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Présenté par : BAKLI Mohammed Essaddik

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Thème

Application d’un nouvel Algorithme d’Optimisation pour la Répartition Economique non Linière d’un Système Electrique de grande taille

Jury de soutenance :

Nom et Prénom	**Grade**	**Qualité**
ARIF Salem	Prof	Président
OUBBATI Youcef	M.C.B	Examinateur
CHETTIH Saliha	Prof	Rapporteur
BENTOUATI Bachir	Doctorant	Co-Rapporteur

Promotion : 2019-2020

إهداء

الحمد لله الذي وفقني إلى إكمال هذا العمل حمدا كثيرا.

أهدي هذا العمل إلى:

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تطبيق خوارزمية جديدة غير خطية للتوزيع الاقتصادي للطاقة في شبكة ذات حجم كبير

الملخص

التوزيع الاقتصادي للطاقة (ED) هو أحد المشاكل المهمة لتحسين في الأنظمة الكهربائية، هذا المشكل يتميز بعدم التحدب وعدم الخطية وانقطاع عالي في منحى الدالة. تأثير نقطة الصمام (VP) والمولدات ذات الوقود المتعدد(MF)تجعل المشكلة أكثر صعوبة. خوارزميات (ED) التقليدية لا تقدم حلا مثاليا لهذا المشكل بالتحديد، فالحلول التي تقدمها هذه الخوارزميات تتقارب إلى حل موضعي عوضا عن حل عام، نتيجة لذلك كل الدراسات في هذا الاختصاص توجهت إلى طرق جديدة لحل مشكلة عدم التحدب العالي وعدم الخطية في دالة التكلفة.

في هذه المذكرة، سوف نطبق باستعمال برنامج خوارزمية تحسين جديدة تسمى krill herd مستوحاة من سلوك العيش لحيوان بحري يسمى krill في ثلاثة شبكات كهربائية ذات حجم كبير. كلا من الجانبين النظري والتطبيقي مقدم في هذه المذكرة.

النتائج أظهرت أن طريقة KH تعطي أحسن النتائج وأجودها للحلول العامة مع إيجابيات عديدة مقارنة مع طرق جديدة أخرى برهنت على أنها الأحسن في حل مشكلة التوزيع الاقتصادي للطاقة لمولدات متعددة الوقود في شبكات ذات حجم كبير.

Application of a new non-linear economic dispatch algorithm in a large-scale network

Abstract

Economic dispatch (ED) is one of the important optimization problems in power systems; it is characterized by high non-convexity, non-linearity and discontinuity. Both of valve point (VP) effect and multiple fuel (MF) generators make the problem more difficult. Traditional ED algorithms stuck one treating this specific kind of problems; it converges to locale optimal rather than global optimal solution. Therefore studies in this field turned to a new pattern to solve a high non-convexity, non-linearity of cost function.

In this study we will implement using MATLAB a modern metaheuristic algorithm of optimization called krill herd inspired from a herding behavior of a sea animal named krill in three different large-scale networks, both theoretical and practical side aspects are introduced in this thesis.

The results show that KH approach produces higher quality and best solutions of the overall optimality with many advantages compared with other metaheuristic algorithms proven the best till nowadays especially for solving large-scale ED problems with multiple fuel options.

Application d'un nouvel algorithme de répartition économique non linéaire dans un réseau de grande taille

Résumé

La répartition économique (ED) est l'un des problèmes d'optimisation importants dans les systèmes électriques; il se caractérise par une non-convexité, une non-linéarité et une discontinuité élevées. L'effet de point de soupape (VP) et les générateurs à carburant multiple (MF) rendent le problème plus difficile. Les algorithmes ED traditionnels ne traitent pas bien ce type spécifique de problèmes; ils convergent vers une solution optimale locale plutôt qu'une solution optimale globale. Par conséquent, les études dans ce domaine se sont tournées vers un nouveau modèle pour résoudre la non-convexité élevée, et la non-linéarité de la fonction de coût.

Dans cette étude, nous implémenterons en utilisant MATLAB un algorithme d'optimisation méta heuristique moderne appelé krill herd inspiré d'un comportement d'élevage d'un animal marin nommé krill dans trois réseaux différents de grande taille, les deux aspects théorique et pratique sont présentés dans cette thèse.

Les résultats montrent que l'approche KH produit une meilleure qualité et les meilleures solutions de l'optimalité globale avec de nombreux avantages par rapport aux autres algorithmes méta heuristiques qui se sont prouvé les meilleurs jusqu’à présents, en particulier pour résoudre des problèmes de répartition économiques dans des réseaux de grande taille avec plusieurs options de carburant.

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List of Abbreviations

OPF	Optimal Power Flow
BBO	Biogeography Based Optimization
SOx	Sulfur Oxides
NOx	Nitrogen Oxides
UCP	Unit Commitment Problem
EDP	Economic Dispatch Problem
ELD	Economic Load Dispatch
CEED	Combined Economic Emission Dispatch
SU	Start Up Cost
SD	Shut Down Cost
PSO	Particle Swarm Optimization
IDE	Improved Differential Evolution Optimization
POZ	Prohibited Operating Zones
I&D	Inttensification and Diversification
MH	Meta Heuristtic
GA	Genetic Algorithms
DE	Differential Evolution
ES	Evolutionary Strategies
EP	Evolutionary Programming
ACO	Ant Colony Optimization
ABC	Artificial Bee Colony
CS	Cuckoo Search
FA	Firefly Algorithm
BA	Bat Algorithm
GWO	Grey Wolf Optimizer
WOA	Whale Optimization Algorithm
FOA	Fruitfly Optimization Algorithm
KH	Krill Herd Optimization
MF	Multi Fuel Unit
VP	Valve Point Effect
CSO	Cat Swarm Optimization
ORCSA	One Rank Cuckoo Search Algorithm
IGA-MU	Improved Genetic Algorithm with Multiplier Updating
CGA-MU	Conventional Genetic Algorithm with Multiplier Updating
CSA	Crow Search Algorithm
ORCCRO	Oppositional Real Coded Chemical Reaction Optimization
DE/BBO	A Hybrid Differential Evolution with Biogeography Based Optimization
RCCRO	Real Coded Chemical Reaction Optimization
ED-DE	Estimation of Distribution and Differential Evolution Optimization

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General introduction

The best management of available resources in energy production is very important to avoid very expensive investments with horizons spanning decades [1]. Earlier classic economic dispatch were introduced to solve this problem which is to find optimal production for a given combination of generators to reach the lowest cost possible, however this classic methods cannot deal with valve point loading effects and discontinuities due to POZs (prohibited operating zones) [2]. Hence a modern pattern is developed to treat this problem, it is based on a metaheuristic methods which can solve a non-smooth and non-convex cost curve of power plants [3].

In this study we will introduce one of modern methods; it is called krill herd method and we will see how it can help us to reach a very economical production of electrical energy in large-scale power systems compared to other rival methods.

In order to attend this objective we must structure our work like this:

In the first chapter we will see the problem formulation and different constraints and concepts of all; economic dispatch, optimal power flow and unit commitment problems.

In the second chapter we will see the deference between classic and modern economic dispatch as well as the krill herd optimization algorithm.

While in the final chapter will implement using a MATLAB the KH algorithm in three different large-scale networks and we will compare the results with other competitive algorithms such as PSO and CSO to see whether it proves itself the best or not.

Chapter I: Economic Load Dispatch

I.1 Introduction:

Energy production is a very important economic, industrial and political issue, even more so with the internationalization of the electricity market. Despite a collective desire to control consumption, the need tends to grow, not only in quantity, but also and above all in quality of service. However, the available resource is a limited quantity, and it can only be extended at the cost of very expensive investments and on political decisions with horizons spanning decades. All of these criteria lead to the best management of available resources. However, the technical constraints of the generators do not make it possible to respond instantly and under any condition to this request. Therefore it will be necessary to anticipate production according to the forecast needs [4]. The purpose of the OPF is to optimize (minimize or maximize) a certain objective like cost, power loss and voltage stability while satisfying the equality, inequality and security restraints.

While the problem of establishing an optimal ON / OFF program for power plants in energy production system is called the Unit Commitment Problem (UCP). A sub problem of the UCP is to find the optimal production for a given combination of units in operation; this problem is called the Economic Dispatch Problem EDP. It can be treated by correctly arranging the generating units. Such arrangement can be helpful in minimizing the cost of the operating fuel and assure the load demand of the power system. In order to reach such arrangement, we must fulfill all the power balance equality constraints and the power output inequality constraints.

The power systems should be functioning under a high degree of economy so that the system will be operated at lowest cost; hence the economic dispatch concept will show how much should be the output of each generator so that the total operating cost is minimized. Because of economic dispatch studies, generators are modeled by functions that relate their production cost to their power output [5].

In this chapter we will see the problem formulation and different concepts of all economic dispatch, optimal power flow and unit commitment problems.

I.2 Optimal power flow:

Optimal power flow (OPF) is an important tool for power system operators either planning or operating for many years. It is a highly non-convex, non-linear optimization problem.

The principal aim of an OPF is the determination of control variables for both economic and secure power system operation. The OPF optimize the power system operating objective function taking into account equality and inequality constraints.

The equality constraints are power flow equations, while the inequality constraints are for example voltages, transmission line capacity, real and reactive power [6].

Several optimization techniques have been applied so far to solve the OPF problem.

Earlier, OPF algorithms were based on classical methods such as the gradient-based method, Newton-based method…etc, which are applied to solve many OPF problems, but these methods fail dealing with non-convex, non-linear optimization problems.

Due to the magnificent Improvement of computer capacity, evolutionary algorithms like genetic algorithm, particle swarm algorithm, biogeography-based optimization (BBO)…etc, have been applied to solve complex non convex, non liner OPF problems.

There are four objective functions of the optimal power flow:

- Economic dispatch (minimizing of the fuel cost)
- Minimizing of voltage deviation
- Improvement of voltage stability
- Minimizing of emissions

Objective Functions:

1- Minimization of Fuel Cost:

The fuel cost function of each thermal generating unit, considering the valve-point effects, is expressed as:

$$F1 = \sum_{i=1}^{N_G} [a_i + b_i P_{Gi} + c_i P_G^2 + \left| d_i \sin\left\{ e_i \times (P_{Gi}^{min} - P_{Gi}) \right\} \right|] \quad \textbf{(1)}$$

Where a_i, b_i, and $c_i$are the fuel cost coefficients of the ith generator; $d_i$and $e_i$are the coefficients of the ith generator reflecting valve-point effect; P_{Gi} is the active power generation of the ith generator; P_{Gi}^{min} is the minimum active power generation limit of the ith generator; and N_G is the number of committed generators.

The vector of dependent variables *x* may be represented as:

$$X^T = [P_{Gslack}, V_{L1}, \ldots, V_{LNPQ}, Q_{G1}, .., Q_{GNPV}, S_{l1}, \ldots, S_{lNTL}] \qquad \textbf{(2)}$$

Where P_{Gslack} denotes the slack bus power, V_L is the *PQ* bus voltage, Q_G is the reactive power output of the generator, S_l is the transmission line flow, *NPV* is the number of generator buses, *NPQ* is the number of *PQ* buses, and *NTL* is the number of transmission lines.

The vector of control variables *u* may be represented as:

$$U^T = [V_{G1} \ldots, V_{GNPV}, P_{PV} \ldots., P_{GNPV}, Q_{C1} \ldots, Q_C N_C, \times T_1 \ldots, T_{NT}] \qquad \textbf{(3)}$$

Where N_C and N_T are the number of shunt VAR compensators and the number of tap changing transformers, V_G is the terminal voltage at the generator bus, Q_C is the output of shunt VAR compensator, and *T* is the tap setting of the tap changing transformer.

2- Minimization of Emission:

The atmospheric pollutants such as sulfur oxides (SO_X) and nitrogen oxides (NO_X) caused by thermal generating units can be modeled as:

$$F2 = \sum_{i=1}^{N_G} [\alpha_i + \beta_i P_{Gi} + \gamma_i PG^2 + \eta_i \exp(\lambda_i P_{Gi})] \qquad \textbf{(4)}$$

Where α_i, β_i, γ_i, η_i, λ_i are the emission coefficients of the *i*th generator.

3- Minimization of Voltage Deviation:

The objective is to minimize the voltage deviation of all load (*PQ*) buses from 1 p.u. for the operating power system more securely. The objective function can be formulated as follows:

$$\text{Minimize } F3 = \sum_{i=1}^{N_{PQ}} |V_i - 1.0|] \qquad \textbf{(5)}$$

Where N_{PQ} is the number of load buses in the power system.

4- Voltage Stability Enhancement:

The voltage stability problem is the ability of a power system to keep acceptable voltages at all busbars in the system under normal operating condition and even after being exposed to perturbations. A weak system, a system with long transmission lines, and a heavily loaded system are much sensitive to the voltage instability problem [7]. The increasing of voltage stability can be done by minimizing the voltage stability indicator, *i.e.*, the *L*-index value at each bus of a power system. The L-index of a bus reveals the proximity of voltage collapse condition of that bus. L-index $L_j$of the jth bus is defined as follows:

$$L_j = \left|1 - \sum_{i=1}^{N_{PV}} F_{ji} \frac{V_i}{V_j}\right| (\text{Where } j = 1, 2. . . , N_{PQ}) \tag{6}$$

$$F_{ji} = - [Y1]^{-1} [Y2] \tag{7}$$

Where N_{PV} is the number of PV buses and NPQ is the number of the PQ bus.$Y1$ and $Y2$ are the submatrices of the system YBUS obtained after segregating the PQ and PV busbar parameters as described in Eq. (8):

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} \begin{bmatrix} Y_1 Y_2 \\ Y_3 Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \tag{8}$$

The L-index is calculated as follows:

$$L = \max (L_j) \text{ where } j = 1, 2\ldots, N_{PQ} \tag{9}$$

The lower value of L describes a more stable system. To enhance voltage stability and to avoid the voltage collapse point, the objective function can be represented as follows:

$$\text{Minimize } F4 = L \tag{10}$$

Constraints:

The objective functions are subjected to the equality constraints created by the physical laws governing the transmission system as well as the inequality constraints created by the equipment ratings given in what follows.

1- Equality Constraints:

These constraints are load flow equations described as:

$$P_{Gi} - P_{Di} - V_i \sum_{i=1}^{N_G} V_j [\, G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\,] = 0, i = 1,2 \ldots N_B \tag{11}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{i=1}^{N_G} V_j [\, G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0, i = 1,2 \ldots N_B \tag{12}$$

Where N_B is the number of buses, P_{Gi} and Q_{Gi} are active and reactive power generation at the *i*th bus, P_{Di} and Q_{Di} are active and reactive power demand at the *i*th bus, and G_{ij} and B_{ij} are the transfer conductance and susceptance between *i*th bus and *j*th bus, respectively.

2- *Inequality Constraints:*

Generator constraints:

The generator voltage magnitudes and reactive power outputs are limited by design specifications [8].

The lower and upper limits of generator voltage magnitude and reactive power output are given below:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \text{ , i= 1,2…,}N_{PV} \quad \mathbf{(13)}$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \text{ , i= 1,2…,}N_{PV} \quad \mathbf{(14)}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \text{ , i= 1,2…,}N_{PV} \quad \mathbf{(15)}$$

Shunt VAR compensator constraints:

Reactive power output of shunt VAR compensators must be limited within their lower and upper limits as follows:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \text{ , i= 1, 2…, }N_C \quad \mathbf{(16)}$$

Transformer constraints:

The upper and lower values for the discrete transformer tap settings are restricted by physical considerations and these are given below:

$$T_{i}^{min} \leq T_{i} \leq T_{i}^{max} \text{ , i= 1, 2…, }N_C \quad \mathbf{(17)}$$

Security constraints:

These contain the constraints on voltage magnitudes at *PQ* buses and transmission line loadings. Voltage of each *PQ* bus must be in its operating limits. Line flow across each transmission line must be in its capacity limits. These are described as follows:

$$T_{Li}^{min} \leq T_{Li} \leq T_{Li}^{max} \text{ , i= 1, 2…, }N_C \quad \mathbf{(18)}$$

$$SLi \leq S_{Li}^{max}\text{, i= 1, 2..., N}_C \tag{19}$$

I.3 Unit commitment problem:

Unit commitment (UC) is a non-linear complex optimization problem to specify the total load of the test system for all generating units at minimum operating cost which contains both production cost and transition cost by satisfying the constraints, total load, system losses and reserve requirements at any time. The UC problem has to locate the on/off state of each generating units at each hour of the planning time and optimally allocate the load and reserve capacity between the committed units [9]. UC is the most important task in the operation of the power systems. Treating the UC problem for power systems is more difficult and complexity of the UC problems grows with the number of generating units.

UC objective function:

The objective of the UC problem is reducing the total cost which contains fuel cost, start up cost, shot down cost. The fuel cost $FC_i(t)$ of unit *i* at hour *t* is expressed as equation below:

$$FC_i(t) = A_i + B_iP_i(t) + C_iP_i^2(t) \tag{20}$$

Where $P_i(t)$ is the power generation of unit *i* at hour *t*, and A_i, B_i and C_i are the cost coefficients of unit i.

The start-up cost (SU) for restarting a thermal unit, which is linked to the temperature of the boiler, is appeared in the model [10]. If the unit is cold or it has been shut down for a long time, it is necessary to consume more fuel to warm up the boiler. If the unit is de-committed for a short time, less energy will be needed to restart the unit.

If$u_i(t)$= 1, the start up costs is calculated as follows:

$$SU_i(t) = \begin{cases} 0, & if\ u_i(t-1) = u_i(t) \\ H\ cost, & if\ x_i^{off}(t-1) \leq chour \\ C\ cost, & if\ x_i^{off}(t-1) > chour \end{cases} \tag{21}$$

All these plus satisfaction of the condition bellow:

$$x_i^{off}(t-1) \geq MD_i \tag{22}$$

And if $u_i(t)$= 0, the ith start up cost is equal with zero.

Shut-down cost (SD) is constant and the regular value is zero in standard systems.

Hence, the objective function of UC is:

$$TC = \sum_{t=1}^{H}\sum_{i=1}^{N}\{FC_i(t) + \left(P_i(t)\right) + SD_i(t) + SU_i(t)\} \tag{23}$$

Any new kind of cost may be contained or any existing kind of cost may be rejected from the objective function according to the system operators' load.

UC constraints:

The constraints that must be satisfied during the UC optimization process are:

1. The generated power by all the committed units must satisfy the load demand plus the system losses as it is shown below:

$$\sum_{i=1}^{N} U_i(t).\ P_i(t) = D(t) + L(t) \tag{24}$$

2. To maintain system reliability, adequate spinning reserves are required as follows:

$$\sum_{i=1}^{N} U_i(t).\ P_i(t) \geq D(t) + L(t) + R(t) \tag{25}$$

3. Each unit has generation range, which is as follows:

$$P_i^{min} \leq P_i(t) \leq P_i^{max} \tag{26}$$

4. Once a unit is ON or OFF, there is a predetermined minimum time (Minimum up and down time) after it can be OFF or ON again. These constraints are defined by the following equations:

$$\begin{cases} \left(1 - u_i(t+1)\right).MU_i \leq x_i^{on}(t)\ if\ u_i(t) = 1 \\ u_i(t+1).MD_i \leq x_i^{off}(t)\ if\ u_i(t) = 0 \end{cases} \tag{27}$$

5. For each generator unit, production is limited by ramp up/down rate at each hour as follows:

$$P_i^{min}(t) \le P_i(t) \le P_i^{max}(t) \tag{28}$$

Where,

$$P_i^{min}(t) = \max(P_i(t-1) - RD_i, P_i^{min}) \tag{29}$$

$$P_i^{max}(t) = \min(P_i(t-1) - RU_i, P_i^{max}) \tag{30}$$

6. Must run and must out units contain prescheduled units which must be connected, because of functioning reliability and/or economic considerations, and units which are on forced suspensions and maintenance are unavailable to be ON. At the beginning of scheduling, the units' initial status must be taken into consideration also.

I.4 Problem Formulation of economic dispatch:

I.4.1 Objective Function:

The objective of the traditional economic dispatch is to reduce the total system cost by adapting the power output of each of the generators connected to the grid [11]. The total system cost is represented as:

$$min\sum_{i=1}^{N_G} F_i(P_{Gi}) \tag{30}$$

Where $F_i(P_{Gi})$ the cost function of the ith generating unit, P_{Gi} is is the real power output of the ith unit, and N_G is the total number of generators connected to the power system. The cost function of each generator determines the liaison between the power supplied the system by the generator and the cost afforded to load the machine to that capacity. Generators are represented by smooth quadratic functions such as Eq. (31), to simplify the optimization problem, as well as to ease the application of traditional techniques.

$$F_i(P_{Gi}) = a_i + b_iP_{Gi} + c_iP_G{}^2 \tag{31}$$

Where *ai* ,*bi* , and *ci* are known as the cost coefficients of the ith generating unit.

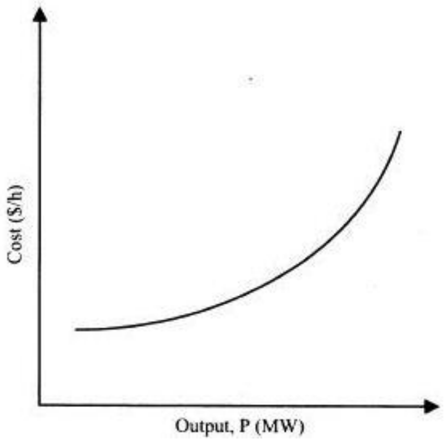

Fig. 1. Typical fuel cost function of a thermal generating unit

I.4.2 Constraints:

Equality Constraint (Power Balance Constraint):

The power balance constraint is an equation constraint that minimizes the power system to a basic principle of equalization between total system generation and total system loads [12]. equalization is only met when the total system generation $\sum(P_{Gi})$ equals the total system load (P_D) plus system losses (P_L), as it is stated in Eq. (32).

$$\sum_{i=1}^{N_G} P_{Gi} = P_D + P_L \tag{32}$$

The value of the system losses can be determined by methods of a power flow solution. The most popular method for finding a close value of the losses is by way of Kron's loss formula of Eq. (33) as it is shown below:

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi}\, B_{ij} P_{Gj} + \sum_{i=1}^{N_G} P_{Gi}\, B_{0i} + B_{00} \tag{33}$$

Where B_{ij},B_{0i}, B_{00} are known as the loss or B-coefficients.

Inequality Constraint (Real Power Generation limits):

Generating units have lower (P_{Gi}^{min}) and upper (P_{Gi}^{max}) production limits, which are related to the conception of the machine. These bounds can be defined as follows:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}\text{, i= 1, 2…,}N_G \tag{34}$$

I.4.3 Non-Smooth Cost Functions:

Generators are often represented using smooth quadratic functions (see Fig. 1), which associate power output to production cost. This kind of cost function simplifies the economic dispatch problem and enhances the number of methods that can be used for its solution. However, there are cases where smooth quadratic curves are no longer correct representations of the generators, hence requiring more appropriate models to offer optimal results in the solution of the economic dispatch problem [13]. More appropriate models usually occur in extremely nonlinear, non-smooth and non-convex cost functions. These kinds of cost functions may result because of valve point loading effects, fuel switching, and prohibited operating zones.

1- Economic dispatch problem considering valve-point effects:

Generally, big power generators have several steam entrance valves that are utilized to command the power output of the unit [14]. When a steam entrance valve starts to open, a sudden rise in losses happens, which causes ripples in the unit's cost function (see Fig. 2). Valve-points are those output levels at which a new entrance valve is open.

When valve point effects are deemed, the ED problem becomes highly difficult to treat via traditional based techniques, because of the sudden changes and discontinuities present in cost functions.

Valve point effects are generally modeled as it is shown in (35).

$$F_i(P_{Gi}) = \sum_{i=1}^{N_G} [a_i + b_i P_{Gi} + c_i P_G^2 + \left| d_i \sin\left\{ e_i \times (P_{Gi}^{min} - P_{Gi}) \right\} \right|] \tag{35}$$

Where a_i, b_i, c_i,d_i and e_i are the cost coefficients of unit i.

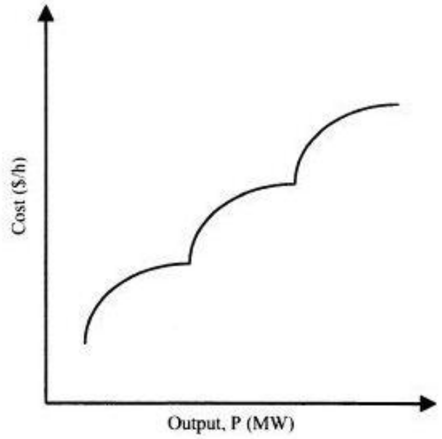

Fig. 2. Fuel cost function for a thermal generation unit with three admission valves

2- Economic dispatch problem considering multiple Fuel types:

Some generating units are able of functioning using several kinds of fuels. Using multiple fuel kinds may cause multiple cost curves that are not always continuous or parallel. The inferior zone of the resulting cost curve defines which fuel type is most economical to bum.

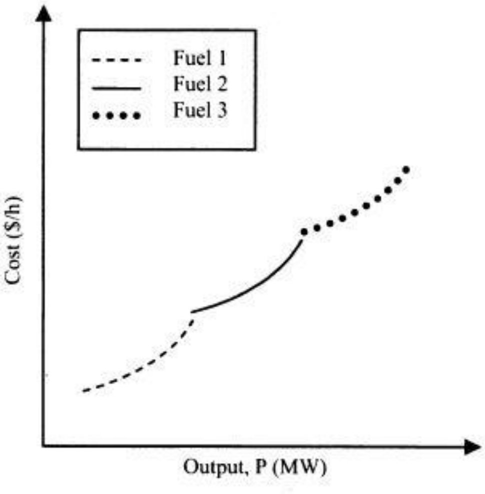

Fig. 3. Fuel cost function of a thermal generation unit supplied with multiple fuel types

This cost function can be modeled by a non-linear curve (see Fig. 3). The ED problem with non-linear quadratic cost curves is very hard to treat by classic techniques. Non-linear quadratic cost functions have as many segments as fuel types as it is shown below:

$$F_i(P_{Gi}) = \begin{cases} a_{i,1} + b_{i,1}P_{Gi} + c_{i,1}{P_{Gi}}^2, & P_{Gi}^1(L) < P_{Gi} < P_{Gi}^1(U) \\ a_{i,2} + b_{i,2}P_{Gi} + c_{i,2}{P_{Gi}}^2, & P_{Gi}^2(L) < P_{Gi} < P_{Gi}^2(U) \\ \quad\quad\quad\quad\quad\quad . & \\ \quad\quad\quad\quad\quad\quad . & \\ \quad\quad\quad\quad\quad\quad . & \\ a_{i,k} + b_{i,k}P_{Gi} + c_{i,k}{P_{Gi}}^2, & P_{Gi}^k(L) < P_{Gi} < P_{Gi}^k(U)) \end{cases} \quad (36)$$

Where $P_{Gi}(L)$ and $P_{Gi}(U)$ are the lower and upper bound respectively of the kth fuel of unit i, and $a_{i,k}$, $b_{i,k}$ and $c_{i,k}$ are the kth fuel cost coefficients of unit i.

3- Economic dispatch problem considering prohibited operating zones:

Generating units may have particular regions where functioning is either unwanted or impossible because of physical restrictions of the machine components or instability problems. These zones create discontinuities in the cost curve because the unit must function under or over particular specified limits (see Fig.4). This type of cost functions are represented as follows:

$$P_{Gi\,min} \leq P_{Gi} \leq P_{Gi,1}^{l} \quad (37)$$

$$P_{Gi,j-1}^{u} \leq P_{Gi} \leq P_{Gi,j}^{l}, \text{ j= 2..., n} \quad (38)$$

$$P_{Gi,n}^{u} \leq P_{Gi} \leq P_{Gi\,max} \tag{39}$$

Where $P_{Gi,j}^{l}$ is the lower bound of the prohibited zone j of unit i, $P_{Gi,j}^{u}$ is the upperbound of the prohibited zone j of unit i, n be the number of prohibited zones in unit i, P_{Gimin} is the minimum generation limit of unit i and P_{Gimax} is the maximum generation limit of unit i.

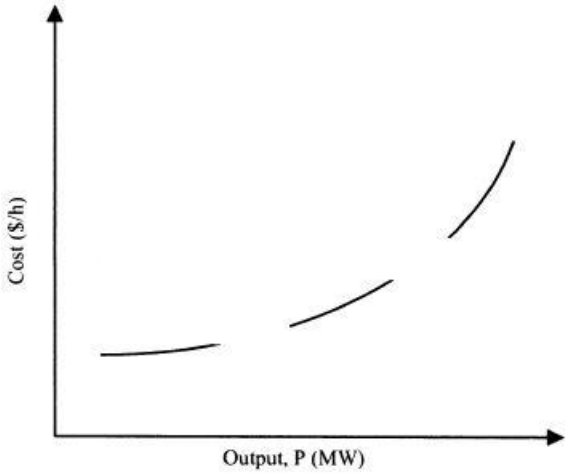

Fig. 4. Fuel cost function for a unit with two prohibited operating zones

I.4.4 Combined economic and emission dispatch problems:

The air pollutants including sulfur oxides, nitrogen oxides and carbon dioxide caused by fuel burned generator can be represented separately. However, the total emission of these pollutants can be expressed as:

$$E_i(P_{Gi}) = \sum_{i=1}^{N_G} E_i(P_{Gi}) = \sum_{i=1}^{N_G} [\, a_i P_{Gi}^{2} + b_i P_{Gi} + c_i + \eta_i * \exp(\delta_i * \delta_j)] \tag{40}$$

Optimization of generation cost has been made based on traditional ELD with emission constraints. The problem is written as follows:

$$\text{Minimize } F = \sum_{i=1}^{N_G} \{F_i(P_{Gi}), E_i(P_{Gi})\} \tag{41}$$

The double-objective CEED problem is transformed into single optimization issue by including a price penalty factor h as follows:

$$\text{Minimize } F = F_i + h * E_i \tag{42}$$

The price penalty factor h, which is the proportion between the maximum fuel cost and maximum emission of the same generator in \$/Kg , combines the emission with fuel cost, then F is the total operating cost in \$.

$$h_i = \frac{F_i(P_{Gi}^{max})}{E_i(P_{Gi}^{max})}, \text{ i= 1...., N}_G \quad \textbf{(43)}$$

The next steps are utilized to determine the price penalty factor for a specific load demand:

A. Determine the proportion between maximum fuel cost and maximum emission of all generators.

B. Settle the values of price penalty factor in incremental order.

C. Add the highest power of each unit (P_{Gi}^{max}) one at a time, starting from the lowesth_i, until $\Sigma P_{Gi}^{max} \geq$PD.

D. $h$iwhich related with the last unit in this procedure is the estimated price penalty factor value (h) for the specific load.

So, an update price penalty factor (h) is utilized to determine the exact value for the specific load demand by introducing the values of (h), related to their load demand values.

I.5 Conclusion:

In this chapter we have seen different concepts of economic dispatch or EDP context and all the terms which include the word cost or economy in power system field to show the difference between them.

So, in the beginning we have started with the larger definition of EDP, which is the optimal power flow problem or OPF, this term or problem defines not only the economic dispatch but also the voltage stability and power flow, in addition to that the power loss…etc.

Then, we have stated the unit commitment problem or UCP. It is the establishment of a program that determines the committed and non-committed units at each hour of the planning period and optimally specifies the load and reserve capacity among the committed units in order to reduce the production cost.

Finally, we have introduced and explained the idea of economic dispatch problem and its application in power system which is our main subject. We have reached out that the economic dispatch problem concerns the reducing of the cost function of generating units in particularly.

In the next chapter we will see the different classification of treating EDP and we will introduce our method in general.

Chapter II: Algorithms of EDP Optimization

II.1 Introduction:

Economic dispatch (ED) is a crucial optimization task in power system operation. Its task in power system is the determination of optimum generation schedule of available generators in the most economical manner while satisfying various physical constraints.

Well known classic techniques based on co-ordination equations are applied to solve ELD problems. These conventional methods cannot solve EDP in a satisfactory manner because they converge into local optimal in addition to its computation complexity [15].

The valve-point effects, prohibited operating zones and other constraints are responsible for the non-convex decision space, so that the calculus-based methods cannot deal very well with this type of problems.

Metaheuristic algorithms have potential to solve complex ED problems. Particle swarm optimization (PSO), improved differential evolution (IDE), cat swarm optimization (CSO)..etc have been proposed and applied to solve ED problems. These methods cannot always attain global optima but they often accomplish near global optima solution [16].

In 2012 Gandomi and Alavi proposed the krill herd algorithm. It’s a bio-inspired optimization algorithm which is developed to solve complex problems of optimization. This algorithm studies krill swarms herding behavior considering the factors influencing the krill individually or in a herd.

In this chapter we will see the deference between classic and modern economic dispatch as well as the krill herd optimization algorithm.

II.2 Classic economic dispatch:

Economic Dispatch is an essential optimization problem in electric power systems which intent at making the generator's fuel consumption or the operating cost of the whole system minimal by defining the power output of each generating unit under the constraint condition of the system load demands [17].

In the traditional ELD problem, the cost function for each generator has been modeled by a quadratic function and is treated using mathematical programming based optimization techniques such as lambda iteration method and gradient-based method, these conventional methods cannot perform correctly for solving such problems as they are sensitive to initial estimates and converge into local optimal solution [18].

In practice, thermal power plants have a non-smooth and non-convex cost curve because of valve point loading effects and discontinuities due to POZs (prohibited operating zones).

A few classic economic dispatch methods:

1- The Lambda –Iteration Method:

In Lambda iteration approach lambda (λ) is the variable introduced in solving constraint optimization problem and is called Lagrange multiplier [19]. Lambda can be solved at hand by solving systems of equation. Because all the inequality constraints to be satisfied in each trial the equations are resolved by the iterative method like this:

i) Assume a proper value of $\lambda^{(0)}$this value should be more than the largest intercept of the incremental cost characteristic of the various generators,

ii) Calculate the individual generations,

iii) Verify the equality,

$$P_d = \sum_{i=1}^{N} P_i \tag{44}$$

iv) If not, make the second guess of λ and repeat steps above .

2- The Gradient Search Method:

The principle of this approach is that the minimum of a function, *f(x)*, can be found by a series of steps that always take us in a downward direction. From any starting point,x^0, we may find the direction of "steepest descent" by noting that the gradient *f* is:

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \cdot \\ \cdot \\ \frac{\partial f}{\partial x_n} \end{bmatrix} \quad \textbf{(45)}$$

Always points are in the direction of maximum ascent. Therefore, if we want to move in the direction of maximum descent, we negate the gradient. Then we should go from x^0 to x^1 using:

$$x^1 = x^0 - \nabla f \alpha \quad \textbf{(46)}$$

Where α is a scalar to allow us to guarantee the process of convergence. The best value of αmust be determined by experiment. In case of power system economic load dispatch f becomes:

$$f = \sum_{i=1}^{N} F_i(P_i) \quad \textbf{(47)}$$

The object is to find the minimum of the function. However we have to take the constraints function into consideration as follows:

$$\phi = P_{Load} - \sum_{i=1}^{N} P_i \quad \textbf{(48)}$$

To solve the economic load dispatch problem which involves minimizing the objective function and keeping the equality constraints, we must apply the gradient technique directly to the Lagrange function which is presented below:

$$\Im = \sum_{i=1}^{N} F_i(P_i) + \lambda(P_{Load} - \sum_{i=1}^{N} P_i) \quad \textbf{(49)}$$

And the gradient of this function is:

$$\nabla \Im = \begin{bmatrix} \frac{\partial \Im}{\partial P_1} \\ \cdot \\ \cdot \\ \frac{\partial \Im}{\partial P_n} \end{bmatrix} \quad \textbf{(50)}$$

The problem with the formulation is the lack of a guarantee that the new points generated each step will lie on the surface ϕ.

The economic dispatch algorithm requires a starting λ value and starting values for P_1, P_2 , and P_3. The gradient for $\Im$ is calculated as above and the new values of λ, P_1, and P_2..etc, are found from:

$$x^1 = x^0 - (\nabla\Im)\alpha \tag{51}$$

Where x is a vector,

$$x = \begin{bmatrix} P_1 \\ P_2 \\ . \\ . \\ \lambda \end{bmatrix} \tag{52}$$

3- *Newton's Method:*

Newton's method is efficient more than the simple gradient method and tries to resolve the economic dispatch by observing that the aim is to always drive the gradient to zero:

$$\nabla\boldsymbol{\Psi}x = 0 \tag{53}$$

Because this is a vector function, we can represent the problem as one of finding the correction that exactly drives the gradient to zero (i.e. to a vector, all of whose elements are zero). Assume we wish to drive the function $\mathrm{g}(x)$ to zero. The function g is a vector and the unknown x are also vectors. Then to use Newton's method, we observe:

$$\mathrm{g}(x + \Delta x) = \mathrm{g}(x) + [\acute{\mathrm{g}}(x)]\Delta x = 0 \tag{54}$$

Where $\acute{\mathrm{g}}(x)$ is the familiar Jacobian matrix. The adjustment at each step is then,

$$\Delta X = -[\acute{\mathrm{g}}(x)]^{-1}\,\mathrm{g}(x) \tag{55}$$

Now, if we let the g function be the gradient vector $\nabla\boldsymbol{\Psi}x$ we get:

$$\Delta X = -\left[\frac{\partial}{\partial \mathrm{x}}\nabla\boldsymbol{\Psi}x\right]^{-1}\nabla\boldsymbol{\Psi}x \tag{56}$$

For the economic load dispatch problem this takes the form:

$$\boldsymbol{\Psi} = \sum_{i=1}^{\mathrm{N}} F_i(P_i) + \lambda(P_{Load} - \sum_{i=1}^{\mathrm{N}} P_i) \quad \textbf{(57)}$$

The $\nabla\boldsymbol{\Psi}x$ is a Jacobean matrix which has now second order derivatives and it is called Hessian matrix. Generally, Newton's method will resolve for the correction that is much closer to the minimum generation cost.

II.3 Metaheuristic algorithms for solving economic dispatch problem:

Metaheuristic algorithms are often nature-inspired, and they are recently among the most used algorithms for optimization, they have many advantages over traditional algorithms.

Metaheuristic or stochastic or Evolutionary Algorithms are random based optimization techniques that search for problems solution using a simple model of the evolutionary process found in nature. These algorithms provide an option for obtaining global optimal solutions, especially in the presence of non-continuous, non-convex, and highly nonlinear solution spaces [20]. The success of evolutionary algorithms is partly due to their capability of processing a population of potential solutions simultaneously, which allows them to perform a global exploration of the search area [21].

Besides, they do not count on derivative information to guide the search toward the problem solution. Instead, they use information directly from the population of candidate solutions. Evolutionary algorithms follow a general and common framework, in which a set of randomly created solutions is enhanced or evolved iteratively. What makes algorithms different in this field is the method of improving this set.

In this sub-title we present some general information about a few metaheuristic methods that have been used to solve the economic dispatch.

II.3.1 Classification of metaheuristic algorithms:

Metaheuristic algorithms are classified into two dominant classes: evolutionary and swarm intelligence techniques. Evolutionary algorithms imitate the concept of evolution in nature. The best most known algorithm in this class is Genetic Algorithms (GA). This algorithm simulates the concepts of Darwinian theory of evolution. In GA , the optimization is initiated with a set of random solution for a particular problem. After evaluating the solutions of the objective function, it changes the variables of solutions based on their fitness value since the best individuals are given the best probability to involve in improving other solutions, the random initial solutions are very likely to be improved. There are several other evolutionary algorithms in the literature such us Differential Evolution (DE), Evolutionary Strategies (ES), and Evolutionary Programming (EP), and Biogeography-Based Optimization (BBO) algorithm as well.

Swarm intelligence techniques imitate the intelligence of swarms, herds of creatures in nature. The foundation of these algorithms is inspired from the collective behavior of a group of creatures. For example ants are able to collectively protect the colony without having a central control unit. Specifically, no one tell ants where and how a source of food could be found, but they cooperatively reach food at even far distances from their nests. The two most popular algorithms in this class are Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) which simulates the collective behavior of birds in navigating and hunting.

Other swarm intelligence techniques in the literature are: Artificial Bee Colony (ABC) algorithm ,Cuckoo Search (CS)algorithm, Firefly Algorithm (FA), Bat Algorithm (BA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Fruitfly Optimization Algorithm (FOA)…etc.

II.3.2 How to choose an optimization algorithm:

To choose the appropriate method for solving EDP, these steps are to take into account:

- ***The ability to avoid local optima:*** for example if the objective function is convex it is recommended to use local method that is quick than global optimization method, however if the objective function is multimodal or no-convex it is necessary to adopt global optimization.
- ***Best robustness:*** it is a key concept that should not be neglected when choosing an optimization algorithm.
- ***Ability to handle single or multi-objective problem:*** multi-objective optimization provides a set of solutions for different problems of many compromises between them.
- ***The speed of convergence:*** finding a compromise between exploration and exploitation leads to know a number of variables to evaluate to converge to the local optimum.

II.3.3 Exploration and exploitation:

Exploration and exploitation are also named diversification and intensification respectively. Generally speaking, diversification means the ability to visit many and different regions of the search space, and intensification means the ability to obtain high quality solutions within those regions. A search algorithm should find a tactical balance between these two sometimes conflicting goals. Most classical MHs have several different components for intensification and diversification. Blum and Roli describe an I&D component as any algorithmic or functional component that has intensification and (or) diversification effect on the search process. Examples are genetic operators, perturbations of probability distributions, the use of Tabu lists, or changes in objective functions [23]. Thus, I&D components are operators, actions, or strategies of MHs. In general, providing a proper balance between the I&D components of an MH is a very complicate task. In fact, although most classical MHs attempt to achieve this objective in their own ways, it turns out that some of them show clear orientation toward intensification and others, on the contrary, toward diversification, i.e., they show certain specialization in intensification or in diversification. An alternative approach to lead MHs to have themselves responsibilities for both I&D involves the design of hybrid MHs with search algorithms specializing in I&D, which gather this type of algorithms with the objective of compensating each other and put together their complementary behaviors (the exploration and exploitation of the search space). The interchange between exploration and exploitation has long been a significant topic in evolutionary computation and other MHs.

The significant point of these algorithms is the way that they search the environment. They use the random search and local search simultaneously to cover search space, but the point is the amount of contribution of these two different kinds of search in each step of solving the problems [24].

Exploitation means “utilizing the solution points in hand” while exploration means “searching for the unknown solution points”. Actually metaheuristic algorithms work through combining “Exploration” and “Exploitation”. If you spent a lot of times in one you do less in the other.

II.4 Krill herd algorithm:

II.4.1 Herding behavior of krill swarms:

The creation of groupings of different species of marine animals is under-dispersed and non-random. Lots of studies have concentrated on capturing the fundamental mechanisms ruling the development of these formations. The important mechanisms determined are related to the feeding ability, enhanced reproduction, protection from predators, and environmental conditions. Some mathematical models have been formulated to estimate the relative contribution of these mechanisms based on experimental observations [25].

Antarctic krill is one of the best-studied species of marine animal. The krill herds are accumulations with no parallel orientation existing on time scales of hours to days and space scales of 10 s to 100 s of meters. One of the main characteristics of this specie is its capability to form large swarms. Several studies have been done to understand the ecology and distribution of krill over the last three decades. Although there are yet notable uncertainties about the forces defining the distribution of the krill herd, theoretical models have been proposed to explain the observed formation of the krill herds. The results obtained by such theoretical structures revealed that the krill swarms form the basic unit of organization for this species. In order to better understand the formation of the krill swarms, the proximate causes and the factors that are adaptive advantages of accumulation formation (ultimate effects) should be known.

When predators, such as seals, penguins or seabirds, attack krill, they remove individual krill. This results in decreasing the krill density. The formation of the krill herd after predation relies on many parameters. The herding of the krill individuals is a multi-objective process including two main goals: (1) increasing krill density, and (2) reaching food. This process is taken into consideration to present a new metaheuristic algorithm for solving global optimization problems. Attraction of krill (increasing density) and finding food (areas of high food concentration) are used as objectives which finally lead the krill to herd around the global minima. In this process, an individual krill goes toward the best solution when it searches for the maximum density and food [26]. That is, the closer the distance to the high density and food, the less the objective function. Generally, some coefficients should be identified for using multi-objective herding behavior for a single objective one. The coefficients are identified on the basis of a specialized literature review of the experimental observations of the krill behavior and also after a trial study.

II.4.2 Lagrangian model of the krill herding:

Predation expels individuals, leads to lowering in the average krill density, and takes away the krill swarm from the food location [27]. This process is supposed to be the initialization phase in the KH algorithm. In the natural system, the fitness of each individual is supposed to be a combination of the distance from the food and from the highest density of the krill swarm.

Therefore, the fitness (imaginary distances) is the value of the objective function. The time dependent position of an individual krill in 2D surface is governed by the following three main actions:

1- Movement provoked by other krill individuals.
2- Feeding activity.
3- Random spreading.

It is known that an optimization algorithm should be able of searching spaces of random dimensionality. Therefore, the following Lagrangian model is generalized to an n dimensional decision space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{59}$$

Where N_i is the motion induced by other krill individuals; F_i is the foraging motion, and D_i is the physical diffusion of the ith krill individuals.

1- ***Movement provoked by other krill individuals:***

According to theoretical proofs, the krill individuals try to keep a high density and move due to their reciprocal effects. The direction of movement provoked α_i, is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect). For a krill individual, this movement can be defined as:

$$N_i^{new} = N^{max}\,\alpha_i + \omega_n N_i^{old} \tag{60}$$

Where,

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{61}$$

And N^{max} is the maximum provoked speed, ω_n is the inertia weight of the motion induced in the range [0,1], N_i^{old} is the last movement provoked, α_i^{local} is the local effect provided by the neighbors and α_i^{target} is the target direction effect provided by the best krill individual. According to the measured values of the maximum provoked speed, it is taken 0.01 (ms^{-1}).

The effect of the neighbors can be assumed as an attractive/repulsive tendency between the individuals for a local search.

The effect of the neighbors in a krill movement individual is determined as follows:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \hat{K}_{i,j}\, \hat{X}_{i,j} \qquad \textbf{(62)}$$

$$\hat{X}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \qquad \textbf{(63)}$$

$$\hat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \qquad \textbf{(64)}$$

Where K^{best} and K^{worst} are the best and the worst fitness values of the krill individuals so far; K_i represents the fitness or the objective function value of the ith krill individual; K_j is the fitness of jth (j = 1,2,. . .,NN) neighbor; X represents the related positions; and NN is the number of the neighbors. For avoiding the singularities, a small positive number ε, is added to the denominator.

The right sides of Equations. (62) and (64) include some unit vectors and some normalized fitness values. The vectors show the provoked directions by different neighbors and each value presents the effect of a neighbor. The neighbors' vector can be attractive or repulsive since the normalized value can be negative or positive.

For choosing the neighbor, different strategies can be utilized. For instance, a neighborhood ratio can be simply determined to find the number of the closest krill individuals. Using the actual behavior of the krill individuals, a sensing distance (d_s) should be determined around a krill individual (as shown in Fig. 5) and the neighbors should be found.

The sensing distance for each krill individual can be defined Using different heuristic methods. Here, it is defined using the following formula for each iteration:

$$d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \|X_j - X_i\| \qquad \textbf{(65)}$$

Where $d_{s,i}$ is the sensing distance for the ith krill individual and N is the number of the krill individuals. The factor 5 in the denominator is experimentally obtained. Using Eq. (65), if the distance of two krill individuals is less than the determined sensing distance, they are neighbors.

The known target vector of each krill individual is the lowest fitness of an individual krill. The effect of the individual krill with the best fitness on the ith individual krill is taken into account using Eq. (66). This level leads it to the global optima and is formulated as:

$$\alpha_i^{target} = C^{best}\,\widehat{K}_{i,best}\,\widehat{X}_{i,best} \tag{66}$$

Where C^{best} is the effective coefficient of the krill individual with the best fitness to the ith krill individual. This coefficient is defined since α_i^{target} leads the solution to the global optima and it should be more effective than other krill individuals such as neighbors. Herein, the value of C^{best} is defined as:

$$C^{best} = 2(rand + \frac{I}{I_{max}}) \tag{67}$$

Where $rand$ is a random values between 0 and 1 and it is for enhancing exploration, I is the actual iteration number and I_{max} is the maximum number of iterations.

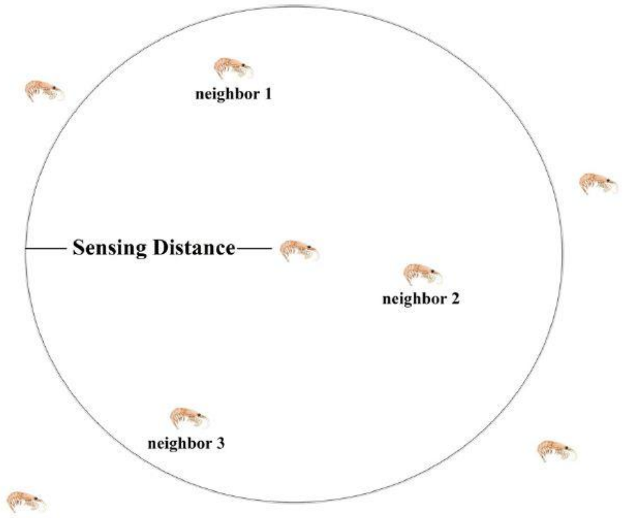

Fig. 5. A schematic representation of the sensing area around a krill individual.

2- ***Feeding movement:***

The feeding movement is formulated in terms of two main effective parameters. The first one is the food location and the second one is the previous experience about the food location. This movement can be expressed for the ith krill individual as follows:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \tag{68}$$

Where,

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{69}$$

And V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0,1], F_i^{old} is the last foraging motion, β_i^{food} is the food attractive and β_i^{best} is the effect of the best fitness of the ith krill so far. According to the measured values of the foraging speed, it is taken 0.02 (ms^{-1}).

The food effect is determined in terms of its location. The center of food should be found at first and then try to formulate food attraction. This cannot be fixed but can be estimated. The virtual center of food concentration is estimated according to the fitness distribution of the krill individuals, which is inspired from ‘‘center of mass’’. The center of food for each iteration is formulated as:

$$X^{food} = \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \tag{70}$$

Therefore, the food attraction for the ith krill individual can be determined as follows:

$$\beta_i^{food} = C^{food} \widehat{K}_{i,food} \widehat{X}_{i,food} \tag{71}$$

Where C^{food} is the food coefficient. Because the effect of food in the krill herding decreases during the time, the food coefficient is determined as:

$$C^{food} = 2(1 + \frac{I}{I_{max}}) \tag{72}$$

The food attraction is determined to possibly attract the krill swarm to the global optima. Based on this description, the krill individuals normally gather around the global optima after some iteration. This can be considered as an effective global optimization strategy which helps upgrading the globality of the KH algorithm.

The effect of the best fitness of the ith krill individual is also handled using the following equation:

$$\beta_i^{best} = \widehat{K}_{i,best}\hat{X}_{i,best} \tag{73}$$

Where $\widehat{K}_{i,best}$ is the best previously visited position of the ith krill individual.

3- *Physical diffusion:*

The physical diffusion of the krill individuals is deemed to be a random process. This movement can be state in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$D_i = D^{max}\,\delta \tag{74}$$

Where D^{max} is the maximum diffusion speed, and δ is the random directional vector and its arrays are random values between -1 and 1. Wolpert and Macready proposed a range for the maximum diffusion speed of the krill individuals as D^{max} ∈[0.002, 0.010] (ms^{-1}) and a random number in this range is also used in this dissertation. The better the position of the krill is, the less random the movement is. So, another term is added to the physical diffusion formula to count this effect. The effects of the movement provoked by other krill individuals and feeding movement gradually reduce with increasing the time (iterations). Referring to Eq. (74), the physical diffusion is a random vector and does not steadily decrease with the increases of the iteration number. Hence, another term (Eq. (75)) is added to Eq. (74). This term linearly reduces the random speed with the time and works on the basis of a geometrical annealing schedule:

$$D_i = D^{max}\,(1 - \frac{I}{I_{max}})\delta \tag{75}$$

4- *Motion Process of the KH Algorithm:*

In general, the determined movements frequently transfer the position of a krill individual toward the best fitness. The feeding movement and the movement provoked by other krill individuals include two global and two local strategies [28]. These are operating in parallel which make KH a robust algorithm. According to the formulations of these movements for the ith krill individual, if the related fitness value of each of the abovementioned effective factor (K_j, K^{best}, K^{food} or K_i^{best}) is better (less) than the fitness of the ith krill, it has an attractive effect; otherwise, it has a repulsive effect. It is also clear from the above formulations that a better fitness is more efficient on the movement of ith krill individual. The physical diffusion does a random search in the proposed method. Using different effective parameters of the movement during the time, the position vector of a krill individual during the interval t to $t + \Delta t$ is given by the following equation:

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \quad \textbf{(76)}$$

It should be noted that Δt is one of the most important constants and should be carefully set according to the optimization problem. This is because this parameter works as a scale factor of the speed vector. Δt completely depends on the search space and it seems it can be simply obtained from the following formula:

$$\Delta t = C_t \sum_{j=1}^{NV} (UB_j - LB_j) \quad \textbf{(77)}$$

Where NV is the total number of variables, and LB_j and UB_j are lower and upper bounds of the jth variables (j = 1, 2,. . ., NV), respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that C_t is a constant number between [0,2]. It is also obvious that low values of C_t let the krill individuals to search the space carefully.

II.4.3 Methodology of the KH algorithm:

Various krill-inspired algorithms can be improved by idealizing the movement characteristics of the krill individuals. Generally, the KH algorithm can be formed by the following steps:

I. Data Structures: Define the simple bounds, determination of algorithm parameter(s) and etc.
II. Initialization: Randomly create the initial population in the search space.
III. Fitness evaluation: Evaluation of each krill individual according to its position.
IV. Motion calculation:
    - Motion induced by the presence of other individuals.
    - Foraging motion.
    - Physical diffusion.
V. Updating: updating the krill individual position in the search space.
VI. Repeating: go to step III until the stop criteria is reached.
VII. End.

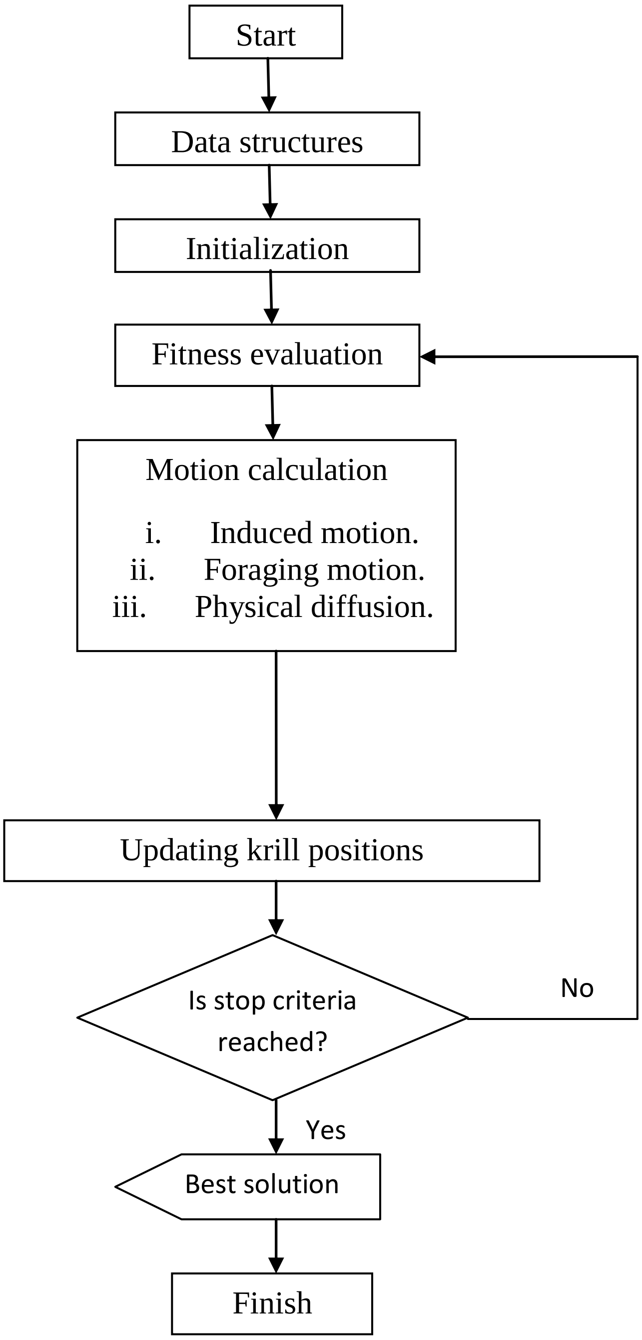

Fig.6. Flowchart of krill herd optimization

II.4.4 Simulation Using the KH algorithm:

As an example, the proposed algorithm is tested using the Peak Function (see Fig. 7). The Peak Function is defined as:

$$Z = X_1 e^{-(X_1^2+X_2^2)} \tag{78}$$

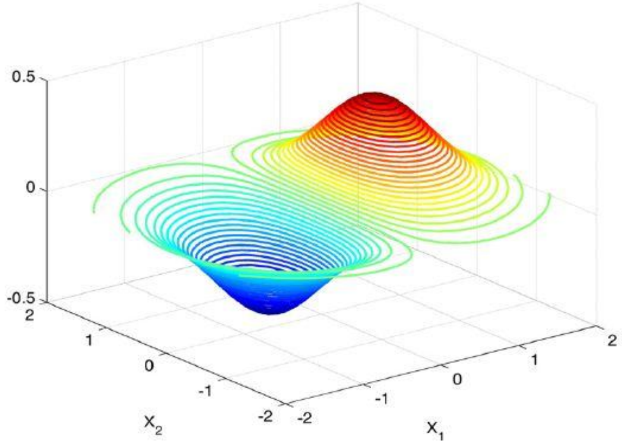

Fig. 7. 3-D contours of the Peak Function.

In this problem, 10 krill individuals are used to find the minima with the time interval equal to 2 second. Different positions of the krill individuals and the virtual food place are shown in Fig. 8. The positions in spread of the individuals after 1st, 5th, 10th and 15th iterations are respectively shown in Fig. 8.(a)–(d). The krill individuals are shown by ● marks and the virtual food place is shown by * mark. As it is seen, the positions of the krill individuals and the location of the food concentration go toward the global minimum with increasing the iterations.

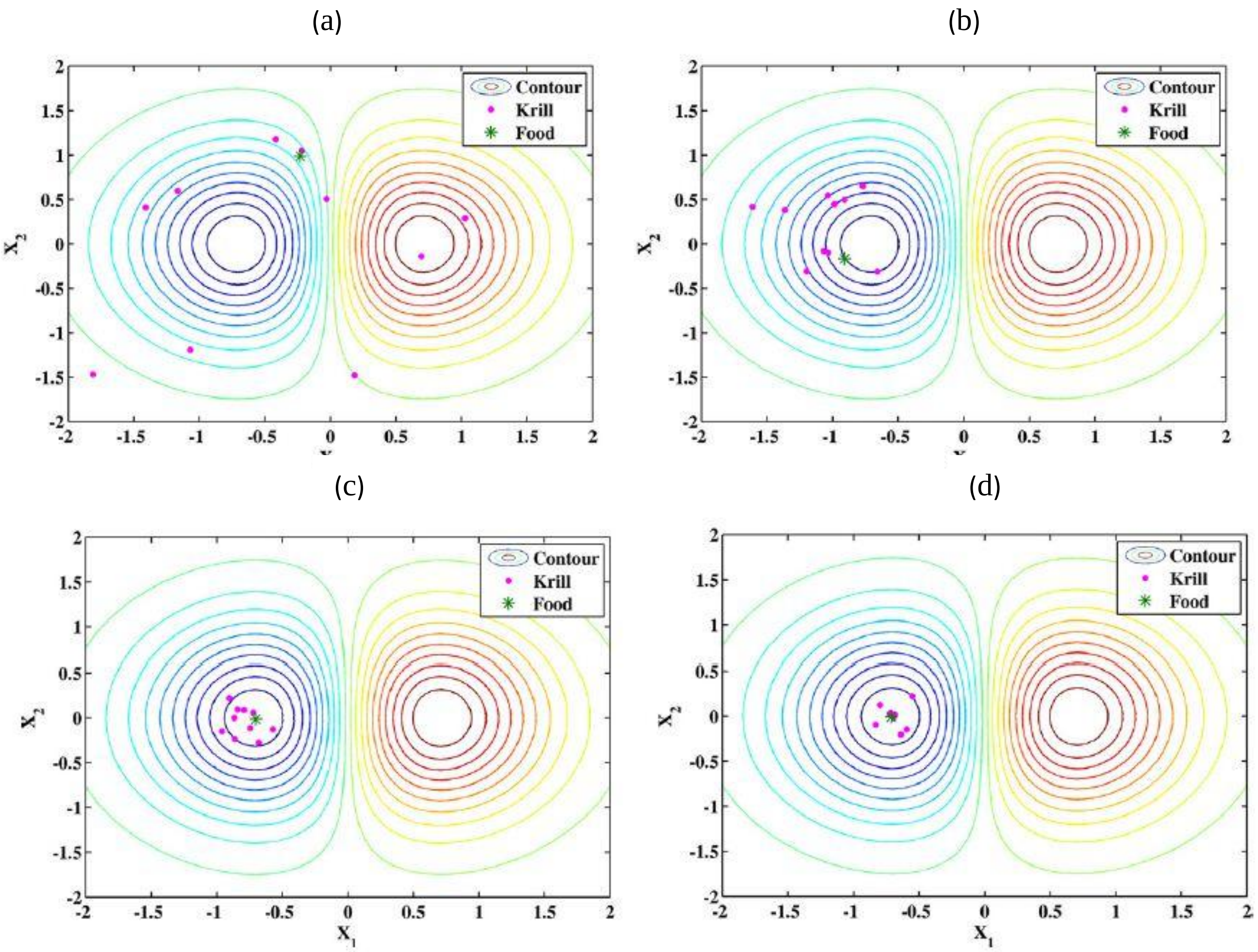
(a)
(b)
(c)
(d)

Fig. 8. The positions of the krill individuals and food after (a) 1st iteration, (b) 5th iteration, (c) 10th iteration, and (d) 15th iteration.

II.5 Conclusion:

In this chapter we have seen the difference between the two known concepts of the economic dispatch; the first is the convention or classic economic dispatch which includes mathematical programming for solving EDP because the function is considered as quadratic. While the second concept is economic dispatch using metaheuristic methods, here we talk about taking into account valve point effects and POZs (prohibited operating zones) in the optimization which makes the cost curve function non-smooth and non-convex.

Each concept has its proper methods for solving the economic dispatch problem, but the more efficient and the nearest to the reality and the truth of the EDP optimization is evolutionary algorithms such as particle swarm, cat swarm optimization and improved differential evolution..etc.

Finally we have introduced our method which is krill herd optimization. This method is inspired from krill's behavior in the sea. Those sea fishes use a particular approach to find their food and increase their density after predation. Attraction of krill (increasing density) and finding food (areas of high food concentration) are used as objectives which finally lead the krill to herd around the global minimum. That is, the closer the distance to the high density and food, the less the objective function. This method is deemed as a modern algorithm to treat the economic dispatch problem.

In the next chapter we will see the application of krill herd method in large-scale networks to show advantages and maybe drawbacks of using this method.

Chapter III: Application of Krill Herd Method

III.1 Introduction:

In previous chapters we have seen theoretical aspect of EDP in its two ways either classic or modern and we have introduced the Krill Herd method, then we assumed that it will be a good chose for our study subject which is the application of a new algorithm for economical non linear reparation in a big size electrical network.

In this chapter we will prove a Krill Herd method if it could guaranty acceptable results in three different network sizes contain: 80, 160, and 640 thermal unit generators using a MATLAB algorithm, then we will compare our results with other metaheuristic methods proven the best till nowadays such us PSO (particle swarm optimization) and CSO (cat swarm optimization).

This chapter will contain tables, figures and diagrams to illustrate the efficiency of the algorithm, in addition to that observation and discussion of the results to sum up with a general conclusion of our study.

III.2 Results and Discussion:

In this chapter, three different case studies are explored to test the robustness and super performance of KH. All the test systems are treated with MF options and VP effects. KH is compared with the basic PSO and other most advanced methods. ***In all figures the black color represents the proposed KH method, else the PSO method.***

<u>Parameter setting:</u>

In the following simulations, the invariant parameters of the KH are: foraging speed V_f =0.02, maximum induced speed N_{max}=0.01 and maximum diffusion speed D_{max}=0.005, $C_t = 0.5$, Inertia weight (W) may be linearly varied between 0.9 to 0.4.

The invariant parameters of the PSO are: an inertial constant=0.3, a cognitive constant=1, a social constant for a swarm interaction=1. The metaheuristic algorithm is based on some random distributions, therefore it achieves approximately 20 times independent operation to obtain the illustrative results.

Table 1: The data of 10 generator units.

Unit	Generation							Fuel type	Cost coefficient				
	Min	F_1	P_1	F_2	P_2	F_3	Max		a_{ik}	b_{ik}	c_{ik}	e_{ik}	f_{ik}
1	100	1	196	2			250	1	0.2697e2	-0.3975e0	0.2176e-2	0.2697e-1	-0.3975e1
								2	0.2113e2	-0.3059e0	0.1861e-2	0.2113e-1	-0.3059e1
2	50	2	114	3	157	1	230	1	0.1184e3	-0.1269e1	0.4194e-2	0.1184e0	-0.1269e2
								2	0.1865e1	-0.3988e-1	0.1138e-2	0.1865e-2	-0.3988e0
								3	0.1365e2	-0.1980e0	0.1620e-2	0.1365e-1	-0.1980e1
3	200	1	332	3	388	2	500	1	0.3979e2	-0.3116e0	0.1457e-2	0.3979e-1	-0.3116e1
								2	-0.5914e2	0.4864e0	0.1176e-4	-0.5914e-1	0.4864e1
								3	-0.2875e1	0.3389e-1	0.8035e-3	-0.2876e-2	0.3389e0
4	90	1	138	2	200	3	265	1	0.1983e1	-0.3114e-1	0.1049e-2	0.1983e-2	-0.3114e0
								2	0.5285e2	-0.6348e0	0.2758e-2	0.5285e-1	-0.6348e1
								3	0.2668e3	-0.2338e1	0.5935e-2	0.2668e0	-0.2338e2
5	190	1	338	2	407	3	490	1	0.1392e2	-0.8733e-1	0.1066e-2	0.1392e-1	-0.8733e0
								2	0.9976e2	-0.5206e0	0.1597e-2	0.9976e-1	-0.5206e1
								3	-0.5399e2	0.4462e0	0.1498e-3	-0.5399e-1	0.4462e1
6	85	2	138	1	200	3	265	1	0.5285e2	-0.6348e0	0.2758e-2	0.5285e-1	-0.6348e1
								2	0.1983e1	-0.3114e-1	0.1049e-2	0.1983e-2	-0.3114e0
								3	0.2668e3	-0.2338e1	0.5935e-2	0.2668e0	-0.2338e2
7	200	1	331	2	391	3	500	1	0.1893e2	-0.1325e0	0.1107e-2	0.1893e-1	-0.1325e1
								2	0.4377e2	-0.2267e0	0.1165e-2	0.4377e-1	-0.2267e1
								3	-0.4335e2	0.3559e0	0.2454e-3	-0.4335e-1	0.3559e1
8	99	1	138	2	200	3	265	1	0.1983e1	-0.3114e-1	0.1049e-2	0.1983e-2	-0.3114e0
								2	0.5285e2	-0.6348e0	0.2758e-2	0.5285e-1	-0.6348e1
								3	0.2668e3	-0.2338e1	0.5935e-2	0.2668e0	-0.2338e2
9	130	2	213	1	370	3	440	1	0.8853e2	-0.5675e0	0.1554e-2	0.8853e-1	-0.5675e1
								2	0.1530e2	-0.4514e-1	0.7033e-2	0.1423e-1	-0.1817e0
								3	0.1423e2	-0.1817e-1	0.6121e-3	0.1423e-1	-0.1817e0
10	200	1	362	3	407	2	490	1	0.1397e2	-0.9938e-1	0.1102e-2	0.1397e-1	-0.9938e0
								2	-0.6113e2	0.5084e0	0.4164e-4	-0.6113e-1	0.5084e1
								3	0.4671e2	-0.2024e0	0.1137e-2	0.4671e-1	-0.2024e1

1- *Simulation results for Case Study 1 (80-Units):*

For the first test system, a wide test system with 80-units and 21600 MW load requirements is used, to prove the robustness of KH when solving non-convex ED with both MF options and VP effects on heat generators. The curse of the dimension and the local minimum is increased 8 times larger than the 10-units system. Table 2 shows the optimal power scheduling, the related fuel costs, and the type of KH. Table 3 presents the KH results compared with other algorithms referenced in the literature. Figure 9 shows the convergence characteristics of KH and PSO, while figure 10 exposes the distribution of total cost during the 20 isolation tests.

Table 2: The optimal power output of 80 units system, 21600 MW demand using KH method.

Units	Energy production	Fuel type	Units	Energy production	Fuel type	Units	Energy production	Fuel type	Units	Energy production	Fuel type
1	218,312276	2	21	217,966294	2	41	209,688762	2	61	219,439987	2
2	215,42356	1	22	207,356663	1	42	210,719265	1	62	212,122993	1
3	287,089105	1	23	283,465654	1	43	283,876516	1	63	287,272845	1
4	244,073667	3	24	236,548902	3	44	240,445665	3	64	238,295762	3
5	273,242507	1	25	287,463079	1	45	270,18834	1	65	285,203215	3
6	243,267462	3	26	243,267413	3	46	240,983122	3	66	238,83319	3
7	296,84337	1	27	299,068141	1	47	293,964012	1	67	301,310954	1
8	240,848791	3	28	234,130246	3	48	240,579996	3	68	237,758241	3
9	436,081752	3	29	422,494267	3	49	427,481917	3	69	417,585268	3
10	271,087387	1	30	272,548991	1	50	283,315564	1	70	275,83833	1
11	223,553427	2	31	224,055082	2	51	222,798067	2	71	219,511973	2
12	209,820426	1	32	219,136961	1	52	219,873764	1	72	201,069443	1
13	285,414744	1	33	287,532794	1	53	283,009663	1	73	283,865695	1
14	236,548889	3	34	239,773839	3	54	235,608289	3	74	240,580037	3
15	277,29639	1	35	282,597418	1	55	271,470038	1	75	289,803737	1
16	240,311229	3	36	242,729941	3	56	239,505064	3	76	242,998709	3
17	289,476272	1	37	286,399087	1	57	305,597082	1	77	299,851046	1
18	239,639428	3	38	241,520634	3	58	241,520601	3	78	242,19242	3
19	432,547184	3	39	439,157436	3	59	351,50465	3	79	346,181651	3
20	273,831634	1	40	273,758448	1	60	279,446056	1	80	293,027276	1
Total energy production		21600			Power generation cost ($/h)				**4990.124**		

Table 3: Statistical analysis results of KH compared with other methods of 80 unit systems.

Methods	Power generation cost ($/h)			Std
	Min	Avg	Max	
KH	**4990.124**	**4990.3462**	**4990.91**	**0.236**
CSO	4990.9267	4991.2948	4992.0014	0.30746
PSO	**4991.45**	**4992.8321**	**4994.54**	**0.8745**
ORCSA	4992.4215	4994.4987	4995.6717	0.4939
CSA	4992.6853	4993.7307	5003.4294	1.0931
IGA-MU	5003.8832	-	-	-
CGA-MU	5008.1426	-	-	-

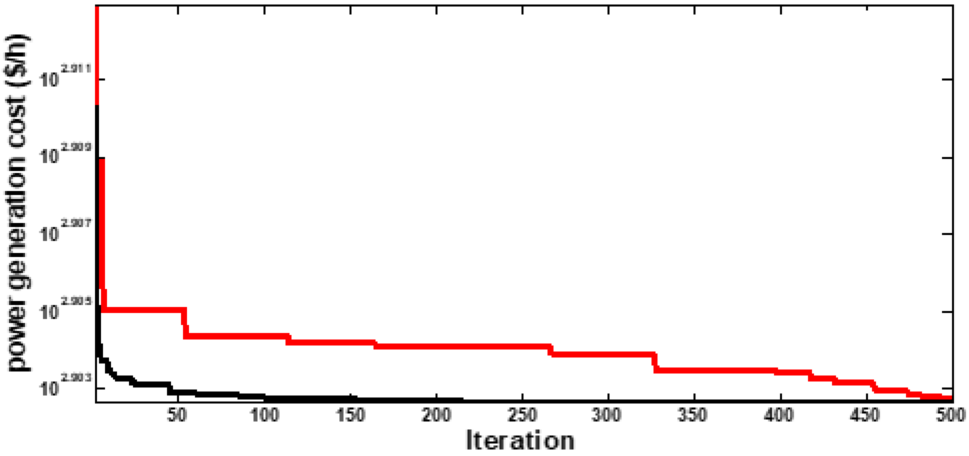

Fig. 9. The convergence diagram of KH and PSO of the 80 units system.

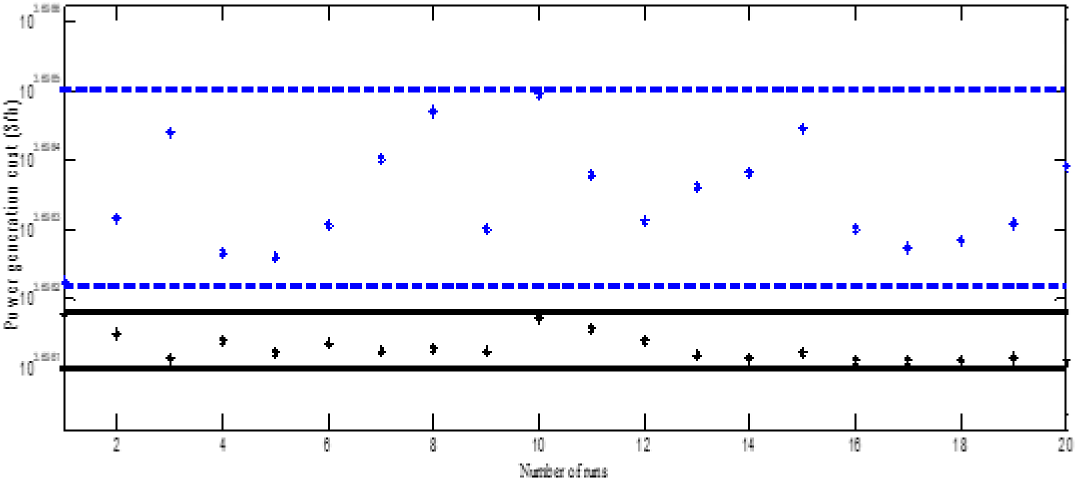

Fig. 10. Distribution the fuel cost of KH and PSO for 80 units.

2- Simulation results for Case Study 2 (160-Units):

To make an actual scenario, a wider test system with 160 thermal generators was realized to check the robustness and performance of the KH solution for the ED problem. The load requirement is 43200 MW. In order to compare this later with PSO and other methods in the literature, MF options and VP effects are also treated. Table 4 shows the optimum power distribution and the related best fuel the types using KH method. Table 5 shows the statistical analysis of the proposed KH algorithm compared with a previous optimization algorithm. It is cleared that the proposed KH leads to the most economical solution (9982.1457 $/h). In addition, the proposed KH method has a standard deviation (0.8704) which is a responsible level compared with the previous methods. Figure 11 displays the convergence characteristics of PSO and KH. Figure 12 shows the distribution characteristics of thebest fuel cost function original PSO and KH for 20 runs.

Table 4: The optimal power output of 160 units system, 43200MW demand using KH method.

Units	Energy production	Fuel type	Units	Energy production	Fuel typ	Units	Energy production	Fuel typ	Units	Energy production	Fuel type	Units	Energy production	Fuel typ
1	223.501194	2	2	209.597552	1	3	285.421762	1	4	238.430076	3	5	257.224906	1
6	244.07364	3	7	278.912625	1	8	241.117526	3	9	432.311298	3	10	259.739528	1
11	216.790847	2	12	209.914567	1	13	450.954328	1	14	237.758254	3	15	274.033359	1
16	240.579968	3	17	292.369162	1	18	236.145796	3	19	335.909717	3	20	268.146965	1
21	218.614237	2	22	213.443761	1	23	460.728053	1	24	243.670561	3	25	270.692363	1
26	238.833191	3	27	307.760971	1	28	239.101889	3	29	340.312465	3	30	271.080354	1
31	204.658351	2	32	213.643293	1	33	450.260824	1	34	243.536225	3	35	300.442424	1
36	235.608213	3	37	280.915302	1	38	239.505067	3	39	422.027454	3	40	268.195383	1
41	208.299165	2	42	209.823391	1	43	283.103907	1	44	237.355175	3	45	270.954655	1
46	244.611204	3	47	290.959577	1	48	237.758214	3	49	430.07095	3	50	271.595505	1
51	206.067564	2	52	212.408418	1	53	271.854662	1	54	241.789327	3	55	262.157996	1
56	240.714401	3	57	300.708193	1	58	240.579966	3	59	431.618863	3	60	261.90188	1
61	219.446346	2	62	207.008142	1	63	287.209069	1	64	240.176874	3	65	284.716133	1
66	243.401826	3	67	281.012815	1	68	237.489515	3	69	334.944222	3	70	279.788494	1
71	224.333655	2	72	210.388087	1	73	294.468841	1	74	237.355133	3	75	281.307947	1
76	241.386314	3	77	286.318982	1	78	237.086406	3	79	412.638374	3	80	286.665379	1
81	208.748084	2	82	213.600942	1	83	274.438006	1	84	235.20521	3	85	276.219499	1
86	241.655007	3	87	281.387261	1	88	235.742675	3	89	435.21776	3	90	267.627871	1
91	215.316173	2	92	210.835519	1	93	278.313885	1	94	244.342448	3	95	277.826754	1
96	239.236305	3	97	288.350329	1	98	242.730002	3	99	417.373452	3	100	266.784227	1
101	229.88392	2	102	218.199922	1	103	456.876572	1	104	237.489488	3	105	277.940502	1
106	240.176924	3	107	283.628267	1	108	240.445642	3	109	420.57921	3	110	260.115325	1
111	216.371644	2	112	213.187475	1	113	274.423461	1	114	242.461211	3	115	270.621615	1
116	239.101912	3	117	290.188366	1	118	241.52062	3	119	425.377679	3	120	277.52576	1
121	218.535236	2	122	205.752767	1	123	270.690298	1	124	241.92373	3	125	282.287469	1
126	236.952047	3	127	279.647308	1	128	234.936428	3	129	336.138553	3	130	258.003768	1
131	215.835415	2	132	209.718627	1	133	283.51506	1	134	239.236333	3	135	267.636199	1
136	243.804859	3	137	286.12867	1	138	236.817623	3	139	421.583895	3	140	266.924859	1
141	209.255566	2	142	214.68551	1	143	288.705691	1	144	238.026936	3	145	275.752433	1
146	234.264587	3	147	269.335774	1	148	239.773857	3	149	408.369225	3	150	266.463425	1
151	200.818254	2	152	207.809102	1	153	269.556583	1	154	233.189669	3	155	271.330039	1
156	235.742668	3	157	291.861909	1	158	234.130213	3	159	425.663872	3	160	264.689592	1
Total energy production			43200			Power generation cost ($/h)				**9982.1457**				

Table 5: Statistical analysis of KH compared with other methods of 160 unit systems.

Methods	Power generation cost ($/h)			Std
	Min	Avg	Max	
KH	9982.1457	9983.5066	9984.570	0.8704
CSO	9984.2438	9984.9163	9986.3640	0.40321
PSO	9984.58	9986.3868	9988.64	1.4369
ORCSA	9989.9444	9992.0503	9996.8317	1.4138
CSA	9996.6390	9996.6390	10014.0183	4.9268
ORCCRO	10004.20	10004.21	10004.45	-
DE/BBO	10007.05	10007.56	10010.26	-
BBO	10008.71	10009.16	10010.59	-
RCCRO	10009.5183	10009.5222	10009.5827	-
ED-DE	10012.68	-	-	-
IGA-MU	10042.47	-	-	-

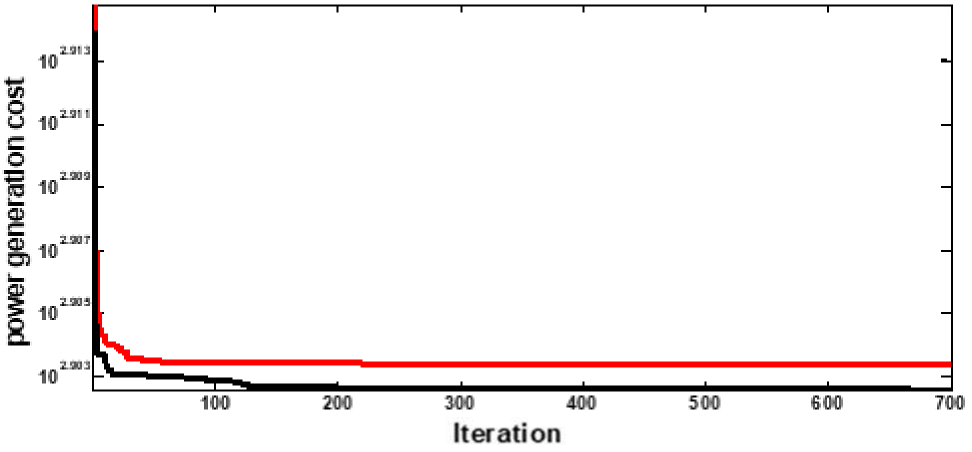

Fig. 11. The convergence diagram of KH and PSO of the 160 units system.

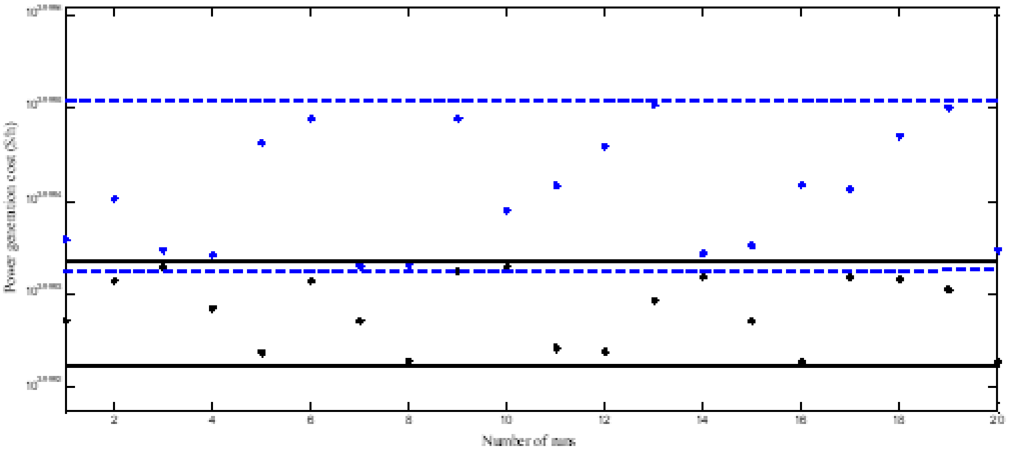

Fig. 12. Distribution the best fuel cost of KH and PSO for 160 units

3- *Simulation results for Case Study 3 (640-Units):*

Table 6 shows the simulation results of the proposed algorithm compared with other algorithms in the literature for case study 3 that includes the 640-unit system. Using KH method we obtained the most economical solution (39955.351$/h) while total power demand equals 172800 MW. In addition, KH and PSO are more reliable than other algorithms. Hence, the genetic reproduction in the original KH increases the precision of the overall optimality of the solution. Figure 13 presents the convergence curve of KH and PSO for their best fuel costs while Figure 14 expresses the distribution of total costs during 20 isolated tests. It can be seen that a few generations have been taken using KH to converge to the best solution according to the large scale of the power system and confirm quick convergence speed of the improved algorithm. Thus, KH is the best to deal with the difficult situation in the non-convex ED problems. Global performance of KH illustrates the higher quality of the solution, strongly better than other methods. The premature convergence obtained with PSO is caused by the worst position of particles in both local and global optima for solving the ED problem. The best final value of fuel cost is achieved by KH, which proves the progressive precision of the solution and the additional reliable efficiency of the KH than other algorithms. Therefore, the KH achieves the higher precision of the overall performance of solutions.

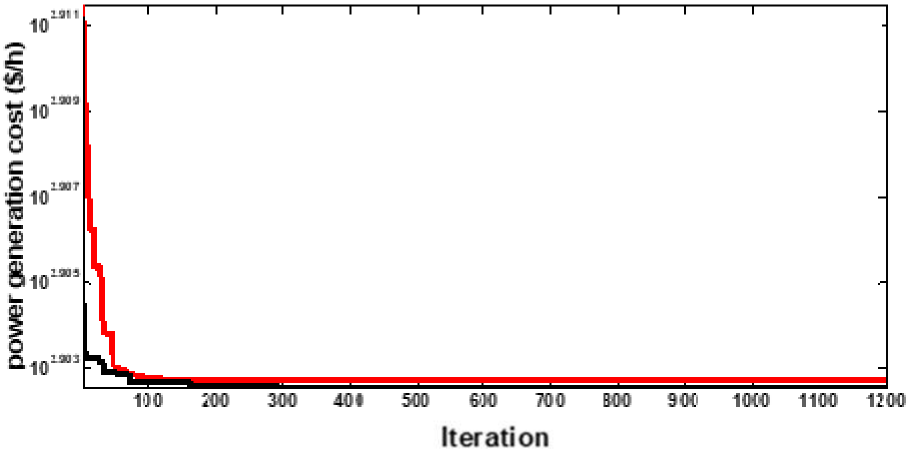

Fig. 13. The convergence diagram of KH and PSO of the 640 units system.

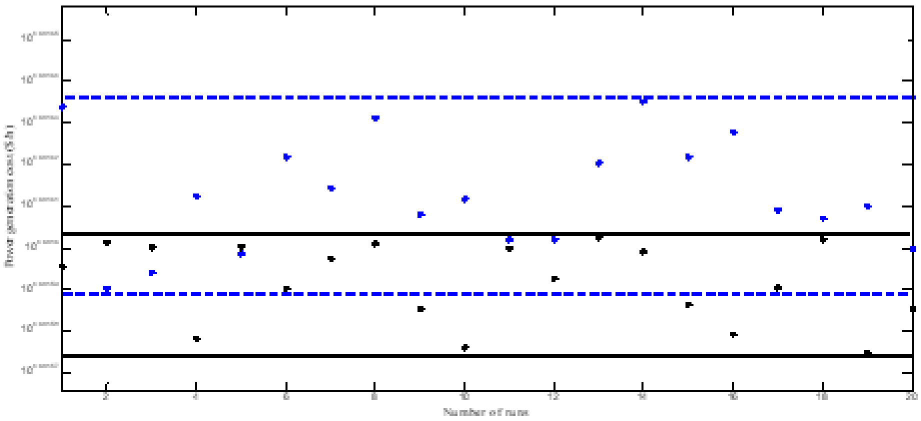

Fig. 14. Distribution the best fuel costs of KH and PSO for 640 units.

Table 6: Statistical results of KH compared with other methods of 640 unit systems.

Methods	Total fuel costs ($/h)			Std.
	Min	Avg	Max	
KH	39955.351	39956.92	39959.894	0.8654
PSO	39958.45	39958.8194	39962.8977	1.2216
CSO	39964.0603	39968.03007	39974.1858	1.9075

III.3 Conclusion:

In this chapter we simulated using MATLAB software a modern heuristic algorithm called krill herd to see if it can give better results for treating EDP in three large-scale networks.

As we can see in the results above; the krill herd optimization algorithm gave better results for all the networks data simulated either 80, 160 or 640 generator units compared with other heuristic best algorithms dealing with large-scale EDP such as PSO and CSO. Number of iterations and total cost average are lower than PSO algorithm results which are deemed the best after krill herd in 640 generating units' network but in 80 and 160 generating units CSO outmatch PSO and gave better results, but KH still always the best as we can notice in the diagrams and result tables above.

As a conclusion after the simulation of KH in large-scale networks, we can consider KH optimization is the best to obtain satisfactory robust results in shorter time for an economical power generating units in a large-scale power system.

General conclusion

In this work we have seen ED problem in general and its differences with two other similar concepts OPF and UCP, then we introduced our subject which is EDP and we have explained the real problem it can be treated with modern mathematical algorithms which deals very well with non-linear, non-convex and non-smooth cost function of heat generators caused by VP effects, POZ and MF power plants, unlike old methods.

In the third chapter we chose a new metaheuristic algorithm called krill herd and we apply it in three different large power systems which is a new study.

In our application of the algorithm we have noticed some advantages over other modern methods such as:

- Quick convergence speed: a few generations have been taken to converge to the best solution.
- The algorithm gets out of the local minimum very easily.
- It deals easily with complex optimization problems.
- Weak values of standard deviation prove a good stability of the algorithm.
- The algorithm has fewer parameters for adjustments.
- It is insensitive to the convexity or the continuity of the objective function.
- Best solutions are fulfilled no matter was the size of the network proves the robustness of the algorithm.
- Contrary to the traditional technologies it is a derivative-free algorithm.

These advantages prove the efficiency and the supremacy of the algorithm when dealing with such problem.

The KH algorithm for solving EDP problem in a large network scale could be extended to use as a hybrid tool to combine with other optimization techniques or to treat other problems like combined economic and emission dispatch problem, or it can be modified to obtain more satisfactory results.

The problem studied in this thesis will be useful for electric power system utilities and solve economic dispatch problems in large electrical networks.

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