profiles of several buses

V. CONCLUSION

This paper proposes an optimization platform using Genetic Algorithm to find the optimal electrical system design for offshore wind farms. The optimization objective involves both the Levelized Production Costs (LPC) and the reliability. The LPC is a combined index regarding the capital costs, maintenance costs, wind power generation and power losses etc. The optimization variables include the topology design, the voltage level, the selection of key components etc. The research reported in this paper could be used both for wind farm design and evaluation of existing wind farms.

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