Wind Farm Layout Optimization using Ant Colony and Particle Filtering Approaches

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ABSTRACT

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Renewable energy resources are important equity capital of countries and have increasing trends in terms of continuity and sustainability of energy production. Wind energy has begun to have an important share in energy production with the improvements in wind turbine technology and decrease in costs. Generally, investors prefer to wind farms, which consist of more than one wind turbines, in order to produce more energy in a single windy site. On the other hand, one of the most important problems that decrease the profitableness of a wind farms is wake effect which causes the decrease on maximum expected energy production. In this study, layout of wind turbines that gives the maximum energy production of a wind farm is optimized and this is known as wind farm layout optimization problem. Because the problem is NP-hard, heuristic approaches are used in order to solve the problem. One of the solution approaches of this study is Ant Colony Optimization which gives competent results in many optimization problems. The other approach is Particle Filtering approach which has been never applied in an optimization problem before. Experimental results show that the proposed approaches give better results than the best known solutions of the problem.

Key Words: Wind Farm, Wake effect, Optimization, Layout Design, Particle Filtering, Ant Colony Optimization, Renewable Energy

ÖZET

KARINCA KOLONİSİ VE PARÇACIK SÜZGECİ YAKLAŞIMLARI İLE RÜZGAR ÇİFTLİĞİ YERLEŞİM OPTİMİZASYONU

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Yenilenebilir enerji kaynakları ülkelerin önemli öz kaynaklarındandır ve enerji üretiminin sürekliliği ve sürdürülebilirliği açısından yenilenebilir enerjiye yönelimler artmaktadır. Rüzgar türbin teknolojisindeki gelişmeler ve maliyetlerin azalmasıyla beraber rüzgar enerjisi enerji üretiminde önemli bir pay sahibi olmaya başlamıştır. Genellikle yatırımcılar, tek bir bölgeden daha fazla enerji üretebilmek için birden fazla rüzgar türbinlerinden oluşan rüzgar çiftliklerini tercih ederler. Diğer taraftan, rüzgar çiftliklerinde karlılığı azaltan en önemli sorunlardan birisi üretilebilecek maksimum enerjinin düşmesine sebep olan rüzgar izi etkisidir. Bu çalışmada, rüzgar çiftliklerinde en çok enerji üretimini sağlayan rüzgar türbinlerinin optimum yerleşimi problemi ele alınmıştır. Problemin karmaşıklık düzeyi yüksek olduğu için sezgisel yöntemlerden yararlanılmıştır. Bu çalışmada kullanılan çözüm yaklaşımları, bir çok problemin çözümünde iyi sonuçlar veren Karınca Kolonisi Optimizasyonu ve daha önce herhangi bir optimizasyon probleminde uygulanmasına rastlanmayan Parçacık Süzgeci'dir. Sonuçlar, önerilen her iki yaklaşımın da problemin bilinen en iyi çözümü ile kıyaslandığında daha iyi sonuçlar verdiğini göstermektedir.

Anahtar Kelimeler: Rüzgar Çiftliği, Rüzgar izi, Optimizasyon, Yerleşim Tasarımı, Parçacık Süzgeci, Karınca Kolonisi optimizasyonu, Yenilenebilir Enerji

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LIST OF SYMBOLS/ABBREVIATIONS[1]

(x_i, y_i) : The two-dimensional Cartesian coordinates of *ith* turbine

c : Scale parameter of the Weibull distribution

$c(\theta)$ = The Weibull scale parameter at wind direction θ

$c_i(\theta)$ = The Weibull scale parameter at wind direction θ after wake effect

C_T : Trust coefficient of the wind turbine

d : Distance of the wind turbines according to wind direction

D_i : The wake loss of ith turbine

$d_{i,j}$: Distance of the wind *ith* and *jth* turbines according to wind direction

$F\_z_{i,t}$: The observation function of *ith* turbine at time t according to wind farm's power generation capability

f_h : The observation function of the system

f_s : The state function of the system

f_v : The power output of a turbine for wind speed v

ij= Portion of entire solution (trail)

k : Shape parameter of the Weibull distribution

l : Wind direction interval

L_l : The length of a location

m = Number of ants in population

N_i = Neighborhoods of location i

Np : The number of particles

Np_t^i : The number of particles of *ith* turbine at time t

Nt : The number of turbines in the farm

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[1] First Latin, then Greek letters, both in alphabetical order

Nv : The number of wind speed intervals

$N\theta$: The number of wind direction intervals

P : The expected power

$p(x_t|x_0, Z_{1:t})$: The posteriori probability distribution

$P(\theta)$: The expected power output of a turbine for the wind direction θ

P_f : The expected power for the wind farm

$P_{f,t}^n$: The expected power for the farm at time t and particle n

P_i : The expected power for the *ith* turbine

$P_{i,t}^n$: The expected power for the *ith* turbine at time t and particle n

P_r = The partial power related with linear power curve in terms of rated speed

Pup_i : theoretical power generations of each turbine

$p_v(.)$: The probability density function

P_η = The partial power related with linear power curve in terms of η

P_λ = The partial power related with linear power curve in terms of λ

r : Radius of the circular farm area

R : Rotor radius of the wind turbine

$T\_z_{i,t}$: The observation function of *ith* turbine at time t
according to that turbine's power generation capability

T= Number of iterations (generations)

$Tant_i$: Number of ants for *ith* turbine proportional to its pheromone intensity

TD : The wake loss of the wind farm

$totPup$: Ideal power of the farm

v : Wind speed

v_{cutin}: Minimum wind speed that the turbine starts to generate
power from this speed

v_{cutout}: Maximum wind speed that the turbine cut outs
generating power after this speed

v_{down}: Wind speed after wake effect

v_{down-c} : Wind speed after cumulative wake effect

Vel_def : Velocity deficit

Vel_def_i : The cumulative wake effect for turbine I

$Vel\_def_{i,j}$: The wake effect for the *ith* turbine in the wake of *jth* turbine

v_{rated}: The turbine starts to generate a rated power from this speed to v_{cutout}

v_{up} : Free stream wind speed

w : Wind blowing probability

WFLOP : Wind farm layout optimization problem

WWEA : World Wind Energy Association

x_0 : The initial state of the system to start the observations

x_t : The state of the system at time t

x_t^n : The state vector of *nth* particle at time t

$Z_{1:t}$: The observations beginning from initial time to t of the system

$z_{i,t-1}$: The observation value for *ith* turbine at time $t-1$

α : Relative importance of pheromone

β : Relative importance of heuristic

γ : The importance coefficient for observation function at time $t-1$

δ : The importance coefficient related with a turbine's power
generation capability

$\Delta \pi_{ijt}$ = Addition of pheromone on trail ij at time t

ζ : The importance coefficient related with the farm's power generation capability

η = The intercept parameter of the linear power curve function

$\acute{\eta}_{ij}$: Heuristic regarding trail ij

θ : The wind direction

κ : Wake spreading constant of the wind turbine

λ = The slope parameter of the linear power curve function

π_i : The pheromone quantity of *ith* turbine

π_{ijt} = Amount of pheromone on trail ij at time t

ρ : Evaporation factor ($0 < \rho < 1$)

τ_t^n : The weight vector of *nth* particle at time t

CHAPTER 1

TECHNICAL BACKGROUND

1.1 Introduction

Energy is a modern weapon for the countries whose economies are industry-dependent. Industrialized countries have to meet their energy consumption in order to have economical freedom, so the countries are challenging in order to fight climate change, improve energy security, enhance competitiveness, and maintain technological leadership.

Although there are many ways to generate electricity such as thermal reactors, nuclear reactors, and other fossil resources; renewable energy resources have began to have a big importance in energy policies of the countries because they have inexhaustible structure and are local resource for countries.

The most used renewable resource is hydro-based generation systems such as dams and small hydroelectric power generation stations but this resource has some environmental disadvantageous in the case of global warming. So, other renewable energy alternatives have become a current issue. Solar energy, geothermal energy, and bio-mass energy are the alternatives for generating electricity but they have still growing technologies. This makes them weak in order to be competitive. Meanwhile technological developments in wind turbine industry and easy construction ability of wind energy stations have made wind energy one of the important competitive renewable energy resources.

All these circumstances underline the main subject of this study. The objective is maximizing power generation in a wind energy station. The wake effect is the most important constraint and it occurs through the positions of the wind turbines in the wind power station. This chapter gives some technical information about wind energy, wake effect models, and literature survey about the main study.

1.2 Wind Energy

Wind energy is a solar based energy which is generated by blowing air and transform in kinetic energy. It has been used as a kind of energy, such as to sailing boats, windmills in agriculture, and today, to generate electricity (Burton et al., 2001). Although wind energy is still a growing sector, it is now one of the most cost-effective sources of new electricity generation in wind-rich regions (American Wind Energy Association, 2011).

A wind turbine can be described as a machine which converts the power in the wind into electricity (Manwell et al., 2008). It consists of several parts such as rotor, blade, gear box, and etc. and its main bodies are shown in figure 1.1 (Alternative Energy News, 2011). As it can be seen from the figure 1.1, modern wind turbines are kind of traditional windmills.

In the early years of wind turbine technology, it was not economical to generate electricity. The cost of wind energy technology is reducing rapidly because of growing new turbine technologies and new alternative manufacturers. Thus, increasing annual profit and getting more power in a single site has become an important issue for investors. If there are more than one wind turbine in a windy area which connected to the power system as a single electricity to produce power, that wind power station can be called as **wind farm.** A wind farm representation is given in figure 1.2, Gökçedağ Wind Farm – Bahçe/Osmaniye - Turkey.

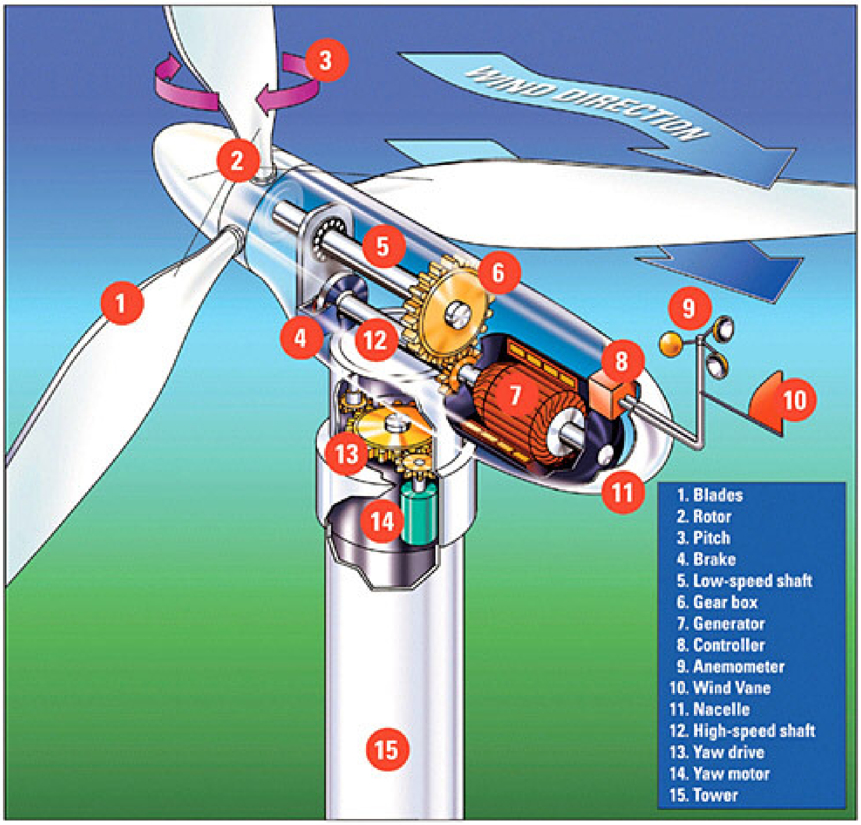

Figure 1. 1. The main structure of a wind turbine

Figure 1. 2. Gökçedağ Wind Farm - Bahçe/Osmaniye - Turkey

However, it is still needed to produce more energy because of the increase in energy demand. Decreasing cost of wind technology and increasing energy demands lead to growing of wind farms around the world.

1.3 Wind Energy on the World

It is known that the wind energy has been used as a windmill for 3000 years on the world (Burton et al, 2001). World Wind Energy Association (WWEA) has prepared a report about wind energy situation on the world for the year 2010 (WWEA, 2011). According to this report;

- The wind capacity reached worldwide at 196.630 Megawatts
- The growth rate is 23,6 % according to past year
- 40 billion Euros are the turnover of the wind sector in 2010 and 670.000 persons are employed worldwide
- China has the biggest installed capacity

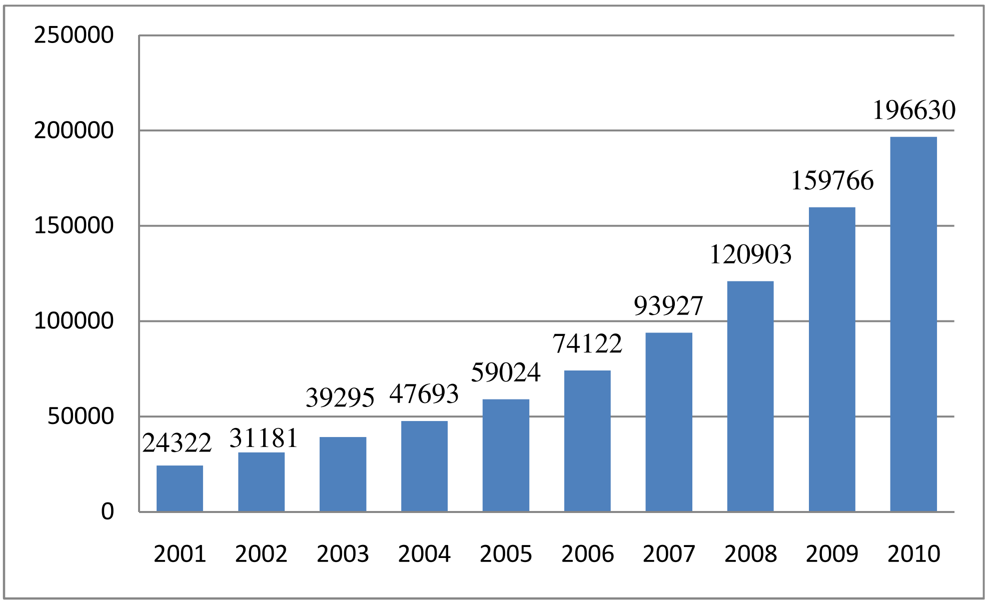

Figure 1. 3. World Total Wind Energy Installed Capacity (MW)

World total installed capacity is shown in figure 1.3. It can be understood that the installation of wind turbines are still growing, on the other hand figure 1.4 shows the growth rate of the wind sector and it is the second lowest rate from 1998 to 2010. The decrease on the growth rate can be commented as that the sector has stabilization or economic crises may cause such a decrease.

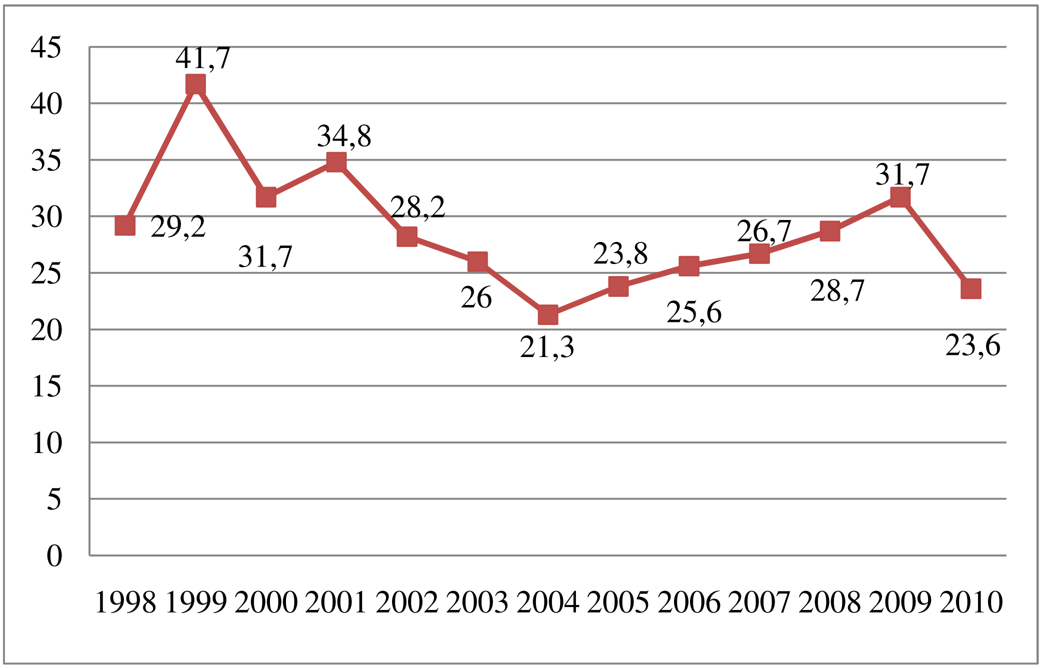

Figure 1. 4. World Growth Rate in Wind Energy Sector (%)

According to total installed capacity of the countries, top ten lists can be given in figure 1.5. In spite of USA has the highest installed capacity with 35159 MW in 2009, China has the highest capacity in 2010 with a highest growth rate.

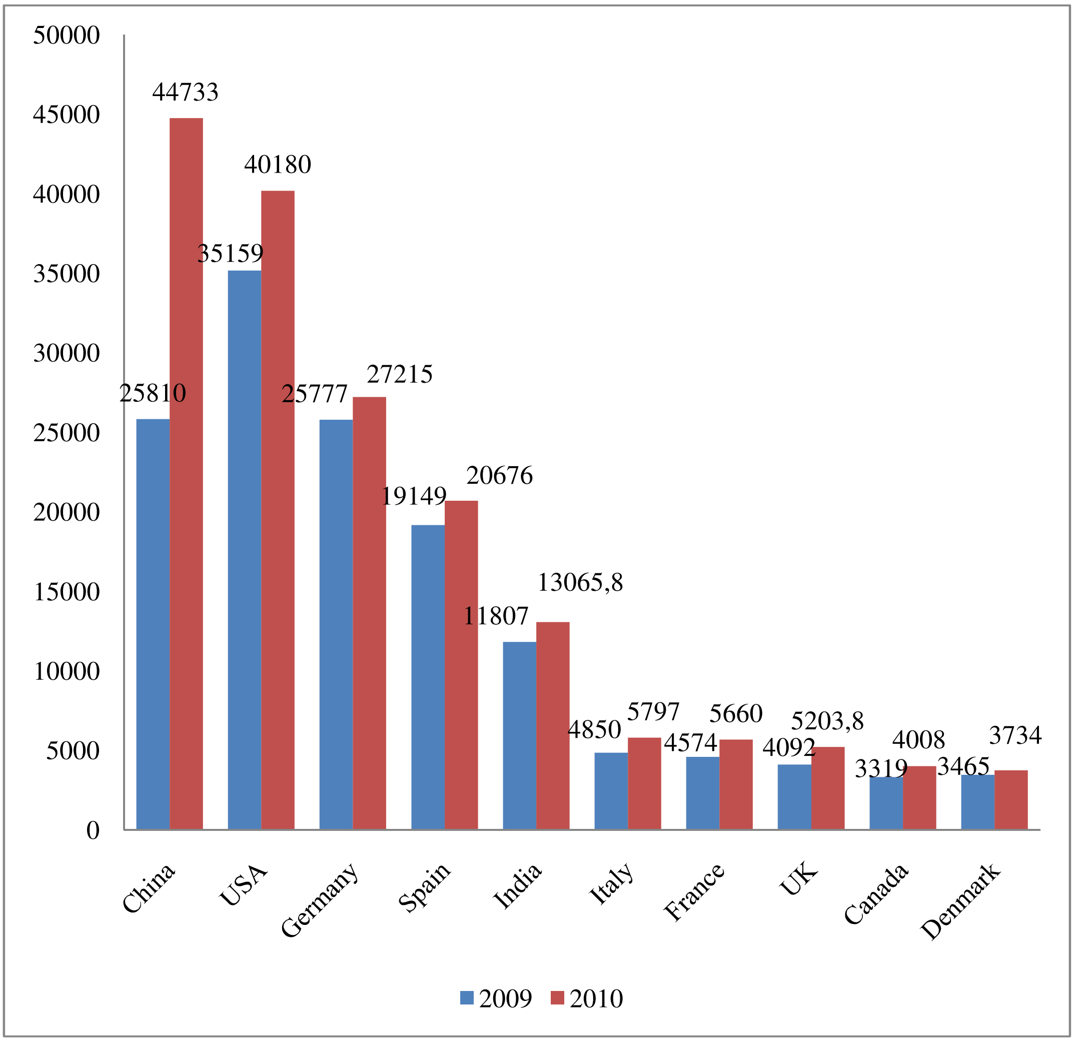

Figure 1. 5. Installed Capacities of Top 10 Countries in 2009 and 2010 (MW)

The world's interest on wind energy keeps increasing. Wind farms around the world are rising day by day and optimization of wind farms has become more important. There are many ways to optimize wind farms, such as optimization of layout before the wind farm is constructed or utilization of it after construction. The main objective of this study is maximization of generated power by handling wake effects of the turbines. Actually, it is a layout optimization and related with turbines' coordinates in the wind farm. The problem has two constraints. The first one is that all turbines must be in the wind farm area and the other one is that any two turbines are separated from each other by at least 4 rotor diameters in order to prevent wind turbulences. Details of the problem were mentioned in chapter two.

1.4 Wake Effect Models

Wake effect is a main subject which causes power losses for turbines in wind farms. A real case study shows that power losses can be 50% or 100% according to the wind direction, wind speed, and positions of the turbines in the farm and a representation of the wake effect can be seen in figure 1.6 (Mechali et al., 2006). There are many wake models in literature. The first known models are Lanchester's (1915) and Betz's (1920) analytical wake models. The most used wake model is Jensen's (1983) (Katic et al., 1986) model. It is an analytical wake model which characterizes the velocity in a wake by a set of analytical expressions (Mittal, 2010). The wake is considered as turbulence and tip vortices are neglected in this model. Thus, this wake model is strictly applicable only in the far wake region (Jensen N. , 1983) (Katic et al., 1986). Another early wake model was introduced by Frandsen (1992) and the wake effect considered as roughness elements.

A survey about wake models was made by Crespo et al. in 1999. They discussed the wake models and reported a computational wake model UPMWAKE to be one of the best wake models. In that model, the wind turbines are modeled by taking into account atmospheric stability and surface roughness. Ishihara et al. (2004) introduced a new wake model by taking account the rate of wake recovery. They used an analytic wake model which is based on turbulence and made a wind tunnel experiment. Then, Frandsen et al. (2006) improved their wake model by taking account multiple wake interactions. But their improved wake model handled only regular array models of the wind farm. The main disadvantage of their model was that the wind turbines had to be located with equal distances from each other. This limited the layout design of turbines in the farm and turbines were not allowed to be placed in different coordinates except predetermined rows in the farm.

Figure 1. 6. Wake effects in a wind farm (Mechali, et al., 2006)

In this study, Jensen model is used. It is global momentum conservation based analytical model to compute power generation of a wind turbine which is in the wake of one or more turbines. The model representation is given in figure 1.7. While dashed arrows represent free stream wind velocity of the area, minor arrows represent affected wind speeds after wake. The wake model is derived by conserving momentum across a control volume in the wake of a turbine and Mittal gave in detail all derivations in his study (Mittal, 2010). The velocity deficit is computed by equation 1.1.

$$Vel\_def = 1 - v_{down} / v_{up} = (1 - \sqrt{1 - C_T} / (1 + \kappa d/R)^2) \quad (1.1)$$

Vel_def represents the velocity deficits and is calculated by one minus the proportion of wind speed after wake effect v_{down} to initial wind speed v_{up}. Velocity deficit depends on the distance of turbines d to each other and some properties of turbines such as; C_T is the thrust coefficient, κ is the wake spreading constant, and R is the rotor radius of the wind turbines.

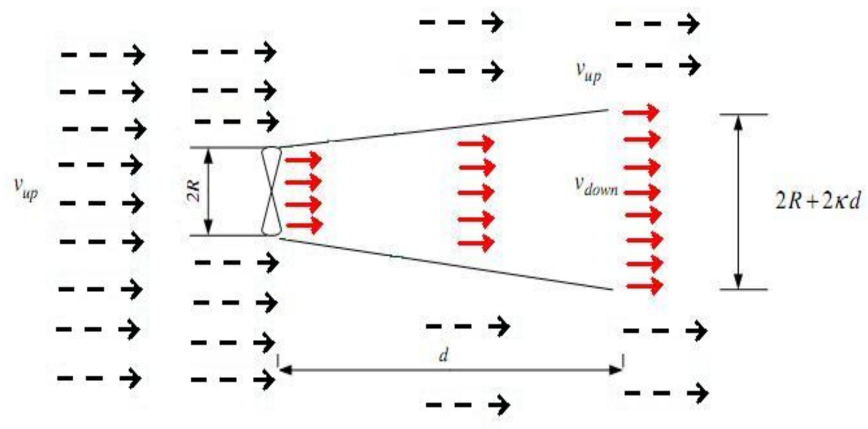

Figure 1. 7. Schematic representation of Jensen's Wake Model for a single wind turbine wake effect

For the large wind farms, commonly a wind turbine can be affected more than one turbine's wakes. If such a situation occurs, the cumulative wake effect for the *ith* turbine in the wake of *jth* turbine is computed by the equation 1.2

$$Vel\_def_i = \sqrt{\sum_{j=1,j\neq i}^{Nt} Vel\_def_{i,j}^2} \tag{1.2}$$

where $Vel\_def_{i\,j}$ refers to velocity deficit of the *ith* turbine in the wake of *jth* turbine.

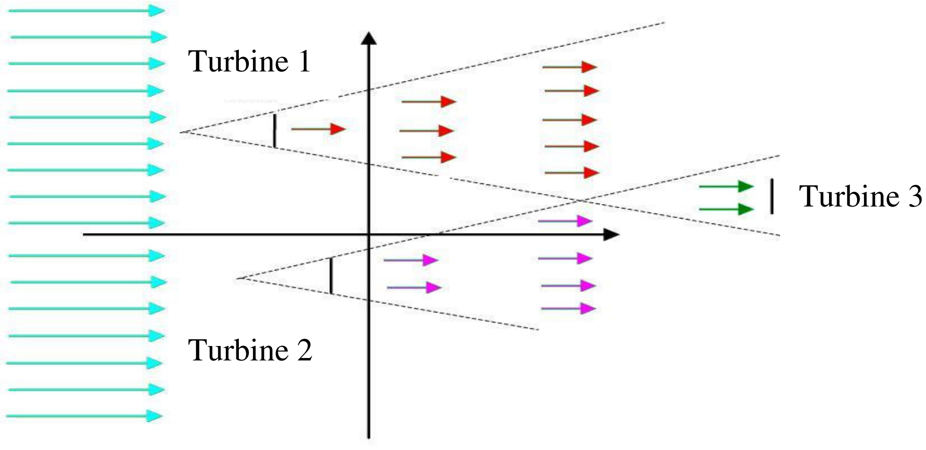

Figure 1. 8. Schematic representation of Jensen's Wake Model for multiple wind turbine wake effect

It can be seen in the figure 1.8 that the third turbine is effected first and second turbines' wakes and turquoise arrows represent free stream wind velocity of the area, red arrows represent affected wind speeds after first turbine's wake, purple arrows represent affected wind speeds after second turbine's wake, and green arrows represent affected wind speeds after cumulative wake.

1.5 Wind Farm Layout Optimization: Literature Review

Wind energy has important share in energy generation systems especially for the last decades. It can be also understood from the sharp increase of the wind farm layout optimization problems literature for the last three years (figure 1.9). The last researches and developments in wind energy sector have increased the sizes of wind turbines and decreased the prices per installed production capacity of energy (Thor & Taylor, 2002). In this regard, developments in wind energy technology were researched by patent analysis of wind energy technology by Daim et al. (2011). New technologies for horizontal wind turbine systems (axis of the turbine is aligned with the wind direction) and vertical wind turbine systems (axis of the turbine is perpendicular to the wind direction) were discussed in their work (Daim et al., 2011). The wind power potential around the world is mentioned in several studies (Erdoğdu, 2009) (Golaita et al., 2009).

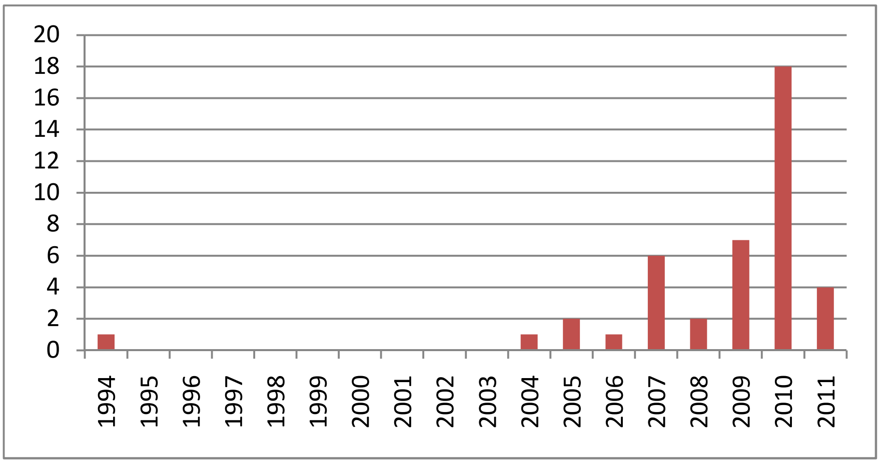

Figure 1. 9. Number of studies according to years

The new trends in wind power such as offshore technologies encourage many researchers to develop new strategies for optimal design and operation of wind energy systems (Henriksen, 2010). Determination of the probable wind power availability according to historical wind data is one of the important work areas in the wind sector (Nigim & Parker, 2007). Power estimation of the wind farm is another important one and many solution methods were used to determine the optimum power generation of a wind farm. Geometrical parameters of the wind turbines could be optimized in order to optimize the generated power of a given windy site. Benini and Toffolo (2002) presented a multi-objective evolutionary algorithm for optimizing geometrical parameters of the rotor configuration of stall-regulated horizontal-axis wind turbines. An optimization model for the design of a typical blade structure of horizontal axis wind turbine was concluded by Maalawi and Negm (2002). By the way, a literature survey of methods applied to the optimal design of wind turbine blades was presented by Jensen et al. (2011). On the other hand, Kusiak et al. studied on optimization of wind power output while minimizing the vibration of the drive train and of the tower by using a multi objective evolutionary algorithm (Kusiak, et al., 2010).

The layout design problems is also aiming the maximum power output of a wind farm and consist of determining the optimum positions of the wind turbines within the wind farm (Rasuo & Bengin, 2010). The positions of the turbines affect each other in the way of energy production. If the location of a turbine changes in the farm, the energy production of other turbines will be affected dynamically through wake effect. This makes the problem complex to determine the generated power and optimum locations of the turbines.

Heuristic approaches have become important by the fast development of the information technologies. Thus, such a complex problem, which needs computer based algorithms, has been more studied after 2005. Elkinton et al. surveyed the algorithms for offshore wind farm layout designs (Elkinton et al., 2008). Another survey (Samorani, 2010) was directly related with the wind farm layout optimization problem (WFLOP) but it could be understood that it was inadequate because most of the studies raised in the year 2010 and later. The last survey is about optimization methods applied to renewable and sustainable energy (Banos et al., 2011) but wind farm layout optimization problem was not considered properly.

In this section, the lack of literature survey on wind farm layout optimization problems is fixed by surveying eighteen articles in different journals, twenty proceedings in different congress and conferences, and three Master of Science and Doctor of Philosophy theses.

Wind farm layout optimization is first considered by Mosetti et al. in 1994 and the maximum generated energy was the main objective subject to minimum installation costs. Because the problem has very complex mathematical models, they used a discrete wind farm representation for the wind farm and a genetic search approach was used to get solution. They used a square grid approach for the wind farm representation which is divided into 100 possible turbine locations with each have 5 wind turbine rotor diameters distances from each other. Three case studies were mentioned according to wind speeds and directions. In the first case the wind had fixed speed and was blowing at one direction, in the second case the wind had fixed speed but was blowing uniform directions, and in the third one the wind had different speeds and was blowing different directions. Many of the researchers have studied the same problem by different approaches.

Öztürk and Norman (2004) handled the same problem with a non-linear problem approach and they discussed that the problem could be converted to a non-linear optimization problem without taking account wake effects. They also compared the problem in continuous search space in the farm with the discrete one and discussed that the using a continuous representation of the area prevent from putting a grid structure like a predetermined coordinates for the turbines. A Greedy Search algorithm was used for different scenarios which they improved to test their approach.

Grady et al. (2005) used a genetic algorithm approach for the same problem and they discussed the results with best known solutions of the problem. Because the genetic algorithm approach is very appropriate for the discrete representation of the problem, a distributed genetic algorithm was suggested by Huang (2007) for the same problem and objective function. He also used a hybrid genetic algorithm with steepest ascent hill-climbing approach (Huang, 2009) and concluded that the proposed strategy was better the previous ones by means of the objective function and termination times of computing.

A Monte Carlo simulation method brought a different perspective to the solution approach of wind turbine placement problem with the statistical and mathematical characteristics of the method (Marmidis et al., 2008). The solution methodology depended on the previous solutions generated by the Monte Carlo Simulation method by taking account the probabilities of the previous turbine coordinates which make the wind farm more powerful.

Bilbao and Alba (2009-a) used a simulated annealing and the improved the known best results of the same problem according to previous studies. Then, they studied on a real data for the same problem and used genetic algorithm and particle swarm optimization method (Bilbao & Alba, 2009-b). They also discussed the real data application for wind farm optimization with genetic algorithms and simulated annealing approaches (Bilbao & Alba, 2010). The conclusion of their study was that the proposed methods outperformed existing ones and produced useful results for real wind farms. Meanwhile, Emami and Noghreh (2010) presented a new coding approach and novel objective function. The cost, power and efficiency of wind farm could be more controllable by the proposed objective function and they also used genetic algorithm approach.

Mittal subjected to the same problem for his Master of Science Degree (Mittal, 2010). He discussed the problem with larger search space than previous studies by taking the grid spacing 1/40 wind turbine rotor diameter which was 5 rotor diameters in previous studies and used a genetic algorithm approach. Thus, the wind farm area has looked more realistic. Results were compared with previous studies and structural differences have provided to get better solutions.

Wan et al. (2009-a) used improved wind and turbine models by using genetic algorithms and results compared with previous studies. All mentioned before genetic algorithms have a zero-one based gen codes. By the way, real coordinate coded genetic algorithm approach was performed and better solutions were concluded (Wan et al., 2009-b). They discussed that the proposed models have given the better realistic results than previous studies. Wang et al. (2009-a) studied the same problem with a non-linear wake effect function with a genetic algorithm solution approach. They concluded that the non-linear wake effect approach was more suitable than traditional one-dimensional one. Wang et al. also (2009-b) proposed a genetic algorithm by introducing the shape of grids, arranging the direction of grids, and the density of the grids. They discussed the grids' division method to increase the power capacity of the wind farm. Li et al. (2010) presented a novel approach to the problem by implementing Equilateral-Triangle Mash method into genetic algorithm approach and concluded that if there was a dominated wind direction in a wind farm, the mashing method had advantageous. Wan et al. (2010) also used a particle swarm optimization approach by taking search space as continuous wind farm area. Rasou et al. (2010) (Rasuo & Bengin, 2010) also studied the same problem as continuous and used genetic algorithm. They concluded that the positions of the turbines should be adjusted freely so that the wake effects could be reduced. It was seen that the proposed approach has given better results than traditional binary genetic algorithm approaches.

DuPont and Cagan (2010) suggested an extended pattern search approach by infusing stochastic characteristics to aid escaping local optima. They concluded that the extended pattern search algorithm was able to generate slightly higher efficiency and higher power capable layouts.

An analytical frame work was suggested by converting the cost of energy into a function of turbine positions (Lackner & Elkinton, 2007). The continuous functions of the wind speed data were characterized by direction sector and fitted to the Weibull parameters for each. Thus, the wake losses could be computed as a reflection of Weibull scale parameter and the energy costs could be calculated with respect to the positions of turbines only.

Elkinton (2007) has developed an analysis tool capable of estimating cost of energy from offshore wind farms in his Doctor of Philosophy degree. The tool consists of several models components such as major costs, energy production, and energy losses. He used a Greedy search and genetic algorithm in his study. By the way, Rivas also was interested in offshore wind farm layout optimization in his Master of Science degree (Rivas, 2007) (Rivas et al., 2009). He used a simulating annealing algorithm by adding three operations named *remove*, *move*, and *add*. Also Szafron (2010) handled the same problem using Genetic Algorithm Toolbox of Matlab.

The spaces between the turbines generally were taken as fixed distances but Shengping and Li (2010) handled them as decision variable to optimize economic benefits of the wind farm. The wind direction and wind speeds were not case parameters. They analyzed topology, turbulence, geomorphology, wake, and economic features of the wind farm to obtain their objective.

Wake effects have important role for maximizing power output of wind farms. Wagner et al. (2011) proposed an evolutionary algorithm to solve the WFLOP for from 100 to 1000 turbines. This study differs from others in the way of very big number of turbines. Thus, the wake effects could be more understandable.

Many researchers take the one type turbine in a wind farm with the same hub height and capacity specifications, on the other hand, Mora et al. (2007-a) interested in different turbine types to optimize the profit given an investment on a wind farm. Genetic algorithm and evaluative algorithm was the solution procedure of that study and the main purpose of the algorithms was to determine the turbine type and location to minimize the investment cost and the most efficient use of the wind sources. Then, Mora et al. (2007-b) added new parameters to the same problem such as low and high voltage lines, substations, and existing transmission lines etc. Thus, the problem was divided to two sub-problems having two objective functions for the first part was optimization of turbine layout and the second part was optimization of wind farm network configuration. After that, Gonzales et al. (2009) (2010-a) discussed the problem by taking account the costs of roads and towers and used a genetic algorithm and evaluative algorithm. By including the future risks on the change of electricity prices, discount rate of the money and etc. the problem was remodeled and solved by Gonzales et al. (2010-b) using genetic algorithm and evaluative algorithm. After all, Gonzales et al. (2011) studied on overall design optimization of wind farms including different type of turbines, future risks, and investment projects to optimize the profits using evaluative algorithms.

While heuristic methods were used in most of the WFLOPs, there have been few studies which use integer programming models to obtain optimum layout configurations. Donovan (2005) proposed three integer models, two of them vertex packing models and the third one was a mixed-integer programming model. Then he improved his approach with a more effective branching strategy, a stronger model formulation, and dynamic constraint generation (Donovan, 2006). Mustakerov and Borissova also studied the WFLOP with different type of wind turbines and proposed mixed-integer nonlinear programming approach (Mustakerov & Borissova, 2010) (Borissova & Mustakerov, 2010). They tested the proposed approach for several test cases and used predominant and uniform wind directions. Also they explained their approach in a book chapter in details (Mustakerov & Borissova, 2011). It was seen that the cases including non-uniform wind directions and different wind speeds were not considered as a combinatorial optimization process.

A real case study was mentioned by Şişbot et al. (2010) for the Gökçeada wind farm using multi-objective genetic algorithm. The budget was one of the main constraints. Fixed wind speed and single wind direction were considered.

Most of the studies are related to find number of turbines or to determine the type of turbines. Nearly all of them suggest that the wind farm has a grid area and this is a disadvantage for the placement of turbines to any place in the farm. Kusiak and Song (2010) made some assumptions for the WFLOP by taking account industrial applications of wind energy. They assumed that it was not necessary to determine the wind turbine number because it must been known before the investment so it fixed. The wind must be homogenous to decrease the maintenance costs so the turbines must have similar specifications; actually they have to be the same brand. By taking account these assumptions; they developed an evolutionary strategy algorithm for the WFLOP with continuous variable for turbine locations. Two wind scenarios were used to test the model and algorithm. Eroğlu and Seçkiner (2010, 2011) were also interested in the same problem and developed an Ant Colony Approach with continuous wind farm variables to test performance of the algorithm for WFLOP. Their results showed that Ant Colony Optimization was also a useful and competitive approach for the wind farm layout optimization problems.

Because Kusiak and Song’s study (2010) was more realistic with an industrial application and its assumptions than other problem statements in the literature, this study handles the identical problem statements with it. Problem statements were mentioned in next chapter in detailed. Ant Colony Optimization and a new approach – Particle Filtering – were used as solution strategies. These methods were given in Chapter 3 and explained in detail. Experimental studies were introduced in Chapter 4. Results and discussions were mentioned in Chapter 5. Finally, conclusions and recommendations were given in Chapter 6.

CHAPTER 2

PROBLEM STATEMENT

2.1 Problem Definitions

The problem has some definitions to determine construct the farm area and turbine structures, and the relationship between farm area and turbines. Therefore, the mentioned WFLOP environment consists of following assumptions:

1. The number of turbine is fixed in the farm because; the power capacity of the farm is generally planned at the beginning of the investment. For instance; if an investor has planned a 75MW-wind farm project with budget and other limitations, 50 times 1.5 MW turbines were needed. So, in the model, the number of turbines *Nt* is not a variable.

2. The layout representations of the turbines are two-dimensional Cartesian coordinates (x, y) and length of a location of turbine L_l is computed by equation 2.1

   $$L_l = \sqrt{x^2 + y^2} \qquad (2.1)$$

   The surface roughness of the terrain can be negligible and the optimal solution is represented with two-dimensional Cartesian coordinates (x_i, y_i), where $i = 1, 2, \ldots, Nt$

3. All wind turbines have the same specifications (i.e., the theoretical power, the power curve, the brand and model, the hub height) in the farm so that the farm is homogenous. Thus, the transportation, maintenance, and worker's training costs would be reduced. The visual impact of the farm has also advantage being a homogenous structure.

4. For a given location, height, and direction, wind speed v follows a *Weibull* distribution such as equation 2.2. Determination of the *Weibull* probability density function $p_v(.)$ depends on two parameters; k, a shape factor and c, a scale factor (Manwell et al., 2008).

$$p_v(v, k, c) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \tag{2.2}$$

This assumption is hold for many windy sites in long-term (Manwell et al., 2008).

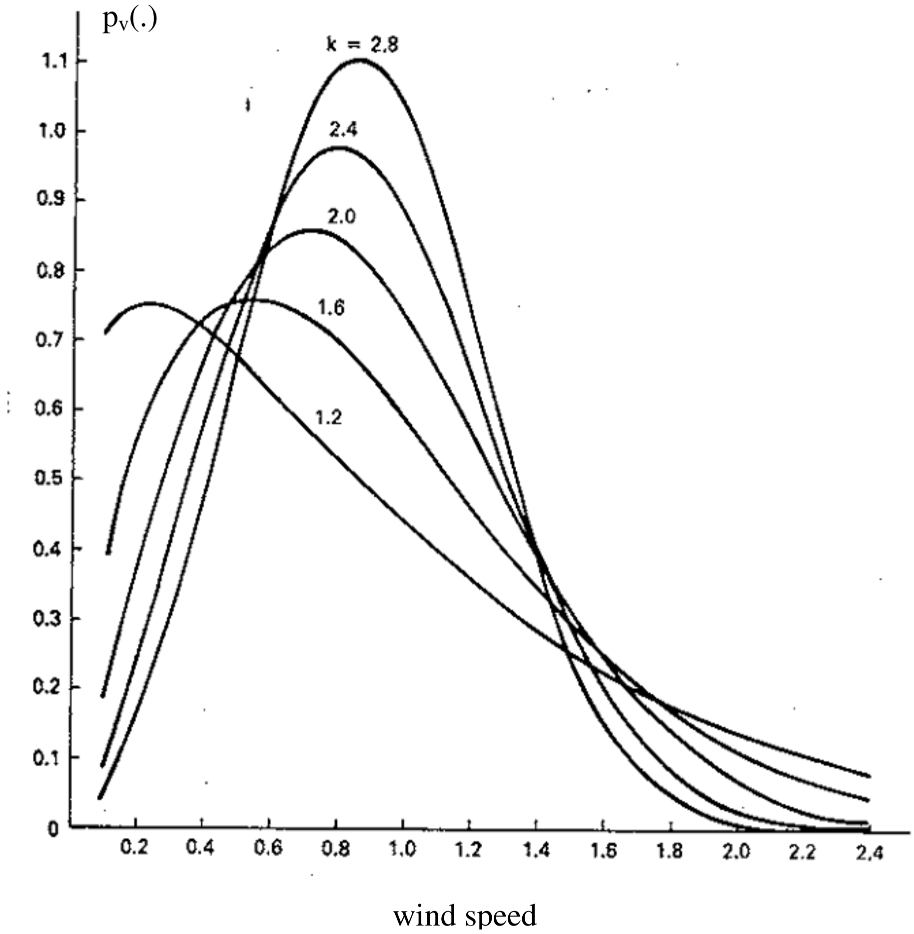

Figure 2. 1. Weibull probability density function p_v for scale parameter c = 1 (Johnson, 2001)

5. Wind speed is given as a parameter of the Weibull distribution function and it is continuous function of the wind direction θ such as $k = k(\theta)$, $c = c(\theta)$, and $0° \leq \theta \leq 360°$). This means that k is a function of θ and c is a function of θ. In a wind farm, wind speeds at different locations with the same directions have the same Weibull parameters. Wind direction is one of the important variables for the WFLOP. The illustration of the wind directions for the model is shown in figure 2.1 where is stand for 0° East and 90° is stand for North directions.

6. There must be a sufficient space between any two turbines to reduce some hazardous loads on the turbine such as wind turbulence. Since this can be a complex constraint, any two turbines are separated from each other by at least 4 rotor diameters in this study. If the rotor radius of turbine is R, any two turbines are located at (x_i, y_i) and (x_j, y_j), then this has to satisfy the inequality $(x_i - x_j)^2 + (y_i - y_j)^2 \geq R^2 * 64$.

7. Because this problem is a layout optimization problem, the shape of the layout –boundary of the farm has to be described. The shape of the farm could be a square, rectangular, triangle, or any other shape or it could be defined as a function with some variables. In this study, a circular wind farm shape is selected as a boundary in the model (Figure 2.1) because the mentioned problem was solved before (Kusiak & Song, 2010) as a circular.

8. Turbines must be in the farm and this is geometrically represented by the equation of $x_i^2 + y_i^2 \leq r^2$ where r is the radius of the circular farm and it is 500 m and (x_i, y_i) is the coordinates of the ith turbine. (The center of the farm is represented by $(0,0)$ on the coordinate system (Figure 2.1))

9. Search space of the problem has continuous coordinate variables and it is restricted with the wind farm shape. Thus, the turbines could be freely located in the farm without a predetermined grid system.

10. The mathematical model of the problem is constructed in two parts. First part is power output and objective function model which is improved by Kusiak

and Song (2010). The second part is the wake effect model that may cause lower power generation of the downstream turbines. The Jensen's model (Jensen N. , 1983) (Katic et al., 1986) is used and adapted the continuous search space area.

11. The objective is to maximize power output so that the wake effect model can be minimized with respect to assumptions sixth and eighth. The layouts of the turbines in the wind farm would cause the wake effects. Because, the maximization of the power output depends on the optimum layout configuration of the wind turbines in the farm, the optimization problem is actually a layout problem.

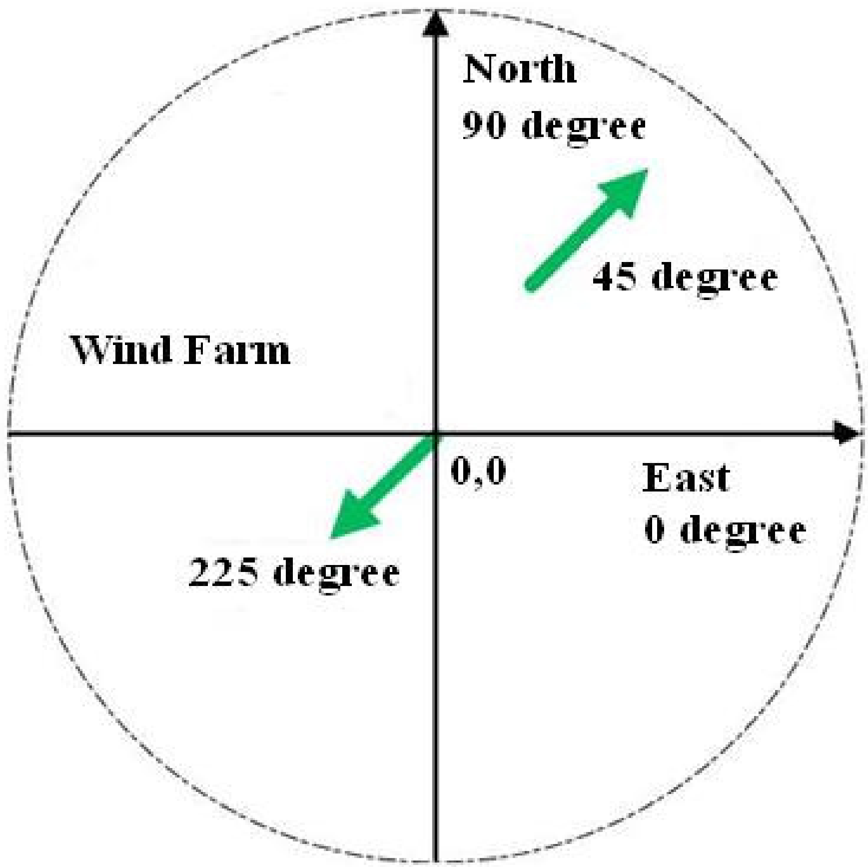

Figure 2. 2. Wind farm boundary and the wind speed directions (Kusiak and Song, 2010)

The problem was considered by three wind scenarios. The wind direction is divided at 24 intervals of 15° each (Kusiak & Song, 2010) in the wind farm layout design environment. In the prior study (Kusiak & Song, 2010), two wind scenarios were used to illustrate the concepts and numerical examples for an industrial case. Addition to this, it is created a new scenario to discuss the wake effects in a uniform wind case. The first case is a fixed wind speed blowing from North dominated directions. The second one is that wind commonly blows from between North West and South West with variable speeds. Case three considers a wind structure which blows from everywhere with uniform probabilities for each direction and a fixed wind speed.

2.1.1 Case A: Wind Blows from the North with Fixed Speed

The first case discusses the fixed wind speed for predominated windy sites. Thus, an investor could determine the layout configuration of the turbines. These kinds of sites have advantageous in terms of project and budget planning steps according to unstable ones. The wake losses could be decreased and more power would be generated. Table 2.1 gives the characteristics of the first case in terms of wind directions, Weibull parameters, and wind blowing probabilities. This table can be read as follows;

Table 2. 1. Wind Characteristics of the farm: Case A

Angle interval (l-1)	Angle (Θ_{l-1})	Angle (Θ_l)	Shape Parameter (k)	Scale Parameter (c)	Blowing Probability (w_{l-1})
0	0	15	2	13	0
1	15	30	2	13	0.01
2	30	45	2	13	0.01
3	45	60	2	13	0.01
4	60	75	2	13	0.01
5	75	90	2	13	0.2
6	90	105	2	13	0.6
7	105	120	2	13	0.01
8	120	135	2	13	0.01
9	135	150	2	13	0.01
10	150	165	2	13	0.01
11	165	180	2	13	0.01
12	180	195	2	13	0.01
13	195	210	2	13	0.01
14	210	225	2	13	0.01
15	225	240	2	13	0.01
16	240	255	2	13	0.01
17	255	270	2	13	0.01
18	270	285	2	13	0.01
19	285	300	2	13	0.01
20	300	315	2	13	0.01
21	315	330	2	13	0.01
22	330	345	2	13	0.01
23	345	360	2	13	0

If the wind direction is between 75° and 90° (the 5th wind direction interval), the wind speed follows a *Weibull* distribution with a shape parameter (*k=2*) and a scale parameter (*c=13*), and the wind blowing probability of that wind direction interval is *0.2*. For example, if the wind speed is 8 meter/second for the 5th interval, the *Weibull* probability density (equation 2.2) would be as follows;

$$P_{v5} = (2/13)*(8/13)^2 e^{-(8/13)\,\hat{}\,2} = 0.03989.$$

2.1.2 Case B: Wind Blows from the North West and South West with Variable Wind Speeds

Variable wind speeds are considered in the second case with predominated larger wind direction intervals between North West and South West. These kinds of sites are more realistic sites and they occurs many of the windy sites on the world. The wake losses could be more than the first case. Table 2.2 gives the characteristics of Case B in terms of wind directions, Weibull parameters, and wind blowing probabilities.

Table 2. 2. Wind Characteristics of the farm: Case B

Angle interval (l-1)	Angle (Θ_{l-1})	Angle (Θ_{l})	Shape Parameter (k)	Scale Parameter (c)	Blowing Probability (w_{l-1})
0	0	15	2	7	0,0002
1	15	30	2	5	0,008
2	30	45	2	5	0,0227
3	45	60	2	5	0,0242
4	60	75	2	5	0,0225
5	75	90	2	4	0,0339
6	90	105	2	5	0,0423
7	105	120	2	6	0,029
8	120	135	2	7	0,0617
9	135	150	2	7	0,0813
10	150	165	2	8	0,0994
11	165	180	2	10	0,1394
12	180	195	2	10	0,1839
13	195	210	2	9	0,1115
14	210	225	2	9	0,0765
15	225	240	2	7	0,008
16	240	255	2	5	0,0051
17	255	270	2	3	0,0019
18	270	285	2	8	0,0012
19	285	300	2	5	0,001
20	300	315	2	6	0,0017
21	315	330	2	5	0,0031
22	330	345	2	5	0,0097
23	345	360	2	4	0,0317

2.1.3 Case C: Wind Blows from the Uniform Directions with Fixed Wind Speeds

Although the Case C has a fixed wind speed with a Weibull shape parameters similar to the Case A, the wind blowing probability of all wind directions is set to 0.041667 identically. This makes the windy site less profitable because the wake losses occur more than first two cases. Table 2.3 gives the characteristics of Case C in terms of wind directions, Weibull parameters, and wind blowing probabilities.

Table 2. 3. Wind Characteristics of the farm: Case C

Angle interval (l-1)	Angle (Θ_{l-1})	Angle (Θ_l)	Shape Parameter (k)	Scale Parameter (c)	Blowing Probability (w_{l-1})
0	0	15	2	13	0.041667
1	15	30	2	13	0.041667
2	30	45	2	13	0.041667
3	45	60	2	13	0.041667
4	60	75	2	13	0.041667
5	75	90	2	13	0.041667
6	90	105	2	13	0.041667
7	105	120	2	13	0.041667
8	120	135	2	13	0.041667
9	135	150	2	13	0.041667
10	150	165	2	13	0.041667
11	165	180	2	13	0.041667
12	180	195	2	13	0.041667
13	195	210	2	13	0.041667
14	210	225	2	13	0.041667
15	225	240	2	13	0.041667
16	240	255	2	13	0.041667
17	255	270	2	13	0.041667
18	270	285	2	13	0.041667
19	285	300	2	13	0.041667
20	300	315	2	13	0.041667
21	315	330	2	13	0.041667
22	330	345	2	13	0.041667
23	345	360	2	13	0.041667

2.2 The Power Model and Objective Function

The power output of a wind turbine is generally represented by a linear model in forms of wind speed (Equation 2.3). The following statement gives the expected power for a given wind speed v. It consists of three parts. The first one is for the wind speeds under cutin wind speed v_{cutin} which is the minimum wind speed that the turbine starts to generate power from this speed and the expected power is *zero*. The second part is a linear equation for the wind speeds between cutin v_{cutin} and rated wind speed v_{rated} (The turbine starts to generate a rated power from this speed to v_{cutout}), where λ is the slope parameter and η is the intercept parameter of the linear power curve function of the linear power curve function. The last part of the model gives the rated power P_{rated} for wind speeds which are between rated wind speed v_{rated} and cutout wind speed v_{cutout} (maximum wind speed that the turbine cut outs generating power after this speed). Next steps express the derivation of the power model (2.3) to the mentioned problem statements.

$$f(v) = \begin{cases} 0, & v < v_{cutin} \\ \lambda * v + \eta, & v_{cutin} \leq v \leq v_{rated} \\ P_{rated}, & v_{cutout} > v > v_{rated} \end{cases} \tag{2.3}$$

In this study, wind is considered as a *Weibull* distribution function and it depends on the wind speed. Thus, the expected power can be represented as follows (Equation 2.4);

$$P(\theta) = \int_0^\infty f(v) p_v\big(v, k(\theta), c(\theta)\big) dv$$

$$= \int_0^\infty f(v) \frac{k(\theta)}{c(\theta)} \left(\frac{v}{c(\theta)}\right)^{k(\theta)-1} e^{-(v/c(\theta))^{k(\theta)}}\, dv \tag{2.4}$$

The *Weibull* distribution function is integrated to the power model, and now it depends on wind directions θ and wind speeds v.

As the wind directions are starting from 0°, ending at 360°; Equation 2.4 is transformed to Equation 2.5 as follows in terms of wind direction θ;

$$P(\theta) = \int_0^{360} p_\theta(\theta)\, d\theta \int_0^{\infty} f(v) \frac{k(\theta)}{c(\theta)} \left(\frac{v}{c(\theta)}\right)^{k(\theta)-1} e^{-(v/c(\theta))^{k(\theta)}} dv \tag{2.5}$$

It can be understood from Equation 2.5 that the wind velocities have to be continuous. To calculate the power generation of the turbines, wind speed is described in Nv+1 equal intervals starting from cut-in wind speed, ending at rated wind speed. Let $v_1, v_2, v_3, \ldots, v_{Nv}$ are the wind speeds and $v_{cutin} < v_1 < v_2 < v_3 < \ldots < v_{Nv} < v_{rated}$, $v_0 = v_{cutin}$ and $v_{Nv+1} = v_{rated}$. After discretization of the wind speed, Equation 2.3 can be transformed by integrating Equation 2.5 as follows (Equation 2.6);

$$P = \lambda \sum_{j=1}^{Nv+1} \frac{v_{j-1} + v_j}{2} \int_0^{360} p_\theta(\theta) \left\{ e^{-\left(\frac{v_{j-1}}{c_i(\theta)}\right)^{k(\theta)}} - e^{-\left(\frac{v_j}{c_i(\theta)}\right)^{k(\theta)}} \right\} d\theta$$

$$+P_{rated} \int_0^{360} p_\theta(\theta)\, e^{-\left(\frac{v_{rated}}{c_i(\theta)}\right)^{k(\theta)}} d\theta$$

$$+\eta \int_0^{360} p_\theta(\theta) \left\{ e^{-\left(\frac{v_{cutin}}{c_i(\theta)}\right)^{k(\theta)}} - e^{-\left(\frac{v_{rated}}{c_i(\theta)}\right)^{k(\theta)}} \right\} d\theta \tag{2.6}$$

As it is mentioned in section 2.1, the wind directions are also divided into 24 intervals. If the $N\theta$+1 = 24, the expected power curves for the *ith* turbine is calculated by integration of $N\theta$ to the equation 2.6 as follows (Equation 2.7a, 2.7b, 2.7c, and 2.7d);

$$P_\lambda = \lambda \sum_{j=1}^{Nv+1} \left(\frac{v_{j-1}+v_j}{2}\right) \sum_{l=1}^{N\theta+1} (\theta_{l-1}-\theta_l) w_{l-1} \left\{ e^{-\left(\frac{v_{j-1}}{c_i\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}\right)^{k\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}} - e^{-\left(\frac{v_j}{c_i\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}\right)^{k\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}} \right\}$$

(2.7a)

$$P_r = P_{rated} \sum_{l=1}^{N\theta+1} (\theta_{l-1}-\theta_l) w_{l-1}\, e^{-\left(\frac{v_{rated}}{c_i\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}\right)^{k\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}} \tag{2.7b}$$

$$P_\eta = \eta \sum_{l=1}^{N\theta+1} (\theta_{l-1}-\theta_l) w_{l-1} \left\{ e^{-\left(\frac{v_{cutin}}{c_i\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}\right)^{k\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}} - e^{-\left(\frac{v_{rated}}{c_i\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}\right)^{k\left(\frac{\theta_{l-1}+\theta_l}{2}\right)}} \right\}$$

(2.7c)

$$P_i = P_\lambda + P_r + P_\eta \tag{2.7d}$$

After computing such a complex power generation equation for one turbine, total expected energy generation of the farm is computed by Equation 2.8.

$$P_f = \sum_{i=1}^{Nt} P_i \tag{2.8}$$

The objective of this study is to maximize power output of the wind farm with respect to assumptions six and eight mentioned in section 2.1 and this is represented by the following mathematical model (Equation 2.9a, 2.9b, and 2.9c);

$$\text{Objective max } P_f \tag{2.9a}$$

Subject to

$$x_i^2 + y_i^2 \leq r^2 \tag{2.9b}$$

$$(x_i - x_j)^2 + (y_i - y_j)^2 \geq 64R^2 \tag{2.9c}$$

The maximum power output (2.9a) of the wind farm is aimed while the all turbines are in the farm (2.9b) and any two turbines are separated from each other by at least 4 rotor diameters (2.9c). Thus, the optimum layouts of the turbines would give the maximum power output.

2.3 The Wake Effect Model

The wake model proposed by Jensen (Jensen N. , 1983) (Katic et al., 1986) is the most suitable wake model for this study because the wind farm characteristics are considered as the far wake region (assumption six: any two turbines are separated from each other by at least 4 rotor diameters).

Because the wind characteristics are based on *Weibull* distribution, only the scale parameter c is affected the wake in the power model (Equation 2.7) (Kusiak & Song, 2010) (Equation 2.10).

$$c_i(\theta) = c(\theta)*(1-Vel\_def_i) \tag{2.10}$$

While computing the velocity deficit by equation 1.1 in section one, the distance of the wind turbines *d* according to wind direction θ is computed as follows (Equation 2.11) for *ith* and *jth* turbines;

$$d_{i,j} = |(x_i - x_j)*\cos(\theta) + (y_i - y_j)*\sin(\theta)| \quad (2.11)$$

The distance $d_{i,j}$ between *ith* and *jth* turbines is computed by absolute value and it can be seen from the equation 2.11 that the wind directions are integrated to the velocity deficit equation as *sin(θ)* for the *y coordinate* distance and *cos(θ)* for the *x coordinate* distance.

CHAPTER 3

METHODOLOGY

The WFLOP has been mentioned in the literature commonly as a discrete optimization problem except Kusiak and Song (2010), Öztürk and Norman (2004), Wan et al. (2010), Rasuo et al. (2010), and Rasuo and Bengin (2010). They handled the problem as a continuous optimization problem. Thus, the problem could be more realistic so that all turbines would be placed freely in the wind farm without predetermined grid-structured zones. In this study, Ant Colony Optimization algorithm was applied to a continuous wind farm layout optimization problem and Particle Filtering approach was firstly introduced for optimization problems and applied to continuous wind farm layout optimization problems, although it was never used before for optimization studies.

The solution approach to solving this problem was similar with Kusiak and Song (2010), but some details were different. In the proposed ACO algorithm and PF approach, sixth assumption (any two turbines are separated from each other by at least 4 rotor diameters) and eighth assumption (all turbines must be in the farm region) were used as constraints instead of the second objective function. Thus, ACO and PF searched the optimum layout of the turbines to maximize power output and satisfy the constraints in such a way that the resulting solution would be feasible.

3.1 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a method to find optimum values for discrete problems in 1992 by Dorigo (1992). The algorithm mimics the real ant colony behavior while they look for food (Socha & Blum, 2007) (figure 3.1). Main steps of the ACO are given as followings;

I. Ants randomly explore the area to find food.
II. They leave a chemical pheromone trail on the way while they are moving the food to the nest.
III. Pheromone quantity increases/decreases according to food quantity and the distance between the food and the nest.
IV. Other ants go to food source according to amount of the pheromone.

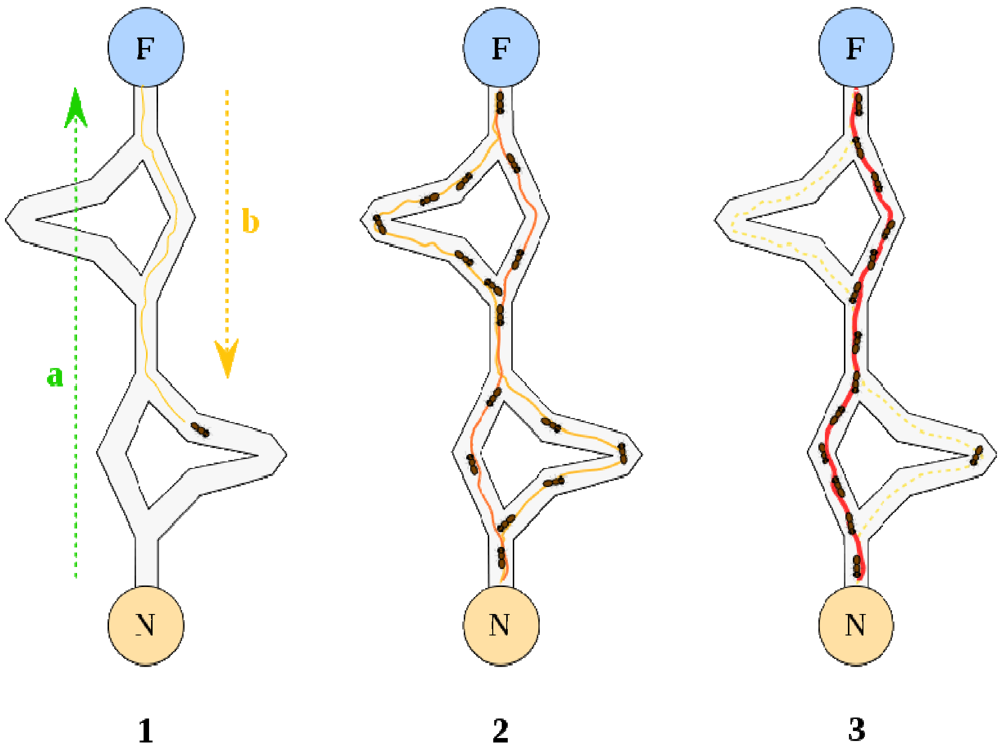

Figure 3. 1. Behavior of ants while taking the food to the nest

The canonical ACO algorithm is illustrated in figure 3.2. The first step consists of initialization of the pheromone trail. Then, each ant constructs a complete solution to the problem according to a probabilistic state transition rule which depends mainly on the state of the pheromone. Finally, quantity of pheromone is updated in two phases; an evaporation phase where a fraction of the pheromone evaporates, and a reinforcement phase where each ant deposits an amount of pheromone which is proportional to the fitness of its solution. This process is iterated until a stopping criterion.

initialize *m, T, best ant,* π_{ij0}

randomly generate m ants using $p_{ij} = \frac{(\tau_{ij0})^{\alpha}(ή_{ij})^{\beta}}{\sum_{l=1}^{N_i}(\tau_{il0})^{\alpha}(ή_{il})^{\beta}}$

for $t = 1$ *to* T {

for $k=1$ *to* m {

evaluate ant k

if ant k better than *best ant k*

best ant=ant k

$\Delta\ \pi_{ijt}$ – fitness of *ant k* if using assignment *ij*

otherwise 0

}

$\Delta\ \pi_{ijt} = \rho\pi_{ijt-1} + \sum_{k=1}^{m} \Delta\tau_{ijt}$

for $k=1$ *to* m{

construct new ant k using $p_{ij} = \frac{(\tau_{ijt})^{\alpha}(ή_{ij})^{\beta}}{\sum_{l=1}^{N_i}(\tau_{ilt})^{\alpha}(ή_{il})^{\beta}}$

}

}

return *best ant*

Figure 3. 2. Canonical Ant Colony Algorithm

The first application of the Ant Colony Optimization (ACO) was introduced by Dorigo et al. in 1997 to the Travelling Salesman Problem. Many other combinatorial optimization problems could be solved by Ant colony Optimization approach and its theory was given in detailed by Dorigo et al. (2005). By the way, Dereli et al. (2009)

presented a detailed survey on the use of swarm intelligence-based techniques for public service problems. They remarked that ACO had been employed in a large number of studies for electricity (power) services, waste management services, gas service, and any other public service problems because ant-inspired algorithms had promising potential for modeling and solving complex and networked problems (Dereli et al. 2009). This encouraged us to handle the wind farm layout optimization problem by Ant Colony approach to find optimum layout configurations of turbines in a wind farm in order to get maximum power output.

3.1.1 Ant Colony Algorithm for Wind Farm Layout Optimization Problem

ACO has a restricted application of continuous optimization problems because of its discrete nature (Zhao et al, 2008). Although there are many different successful approaches on ACO based algorithms to find optimum solution of a continuous problem, most of these approaches do not follow the original ACO framework (Socha & Blum, 2007). For example, Bilchev and Parmee (1995), Monmarche´ et al. (2000), Dréo and Siarry (2002), Mathur et al. (2000), and Socha and Dorigo (2008) have studied on continuous ant colony optimization because of ACO's practicability. Continuous Ant Colony Optimization (CACO), Continuous Interacting Ant Colony (CIAC), Adaptive Ant Colony Algorithm (AACA), and Binary Ant System (BAS) are some of the ACO related works which are constructed to continuous optimization problems (Kovarik, 2006).

The intensity of the pheromone trail is one of the parameter of the ACO algorithm that ants make and its value is associated with a finite set of discrete values related to the decisions. In order to make the pheromone adaptation of ACO to the continuous problem, in the many studies, a solution archive is used as a way of describing the pheromone distribution over the continuous search space (Socha & Blum, 2007) (Socha, 2008) (Afshar & Madadgar, 2008). This solution archive style is based on a ranking of solutions from better to worse and it used for the pheromone structure of this study. Main steps of the proposed algorithm are given in figure 3.3.

First of all, initialization is made by setting initial parameters such as maximum iteration number, number of ants, and number of turbines. An initial solution is generated randomly and theoretical powers of each turbine Pup_i and generated power of the farm total *totPup* are computed without wake effect. These are the ideal power values that can be maximum output. Then, *velocity deficits*, c_i, P_i, and P_f values are computed.

```
1. Initialization;
Set the initial values: Number of turbines Nt, Number of ants
Generate initial solution:   Randomly locate each turbine with respect to
assumptions six and eight and compute Pup_i and totalPup_i as the optimal
solution
2. Compute Vel_def_i, c_i, P_i, and P_f
3. set best=P_f
4. for iter=1 to MaxIter
5. compute π_i and number of ants Tant_i for each turbine proportional with π_i
 if  best ≠ totalPup_i  or iter ≠ MaxIter
   for each turbine i=1 to Nt
     for ant=1 to Tant_i
       re-locate turbine i randomly with respect to assumptions six and eight
      end
      re-compute (2)
      if  P_f > best
       best = P_f and update farm by new best turbine locations
      end
    end
    re-compute (5)
else
STOP
P_f  is the solution and turbine locations (farm) give the optimized layout
```

Figure 3. 3. Ant Colony Optimization algorithm for the WFLOP

The pheromone structure of the proposed ACO algorithm is computed by the following formulas (Equations 3.1 - 3.3),

$$D_i = Pup_i - P_i \tag{3.1}$$

$$TD = \sum_{i=1}^{Nt} D_i \tag{3.2}$$

$$\pi_i = D_i / TD \tag{3.3}$$

D_i is the difference between expected power P_i and the ideal power Pup_i of *ith* turbine. Total difference *TD* is the sum of each turbine's power loses D_i and the pheromone of the ith turbine π_i is equal to the proportion of the power loss of *ith* turbine to the total power loss of the wind farm.

Thus, if the location of a turbine is worse, the pheromone intensity of it would be higher and more ants try to be better of its location. Turbine re-placement is an arguable process in the WFLOP. While it has a procedure in genetic algorithm by using cross-over and mutations (Mosetti et al., 1994) (Grady et al., 2005) (Huang, 2007) (Emami & Noghreh, 2010), a random re-locating process (Bilbao & Alba, 2009-a) can be used if the algorithm does not allow a rule-based re-location process.

In this study, each iteration runs as follows for the ACO algorithm (figure 3.3);

1. A number of ants, which is proportional with pheromone value of the turbine, replace the turbine's coordinates in a random way.
2. New total power output of the wind farm is compared with the best existing solution.
3. If the new solution is the better than existing one, the wind farm is updated by the new coordinates of the turbines.
4. When one of the stopping criteria is matched, the algorithm terminates. (ACO's stopping criteria are maximum iteration number reached or ideal power output generated).

3.2 Particle Filtering (PF)

Particle Filtering (PF) is an approach that goals to obtain good estimates of the state of a stochastic dynamical system based on observations which are recursively in time. It is also known as Sequential Monte Carlo methods (SMC) based on simulation (Zhou,et al., 2008). It was first introduced by Gordon et al. (1993) and they brought on the use of particle filtering for many signal processing problems. It is one of the most used signal processing methods in today and have an importance in computer vision, visual tracking of an object, and control systems (Doucet et al., 2001) (Djuric et al., 2003) (Cappe et al., 2007). Particle filtering that is based on sequential importance sampling and uses Bayesian theory is a powerful approach for non-linear and non-Gaussian problems (Djuric et al., 2003). Many real-world visual tracking applications can be modeled as a dynamic optimization problem (Pantrigo et al. 2011). There are many applications of particle filtering in signal processing related areas in the literature. A particle filter based algorithm was suggested by Aran and Akarun (2008) for tracking face and hands of a signer. Another study based on tracking problems was mentioned by Krzeszowski et al. (2010) to track the three dimensional model based human body. Pantrigo et al. (2011) also used particle filtering approach to solve the visual tracking problem.

A survey of numerical methods for nonlinear filtering problems was presented by Budhiraja et al. (2007). On the other hand, any application for global maximum or global minimum of the Particle Filtering approach has been never observed in the literature except a framework for randomized optimization problems (Zhou et al. (2008).

Particle Filtering tries to find a posteriori probability distribution (Equation 3.4) as other Bayesian filters. PF uses *Np* weighted particles to converge the posteriori probability of the system (Equation 3.5). It has a state function and an observation function. The state function f_s describes the state of a particle for time t by using the state of it at time $t\text{-}1$ (Equation 3.6) and it models the dynamics of the system. The observation function f_h describes that how a particle at time t matches up with the original state of a system (Equation 3.7) and it models the visibility of the system and returns a probability value (Aran & Akarun, 2008).

$$p(x_t|x_0, Z_{1:t}) \tag{3.4}$$

$$\{(x_t^n, \tau_t^n) : n = 1, \ldots, Np\} \tag{3.5}$$

$$x_t = f_s(x_{t-1}) \tag{3.6}$$

$$z_t = f_h(x_t) \tag{3.7}$$

$$\hat{x}_t = \sum_{n=1}^{Np} x_t^n \tau_t^n \tag{3.8}$$

1. Initialization $\{(x_0^n, \tau_0^n)\}$, $n = 1, \ldots, Np$
2. For t > 0
   i. Re-sampling:
      $\{(x_{t-1}^n, \tau_{t-1}^n)\} \rightarrow \{(x'^n_{t-1}, 1/Np)\}$
   ii. Prudence : $x_t^n = f_s(x'^n_{t-1})$
      $\{(x'^n_{t-1}, 1/Np)\} \rightarrow \{(x_{t-1}^n, 1/Np)\}$
   iii. Weighting: $\tau_t^n \propto z_t^n = f_h(x_t^n)$
      $\{(x_t^n, 1/Np)\} \rightarrow \{(x_t^n, \tau_t^n)\}, \sum_{n=1}^{Np} \tau_t^n = 1$
   iv. Prediction : $\hat{x}_t = E[\{x_t^n, \tau_t^n\}]$

Figure 3. 4. Condensation-Conditional density propagation algorithm for Particle Filtering

A condensation-conditional density propagation algorithm for PF is given in figure 3.4 (Isard & Blake, 1998). Firstly, the starting states and weights of the particles are set for initialization. Re-sampling, prudence, and weighting steps respectively generate the new particles' states and weights for time *t* using equations 3.6 and 3.7. The prediction of the system state could be computed by taking the weighted averages of the particles states (Equation 3.8).

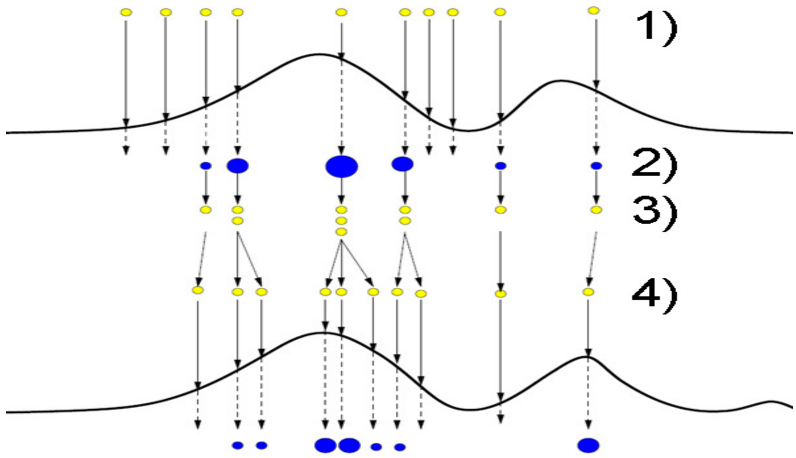

Figure 3. 5. Iterations of Particle Filtering

Figure 3.5 shows the iterations of Particle Filtering. The first step is *Initial Starting* step and all particles have the same weights. The second step is the *Importance Weight* step or *Prudence* step that the weights of the particles could be computed by comparison with real *state* of the object at that *time*. Then *re-sampling* step is the third one that the weights of the particles are re-computed. Finally, particles give *predictions* for the *new states* of the object in the last step.

3.2.1 Particle Filtering Approach for Wind Farm Layout Optimization Problem

Although a framework for randomized optimization problems was suggested by Zhou et al. (2008), any application for combinatorial optimization problems of the Particle Filtering approach has been never observed in the literature. In this study, PF approach was firstly introduced to optimization problems and used for the WFLOP.

The main role of the PF is predicting the current state of an object by using its observed signals in a recursive time. In the WFLOP, each turbine represents identical objects and iteration of the algorithm stand for the time. The observations are the expected power of the turbines P_i, total generated power of the farm P_f, and coordinates of the turbines in the farm. Particles re-locate randomly the turbines in the farm to get new solutions. The observation function f_h gives the probability to a turbine for re-locating in the farm. Initial value for $z_{i,0}$ is equal to 1 that means every turbine has identical probability to be re-located for new solutions.

1. Initialization, Set the initial values: Number of turbines *Nt,*
   $z_{i,0} = 1, i = 1, \ldots, Nt$
   Generate initial solution: Randomly locate each turbine with respect to assumptions six and eight and compute Pup_i and $totalPup_i$ as the optimal solution
2. Compute Vel_def_i, c_i, P_i, and P_f
3. set $best=P_f$
4. for $t=1$ *to MaxIter*
5. while $best \neq totalPup_i$ or $iter \neq MaxIter$
   a. for each turbine $i=1$ *to Nt*
      i. Compute Vel_def_i, c_i, P_i, and P_f
      ii. Compute number of particles Np_t^i
      iii. for $n=1$ *to* Np_t^i
         - re-locate turbine *i* randomly with respect to assumptions 6 and 8
         - re-compute (i)
      iv. best*_particle_farm_P* = maximum ($P_{f,t}^n$),
      v. locations*_particle_farm_P* = locations at maximum ($P_{f,t}^n$)

      end
   b. Compute observation function $z_{i,t}$
   c. *best_turbine_farm_P*=maximum ($P_{f,t}$),
   d. *locations_turbine_farm_P* = locations at maximum ($P_{f,t}$)
   e. if *best_turbine_farm_P > best*
      i. *best = best_turbine_farm_P*
      ii. Turbine locations = locations at *best_turbine_farm_P*
      end

      end

   end

   end
6. t=t+1

Figure 3. 6. Particle Filtering Approach for the WFLOP

The PF algorithm works as illustrated in figure 3.6. First of all, initialization is made by setting initial parameters such as maximum iteration number, number of turbines, and $z_{i,0}$ values for each turbine. An initial solution is generated randomly and theoretical powers of each turbine Pup_i and generated power of the farm *totPup* are computed without wake effect. Then, *velocity deficits*, c_i, P_i, and P_f values are computed as mentioned in section 3.1.1. From the initial step of the algorithm, the best value for the objective function is set to the P_f which is the power of initial wind.

For the time (iteration) $t = 1$ to the number of maximum iteration, if the ideal optimum wind farm is not reached, the number of particles for each turbine at time t Np_t^i is computed (3.9). The particle numbers have a dynamic structure that changes according to a turbine's generated expected power and differs from turbine to turbine and iteration to iteration.

$$Np_t^i = 1 + z_{i,t-1} * Np \tag{3.9}$$

where $z_{i,t-1}$ is the observation function (weight of the particles) for the *ith* turbine at time *t-1* and *Np* is the maximum number of particles.

Then, all turbines are re-located one by one according to the number of their particles. *Velocity deficits*, c_i, P_i, and P_f values are re-computed to discuss optimum solution of the problem according to particles of the *ith* turbine. The maximum power generation of the *ith* turbine and the layout design of the farm are stored to compare the other turbines re-location processes.

The observation function $f_h\ (x_t) = z_{i,t}$ depends on three sub-functions. First one is the previous value of it ($z_{i,t-1}$), the second one is related with the turbine's power generation capability at that position (equation 3.10), and the third one is the farm's power generation capability (equation 3.11). So, $f_h\ (x_t)$ could be calculated by equation 3.12. It can be understood from equation 3.9 that if a turbine had a *zero* for the observation function at time *t*, at least 1 particle would assigned to it. This means that every turbine has an opportunity to re-locate at least one time.

$$T\_z_{i,t} = \frac{\sum_{n=1}^{Np_t^i}(1 - \frac{P_{i,t}^n}{Pup_i})}{Np_t^i} \tag{3.10}$$

$$F\_z_{i,t} = \frac{\sum_{n=1}^{Np_t^i}(1-\frac{P_{f,t}^n}{totPup})}{Np_t^i} \qquad (3.11)$$

$$z_{i,t} = \gamma\, z_{i,t-1} + \delta\, T_{z_{i,t}} + \zeta\, F_{z_{i,t}}, \qquad \gamma + \delta + \zeta = 1 \qquad (3.12)$$

where $T\_z_{i,\ t}$ is the observation function of *ith* turbine at time *t* according to that turbine's power generation capability, $F\_z_{i,\ t}$ refers to observation function of *ith* turbine at time *t* according to wind farm's power generation capability, and $z_{i,t}$ is the observation value for *ith* turbine at time *t.* The equation 3.12 consists of weighted sum of the observation functions. The weight for observation function $z_{i,t-1}$ at time *t-1* is represented by *γ (gamma),* the weight related with *ith* turbine's power generation capability $T\_z_{i,\ t}$ (observation function of the turbine)is represented by *δ (delta),* and the weight related with the farm's power generation capability $F\_z_{i,\ t}$ (observation function of the farm) is represented by the *ζ (zeta)* symbols.

After all turbines are re-located and their observation values are computed, the maximum powers of the farm found by each turbine are compared to each other. If the maximum of them is greater than the best, the best is set to that value and the farm layout design is changed by the coordinates of that solution.

These steps are continued until the stopping criteria are matched. (Particle Filtering algorithm's stopping criteria are maximum iteration number reached or ideal power output generated.)

CHAPTER 4

EXPERIMENTAL STUDY

4.1 Parameters of the Problem

The wind farm properties for this study are summarized in section 2.1. According to the first assumption, all wind turbines have the same specifications. The used wind turbines have the following parameters: *rotor radius R is 38.5 (m)*; *cut-in speed* v_{cutin} *is 3.5 (m/s); rated speed* v_{rated} *is 14 (m/s); rated power* P_{rated} *is 1500 (kW), the slope parameter for the power curve* λ *is 140.86, the intersection parameter for the power curve* η *is -500, trust coefficient* C_t *is 0.8, and the wake spreading constant* κ *is 0.075.* Knowing the *cut-in wind speed* and the *rated wind speed*, wind speed is divided at 20 intervals of 0.5 (m) each.

4.2 Restrictions of the Problem

The mentioned WFLOP in this study has some restrictions in terms of implementations of algorithms. The figure 4.1 gives an example layout for eleven turbines. The big circle (blue circle) represents the wind farm region with respect to assumption eight, the small circles (green circles) represents the restricted area for another turbine to locate near that turbine (assumption six), and stars represent the locations of turbines in the farm. While it was concluded that only six turbines would be placed in the defined windy area with respect to assumptions six and eight in the previous study (Kusiak & Song, 2010), it could be understood from the figure 4.1 that up to eleven turbines would be placed. It means that the used evolutionary algorithm could only place up to six turbines in that farm. In this study, both *ACO and PF* approaches could place *up to eight turbines* in the same constraints. It is clear that the more turbines are in a wind farm, the more power output would occurs. If the main objective is the maximum power output in a single windy site, more than six turbines would be more profitable investment.

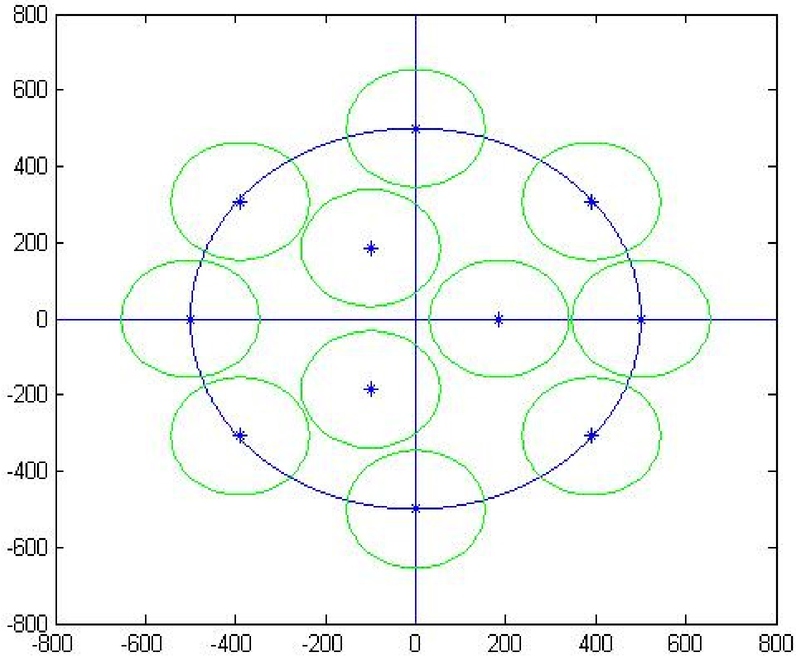

Figure 4. 1. A sample layout design for eleven turbines

The complexity for the proposed algorithms is that the re-placing process depends on the randomization. Randomly re-placing of more than eight turbines with respect to assumptions six and eight is nearly impossible for the proposed algorithms and this is an important incompetence for the WFLOPs.

4.3 Parameter Settings for Ant Colony Optimization

The number of maximum iteration and the number of ants are the parameters for the Ant Colony Optimization. They are set to 300 and 200 respectively throughout all experiments after various evaluations. The *efficiency* of a wind farm is computed as the ratio of the P_f to the *totPup* (Equation 4.1) and can be used as a performance index.

$$Efficiency = 100\,(P_f \;/\; totPup) \tag{4.1}$$

If the expected power P_f of the wind farm is equal to the ideal power *totPup*, the *efficiency* would be 100 and this means that the expected power is the optimum and the layout is the optimum layout.

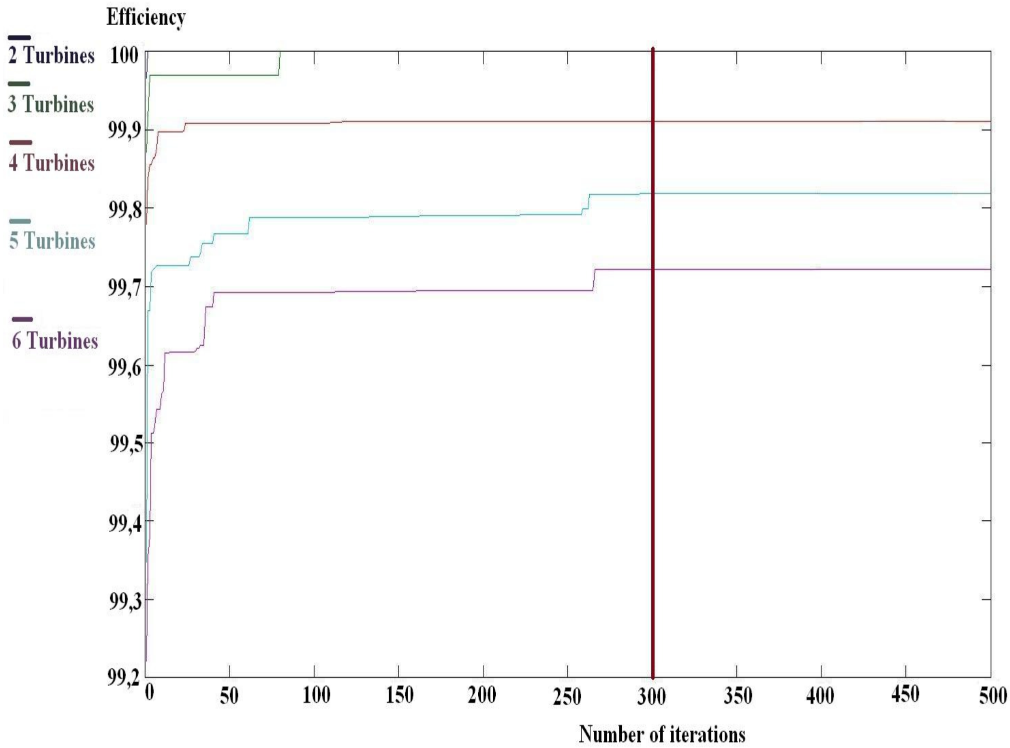

Figure 4. 2. Convergence of ACO for two to six turbines

A convergence test was done to determine the maximum iteration number of the ACO algorithm. It is tested on the Case A and up to six turbines. Figure 4.2 shows that there is no change in efficiencies after the 260th iteration for any number of turbines from two to six while the number of ants is 200. It means that the 300 is a sufficient iteration number for Ant Colony Optimization. Also the optimum layouts for two and three turbines could be found before 150 iterations.

4.4 Parameter Settings for the Particle Filtering

The parameters for the Particle Filtering approach are the number of maximum iteration, the number of maximum particles, the importance coefficient for observation function at time *t-1* γ *(gamma),* the importance coefficient related with a turbine's power generation capability δ *(delta),* and the importance coefficient related with the farm's power generation capability ζ *(zeta).*

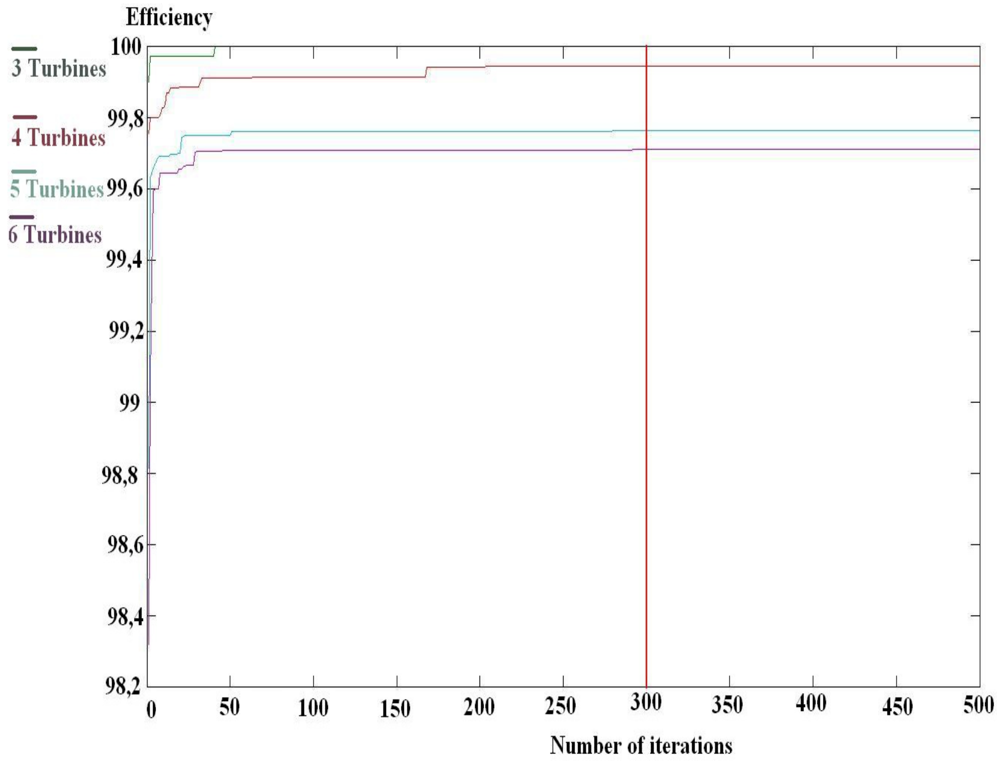

Figure 4. 3. Convergence of PF for two to six turbines

The maximum iteration number of the Particle Filtering approach was determined after a convergence test. It is tested on the Case A and up to six turbines. The number of maximum iterations and the number of maximum particles are set to 300 and 250 respectively throughout all experiments after various evaluations. Figure 4.3 shows that there is no change in efficiencies after the 270^{th} iteration for any number of turbines from two to six while the maximum number of particles is 250. It means that the 300 is a sufficient iteration number for Particle Filtering. The other three parameters are set after an experimental design. The figure 4.3 also shows that the optimum layouts for the two and three turbines were found before 100 iterations.

4.4.1 Experimental design for Particle Filtering parameters

Processes may have unknown effects (with some known effects) which affect the response value. In order to discover unknown effects or to show known effects of a process, an experiment - which is defined as the systematic procedure carried out under controlled conditions - is required. Experiments are used to evaluate which process inputs have a significant impact on the response value. Many different ways are used to collect this data while planning an experiment. DOE can be used at the point of greatest leverage to reduce design costs by speeding up the design process, reducing late engineering design changes, and reducing product material and labor complexity. Designed Experiments are also powerful tools to achieve manufacturing cost savings by minimizing process variation and reducing rework, scrap, and the need for inspection (Montgomery, 1991).

In this study, an experiment is designed to understand the effects of γ, δ, and ζ coefficients of Particle Filtering approach on WFLOP. The parameters have three levels such as *High, Medium*, and *Low* which represent the importance level of those parameters. The effected parameters are selected as efficiency and termination time of the algorithm. The design structure of the experiment consists of the followings;

a. Number of turbines (because more changes in efficiency occurs when the number of turbine is eight, it is taken as *eight*),

b. The coefficients of γ, δ, and ζ are the design parameters

c. The *efficiency* and *termination time* are the response data

d. γ could have *high, medium*, or *low* importance on the observation function,

e. δ could have *high, medium*, or *low* importance on the observation function,

f. ζ could have *high, medium*, or *low* importance on the observation function,

g. Because the WFLOP contains randomization processes, all experiments replicate for *three* times.

Table 4. 1. Experimental design of decision parameters for PF

Ex. No.	Delta (δ)	Zeta (ζ)	Gamma (γ)
1	Low	Low	Low
2	Low	Medium	Medium
3	Low	High	High
4	Medium	Low	Medium
5	Medium	Medium	High
6	Medium	High	Low
7	High	Low	High
8	High	Medium	Low
9	High	High	Medium

Thus, the full experimental design requires $3^3*3 = 81$ experiments. Taguchi uses Orthogonal Arrays for generating balanced combinations of noise factors, on the other hand, the number of experiments decreases (Montgomery, 1991). So, an L-9 Taguchi design is used to analyze unknown effects of changes in importance levels for the γ, δ, and ζ coefficients (figure 4.1). Thus, 9*3 = 27 experiments are done and results are given in table 4.2 and 4.3.

Table 4.2 shows that the highest average efficiency occurred at the fourth and sixth experiments as 99.84 % for the eight turbines in the Case A. This means that if the objective is to maximize the efficiency, the coefficients of γ, δ, and ζ would be similar with the experiments four and six.

Table 4. 2. Efficiencies of wind farms for PF (%)

Ex. No.	Efficiencies Experiment : 1	Efficiencies Experiment : 2	Efficiencies Experiment : 3	Average of efficiencies
1	99,79	99,78	99,83	99,80
2	99,82	99,85	99,83	99,83
3	99,81	99,83	99,82	99,82
4	99,85	99,83	99,84	99,84*
5	99,83	99,84	99,82	99,83
6	99,86	99,79	99,84	99,83
7	99,84	99,84	99,84	99,84*
8	99,84	99,84	99,82	99,83
9	99,79	99,82	99,84	99,82

* The highest average efficiencies

On the other hand, termination time is another performance indicator of the improved algorithms. So, it was secondary response data of the experimental study. Table 4.3 gives the results of the experiments and it can be seen that the fourth experiment has the lowest termination time.

Table 4. 3. Termination times of PF for eight turbines (in seconds)

No.	Termination Times Experiment : 1	Termination Times Experiment : 2	Termination Times Experiment : 3	Average of termination times
1	4,34	4,36	4,62	4,44
2	4,78	4,69	4,74	4,74
3	4,66	4,77	4,16	4,53
4	3,98	4,05	4,12	4,05*
5	4,28	4,22	4,36	4,29
6	4,39	3,77	4,10	4,09
7	4,42	4,34	4,49	4,42
8	4,17	4,16	4,52	4,28
9	4,68	4,27	4,22	4,39

* The lowest mean termination time

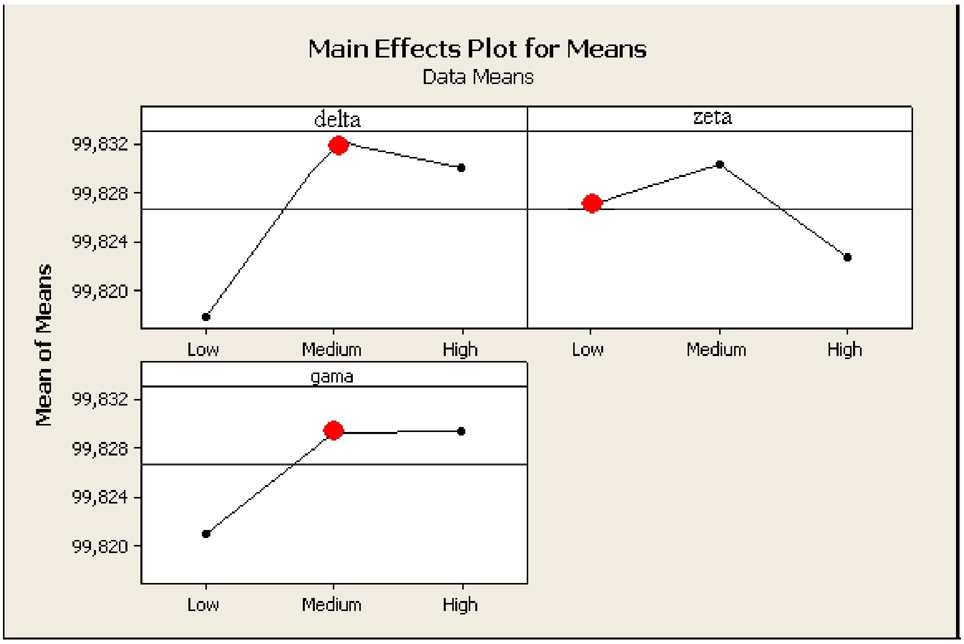

Figure 4. 4. The main effect plot of efficiencies for the coefficients *gamma, delta,* and *zeta*

The main effect of the importance levels for the γ, δ, and ζ is given in figure 4.4. While the change from low to medium in the coefficient of delta (δ) is distinct and affects the efficiency positively, the change of it from medium to high affects negatively but not very important. As it can be seen from the figure 4.4, the main effect of the importance levels for the gamma (γ) is similar with delta (δ). On the other hand, high importance level of the zeta (ζ) is clear and negatively.

Figure 4.5 shows the main effect plots of the importance levels for the γ, δ, and ζ for the response on termination time. The changes on importance level for the gamma (γ) have no distinct effect on termination times and the changes on importance level for the zeta (ζ) also not clear. On the other hand, the change from low to medium and high to medium in the coefficient of delta (δ) is distinct and affects the termination time negatively.

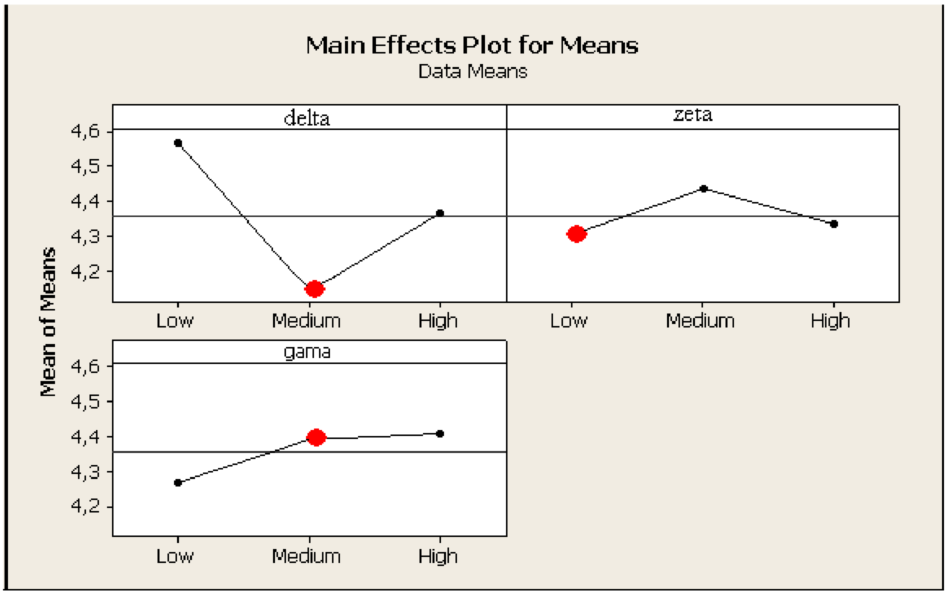

Figure 4. 5. The main effect plot of termination times for the coefficients *gamma, delta,* and *zeta*

As a result, design of experiments showed that the optimum importance levels of the γ*(gamma)*, δ*(delta)*, and ζ*(zeta)* are medium, medium, and low respectively in terms of the efficiencies and termination times (figure 4.4 and 4.5). Thus, the parameters of the Particle Filtering are determined as follows;

- The maximum iterations number is 300,
- The maximum particles number for a turbine is 250,
- γ is 0.375, δ is 0.375, and ζ is 0.25 where $\boldsymbol{\gamma + \delta + \zeta = 1}$.

CHAPTER 5

RESULTS AND DISCUSSIONS

Wind farm layout optimization problem has been solved by many different algorithms in the literature. Actually, heuristics could give better results for the WFLOP's modeling and in many studies, genetic algorithm approach and any other evolutionary algorithms were used. Instead of Ant Colony Optimization problem is very common in combinatorial optimization problems with its remarkable good results, it has never been used for the WFLOP. Meanwhile, the Particle Filtering Approach has been never used in an optimization problem and it was commonly used in signal processing studies in the computer science. In this study, Particle Filtering approach was firstly applied to an optimization problem and Ant Colony Optimization approach was applied to such a mentioned wind farm layout optimization problem with a novel pheromone structure. Results showed that these approaches are better than previous approaches in the literature in many cases.

To illustrate the performance of the proposed algorithms, various numbers of turbines (2-8) are considered with respect to Case A, Case B, and Case C. The algorithms have run 10 times for all scenarios. The results such as optimized powers, wake loses, efficiencies, and termination times for all turbines in the all cases obtained by Ant Colony Optimization algorithm and Particle Filtering approach are given in Appendix 1. The coordinates of optimum solutions are indicated in Appendix 2 and the optimum layouts also are given in Appendix 3.

5.1 Results for the Case A

The first case has a fixed wind speed blowing from a predetermined direction. Expected powers generated by ACO and PF are given in table 5.1 in the Case A. The ideal powers and best known results in the literature are also given in table 5.1. While ACO and PF found optimum solutions for the two and three turbines, PF approach gives better results for five and seven turbines than ACO.

Table 5. 1. Expected Powers for the Case A (in kilowatts)

Number of turbines	Ideal (kW)	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	28091,47	28083,42	28091,47**	28091,47**	28091,47**	28091,47**
3	42137,21	42101,06	42137,21**	42129,79	42137,21**	42128,32
4	56182,95	56057,77	56152,81*	56135,07	56152,58	56135,28
5	70228,69	69922,97	70117,82	70087,10	70122,64*	70085,66
6	84274,42	83758,79	84062,56*	84009,19	84047,05	84007,84
7	98320,16	-	97908,30	97801,82	97918,69*	97869,73
8	112365,90	-	111604,72	111392,07	111694,24*	111498,83

* The best expected powers, ** The ideal expected powers (optimum)

The power loses are given in table 5.2 for the Case A. It is clear that the ACO and PF are able to *zero* power loses for the two and three turbines and this means that there is no wake loses. And also efficiencies are given in table 5.3 and it can be understood that the proposed algorithms are more efficient than the previous study. It can be concluded also that the wake loses increase as the number of turbines increase. On the other hand, efficiencies decrease as the wake loses increase.

Table 5. 2. Power loses for the Case A (in kilowatts)

Number of turbines	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	8,05	0**	0**	0**	0**
3	36,15	0**	7,42	0**	8,89
4	125,18	30,14*	47,88	30,37	47,67
5	305,72	110,87	141,59	106,05*	143,03
6	515,63	211,87*	265,23	227,38	266,58
7	-	411,86	518,34	401,47*	450,43
8	-	761,18	973,83	671,66*	867,07

* The lowest power loses, ** There is no power loses (optimum)

Table 5. 3. Efficiencies for the Case A (%)

Number of turbines	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	99,97	100**	100**	100**	100**
3	99,91	100**	99,98	100**	99,98
4	99,78	99,95*	99,91	99,95*	99,92
5	99,56	99,84	99,80	99,85*	99,80
6	99,39	99,75*	99,69	99,73	99,68
7	-	99,58	99,47	99,59*	99,54
8	-	99,32	99,13	99,40*	99,23

* The best efficiencies, ** The ideal efficiencies

The best layouts for the Case A are given in Appendix 3 and coordinates of them are given in Appendix 2. The best layouts for the eight turbines are given also in figure 5.1 and 5.2 for the ACO and PF respectively in order to understand the characteristics of the first wind case and compare the proposed algorithms.

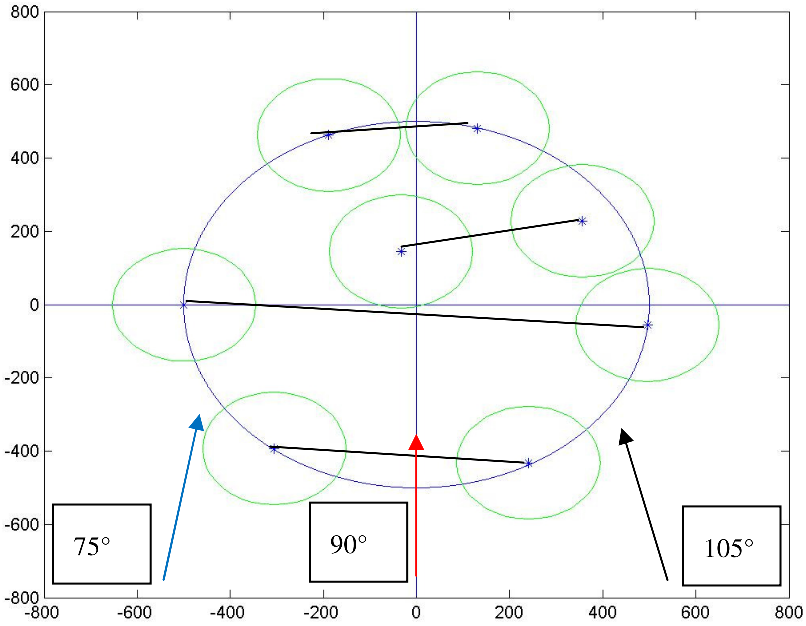

Figure 5. 1. The best layout for eight turbines by ACO in Case A

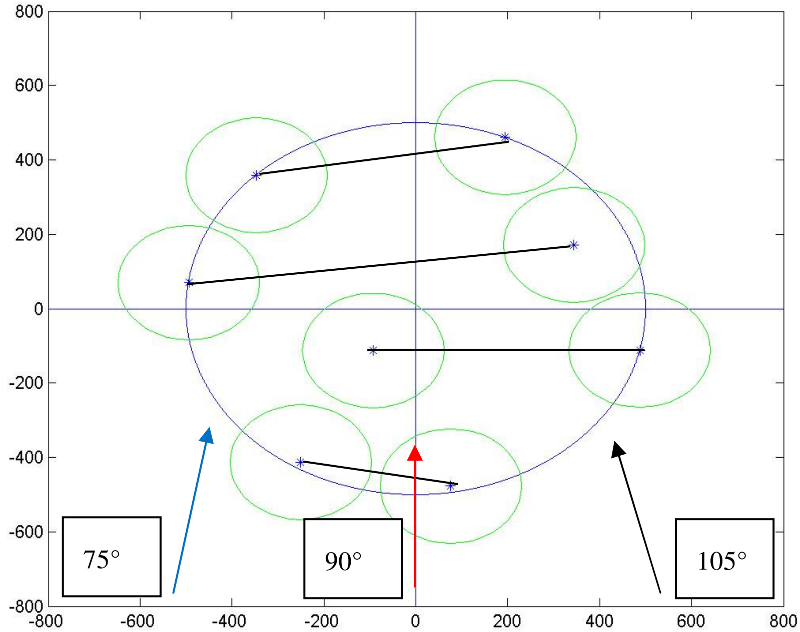

Figure 5. 2. The best layout for eight turbines by PF in Case A

Both ACO and PF algorithms try to locate the turbines across the dominated wind directions (75°-90° with the shape parameter k=2, scale parameter c=13, and wind blowing probability w=0.2, 90°-105° with the shape parameter k=2, scale parameter c=13, and wind blowing probability w=0.6). They are nearly perpendicular and not behind each other to the dominated wind directions to maximize the expected power and minimize the wake effects.

5.2 Results for the Case B

In the Case B, the wind speed is variable and blows from predetermined directions. The ideal powers, expected power generated by the ACO and PF, and previous results of the farms are given in table 5.4 for the Case B. The optimal solutions for the two and three turbines are obtained by the ACO and PF for the second case. As it can be seen from the tables 5.1 and 5.4 that the ideal powers of the second case are less than the first one. This means that the second case is not as suitable as the first windy site for wind energy investors.

Table 5. 4. Expected Powers for the Case B (in kilowatts)

Number of turbines	Ideal (kW)	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	14631,37	14631,21	14631,37**	14631,37**	14631,37**	14631,37**
3	21947,06	21925,16	21947,06**	21913,66	21947,06**	21915,78
4	29262,75	29113,71	29221,13*	29189,42	29217,83	29182,38
5	36578,44	36316,23	36270,06	36228,47	36421,55*	36284,07
6	43894,12	43195,84	43234,15	43136,47	43326,88*	43181,70
7	51209,81	-	49918,79	49783,03	50011,33*	49819,71
8	58525,50	-	56491,86	56322,10	56664,57*	56498,03

* The best expected powers, ** The ideal expected powers (optimum)

The power loses in the second case are given in the table 5.5. The wake effects are greater than the Case A for more than three turbines. For example the power loses generated by ACO for five turbines are 110.87 kilo watts in the first case, while that are 308.37 kilo watts in the Case B. This shows that, the unstable windy sites cause more wake loses. The wind farms projects could be more profitable if the wind speed is not variable and there is a predetermined wind direction.

Table 5. 5. Power loses for the Case B (in kilowatts)

Number of turbines	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	0,16	0,00**	0,00**	0,00**	0,00**
3	21,90	0,00**	33,40	0,00**	31,28
4	149,04	41,62*	73,33	44,92	80,37
5	262,21	308,37	349,97	156,89*	294,37
6	698,28	659,97	757,66	567,25*	712,43
7	-	1291,03	1426,78	1198,48*	1390,10
8	-	2033,64	2203,40	1860,93*	2027,47

* The lowest power loses, ** There is no power loses (optimum)

Table 5.6 gives the efficiencies for the Case B and it can be concluded that the PF approach found more efficient layouts than the other approaches. Meanwhile, the layouts of the Case A are more efficient than Case B. If an investor plans to construct an eight-turbine wind farm in a windy site which has a wind characteristics such as in the Case A, the maximum farm efficiency could be 99.4 %; on the other hand, if the wind site characteristic is like in the Case B, it would be only 96.82 %. This means that the windy sites like Case A are 4% more profitable than like Case B.

Table 5. 6. Efficiencies for the Case B (%)

Number of turbines	Kusiak and Song	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	99,99	100**	100**	100**	100**
3	99,90	100**	99,85	100**	99,86
4	99,49	99,86*	99,75	99,85	99,73
5	99,28	99,16	99,04	99,57*	99,20
6	98,41	98,50	98,27	98,71*	98,38
7	-	97,48	97,21	97,66*	97,29
8	-	96,53	96,24	96,82*	96,54

* The best efficiencies, ** The ideal efficiencies

The best layouts' coordinates for the Case B are given in Appendix 2 and the best layouts of them are given in Appendix 3. Figure 5.3 and 5.4 show the best layouts for the eight turbines generated by the ACO and PF respectively. Turbines are nearly perpendicular and not behind each other to the dominated wind directions.

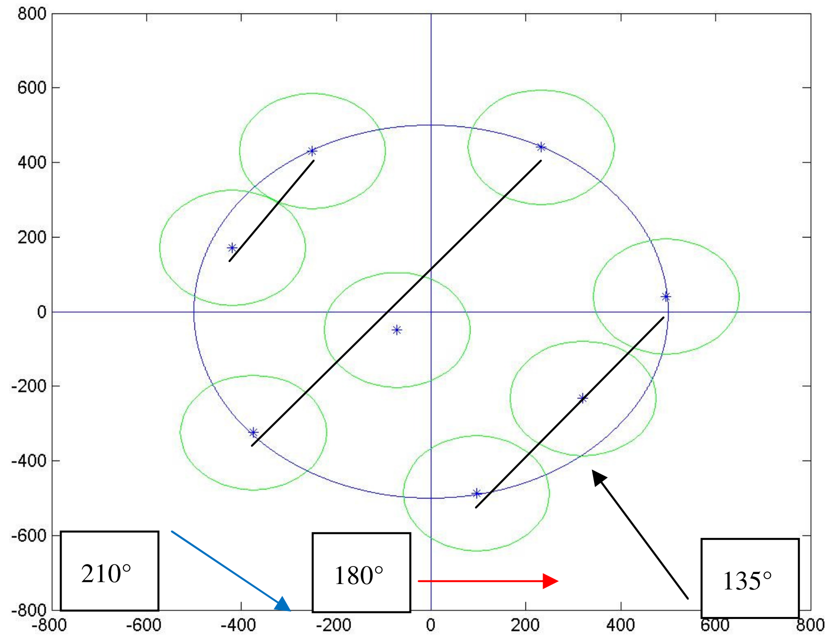

Figure 5. 3. The best layout for eight turbines by ACO in Case B

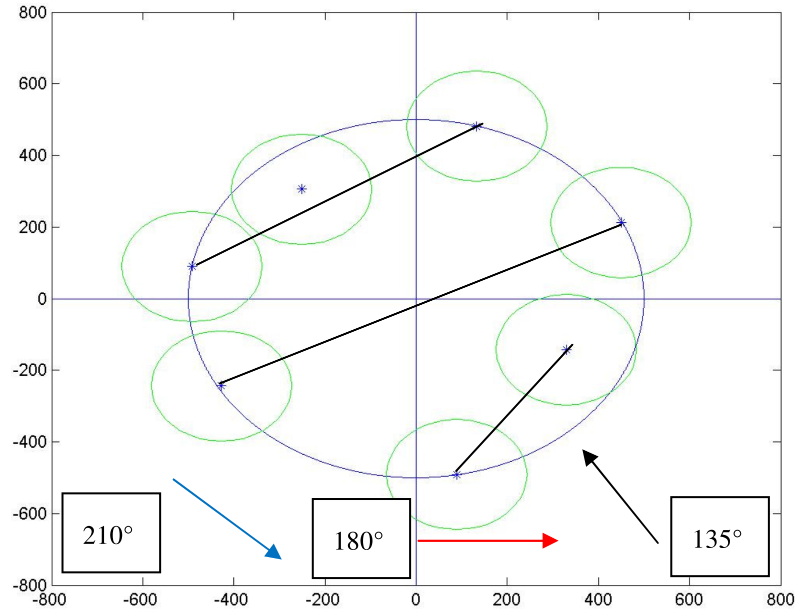

Figure 5. 4. The best layout for eight turbines by PF in Case B

5.3 Results for the Case C

The last case mentioned in this study has a fixed wind speed and blows from every direction with identical probabilities. Table 5.7 gives the ideal powers and expected powers generated by ACO and PF for this case. If the number of turbines is two or three, the ACO and PF could give the optimal solutions for the Case C as in the Case A and B.

Table 5. 7. Expected Powers for the Case C (in kilowatts)

Number of turbines	Ideal (kW)	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	26921,00	26921,00**	26921,00**	26921,00**	26921,00**
3	40381,49	40381,49**	40353,96	40381,49**	40369,49
4	53841,99	53653,03	53626,78	53654,70*	53608,17
5	67302,49	66807,49	66734,39	66837,31*	66753,94
6	80762,99	79821,37	79759,47	79840,04*	79763,60
7	94223,49	92501,76	92446,95	92552,80*	92463,26
8	107683,99	105235,76*	105083,49	105182,38	105096,72

* The best expected powers, ** The ideal expected powers (optimum)

Despite the wind speed is fixed and the same with Case A, the wake losses are more than Case A and Case B (table 5.8). This can be concluded as the wind directions have important role in terms of wake losses. If the wind blows everywhere with equal probabilities, turbines would cause more wake effect that decreases the power generation. In the last case, the biggest wake effect in the best solutions is occurred for the eight turbines as 2501.61 kilo watts by Particle Filtering approach. This is a considerable cost for the investors. As mentioned before, the Case C is not a profitable windy site according to other cases.

Table 5. 8. Power loses for the Case C (in kilowatts)

Number of turbines	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	0,00**	0,00**	0,00**	0,00**
3	0,00**	27,54	0,00**	12,01
4	188,97	215,21	187,30*	233,83
5	495,00	568,10	465,18*	548,55
6	941,62	1003,52	922,95*	999,39
7	1721,73	1776,54	1670,69*	1760,23
8	2448,23*	2600,50	2501,61	2587,26

* The lowest power loses, ** There is no power loses (optimum)

Table 5.9 gives the efficiencies of the layout designs generated by ACO and PF for the Case C. These are not more efficient layouts according to Case A but better than in the Case B. The efficiencies are more than ACO approach except for the eight turbines.

Table 5. 9. Efficiencies for the Case C (%)

Number of turbines	ACO(best)	ACO (average of 10-Run)	PF(best)	PF (average of 10-Run)
2	100**	100**	100**	100**
3	100**	99,93	100**	99,97
4	99,65*	99,60	99,65*	99,57
5	99,26	99,16	99,31*	99,18
6	98,83	98,76	98,86*	98,76
7	98,17	98,11	98,23*	98,13
8	97,73*	97,59	97,68	97,60

* The best efficiencies, ** The ideal efficiencies

Appendix 2 and 3 consists of the best layouts' coordinates and figures respectively. The layouts for the eight turbines generated by ACO and PF are given also in figure 5.5 and 5.6 respectively. It can be concluded that the turbines are located at the boundary of the farm in general. This can be concluded as that if there are no dominant wind directions, turbines will be located as far as possible to the each other and if some lines are drown between the turbines, equilateral polygons would be better layouts.

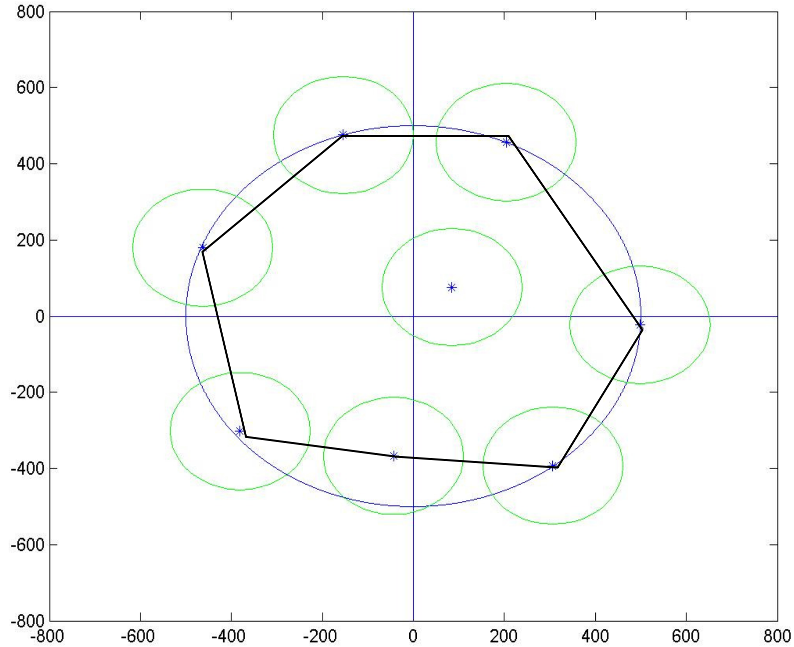

Figure 5. 5. The best layout for eight turbines by ACO in Case C

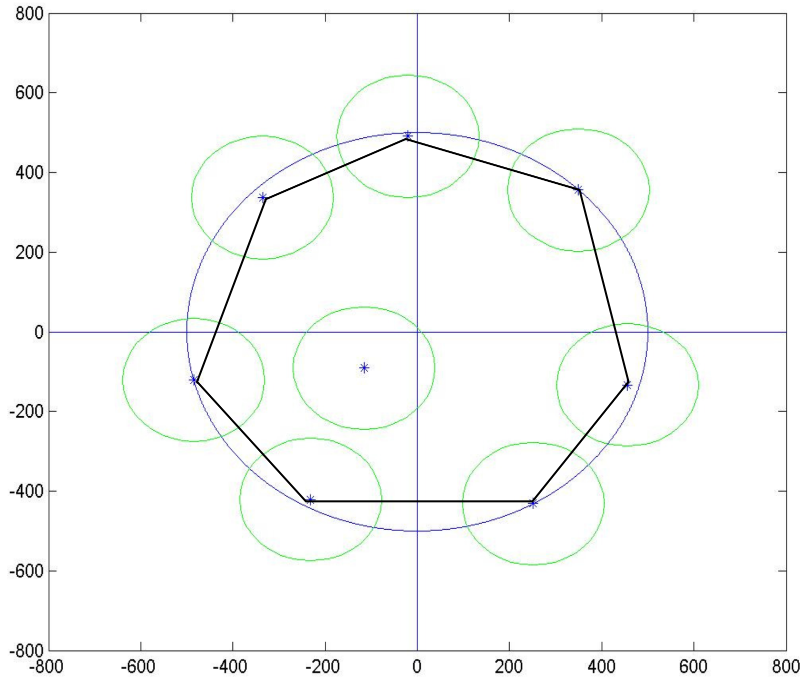

Figure 5. 6. The best layout for eight turbines by PF in Case C

5.3 Comparison of the Developed Algorithms

The mentioned problem is first studied by Kusiak and Song (2010). While their algorithm (Kusiak & Song, 2010) can locate only six turbines in a-500-meter-radius wind farm, proposed ACO algorithm and PF approach can locate up to eight turbines in the same area. They used an evolutionary algorithm and results show that it gives better layout designs in terms of power loses for the second scenario than first one. On the other hand, efficiencies in the second case are less than Case A.

Note that the computational results reveal very encouraging for practical applications of the ACO and PF to find optimal placement of wind turbine in wind farms. In comparison of three approaches, Particle Filtering gives the best results except four and six turbines in the case of A, four turbines in the case of B, and eight turbines in the case of C. ACO reached the best layouts for those turbines and cases. It is showed that both ACO and PF approaches are better than previous study (Kusiak & Song, 2010) in terms of efficiencies, power generation capabilities of wind farms, wake loses, and maximum turbine placing (up to eight) in the same area. Actually, it is possible to locate up to eleven turbines in the same site (in section 4 figure 4.1), but proposed algorithms can locate up to eight turbines (re-locate of a turbine is very hard for a random process with respect to assumptions six and eight).

The codes (given in Appendix 4) of the ACO and PF algorithm were written in Matlab R2009b and performed on a computer which has a Pentium Dual Core E530 @ 2.60 Ghz processor with 2 Gb RAM.

The standard deviations of efficiencies for 10 runs are given in table 5.10. It can be concluded that the algorithms has similar tolerances for the same number of turbines in the same cases. For example, the standard deviations of 10 runs for five turbines are 0.03 for ACO and PF in the Case A. On the other side, standard deviations are generally higher in the Case B than other cases. This means that the solutions of the Case B are a bit more variable from run to run. Also, standard deviations are generally higher for the seven and eight turbines in the first and second cases.

Because there is no major wind direction for the third scenario and wind speed is fixed, the Case C is the most stable case in terms of standard deviations for the algorithms and all number of turbines. It can be inferred that the more wind characteristics are stable, the less standard deviation occurs.

Table 5. 10. Standard Deviations of Efficiencies for 10-Run

Number of Turbines	Case A		Case B		Case C	
	ACO	PF	ACO	PF	ACO	PF
2	0,00	0,00	0,00	0,00	0,00	0,00
3	0,02	0,02	0,10	0,11	0,09	0,06
4	0,02	0,02	0,09	0,07	0,06	0,12
5	0,03	0,03	0,14	0,16	0,06	0,06
6	0,04	0,05	0,14	0,17	0,06	0,07
7	0,12	0,08	0,19	0,26	0,05	0,07
8	0,21	0,14	0,15	0,23	0,07	0,05

Table 5. 11. Average Termination Times of Algorithms (in seconds) for 10-Run

Number of Turbines	Case A		Case B		Case C	
	ACO	PF	ACO	PF	ACO	PF
2	0,14	0,37	0,21	0,46	0,17	0,43
3	41,56	21,52	41,56	32,68	41,97	13,61
4	87,60	62,31	87,60	86,04	86,52	65,23
5	110,09	113,86	110,09	158,84	107,59	119,28
6	134,21	183,63	134,21	266,99	130,39	194,55
7	160,35	273,01	160,35	393,82	154,20	297,56
8	180,74	373,40	204,07	535,44	178,66	393,15

Termination times of the algorithms are shown in table 5.11. Termination times of the solution approach was not mentioned in the existing study (Kusiak & Song, 2010), so, the only Ant Colony Optimization algorithm and Particle Filtering approach are compared with each other. While there is no significant difference in terms of the standard deviations of the algorithms, Ant Colony Optimization approach solves the WFLOP faster than Particle Filtering approach (table 5.11). The biggest termination time is about 9 minutes (535.44 seconds) in this study. It is acceptable for the WFLOPs. Meanwhile, the more turbines are in the farm, the more termination times are required for ACO and PF approaches. Also, it can be concluded that the increase of the termination time is not linear.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The wind farm layout problem was dealt in order to maximize energy production in this study. The farm area is suggested onshore and the problem is considered in continuous variables (the coordinates of the turbines). The Jensen's wake model (Jensen N. , 1983) (Katic et al., 1986) was used in order to compute wake effects. The theoretical background related the wind energy, wake models, and WFLOP and problem statements were carefully explained in chapter one and two so that the approaches suggested in this study could be carefully understood.

The optimal layout of the turbines inside a wind farm is determined by two heuristic methods. The first one is the Ant Colony Optimization algorithm based on a novel pheromone updating scheme. Novel pheromone updating is used to compute pheromone quantity at the end of the each iteration and allows ants to generate new solutions by concentrating to better ants. The other solution approach is the Particle Filtering approach. It has never been used for any optimization problems before. Firstly, the Particle Filtering is adjusted to optimization problems and then it is used for the WFLOP. The solution methodologies were mentioned in detail and explained step by step in chapter three.

The ACO and PF approaches were coded in Matlab and structured in different functions, each of which is able to do a particular operation (computes power, computes wake effects, and etc.). This brings advantageous to the written codes by making them very easy to understand and modify. Also, this makes it easier to insert new parameters in the future. By the way, this structure of the codes also makes it easy to adapt a new wake model in the algorithm. On the other hand, the written codes have some disadvantageous. The main of them is the fact that the layouts are generated randomly in both ACO and PF approaches. This limits the algorithms' ability to place more than eight turbines in the restricted farm area.

The constraints of the problem (assumptions six and eight) were integrated to both ACO and PF algorithms. Thus, the optimization procedure worked on only as a non-linear maximization problem. The optimal solutions via from more accurate layout designs with less energy losses were illustrated with farm layouts and the performances of the proposed algorithms were evaluated on three benchmark problems (Case A, Case B, and Case C). The first and second scenarios had been solved with bi-objective evolutionary strategy algorithm available in literature (Kusiak & Song, 2010).

It is concluded that the use of ACO and PF algorithms can help to find better wind farm layouts than prior study in selected problem within a reasonable solution time. While ACO approach terminates faster than PF approach, the biggest termination time is 535.44 seconds. The more turbines are in the farm, the more termination times will be required. Despite the fact that the solutions were dependent on randomization, the standard deviations showed that the proposed algorithms had not significant diversities trial to trial.

While the best layouts were commonly generated by PF approach, the performances of the proposed algorithms were generally better than that of existing algorithm proposed for continuous problems. So, it is obvious that the ACO and PF algorithms can tackle to find global maximum such as mentioned continuous function in this study.

6.2 Recommendations

Future researches can focus on the more realistic models to optimize wind farm layout designs. Many of the unstudied fields are waiting to be considered. For instance, although the problem optimizes the energy production of the wind farm, it still needs a cost integrated model such as investment cost, maintenance cost, and etc. There are different models for the wake effect to be compared. The foundations, cabling, and human aspects could be considered in the design model. The model also needs integrated parameters of turbine types to select and use the right one in the farm. By the way, the wind farm layout optimization problems could be solved with an integration of Geographic Information Systems (GIS). New strategies could be developed smartly in ACO and PF to re-place the selected turbine in the continuous farm region. Also, the layout design problem could be handled by taking account a different objective such as the maximum working life of turbines. In addition, three dimensional wind farm terrain and irregular wind farm shapes except circle, square, or rectangle shapes could be considered for a real case study. By the way, developing wind turbine technologies lead to construct floating wind turbines offshore and thus, dynamic layout optimization of wind turbines get to be more important and applicable for wind energy investors.

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APPENDIX 1

A1.1 Results of Ant Colony Optimization Algorithm

A1.1.1 Case A

Table A1. 1. Optimized Powers for Case A using ACO (in kilowatts)

Run/Nt	Ideal Powers (kW)						
	28091,47	42137,21	56182,95	70228,69	84274,42	98320,16	112365,90
	Optimized Powers (kW)						
	2	3	4	5	6	7	8
1	28091,47	42137,21	56138,39	70106,76	84016,38	97671,63	111505,91
2	28091,47	42137,21	56137,93	70093,09	84013,14	97894,94	111394,13
3	28091,47	42127,02	56146,19	70081,23	84031,31	97642,80	110769,32
4	28091,47	42123,66	56122,65	70083,85	83967,47	97905,15	111489,95
5	28091,47	42137,21	56152,81	70067,19	84062,56	97887,93	111314,97
6	28091,47	42137,21	56150,46	70057,52	84003,27	97851,29	111588,63
7	28091,47	42137,21	56124,89	70099,08	84006,63	97853,01	111604,72
8	28091,47	42118,98	56126,61	70117,82	83955,24	97908,30	111432,35
9	28091,47	42118,27	56127,96	70078,21	84017,68	97796,23	111354,92
10	28091,47	42123,96	56122,80	70086,25	84018,25	97606,91	111465,78
Average	28091,47	42129,79	56135,07	70087,10	84009,19	97801,82	111392,07
Best	28091,47	42137,21	56152,81	70117,82	84062,56	97908,30	111604,72

Table A1. 2. Power loses for Case A using ACO (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	0	44,56	121,92	258,04	648,53	859,99
2	0	0	45,02	135,59	261,28	425,22	971,77
3	0	10,20	36,76	147,46	243,12	677,36	1596,58
4	0	13,55	60,30	144,84	306,96	415,01	875,95
5	0	0	30,14	161,49	211,87	432,23	1050,92
6	0	0	32,49	171,16	271,15	468,87	777,26
7	0	0	58,06	129,61	267,80	467,15	761,18
8	0	18,23	56,34	110,87	319,18	411,86	933,55
9	0	18,94	54,99	150,47	256,74	523,93	1010,98
10	0	13,26	60,15	142,44	256,17	713,25	900,12
Average	0	7,42	47,88	141,59	265,23	518,34	973,83
Best	0	0	30,14	110,87	211,87	411,86	761,18

Table A1. 3. Efficiencies for Case A using ACO (%)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	100	99,92	99,83	99,69	99,34	99,23
2	100	100	99,92	99,81	99,69	99,57	99,14
3	100	99,98	99,93	99,79	99,71	99,31	98,58
4	100	99,97	99,89	99,79	99,64	99,58	99,22
5	100	100	99,95	99,77	99,75	99,56	99,06
6	100	100	99,94	99,76	99,68	99,52	99,31
7	100	100	99,90	99,82	99,68	99,52	99,32
8	100	99,96	99,90	99,84	99,62	99,58	99,17
9	100	99,96	99,90	99,79	99,70	99,47	99,10
10	100	99,97	99,89	99,80	99,70	99,27	99,20
Average	100	99,98	99,91	99,80	99,69	99,47	99,13
Best	100	100	99,95	99,84	99,75	99,58	99,32
Standard Deviation	0	0,02	0,02	0,03	0,04	0,12	0,21

Table A1. 4. Termination times of ACO in the Case A (in seconds)

Run/Nt	Termination Times (sec.)						
	2	3	4	5	6	7	8
1	0,17	11,46	86,48	107,36	130,14	154,34	181,83
2	0,16	48,87	86,27	107,74	130,40	154,34	180,96
3	0,16	65,78	86,35	107,61	130,36	154,52	179,95
4	0,18	65,79	86,28	107,54	130,39	154,22	180,08
5	0,19	6,81	86,24	107,52	130,33	154,41	179,97
6	0,16	5,73	86,58	112,74	138,68	161,63	180,15
7	0,18	6,65	86,81	107,78	130,90	164,91	179,94
8	0,00	68,00	90,40	114,07	140,41	168,01	181,76
9	0,16	68,06	90,26	114,05	140,11	168,66	181,23
10	0,00	68,42	90,32	114,45	140,34	168,52	181,55
Average	0,14	41,56	87,60	110,09	134,21	160,35	180,74

A1.1.2 Case B

Table A1. 5. Optimized Powers for Case B using ACO (in kilowatts)

	Ideal Powers (kW)						
	14631,37	21947,06	29262,75	36578,44	43894,12	51209,81	58525,50
	Optimized Powers (kW)						
Run/Nt	2	3	4	5	6	7	8
1	14631,37	21897,77	29205,08	36251,87	43089,62	49678,59	56406,42
2	14631,37	21934,12	29152,74	36270,06	43136,86	49797,60	56318,14
3	14631,37	21897,84	29205,34	36195,81	43120,32	49594,89	56337,84
4	14631,37	21935,39	29221,13	36262,62	43234,15	49751,63	56491,86
5	14631,37	21897,76	29156,70	36259,69	43180,09	49803,70	56354,80
6	14631,37	21933,45	29205,52	36136,49	43014,16	49876,73	56278,95
7	14631,37	21897,85	29181,49	36255,74	43163,84	49790,79	56174,46
8	14631,37	21897,73	29220,29	36147,14	43108,39	49861,88	56283,64
9	14631,37	21947,06	29192,85	36252,27	43145,98	49755,75	56322,49
10	14631,37	21897,66	29153,06	36253,03	43171,29	49918,79	56252,42
Average	14631,37	21913,66	29189,42	36228,47	43136,47	49783,03	56322,10
Best	14631,37	21947,06	29221,13	36270,06	43234,15	49918,79	56491,86

Table A1. 6. Power loses for Case B using ACO (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	49,29	57,67	326,57	804,51	1531,23	2119,08
2	0	12,94	110,01	308,37	757,26	1412,21	2207,36
3	0	49,22	57,41	382,63	773,80	1614,93	2187,65
4	0	11,67	41,62	315,82	659,97	1458,19	2033,64
5	0	49,30	106,05	318,75	714,04	1406,11	2170,70
6	0	13,61	57,22	441,95	879,97	1333,09	2246,55
7	0	49,21	81,26	322,70	730,29	1419,02	2351,04
8	0	49,33	42,46	431,30	785,73	1347,93	2241,86
9	0	0,00	69,89	326,17	748,15	1454,06	2203,01
10	0	49,41	109,69	325,41	722,83	1291,03	2273,08
Average	0	33,40	73,33	349,97	757,66	1426,78	2203,40
Best	0	0,00	41,62	308,37	659,97	1291,03	2033,64

Table A1. 7. Efficiencies for Case B using ACO (%)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	99,78	99,80	99,11	98,17	97,01	96,38
2	100	99,94	99,62	99,16	98,27	97,24	96,23
3	100	99,78	99,80	98,95	98,24	96,85	96,26
4	100	99,95	99,86	99,14	98,50	97,15	96,53
5	100	99,78	99,64	99,13	98,37	97,25	96,29
6	100	99,94	99,80	98,79	98,00	97,40	96,16
7	100	99,78	99,72	99,12	98,34	97,23	95,98
8	100	99,78	99,85	98,82	98,21	97,37	96,17
9	100	100	99,76	99,11	98,30	97,16	96,24
10	100	99,77	99,63	99,11	98,35	97,48	96,12
Average	100	99,85	99,75	99,04	98,27	97,21	96,24
Best	100	100	99,86	99,16	98,50	97,48	96,53
Standard Deviation	0	0,10	0,09	0,14	0,14	0,19	0,15

Table A1. 8. Termination times of ACO in the Case B (in seconds)

Run/Nt	Termination Times (sec.) 2	3	4	5	6	7	8
1	0,18	11,46	86,48	107,36	130,14	154,34	187,57
2	0,33	48,87	86,27	107,74	130,40	154,34	193,36
3	0,18	65,78	86,35	107,61	130,36	154,52	206,74
4	0,17	65,79	86,28	107,54	130,39	154,22	206,61
5	0,17	6,81	86,24	107,52	130,33	154,41	206,83
6	0,19	5,73	86,58	112,74	138,68	161,63	206,95
7	0,33	6,65	86,81	107,78	130,90	164,91	206,74
8	0,19	68,00	90,40	114,07	140,41	168,01	211,84
9	0,18	68,06	90,26	114,05	140,11	168,66	206,99
10	0,17	68,42	90,32	114,45	140,34	168,52	207,09
Average	0,21	41,56	87,60	110,09	134,21	160,35	204,07

A1.1.3 Case C

Table A1. 9. Optimized Powers for Case C using ACO (in kilowatts)

Run/Nt	Ideal Powers (kW)						
	26921,00	40381,49	53841,99	67302,49	80762,99	94223,49	107683,99
	Optimized Powers (kW)						
	2	3	4	5	6	7	8
1	26921,00	40321,93	53634,12	66685,71	79760,61	92418,56	105101,87
2	26921,00	40381,49	53641,61	66699,70	79692,14	92457,51	105036,29
3	26921,00	40319,40	53653,03	66707,18	79821,37	92496,25	105235,76
4	26921,00	40381,49	53591,45	66728,01	79762,75	92501,76	104962,48
5	26921,00	40381,49	53648,88	66727,24	79782,44	92428,66	105001,65
6	26921,00	40305,06	53651,57	66737,50	79726,24	92424,27	105087,34
7	26921,00	40381,49	53652,95	66774,50	79760,80	92467,69	105072,87
8	26921,00	40304,23	53586,04	66701,02	79676,61	92379,47	105041,01
9	26921,00	40381,49	53640,61	66807,49	79808,28	92493,17	105131,18
10	26921,00	40381,49	53567,55	66775,52	79803,46	92402,12	105164,43
Average	26921,00	40353,96	53626,78	66734,39	79759,47	92446,95	105083,49
Best	26921,00	40381,49	53653,03	66807,49	79821,37	92501,76	105235,76

Table A1. 10. Power loses for Case C using ACO (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	59,57	207,88	616,78	1002,38	1804,93	2582,12
2	0	0	200,38	602,80	1070,85	1765,97	2647,70
3	0	62,10	188,97	595,31	941,62	1727,24	2448,23
4	0	0	250,54	574,48	1000,24	1721,73	2721,51
5	0	0	193,11	575,25	980,55	1794,83	2682,34
6	0	76,44	190,42	564,99	1036,75	1799,22	2596,65
7	0	0	189,04	527,99	1002,19	1755,80	2611,12
8	0	77,26	255,96	601,47	1086,38	1844,02	2642,98
9	0	0	201,39	495,00	954,71	1730,32	2552,81
10	0	0	274,45	526,97	959,53	1821,37	2519,56
Average	0	27,54	215,21	568,10	1003,52	1776,54	2600,50
Best	0,00	0	188,97	495,00	941,62	1721,73	2448,23

Table A1. 11. Efficiencies for Case C using ACO (%)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	99,85	99,61	99,08	98,76	98,08	97,60
2	100	100	99,63	99,10	98,67	98,13	97,54
3	100	99,85	99,65	99,12	98,83	98,17	97,73
4	100	100	99,53	99,15	98,76	98,17	97,47
5	100	100	99,64	99,15	98,79	98,10	97,51
6	100	99,81	99,65	99,16	98,72	98,09	97,59
7	100	100	99,65	99,22	98,76	98,14	97,58
8	100	99,81	99,52	99,11	98,65	98,04	97,55
9	100	100	99,63	99,26	98,82	98,16	97,63
10	100	100	99,49	99,22	98,81	98,07	97,66
Average	100	99,93	99,60	99,16	98,76	98,11	97,59
Best	100	100	99,65	99,26	98,83	98,17	97,73
Standard Deviation	0	0,09	0,06	0,06	0,06	0,05	0,07

Table A1. 12. Termination times of ACO in the Case C (in seconds)

Run/Nt	Termination Times (sec.)						
	2	3	4	5	6	7	8
1	0,17	66,11	86,67	107,53	130,28	153,96	178,16
2	0,16	32,60	86,40	107,49	130,34	154,13	178,42
3	0,16	66,16	86,41	107,48	130,64	154,28	178,56
4	0,16	44,33	86,54	107,47	130,42	154,23	178,45
5	0,17	22,50	86,45	107,50	130,35	154,26	178,48
6	0,16	66,13	86,52	107,60	130,36	154,20	178,20
7	0,16	37,51	86,63	107,57	130,33	154,05	178,58
8	0,20	66,19	86,53	107,53	130,35	154,39	178,56
9	0,18	13,05	86,53	107,69	130,31	154,14	179,42
10	0,19	5,13	86,55	107,99	130,50	154,33	179,74
Average	0,17	41,97	86,52	107,59	130,39	154,20	178,66

A1. 2 Results of Particle Filtering

A1.2.1 Case A

Table A1. 13. Optimized Powers for Case A using PF (in kilowatts)

Run/Nt	Ideal Powers (kW)						
	28091,47	42137,21	56182,95	70228,69	84274,42	98320,16	112365,90
	Optimized Powers (kW)						
	2	3	4	5	6	7	8
1	28091,47	42124,88	56125,24	70104,05	84044,06	97892,18	111538,46
2	28091,47	42127,73	56152,58	70058,02	84038,01	97890,93	111564,71
3	28091,47	42119,23	56122,31	70090,55	84040,80	97851,24	111329,58
4	28091,47	42137,21	56135,60	70059,14	83966,85	97646,89	111694,24
5	28091,47	42124,20	56126,30	70087,44	83990,05	97893,04	111510,76
6	28091,47	42118,79	56129,30	70080,84	84021,15	97903,10	111310,83
7	28091,47	42137,21	56150,04	70122,64	83957,44	97918,69	111567,32
8	28091,47	42137,21	56151,07	70072,69	83928,05	97883,47	111692,01
9	28091,47	42119,49	56128,51	70094,26	84047,05	97910,16	111247,71
10	28091,47	42137,21	56131,90	70086,99	84044,98	97907,64	111532,70
Average	28091,47	42128,32	56135,28	70085,66	84007,84	97869,73	111498,83
Best	28091,47	42137,21	56152,58	70122,64	84047,05	97918,69	111694,24

Table A1. 14. Power loses for Case A using PF (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	12,33	57,71	124,63	230,36	427,98	827,43
2	0	9,48	30,37	170,67	236,42	429,24	801,18
3	0	17,98	60,64	138,14	233,62	468,93	1036,32
4	0	0	47,35	169,55	307,57	673,27	671,66
5	0	13,01	56,65	141,25	284,37	427,12	855,14
6	0	18,42	53,65	147,85	253,27	417,06	1055,07
7	0	0	32,91	106,05	316,98	401,47	798,58
8	0	0	31,88	156,00	346,37	436,69	673,89
9	0	17,72	54,44	134,43	227,38	410,00	1118,19
10	0	0	51,05	141,70	229,45	412,52	833,20
Average	0	8,89	47,67	143,03	266,58	450,43	867,07
Best	0	0	30,37	106,05	227,38	401,47	671,66

Table A1. 15. Efficiencies for Case A using PF (%)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	99,97	99,90	99,82	99,73	99,56	99,26
2	100	99,98	99,95	99,76	99,72	99,56	99,29
3	100	99,96	99,89	99,80	99,72	99,52	99,08
4	100	100	99,92	99,76	99,64	99,32	99,40
5	100	99,97	99,90	99,80	99,66	99,57	99,24
6	100	99,96	99,90	99,79	99,70	99,58	99,06
7	100	100	99,94	99,85	99,62	99,59	99,29
8	100	100	99,94	99,78	99,59	99,56	99,40
9	100	99,96	99,90	99,81	99,73	99,58	99,00
10	100	100	99,91	99,80	99,73	99,58	99,26
Average	100	99,98	99,92	99,80	99,68	99,54	99,23
Best	100	100	99,95	99,85	99,73	99,59	99,40
Standard Deviation	0	0,02	0,02	0,03	0,05	0,08	0,14

Table A1. 16. Termination times of PF in the Case A (in seconds)

Run/Nt	Termination Times (sec.)						
	2	3	4	5	6	7	8
1	0,41	26,11	59,51	106,29	165,33	240,72	392,76
2	0,40	28,76	53,80	106,15	161,67	274,33	323,25
3	0,00	28,14	62,06	97,28	173,31	263,46	386,19
4	0,40	22,18	57,24	113,06	190,54	298,76	375,71
5	0,42	32,90	60,64	110,95	196,81	274,30	364,16
6	0,42	33,64	55,74	116,24	165,42	245,80	370,50
7	0,44	3,40	77,48	97,50	198,99	255,13	361,66
8	0,42	3,47	54,82	141,19	171,63	276,85	426,12
9	0,41	30,54	74,23	120,15	210,05	304,81	367,15
10	0,41	6,03	67,57	129,76	202,57	295,95	366,53
Average	0,37	21,52	62,31	113,86	183,63	273,01	373,40

A1.2.2 Case B

Table A1. 17. Optimized Powers for Case B using PF (in kilowatts)

Run/Nt	Ideal Powers (kW)						
	14631,37	21947,06	29262,75	36578,44	43894,12	51209,81	58525,50
	Optimized Powers (kW)						
	2	3	4	5	6	7	8
1	14631,37	21930,16	29159,90	36315,78	43102,52	49563,01	56320,42
2	14631,37	21947,06	29194,41	36254,35	43170,74	49994,65	56606,06
3	14631,37	21897,82	29206,28	36221,36	43147,71	49859,75	56664,57
4	14631,37	21897,81	29184,97	36246,07	43071,55	49773,98	56331,35
5	14631,37	21947,06	29153,80	36297,26	43187,31	49889,58	56418,86
6	14631,37	21947,06	29152,78	36269,95	43257,89	49771,73	56368,62
7	14631,37	21897,69	29185,59	36288,62	43167,01	49675,67	56578,88
8	14631,37	21897,74	29217,83	36294,07	43242,41	49841,65	56603,24
9	14631,37	21897,62	29189,92	36231,68	43142,96	50011,33	56659,11
10	14631,37	21897,80	29178,30	36421,55	43326,88	49815,73	56429,17
Average	14631,37	21915,78	29182,38	36284,07	43181,70	49819,71	56498,03
Best	14631,37	21947,06	29217,83	36421,55	43326,88	50011,33	56664,57

Table A1. 18. Power loses for Case B using PF (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	16,90	102,85	262,65	791,60	1646,80	2205,08
2	0	0	68,34	324,09	723,38	1215,16	1919,44
3	0	49,25	56,47	357,07	746,42	1350,06	1860,93
4	0	49,25	77,78	332,36	822,58	1435,83	2194,15
5	0	0	108,95	281,18	706,81	1320,24	2106,64
6	0	0	109,97	308,49	636,24	1438,09	2156,88
7	0	49,37	77,16	289,81	727,12	1534,14	1946,62
8	0	49,33	44,92	284,37	651,71	1368,16	1922,25
9	0	49,44	72,83	346,76	751,16	1198,48	1866,39
10	0	49,27	84,45	156,89	567,25	1394,08	2096,33
Average	0	31,28	80,37	294,37	712,43	1390,10	2027,47
Best	0,00	0	44,92	156,89	567,25	1198,48	1860,93

Table A1. 19. Efficiencies for Case B using PF (in kilowatts)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	99,92	99,65	99,28	98,20	96,78	96,23
2	100	100	99,77	99,11	98,35	97,63	96,72
3	100	99,78	99,81	99,02	98,30	97,36	96,82
4	100	99,78	99,73	99,09	98,13	97,20	96,25
5	100	100	99,63	99,23	98,39	97,42	96,40
6	100	100	99,62	99,16	98,55	97,19	96,31
7	100	99,78	99,74	99,21	98,34	97,00	96,67
8	100	99,78	99,85	99,22	98,52	97,33	96,72
9	100	99,77	99,75	99,05	98,29	97,66	96,81
10	100	99,78	99,71	99,57	98,71	97,28	96,42
Average	100	99,86	99,73	99,20	98,38	97,29	96,54
Best	100	100	99,85	99,57	98,71	97,66	96,82
Standard Deviation	0	0,11	0,07	0,16	0,17	0,26	0,23

Table A1. 20. Termination times of PF in the Case B (in seconds)

Run/Nt	Termination Times (sec.)						
	2	3	4	5	6	7	8
1	0,43	43,19	71,89	153,97	251,16	353,46	534,99
2	0,45	13,71	86,97	145,22	254,02	374,44	587,30
3	0,42	37,20	86,25	149,06	247,08	378,86	543,05
4	0,61	40,47	85,39	163,48	244,44	419,92	523,44
5	0,46	24,55	84,09	166,83	295,77	411,30	521,20
6	0,44	7,16	95,89	165,50	280,77	402,92	530,48
7	0,43	38,07	78,38	176,80	277,01	377,30	520,18
8	0,45	46,03	86,02	164,53	262,42	398,68	534,68
9	0,45	34,83	97,68	146,76	281,48	412,99	528,81
10	0,45	41,62	87,86	156,23	275,72	408,32	530,28
Average	0,46	32,68	86,04	158,84	266,99	393,82	535,44

A1.2.3 Case C

Table A1. 21. Optimized Powers for Case C using PF (in kilowatts)

Run/Nt	Ideal Powers (kW)						
	26921,00	40381,49	53841,99	67302,49	80762,99	94223,49	107683,99
	Optimized Powers (kW)						
	2	3	4	5	6	7	8
1	26921,00	40381,49	53639,75	66727,97	79709,17	92407,99	105112,76
2	26921,00	40320,00	53653,17	66777,08	79640,86	92528,49	105140,80
3	26921,00	40381,49	53534,27	66741,53	79840,04	92489,49	105137,27
4	26921,00	40381,49	53464,51	66837,31	79766,43	92393,51	105156,96
5	26921,00	40381,49	53654,70	66734,99	79784,69	92445,45	105050,79
6	26921,00	40381,49	53652,45	66737,20	79762,79	92366,96	105062,11
7	26921,00	40322,91	53637,65	66704,70	79750,64	92528,34	105014,94
8	26921,00	40381,49	53647,50	66779,13	79766,69	92408,57	105182,38
9	26921,00	40381,49	53580,75	66775,99	79832,93	92552,80	105069,57
10	26921,00	40381,49	53616,93	66723,51	79781,80	92510,98	105039,67
Average	26921,00	40369,49	53608,17	66753,94	79763,60	92463,26	105096,72
Best	26921,00	40381,49	53654,70	66837,31	79840,04	92552,80	105182,38

Table A1. 22. Power loses for Case C using PF (in kilowatts)

Run/Nt	Power Losses (kW)						
	2	3	4	5	6	7	8
1	0	0	202,24	574,52	1053,82	1815,50	2571,23
2	0	61,50	188,83	525,42	1122,13	1695,00	2543,19
3	0	0	307,72	560,96	922,95	1734,00	2546,71
4	0	0	377,49	465,18	996,56	1829,98	2527,02
5	0	0	187,30	567,50	978,30	1778,04	2633,20
6	0	0	189,54	565,29	1000,20	1856,53	2621,87
7	0	58,59	204,35	597,80	1012,35	1695,15	2669,05
8	0	0	194,49	523,36	996,30	1814,91	2501,61
9	0	0	261,24	526,50	930,06	1670,69	2614,42
10	0	0	225,06	578,98	981,19	1712,51	2644,32
Average	0	12,01	233,83	548,55	999,39	1760,23	2587,26
Best	0	0	187,30	465,18	922,95	1670,69	2501,61

Table A1. 23. Efficiencies for Case C using PF (%)

Run/Nt	Efficiencies						
	2	3	4	5	6	7	8
1	100	100	99,62	99,15	98,70	98,07	97,61
2	100	99,85	99,65	99,22	98,61	98,20	97,64
3	100	100	99,43	99,17	98,86	98,16	97,64
4	100	100	99,30	99,31	98,77	98,06	97,65
5	100	100	99,65	99,16	98,79	98,11	97,55
6	100	100	99,65	99,16	98,76	98,03	97,57
7	100	99,85	99,62	99,11	98,75	98,20	97,52
8	100	100	99,64	99,22	98,77	98,07	97,68
9	100	100	99,51	99,22	98,85	98,23	97,57
10	100	100	99,58	99,14	98,79	98,18	97,54
Average	100	99,97	99,57	99,18	98,76	98,13	97,60
Best	100	100	99,65	99,31	98,86	98,23	97,68
Standard Deviation	0	0,06	0,12	0,06	0,07	0,07	0,05

Table A1. 24. Termination times of PF in the Case C (in seconds)

Run/Nt	Termination Times (sec.)						
	2	3	4	5	6	7	8
1	0,41	7,76	60,72	111,33	184,27	271,58	392,60
2	0,43	29,29	64,05	114,04	181,53	281,84	397,26
3	0,43	6,57	61,45	114,51	193,39	296,15	389,75
4	0,45	15,40	67,39	123,82	201,58	302,69	387,68
5	0,00	10,89	66,28	122,01	203,56	311,84	395,65
6	0,49	4,34	65,98	120,77	197,17	291,78	393,10
7	0,46	32,89	65,91	121,15	195,30	306,17	390,20
8	0,65	16,69	68,39	122,98	197,04	305,53	390,34
9	0,49	3,40	65,95	120,55	194,16	309,20	397,84
10	0,52	8,90	66,22	121,64	197,45	298,79	397,13
Average	0,43	13,61	65,23	119,28	194,55	297,56	393,15

APPENDIX 2

A2.1 Generated Optimum Coordinates by Ant Colony Optimization Algorithm

Table A2. 1. Generated Optimum Coordinates by ACO for the turbines two to six (in meters)

	Case A		Case B		Case C	
	X	Y	X	Y	X	Y
	Two Turbines		Two Turbines		Two Turbines	
1st Turbine	-411,5957	229,3238	349,4964	329,3744	329,9761	-320,1248
2nd Turbine	308,6482	-336,8974	-356,4236	-204,3162	-252,5899	421,6483
	Three Turbines		Three Turbines		Three Turbines	
1st Turbine	-312,3446	-389,0610	-457,1717	153,5314	102,3403	-488,5950
2nd Turbine	45,3067	490,4342	354,2908	264,3407	-393,7558	158,9688
3rd Turbine	466,3102	-58,4130	33,9231	-495,1729	411,9390	264,9441
	Four Turbines		Four Turbines		Four Turbines	
1st Turbine	240,1864	-437,6393	-469,4887	-120,2094	276,7249	-388,8853
2nd Turbine	347,9085	349,9920	253,7420	-425,7300	371,4466	331,8118
3rd Turbine	-361,2321	335,1316	-308,8179	330,7173	-225,2399	-442,0210
4thTurbine	-257,7502	-419,7705	409,6989	236,7260	-326,0056	370,8162
	Five Turbines		Five Turbines		Five Turbines	
1st Turbine	66,1502	334,7617	41,0701	-495,8798	-465,1206	183,2794
2nd Turbine	449,4681	201,0570	287,2360	166,5222	-46,3531	465,8386
3rd Turbine	175,9873	-458,1602	215,8213	-233,4172	-173,7122	-428,8238
4thTurbine	-342,0566	306,2755	66,5992	490,2714	391,1877	304,2404
5thTurbine	-246,4971	-430,3538	-496,1798	57,4862	300,4103	-392,4911
	Six Turbines		Six Turbines		Six Turbines	
1st Turbine	476,9868	-88,5476	211,5609	-444,0081	155,3508	-442,5560
2nd Turbine	158,5443	-454,4621	340,6291	-24,6962	315,6777	387,1061
3rd Turbine	-495,3368	54,0485	406,7647	283,9437	-489,5340	48,0212
4thTurbine	266,6344	378,2349	-381,5528	-320,9567	463,8926	-87,1513
5thTurbine	-302,3951	-379,9514	-476,1162	85,4497	-289,7722	-398,6049
6thTurbine	-190,8742	424,7316	-279,2856	373,9544	-189,9984	417,1850

Table A2. 2. Generated Optimum Coordinates by ACO for the turbines seven and eight (in meters)

	Case A		Case B		Case C	
	X	Y	X	Y	X	Y
	Seven Turbines		Seven Turbines		Seven Turbines	
1st Turbine	2,0995	-32,0445	255,3260	-425,4339	30,2036	-492,7519
2nd Turbine	493,7024	77,7092	419,2986	169,5069	166,3188	451,7745
3rd Turbine	192,1010	-436,0054	400,9547	-140,5883	400,9154	-298,0126
4thTurbine	294,4805	397,7794	-270,7621	-419,9001	488,9282	102,8231
5thTurbine	-473,2459	72,0970	-78,7737	492,2522	-470,3416	-32,0045
6thTurbine	-297,3937	400,8264	-284,4615	262,5188	-280,3618	-387,7969
7thTurbine	-193,4545	-452,9596	-475,2972	-32,9581	-176,5855	466,6645
	Eight Turbines		Eight Turbines		Eight Turbines	
1st Turbine	240,5539	-431,6503	320,1845	-232,8029	84,9315	76,2370
2nd Turbine	356,1448	228,4407	495,6949	40,6463	498,3476	-22,6264
3rd Turbine	-33,3256	144,9450	232,1130	440,7727	-43,6876	-366,7806
4thTurbine	130,7642	481,5358	-71,8902	-49,3737	306,6769	-392,5402
5thTurbine	496,3485	-55,7917	95,9426	-486,9583	203,7399	456,6018
6thTurbine	-188,7622	462,8528	-374,5372	-324,3386	-380,7317	-302,3740
7thTurbine	-499,5431	-0,6796	-419,0102	171,2325	-154,2143	475,5814
8thTurbine	-305,7072	-392,8428	-250,6746	430,2226	-462,8429	179,3085

A2.2 Generated Optimum Coordinates by Particle Filtering Approach

Table A2. 3. Generated Optimum Coordinates by PF for the turbines two to six (in meters)

	Case A		Case B		Case C	
	X	Y	X	Y	X	Y
	Two Turbines		Two Turbines		Two Turbines	
1st Turbine	424,0828	-240,2306	-237,1733	-348,8799	-498,9746	-14,3537
2nd Turbine	-360,0897	341,0447	300,5178	370,8409	342,4364	-354,6074
	Three Turbines		Three Turbines		Three Turbines	
1st Turbine	-375,5418	-292,9995	-457,6635	196,7204	449,0751	181,6519
2nd Turbine	-62,8431	483,7913	61,9709	-474,4329	-77,8134	-491,3139
3rd Turbine	458,9816	-190,9826	379,8242	313,7369	-209,3410	453,5159
	Four Turbines		Four Turbines		Four Turbines	
1st Turbine	-334,5878	-357,1771	-422,0827	-163,3157	347,9724	347,2025
2nd Turbine	365,1331	-337,4756	409,6325	171,3877	-357,3363	339,1881
3rd Turbine	-231,9971	431,8640	-226,9028	435,2676	-257,4023	-419,7468
4thTurbine	265,0063	409,0217	302,8696	-258,1033	247,2926	-426,7857
	Five Turbines		Five Turbines		Five Turbines	
1st Turbine	-387,9997	-304,4537	-378,8065	141,1406	-387,0682	-310,2345
2nd Turbine	171,7308	447,1470	303,7194	-394,7365	-294,4542	399,1462
3rd Turbine	487,8024	74,5162	-385,3759	-303,6987	60,4006	-482,3116
4thTurbine	-294,7177	400,1465	-143,2821	477,2835	177,1771	446,5797
5thTurbine	285,9536	-370,4940	435,3416	33,6433	446,9897	-208,0356
	Six Turbines		Six Turbines		Six Turbines	
1st Turbine	299,5513	375,5424	155,8929	-471,9650	287,4829	-368,2276
2nd Turbine	-236,0552	-372,5390	367,6996	-158,6158	416,9256	88,8798
3rd Turbine	199,7991	-406,1111	-125,7793	483,5111	-194,0782	-385,6635
4thTurbine	495,3017	-67,3273	441,2388	213,4477	169,7870	468,1224
5thTurbine	-135,2689	414,1859	-426,7807	-259,7184	-296,5647	384,7620
6thTurbine	-496,3642	51,3616	-298,2398	115,2641	-497,6564	-37,3903

Table A2. 4. Generated Optimum Coordinates by PF for the turbines seven and eight (in meters)

	Case A		Case B		Case C	
	X	Y	X	Y	X	Y
	Seven Turbines		Seven Turbines		Seven Turbines	
1st Turbine	-485,9543	-58,9815	-251,2019	305,2292	256,7603	-428,2424
2nd Turbine	-216,1158	440,6319	89,2080	-490,9133	-69,5850	-355,9185
3rd Turbine	304,2244	-396,5339	329,5489	-142,4787	-405,7102	-282,9211
4thTurbine	-317,8914	-385,5659	449,8984	212,0337	-477,4863	119,8362
5thTurbine	-12,5805	-20,4170	-427,1132	-243,8260	496,0367	-8,9040
6thTurbine	462,5104	-69,2110	-491,7504	89,5196	-105,3241	454,4037
7thTurbine	194,5513	452,6578	132,9236	481,6137	259,4824	427,3260
	Eight Turbines		Eight Turbines		Eight Turbines	
1st Turbine	487,3907	-111,4062	-350,1438	-356,8218	-20,5869	490,5726
2nd Turbine	194,3908	460,4387	-325,1423	199,4589	-484,8317	-120,6966
3rd Turbine	-92,6672	-112,6031	402,4185	294,4116	349,2419	355,6559
4thTurbine	-250,1882	-413,3053	231,8047	35,0829	455,6442	-133,4421
5thTurbine	343,9981	171,3106	192,4008	-461,0343	-335,8469	337,0877
6thTurbine	76,1913	-477,2282	-495,3587	-60,6768	-231,6041	-421,1178
7thTurbine	-493,9066	69,7913	428,7091	-253,0895	251,2118	-431,3187
8thTurbine	-346,7354	358,4307	-147,9679	476,0117	-115,5933	-91,3955

APPENDIX 3

A3.1 Generated Optimum Layouts by Ant Colony Optimization Algorithm

A3.1.1 Case A

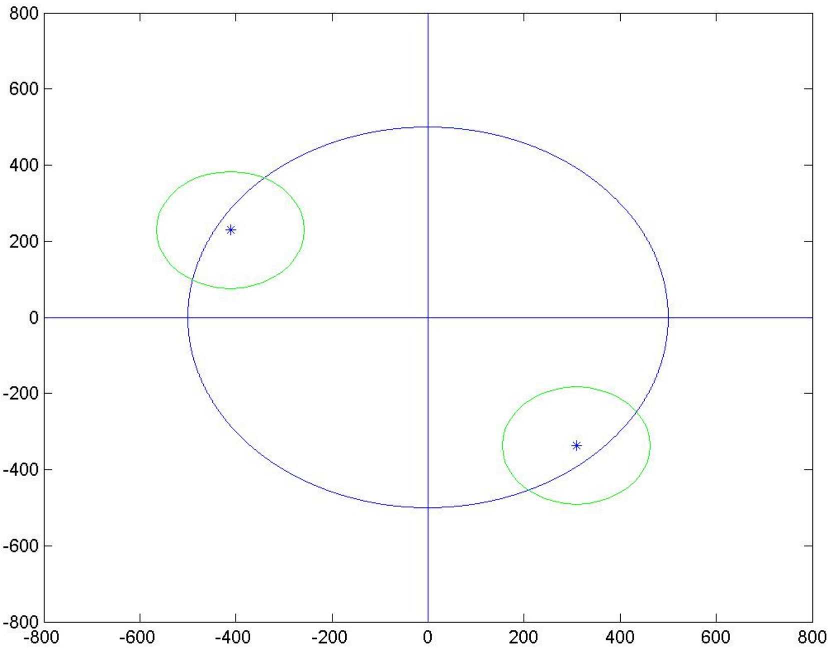


Figure A3. 1. Layout for Two Turbines by ACO in Case A

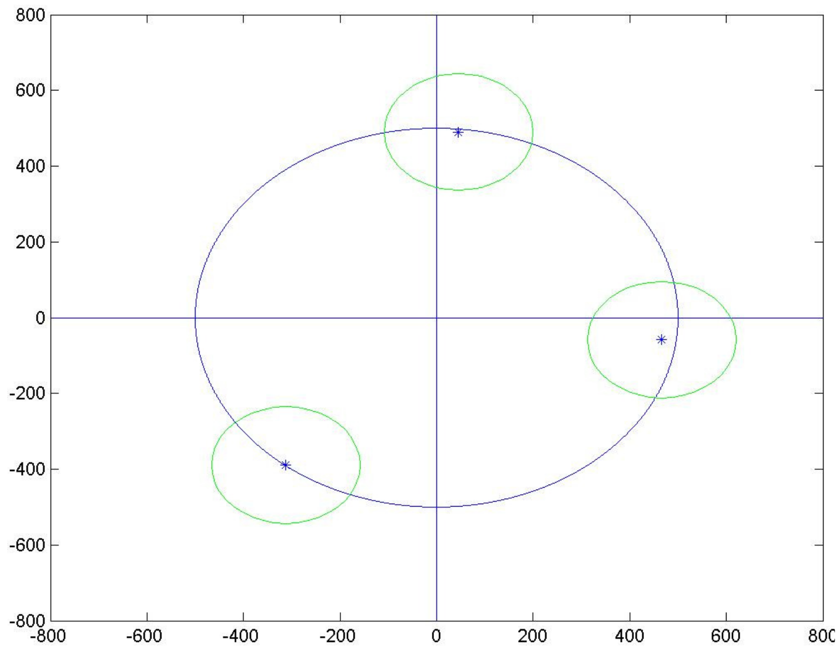


Figure A3. 2. Layout for Three Turbines by ACO in Case A

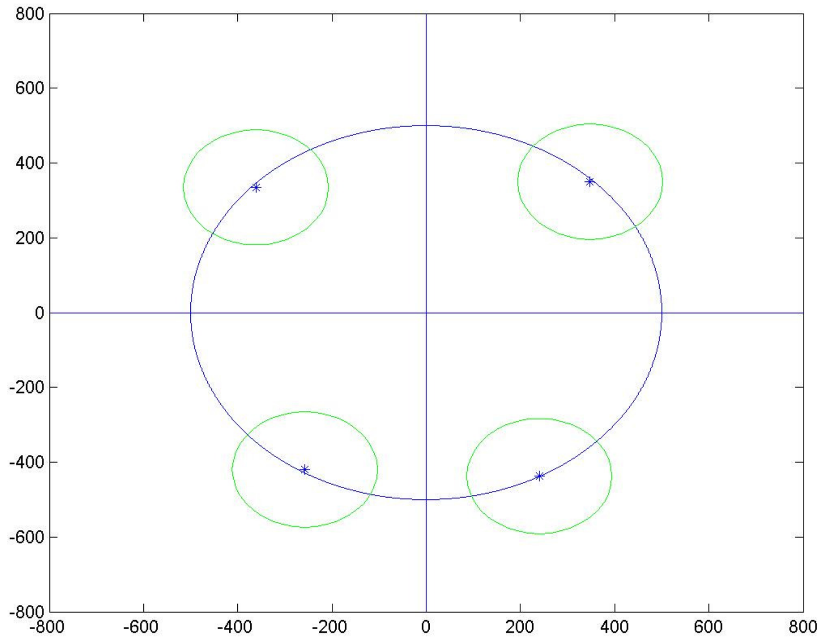
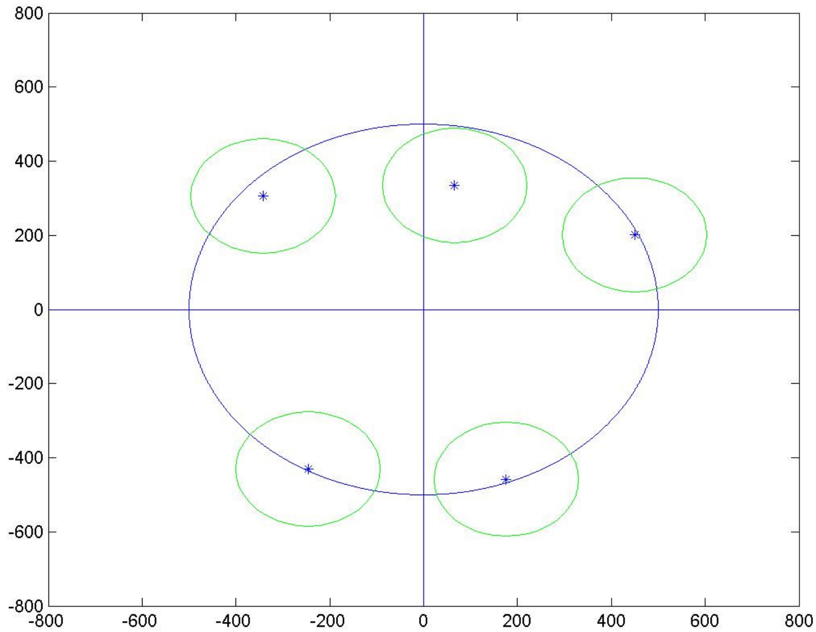


Figure A3. 3. Layout for Four Turbines by ACO in Case A



9

Figure A3. 4. Layout for Five Turbines by ACO in Case A

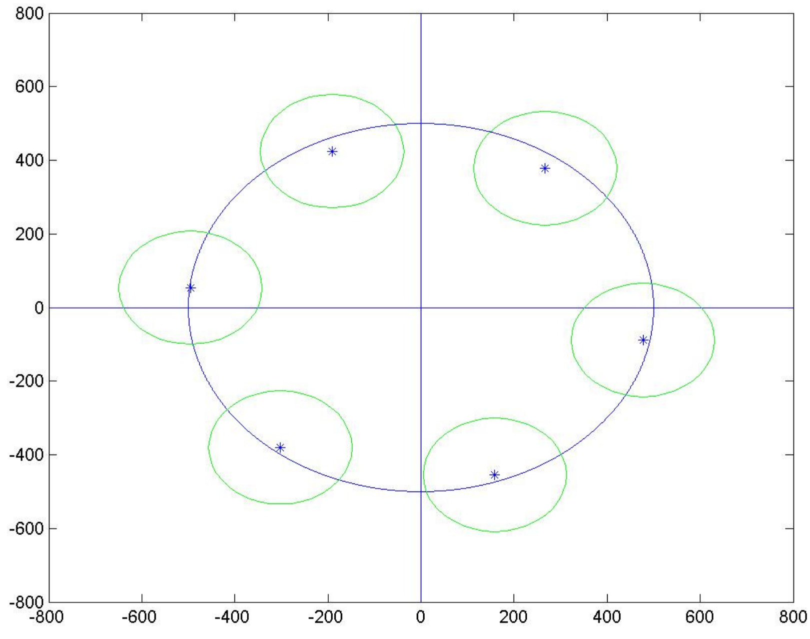


Figure A3. 5. Layout for Six Turbines by ACO in Case A

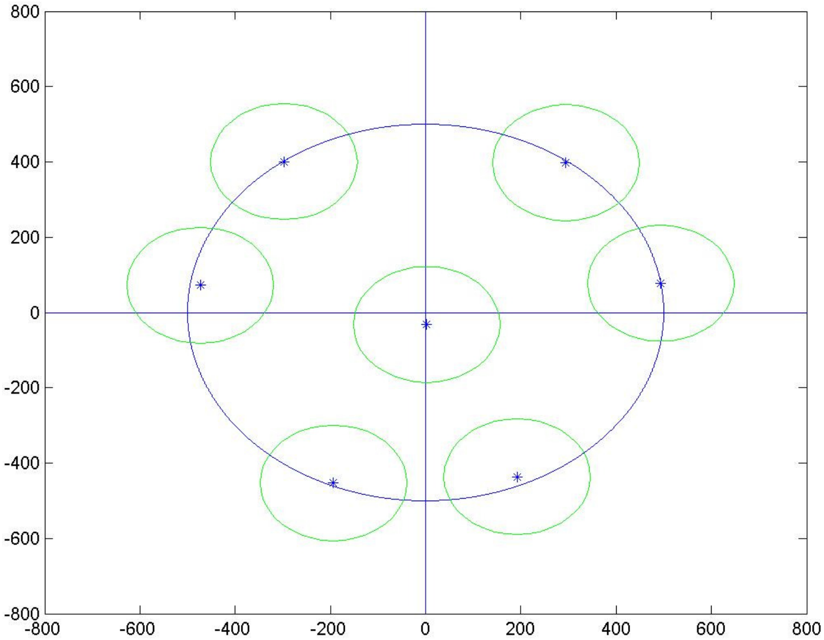


Figure A3. 6. Layout for Seven Turbines by ACO in Case A

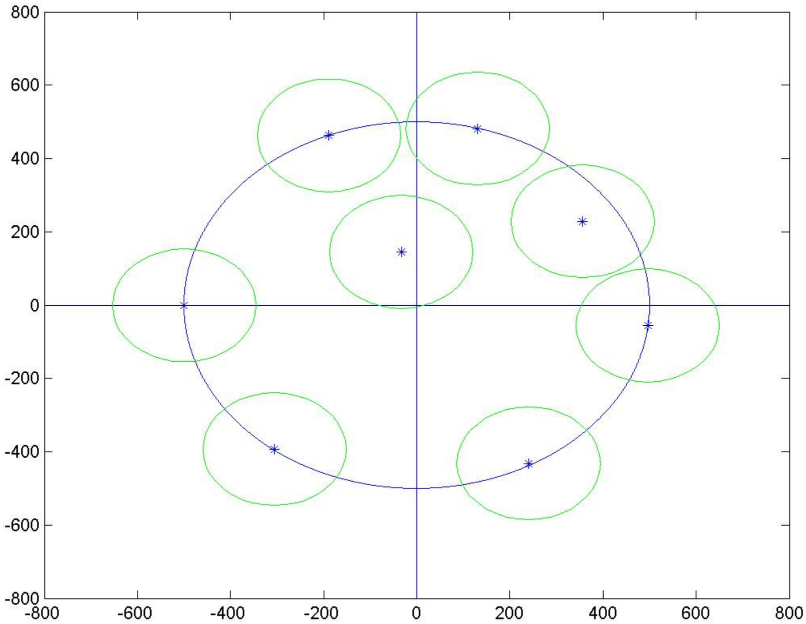


Figure A3. 7. Layout for Eight Turbines by ACO in Case A

A3.1.2 Case B

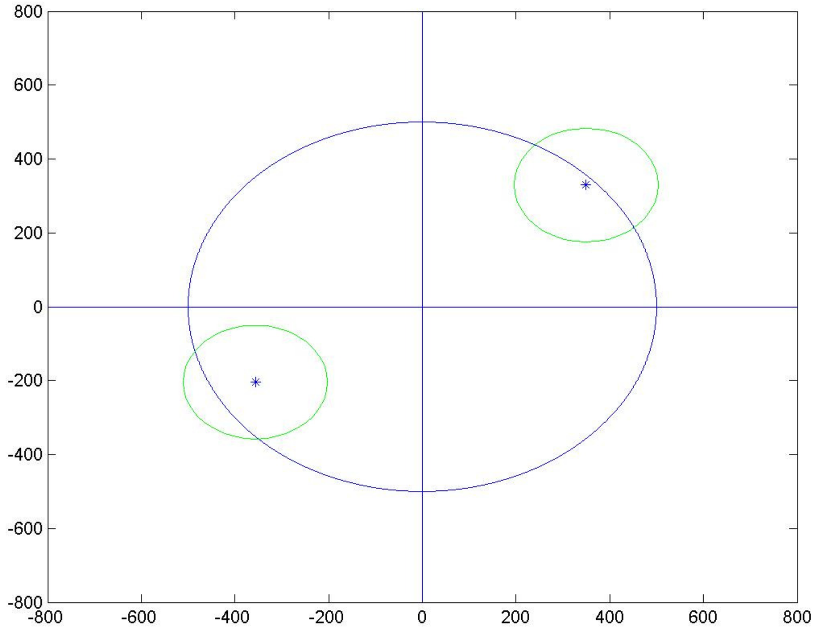


Figure A3. 8. Layout for Two Turbines by ACO in Case B

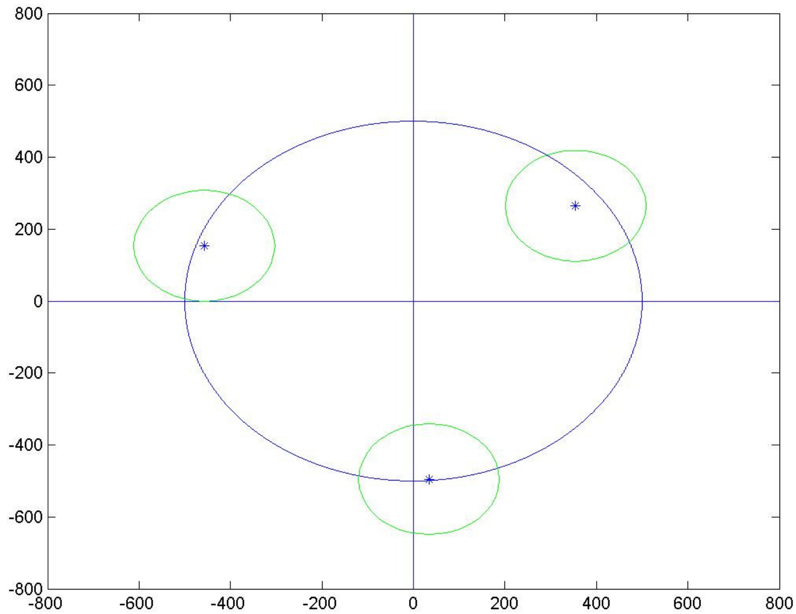


Figure A3. 9. Layout for Three Turbines by ACO in Case B

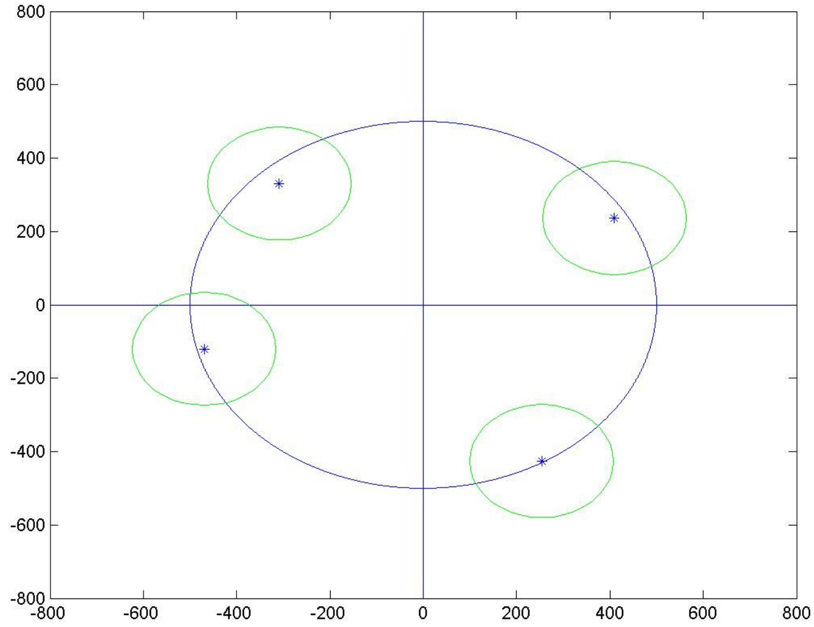


Figure A3. 10. Layout for Four Turbines by ACO in Case B

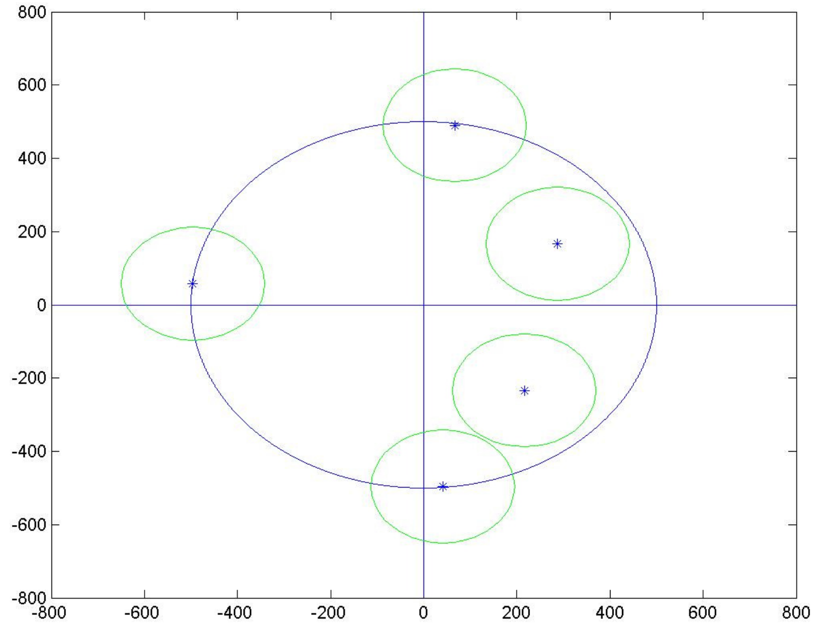


Figure A3. 11. Layout for Five Turbines by ACO in Case B

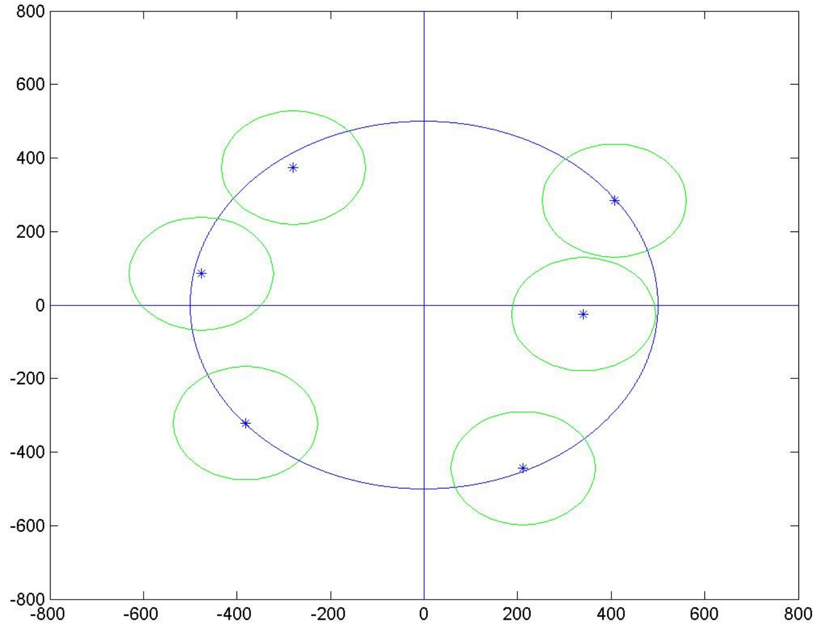


Figure A3. 12. Layout for Six Turbines by ACO in Case B

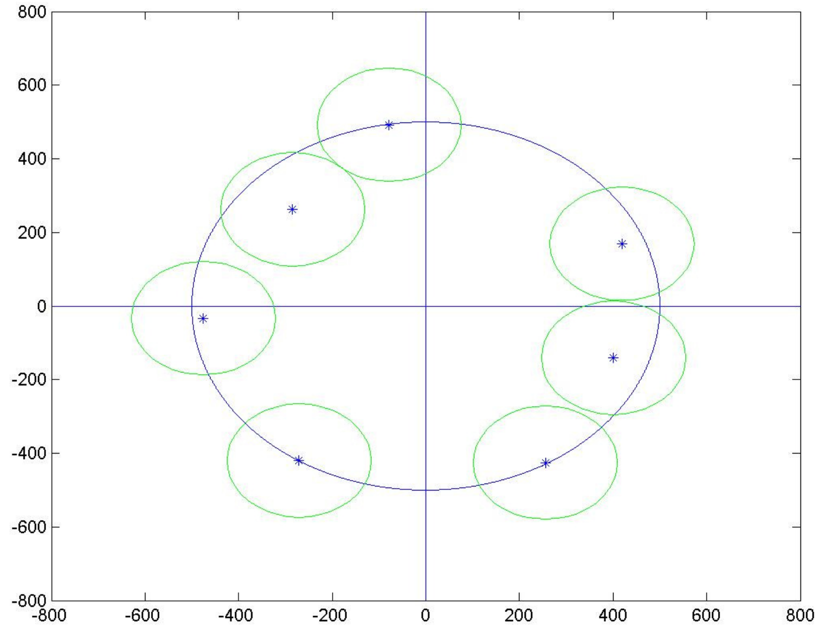


Figure A3. 13. Layout for Seven Turbines by ACO in Case B

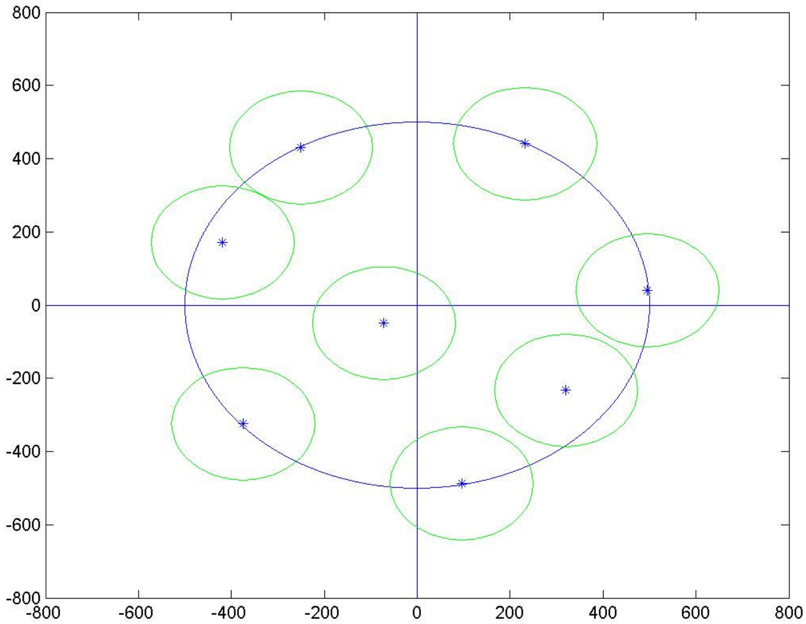


Figure A3. 14. Layout for Eight Turbines by ACO in Case B

A3.1.3 Case C

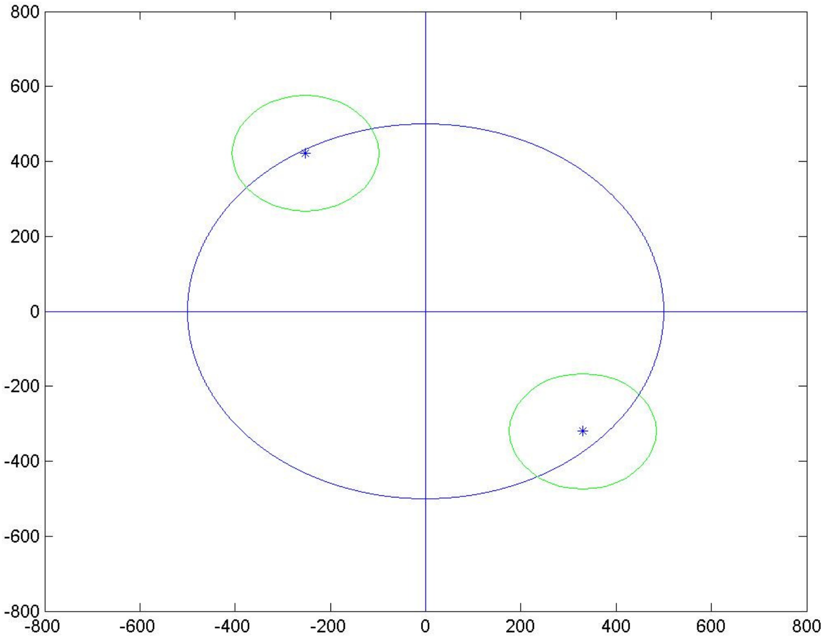


Figure A3. 15. Layout for Two Turbines by ACO in Case C

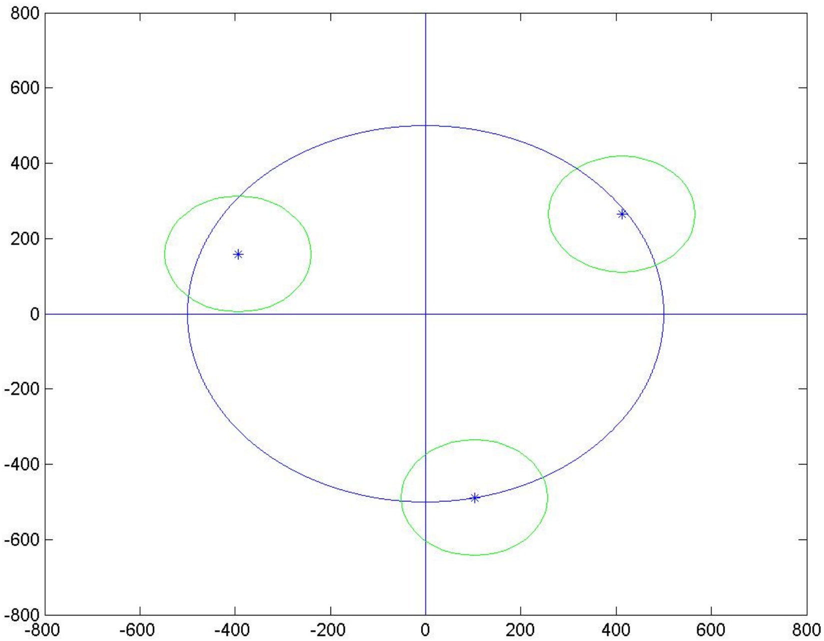


Figure A3. 16. Layout for Three Turbines by ACO in Case C

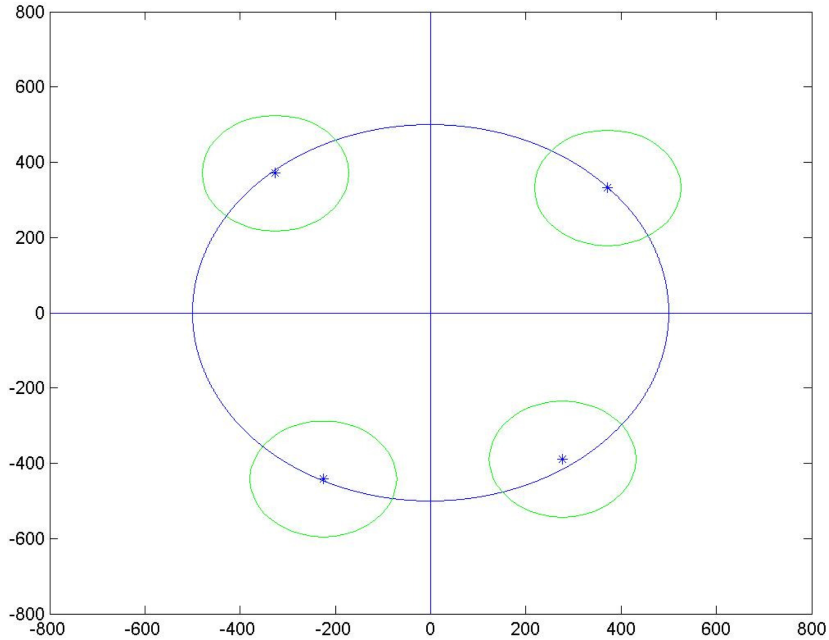


Figure A3. 17. Layout for Four Turbines by ACO in Case C

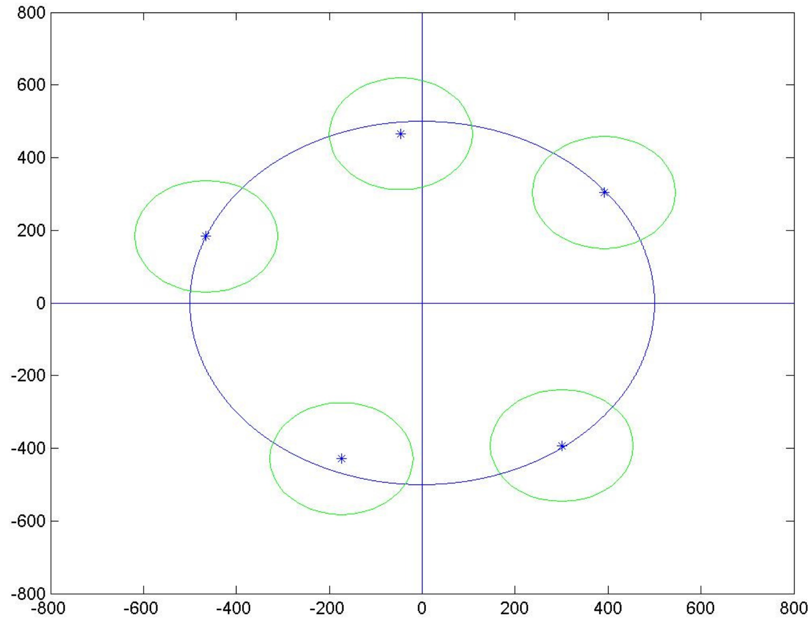


Figure A3. 18. Layout for Five Turbines by ACO in Case C

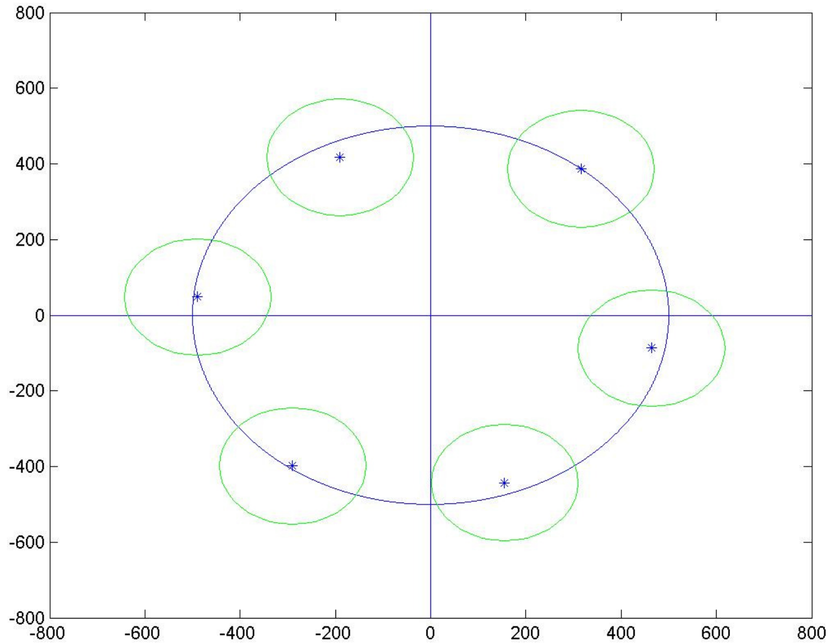


Figure A3. 19. Layout for Six Turbines by ACO in Case C

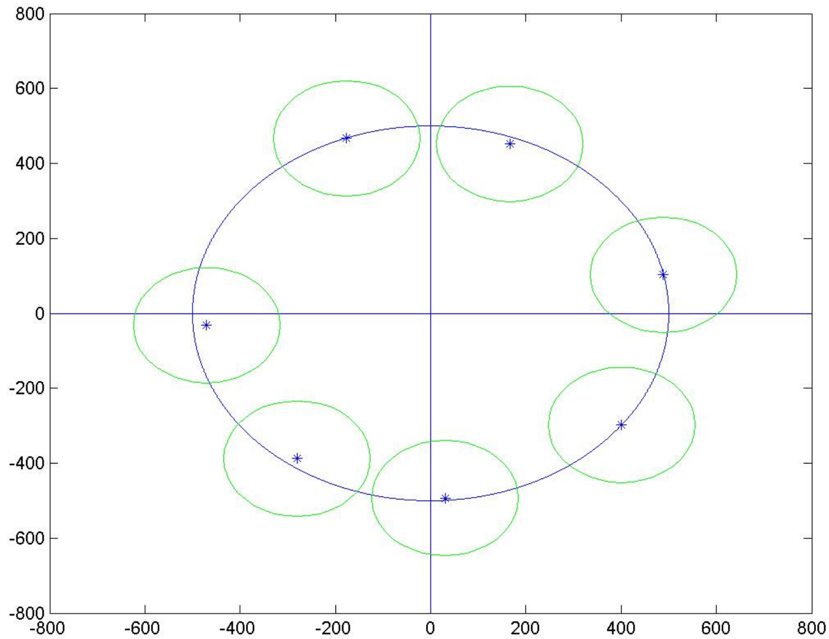


Figure A3. 20. Layout for Seven Turbines by ACO in Case C

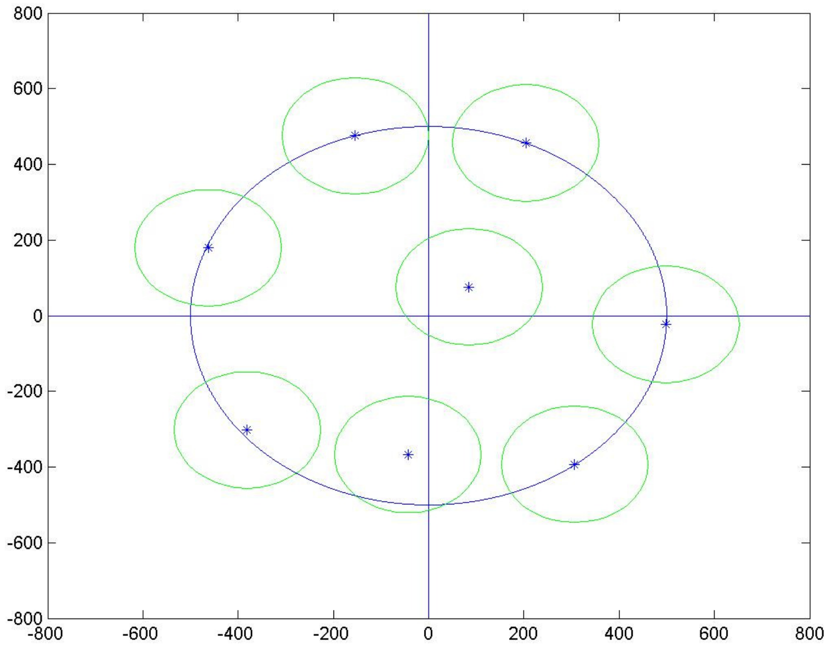


Figure A3. 21. Layout for Eight Turbines by ACO in Case C

A3.2 Generated Optimum Layouts by Particle Filtering Approach

A3.2.1 Case A

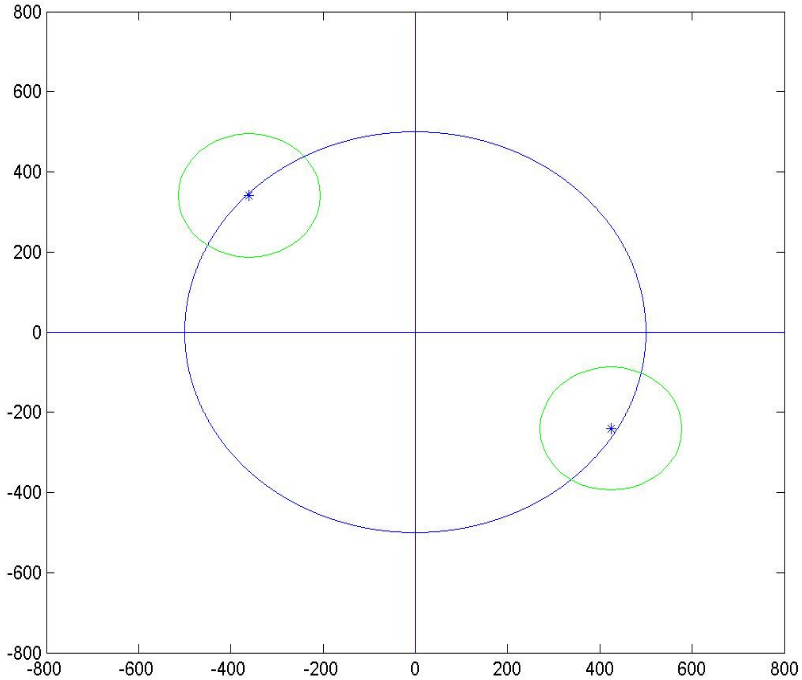


Figure A3. 22. Layout for Two Turbines by PF in Case A

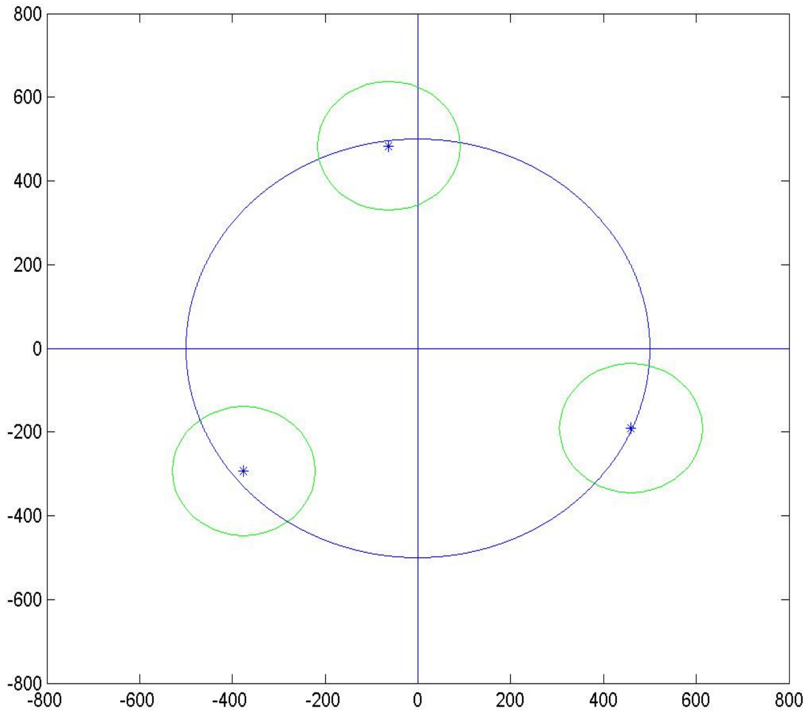


Figure A3. 23. Layout for Three Turbines by PF in Case A

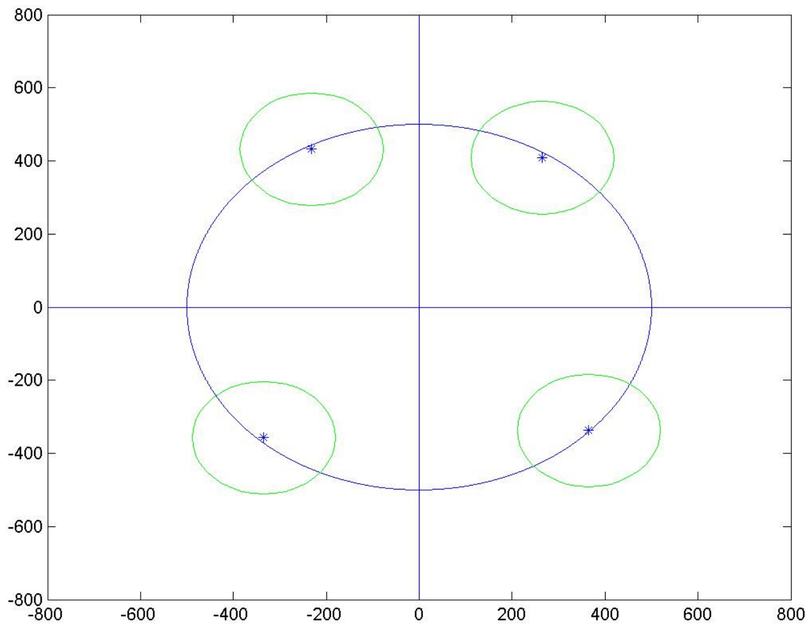


Figure A3. 24. Layout for Four Turbines by PF in Case A

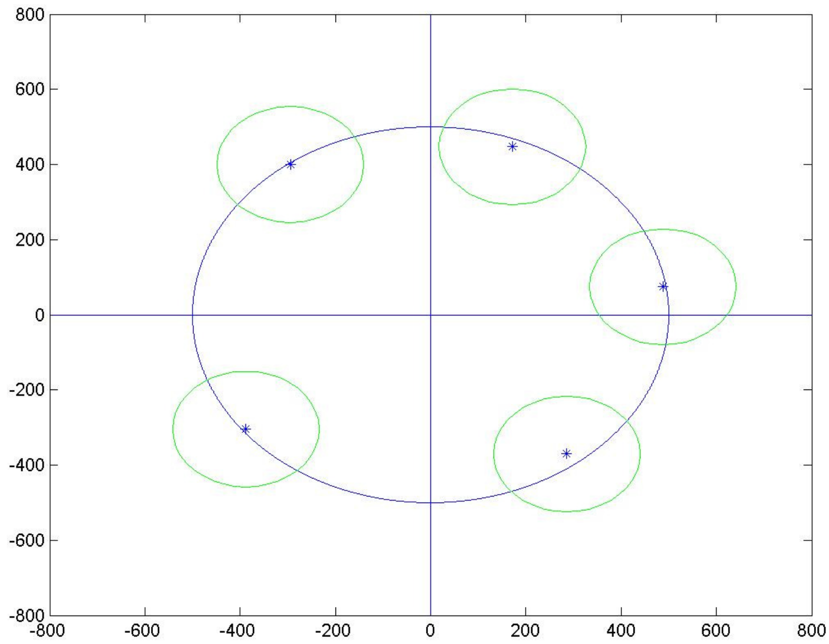


Figure A3. 25. Layout for Five Turbines by PF in Case A

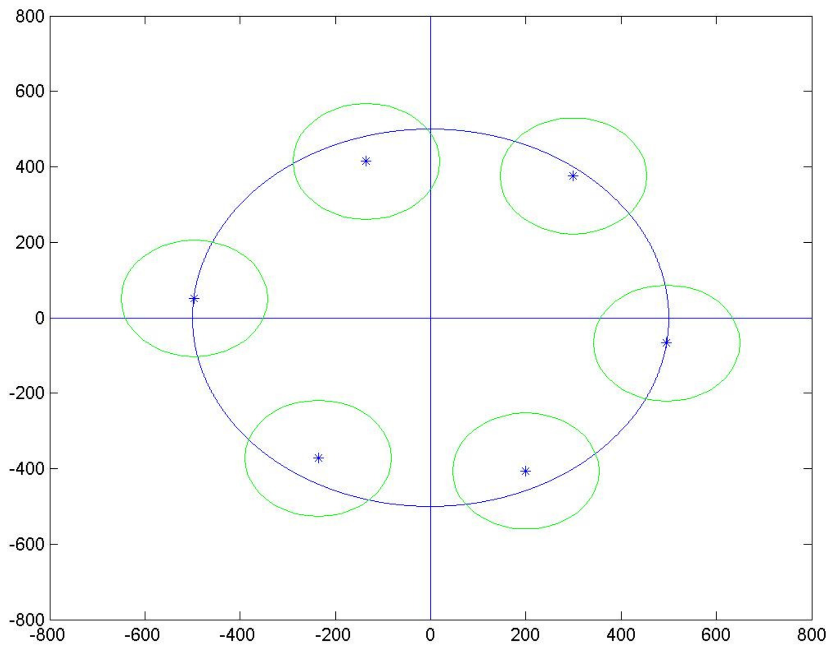


Figure A3. 26. Layout for Six Turbines by PF in Case A

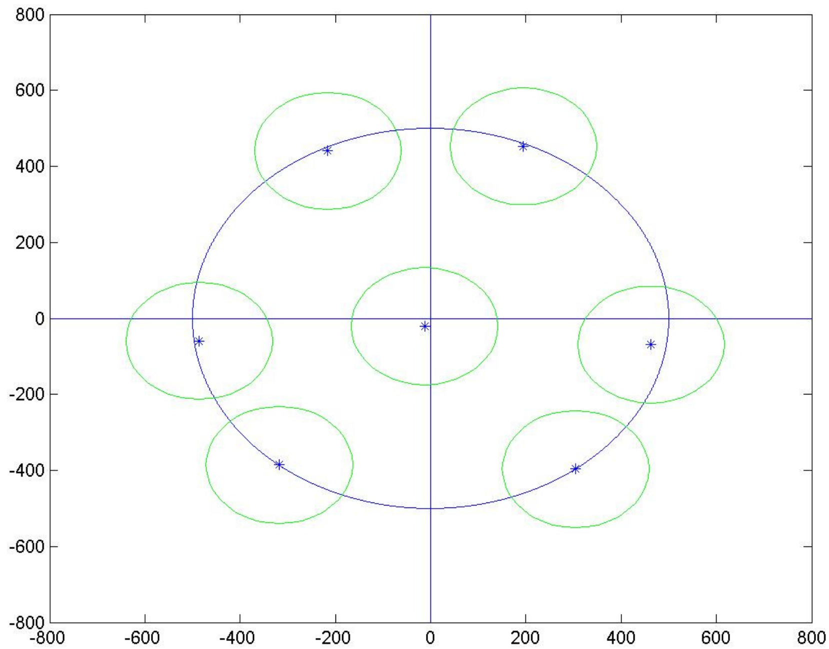


Figure A3. 27. Layout for Seven Turbines by PF in Case A

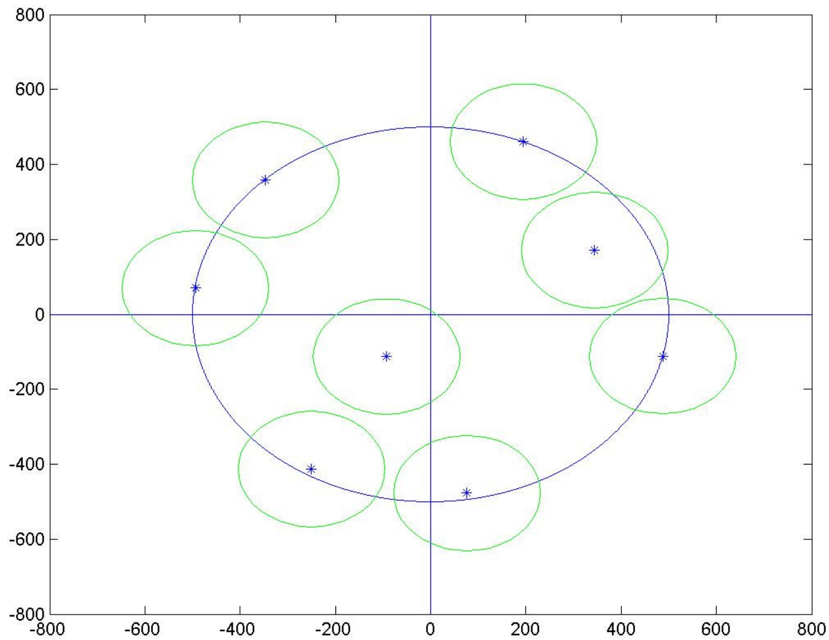


Figure A3. 28. Layout for Eight Turbines by PF in Case A

A3.2.2 Case B

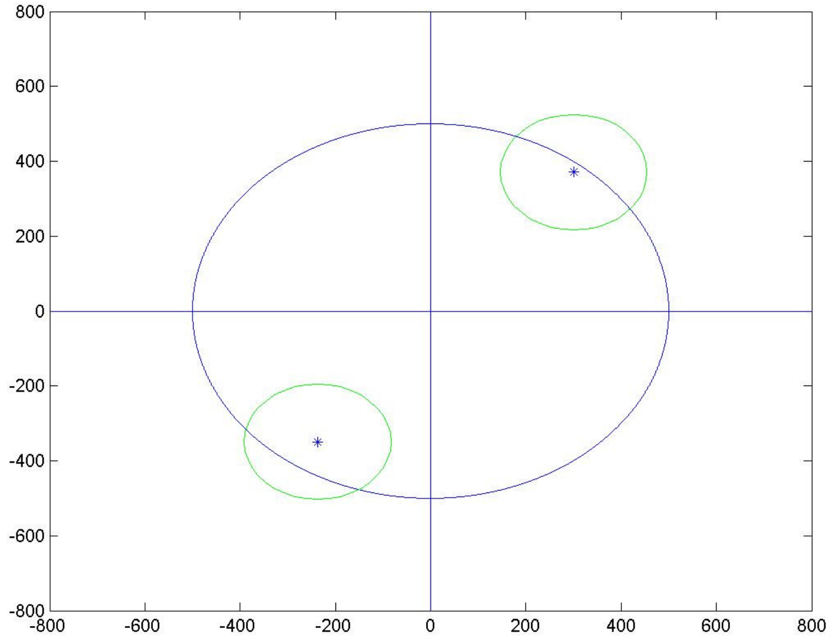


Figure A3. 29. Layout for Two Turbines by PF in Case B

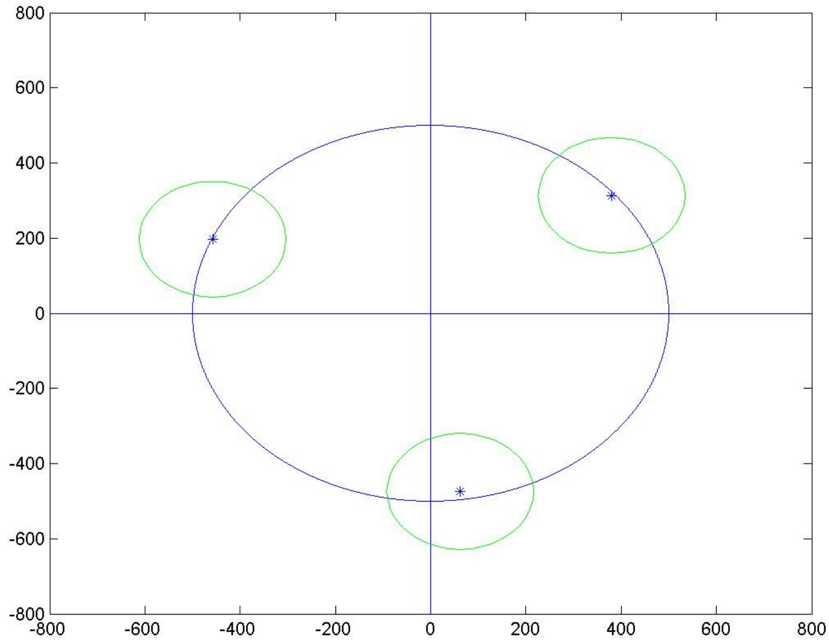


Figure A3. 30. Layout for Three Turbines by PF in Case B

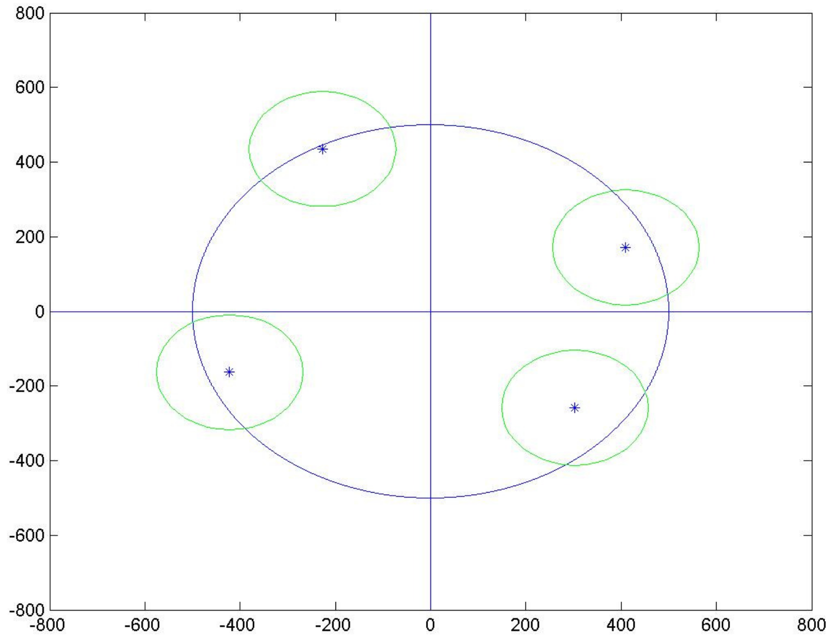


Figure A3. 31. Layout for Four Turbines by PF in Case B

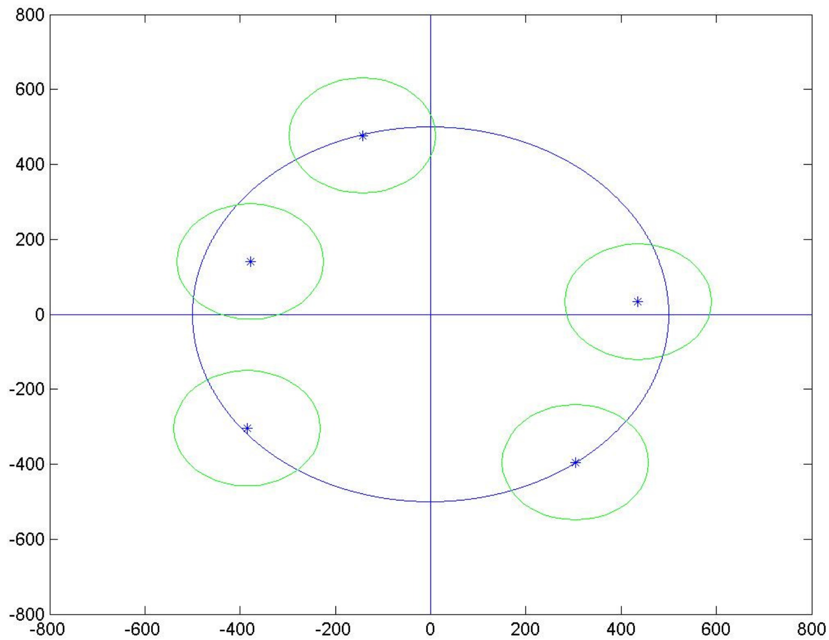


Figure A3. 32. Layout for Five Turbines by PF in Case B

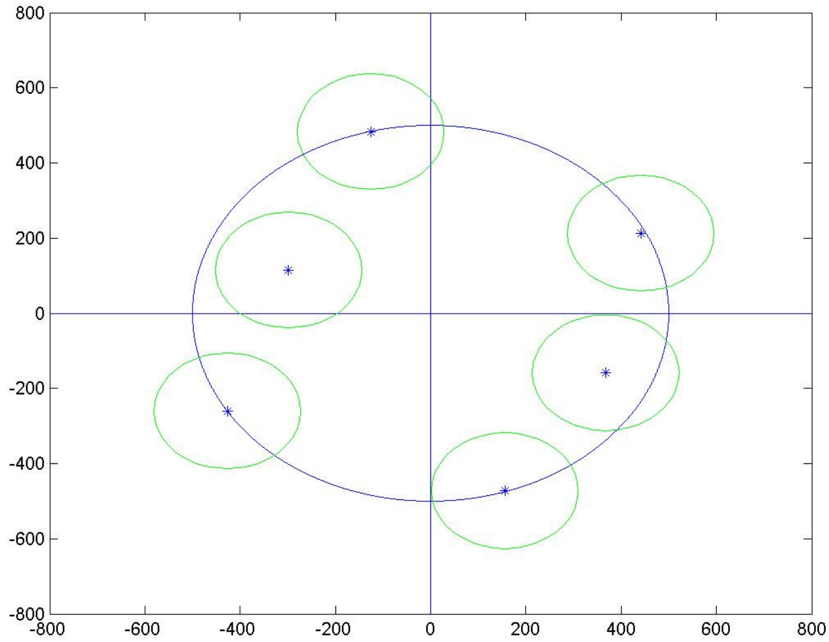


Figure A3. 33. Layout for Six Turbines by PF in Case B

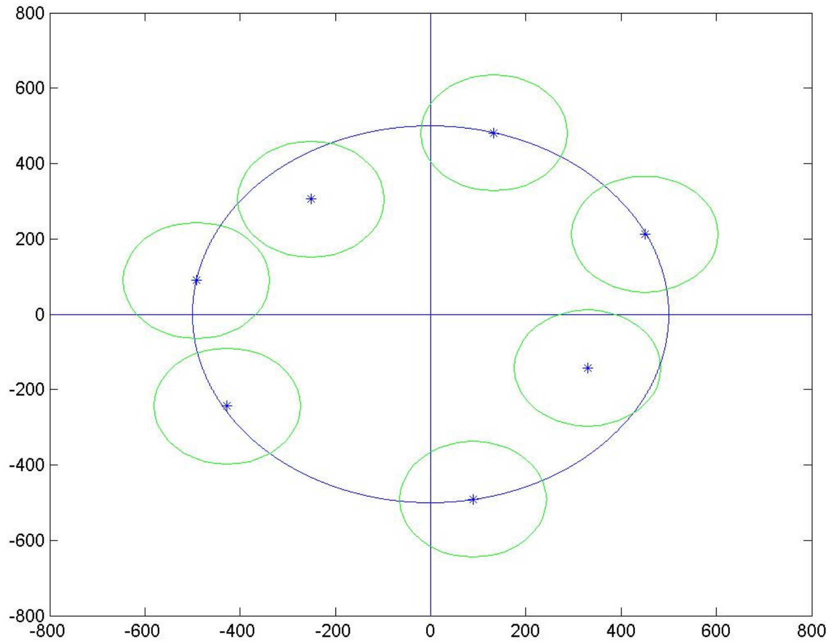


Figure A3. 34. Layout for Seven Turbines by PF in Case B

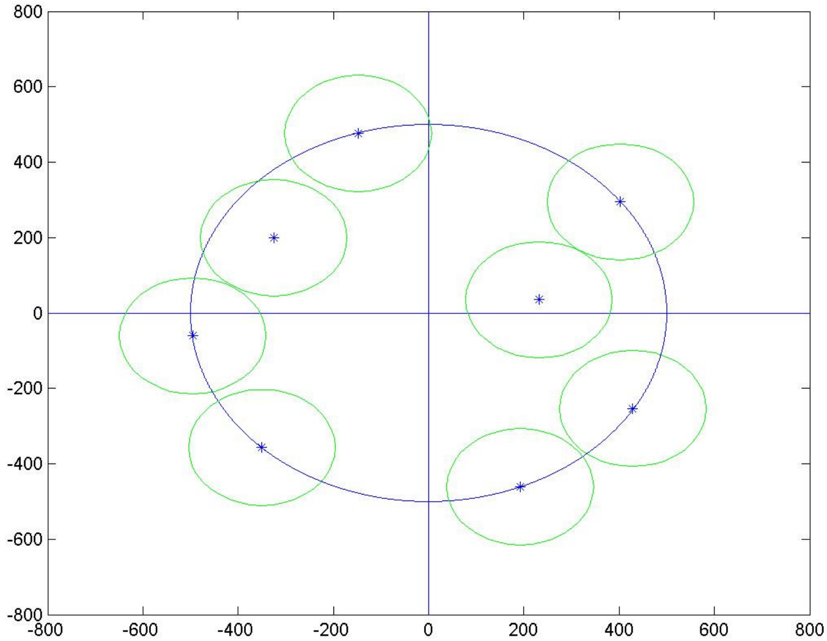


Figure A3. 35. Layout for Eight Turbines by PF in Case B

A3.2.3 Case C

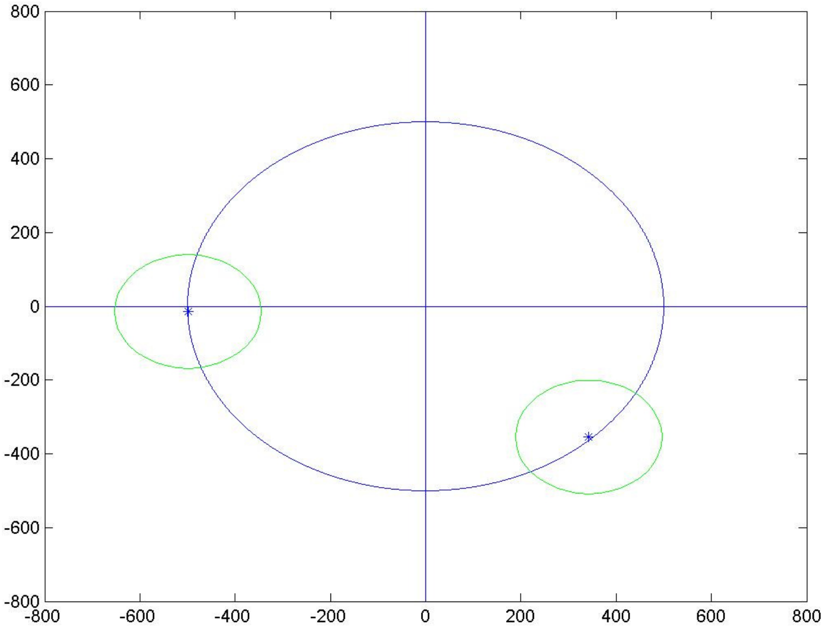


Figure A3. 36. Layout for Two Turbines by PF in Case C

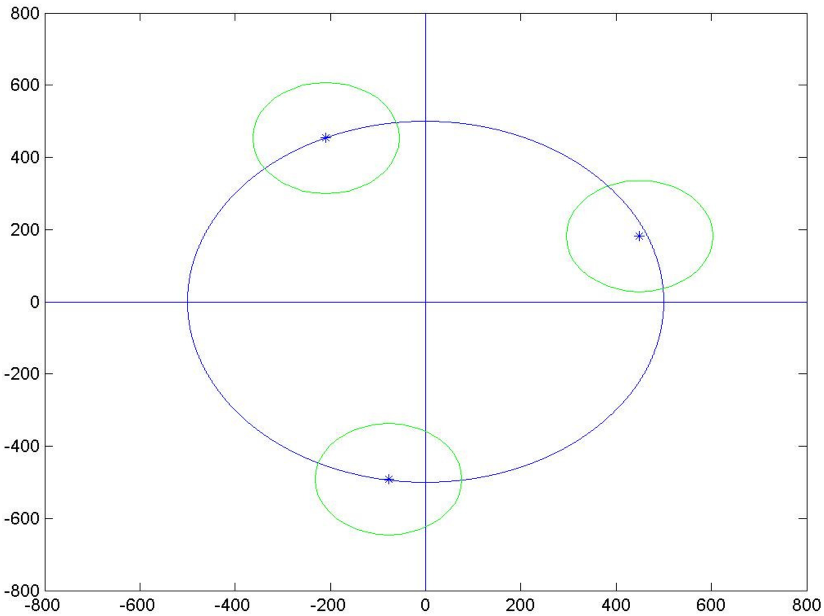


Figure A3. 37. Layout for Three Turbines by PF in Case C

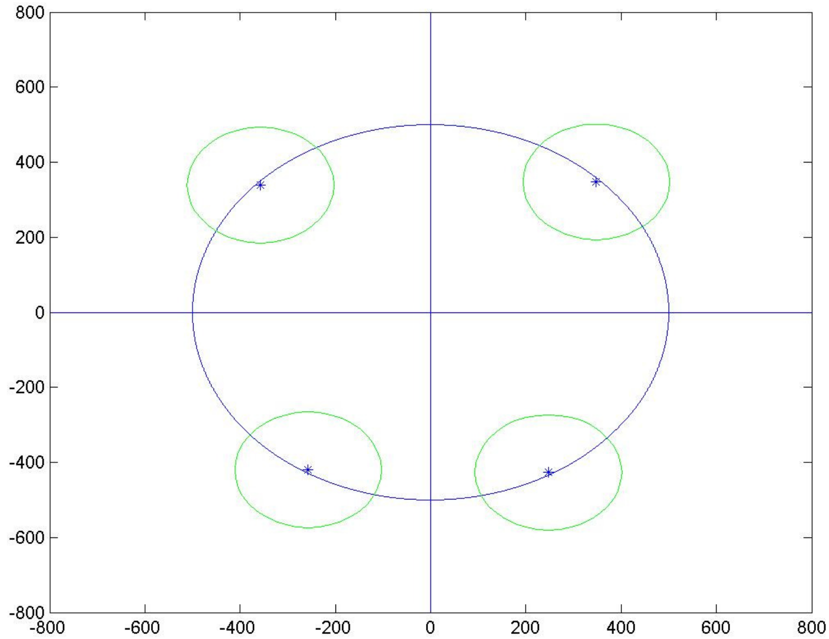


Figure A3. 38. Layout for Four Turbines by PF in Case C

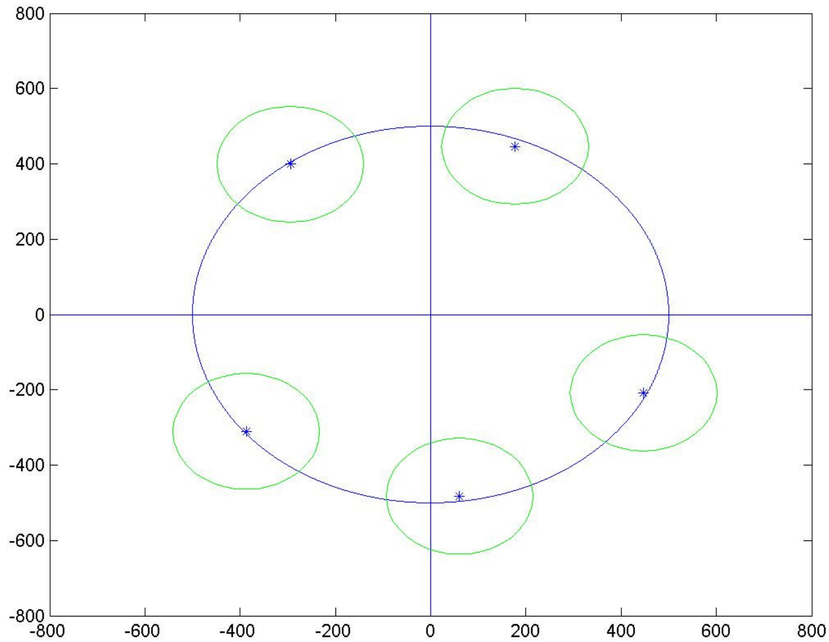


Figure A3. 39. Layout for Five Turbines by PF in Case C

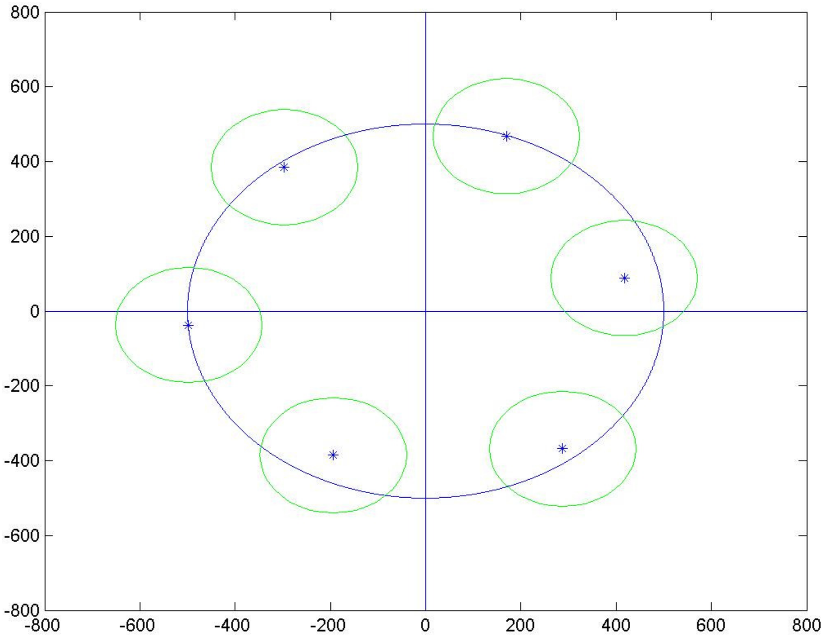


Figure A3. 40. Layout for Six Turbines by PF in Case C

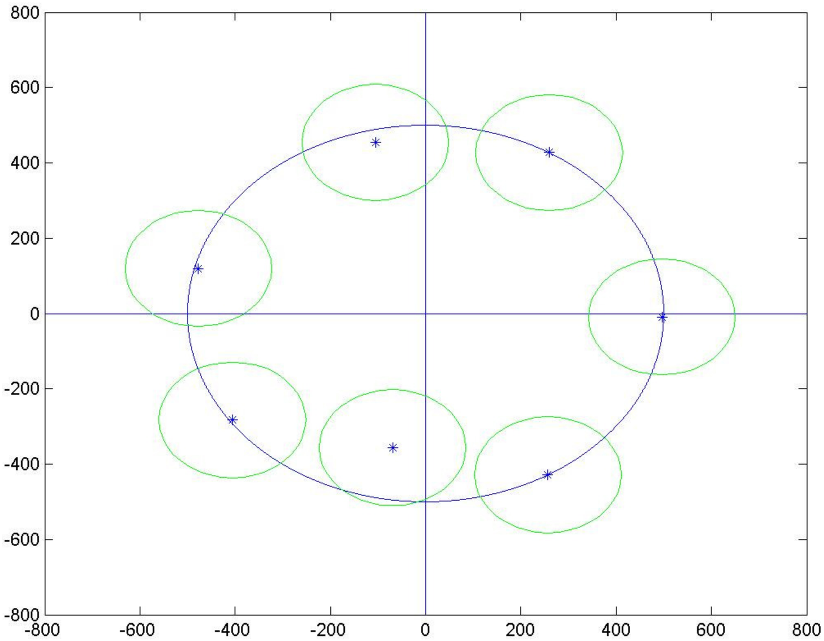


Figure A3. 41. Layout for Seven Turbines by PF in Case C

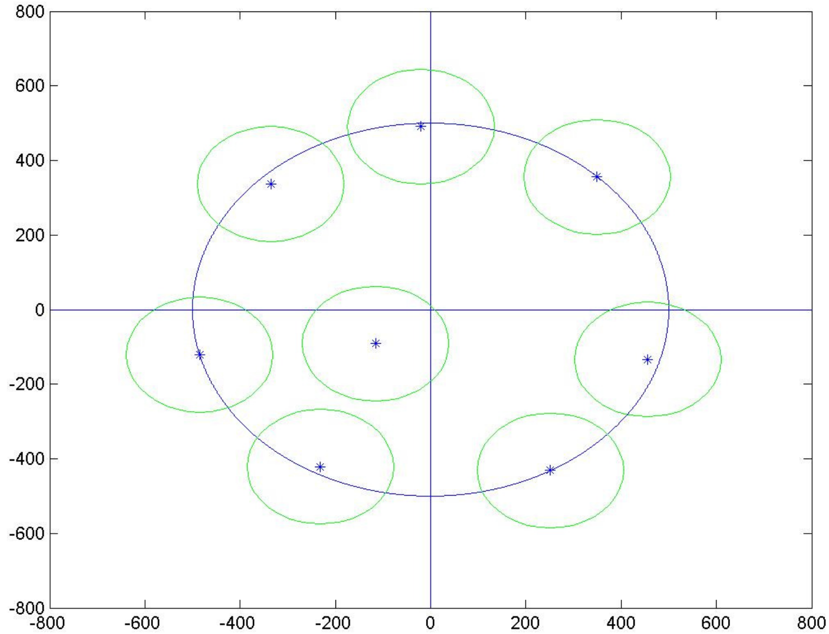


Figure A3. 42. Layout for Eight Turbines by PF in Case C

APPENDIX 4

A4.1 The Functions for ACO and PF

A4.1.1 The function 'rassalNt'

```
% This function creates initial randomized wind farms
function rFarm=rassalNt(Nt,r,R)
for i=1:Nt
    rFarm(i,1)=-r + (2*r).*rand;
    rFarm(i,2)=-r + (2*r).*rand;
    while (rFarm(i,1)^2+rFarm(i,2)^2)>r^2
        rFarm(i,1)=-r + (2*r).*rand;
        rFarm(i,2)=-r + (2*r).*rand;
    end
    j=1;
    if i>1
        while (j~=i)
            while (((rFarm(j,1)-rFarm(i,1))^2+(rFarm(j,2)-
rFarm(i,2))^2)<=64*R^2)||((rFarm(i,1)^2+rFarm(i,2)^2)>r^2)
                rFarm(i,1)=-r + (2*r).*rand;
                rFarm(i,2)=-r + (2*r).*rand;
                while (((rFarm(j,1)-rFarm(i,1))^2+(rFarm(j,2)-
rFarm(i,2))^2)<=64*R^2)||((rFarm(i,1)^2+rFarm(i,2)^2)>r^2)
                    rFarm(i,1)=-r + (2*r).*rand;
                    rFarm(i,2)=-r + (2*r).*rand;
                end
                j=1;
            end
            j=j+1;
        end
    end
end
```

A4.1.2 The Function ‘Power’

```
% Computes the power generations

function [Pe TeP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c)
for i=1:Nt

    for j=1:Nv+1

        for l=1:Nteta

            AAA(i,l)=(SCN1(l,2)-SCN1(l,1))*SCN1(l,5)*(exp(-
(SCN1(j,6)/((Wel_Def_c(i,l)+Wel_Def_c(i,l+1))/2))^SCN1(l,3))-exp(-
(SCN1(j+1,6)/((Wel_Def_c(i,l)+Wel_Def_c(i,l+1))/2))^SCN1(l,3)));

            B(i,l)=(SCN1(l,2)-SCN1(l,1))*SCN1(l,5)*exp(-
(SCN1(22,6)/((Wel_Def_c(i,l)+Wel_Def_c(i,l+1))/2))^SCN1(l,3));

            C(i,l)=(SCN1(l,2)-SCN1(l,1))*SCN1(l,5)*(exp(-
(SCN1(1,6)/((Wel_Def_c(i,l)+Wel_Def_c(i,l+1))/2))^SCN1(l,3))-exp(-
(SCN1(22,6)/((Wel_Def_c(i,l)+Wel_Def_c(i,l+1))/2))^SCN1(l,3)));

        end

        A(i,j)=sum(AAA(i,:)).*((SCN1(j+1,6)+SCN1(j,6))/2);

    end

    AA(i)=sum(A(i,:));

    BB(i)=sum(B(i,:));

    CC(i)=sum(C(i,:));

    Pe(i)=lambda*AA(i)+Prated*BB(i)+Nu*CC(i);

end

TeP=sum(Pe);
```

A4.1.3 The Function 'WelDefc'

```
% Computes the velocity deficits in terms of the Weibull scale
%parameter c
function Weldefc=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct)
Tot=zeros(Nteta+1,Nt);
velocitydeficite=zeros(Nteta+1,Nt);
Beta=zeros(Nteta+1,Nt,Nt);
Vel_def=zeros(Nteta+1,Nt,Nt);
for a=1:Nteta+1
    for i=1:Nt
        for j=1:Nt
            if j~=i
                X=Farm(i,1)-Farm(j,1);
                Y=Farm(i,2)-Farm(j,2);
                sina=sin(SCN1(a,1)*pi/180);
                cosa=cos(SCN1(a,1)*pi/180);
                ATI1(a,i,j)=X*cosa+Y*sina+R/Ck;

ATI2(a,i,j)=sqrt((X+(R/Ck)*cosa)^2+(Y+(R/Ck)*sina)^2);
                B(a,i,j)=ATI1(a,i,j)/ATI2(a,i,j);
                Beta(a,i,j)=(180/pi)*acos(B(a,i,j));
                d(a,i,j)=abs(X*cosa+Y*sina);
                if (Beta(a,i,j)<atan(Ck)*180/pi)
                    Vel_def(a,j,i)=(1-sqrt(1-
Ct))/(1+(Ck/R)*d(a,i,j))^2;
                    Tot(a,j)=Tot(a,j)+Vel_def(a,j,i)^2;
                end
            end
        end
    end
end


for a=1:Nteta+1
    for i=1:Nt
        velocitydeficite(a,i)=sqrt(Tot(a,i));
        Weldefc(i,a)=(1-velocitydeficite(a,i))*SCN1(a,4);
    end
end
```

A4.1.4 The Function 'garpph'

```
%% Graphing Wind farm
function graphh(The_Run,ttt,Farm,Nt,r,R)
figure(ttt)
x=-r:0.1:r;
y=sqrt(r^2-x.^2);
X=Farm(:,1);
Y=Farm(:,2);
xxx=-800:0.1:800;
yyy=zeros(1,16001);
plot(x,y,'b')
hold on
plot(x,-y,'b')
hold on
plot(X,Y,'*')
hold on
plot(xxx,yyy)
hold on
plot(yyy,xxx)
t=0:pi/20:2*pi;

hold on
for i=1:Nt
    plot(X(i)+4*R*cos(t),Y(i)+sin(t)*4*R,'g')
    hold on
end

FigureName=strcat(int2str(ttt+1),'_Turbines_Optimized_Layout_Figure_
for_1st_Scenario_and_',The_Run,'.jpg');
saveas(ttt,FigureName)
hold off
```

A4.1.5 The Function 'AFarm'

```
% checks the new coordinates of the turbines if they satisfy the
%assumtions six and egiht

function MFarm=AFarm(i,Nt,MFarm,R,r)

if i==1

    j=2;

    while (j<=Nt)

        while ((MFarm(j,1)-MFarm(i,1))^2+(MFarm(j,2)-
MFarm(i,2))^2<=64*R^2)||((MFarm(i,1)^2+MFarm(i,2)^2)>r^2)

            MFarm(i,1)=-r + (2*r).*rand;

            MFarm(i,2)=-r + (2*r).*rand;

            while ((MFarm(j,1)-MFarm(i,1))^2+(MFarm(j,2)-
MFarm(i,2))^2<=64*R^2)||((MFarm(i,1)^2+MFarm(i,2)^2)>r^2)

                MFarm(i,1)=-r + (2*r).*rand;

                MFarm(i,2)=-r + (2*r).*rand;

            end

            j=2;

        end

        j=j+1;

    end

end

if i>1

    j=1;

    while (j<=Nt)

        if j~=i

            while ((MFarm(j,1)-MFarm(i,1))^2+(MFarm(j,2)-
MFarm(i,2))^2<=64*R^2)||((MFarm(i,1)^2+MFarm(i,2)^2)>r^2)

                MFarm(i,1)=-r + (2*r).*rand;

                MFarm(i,2)=-r + (2*r).*rand;

                while ((MFarm(j,1)-MFarm(i,1))^2+(MFarm(j,2)-
MFarm(i,2))^2<=64*R^2)||((MFarm(i,1)^2+MFarm(i,2)^2)>r^2)

                    MFarm(i,1)=-r + (2*r).*rand;

                    MFarm(i,2)=-r + (2*r).*rand;

                end

                j=1;

            end

        end

        j=j+1;

    end

end
```

A4.2 Code for the Ant Colony Optimization

A4.2.1 The Main Code for the ACO

```
% Parameter settings of the problem, initialization, and resulting
part
clear all;
load('SCN1.mat');
maxiter=300; %maximum iteration number
r=500; %farm area radius
Vrated=14; %rated velocity
Cutin=3.5; %cut in speed
Prated=1500; % rated power
R=38.5; %rotor radius of turbine
lambda=140.86; %for linear power curve function
Nu=-500; %for linear power curve function
Ck=0.075; % spreading constant
Ct=0.8; % trust coefficient
Nv=20; % wind speed interval of each 0.5 m
Nteta=23; %wind direction interval of each 15 degree
theExcellFileName='ACO_1st_Scenario_WFLOP.xls';
%% all the number of turbines are tried at one run
for ii=1:10;
    The_Run=strcat('The_Run_is_',int2str(ii),'_');
for Nt=2:8  %turbine number
ants=200; % number of ants
%% randomly turbine locations generating between the farm region
Farm=rassalNt(Nt,r,R);
Farm1=Farm;
for i=1:Nt
    TotFarm1(Nt,i,1)=Farm1(i,1);
    TotFarm1(Nt,i,2)=Farm1(i,2);
end
%% Theoritical power
for i=1:Nt
    for l=1:Nteta+1
        Wel_Def_c(i,l)=SCN1(l,4);
    end
end
[P TP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
```

```
for i=1:Nt
    TotP(Nt,i)=P(i);
end
TotTP(Nt)=TP;
%% Computing velocity deficits and powers after wake
Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);
[uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
%% storing initial efficiency
best1=uTP;
Totbest1(Nt)=best1;
%% Ant Colony Algorithm starts here
[Farm founditer timeis best
Biter]=ACO_T(maxiter,Nt,Nteta,Farm,SCN1,R,Ck,Ct,Nv,lambda,Prated,Nu,
P,TP,ants,r);
%% Finally it is shown the results
for aa=1:maxiter
    Convergence(aa,Nt)=Biter(aa,Nt);
end
for i=1:Nt
    TotFarm(Nt,i,1)=Farm(i,1);
    TotFarm(Nt,i,2)=Farm(i,2);
end
Totbest(Nt)=best;
improvement=best-best1 %% final improvement
Totimprovement(Nt)=improvement;
%TP
Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);
[uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
%uTP
for i=1:Nt
    TotuP(Nt,i)=uP(i);
end
TotuTP(Nt)=uTP;
difference=TP-uTP
Totdifference(Nt)=difference;
efficiency=(uTP/TP)*100 %% final efficiency
Totefficiency(Nt)=efficiency;
Totfounditer(Nt)=founditer;
Tottimeis(Nt)=timeis;
```

```
%% Graphing final farm
graphh(The_Run,(Nt-1),Farm,Nt,r,R);
%% Writing the data to excell
TheExcel_Cell1=0;
for iii=2:Nt
    TheExcel_Cell1=TheExcel_Cell1+iii;
end
    TheExcel_Cellc=TheExcel_Cell1-1;
    StrNt=int2str(Nt);
    TheExcel_Cell2=int2str(TheExcel_Cell1);
    TheExcel_Cella=strcat('a',TheExcel_Cell2);
    TheExcel_Celld=strcat('d',TheExcel_Cell2);
    TheExcel_Celli=strcat('Initial_', int2str(Nt),'_Turbines');
    TheExcel_Cellf=strcat('Final_', int2str(Nt),'_Turbines');

for i=1:Nt
    Writing_Farm1(i,1)=TotFarm1(Nt,i,1);
    Writing_Farm1(i,2)=TotFarm1(Nt,i,2);
    Writing_Farm(i,1)=TotFarm(Nt,i,1);
    Writing_Farm(i,2)=TotFarm(Nt,i,2);
end
xlswrite(theExcellFileName, Writing_Farm1, The_Run,TheExcel_Cella);
xlswrite(theExcellFileName, Writing_Farm, The_Run,TheExcel_Celld);
xlswrite(theExcellFileName, {TheExcel_Celli,' ',' ',
TheExcel_Cellf,''}, The_Run, int2str(TheExcel_Cellc));


xlswrite(theExcellFileName, TotP, The_Run, 'a44');
xlswrite(theExcellFileName, TotuP, The_Run, 'a53');
xlswrite(theExcellFileName, TotTP, The_Run, 'a62');
xlswrite(theExcellFileName, TotuTP, The_Run, 'a64');
xlswrite(theExcellFileName, Totdifference, The_Run, 'a66');
xlswrite(theExcellFileName, Totefficiency, The_Run, 'a68');
xlswrite(theExcellFileName, Totbest1, The_Run, 'a70');
xlswrite(theExcellFileName, Totimprovement, The_Run, 'a72');
xlswrite(theExcellFileName, Totfounditer, The_Run, 'a74');
xlswrite(theExcellFileName, Tottimeis, The_Run, 'a76');
```

```
xlswrite(theExcellFileName, {'Ideal power of each Turbines',' '},
The_Run, 'a43');

xlswrite(theExcellFileName, {'Optimized power of each Turbines','
'}, The_Run, 'a52');

xlswrite(theExcellFileName, {'Ideal power of Wind Farm',' '},
The_Run, 'a61');

xlswrite(theExcellFileName, {'Optimized power of Wind Farm',' '},
The_Run, 'a63');

xlswrite(theExcellFileName, {'Power losses of the Wind Farm',' '},
The_Run, 'a65');

xlswrite(theExcellFileName, {'Efficiency of the Wind Farm',' '},
The_Run, 'a67');

xlswrite(theExcellFileName, {'Optimized power of the Wind Farm at
initial solution',' '}, The_Run, 'a69');

xlswrite(theExcellFileName, {'Improvement of the algorithm',' '},
The_Run, 'a71');

xlswrite(theExcellFileName, {'Iteration number that the optimized
layout was found',' '}, The_Run, 'a73');

xlswrite(theExcellFileName, {'Termination time of the algorithm','
'}, The_Run, 'a75');


end

end
```

A4.2.2 The Function 'ACO_T'

```
% Ant Colony Optimization

function [Farm founditer timeis best
Biter]=ACO_T(maxiter,Nt,Nteta,Farm,SCN1,R,Ck,Ct,Nv,lambda,Prated,Nu,
P,TP,ants,r)%% ACO search starts here

tic;

founditer=0;

iter=1;

while maxiter-iter+1~=0

    TFark=0;

    Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);

    [uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);

    best=uTP;

    for i=1:Nt

        Fark(i)=P(i)-uP(i);

        TFark=TFark+Fark(i);

    end


    [Ranked R_index]=sort(Fark); %%%burada kötü türbinden iyi
türbine doğru sıralama yapılıyor

    for i=1:Nt

        RankedT(Nt-i+1,1)=Farm(R_index(i),1);

        RankedT(Nt-i+1,2)=Farm(R_index(i),2);

    end

    Farm=RankedT;


    if TFark>0

        Tant=AntedT(Nt,ants,Ranked,TFark);

        for i=1:Nt

            MFarm=Farm;

            for a=1:Tant(i)

                MFarm(i,1)=-r + (2*r).*rand;

                MFarm(i,2)=-r + (2*r).*rand;

                MFarm=AFarm(i,Nt,MFarm,R,r); %checking the new farm
coordinates if they are in the farm or not and etc

                Wel_Def_c=WelDefc(Nt,Nteta,MFarm,SCN1,R,Ck,Ct);

                [uP
uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);

                if best<uTP
```

```
                    Farm(i,1)=MFarm(i,1);
                    Farm(i,2)=MFarm(i,2);
                    best=uTP;
                    founditer=iter;
                end
            end
        end
    else
        Biter(iter,Nt)=(best/TP)*100;
        iter=maxiter;
    end
   Biter(iter,Nt)=(best/TP)*100;
   iter=iter+1;
end
timeis=toc;
```

A4.2.3 The Function 'AntedT'

```
% computes the number of ants for each turbine
function Tant=AntedT(Nt,ants,Fark,TFark)
for i=1:Nt
    Feromen(i)=Fark(i)/TFark;
end

r_ants=ants-3*Nt;

for i=1:Nt
    Tant(i)=round(Feromen(i)*r_ants);
end
v=sum(Tant);
[maxant,maxantind]=max(Tant);
while v~=r_ants
    if v>r_ants
        p=r_ants-v;
        maxant=maxant+p;
        Tant(maxantind)=maxant;
        v=sum(Tant);
    elseif v<r_ants
        t=round(rand*Nt);
        while t==0
            t=round(rand*Nt);
        end
        rr=Tant(t);
        rr=rr+1;
        Tant(t)=rr;
        v=sum(Tant);
    end
end

for i=1:Nt
    Tant(i)=Tant(i)+3;
end
```

A4.3 Codes for Particle Filtering Approach

A4.3.1 The Main Code for the PF

```
% Parameter settings of the problem, initialization, and resulting
part
clear all;
load('SCN1.mat');
maxiter=300; %maximum iteration number
r=500; %farm area radius
Vrated=14; %rated velocity
Cutin=3.5; %cut in speed
Prated=1500; % rated pover
R=38.5; %rotor radius of turbine
lambda=141.9684; %for linear power curve function
Nu=-500; %for linear power curve function
Ck=0.075; % spreading constant
Ct=0.8; % trust coefficient
Nv=20; % wind speed interval of each 0.5 m
Nteta=23; %wind direction interval of each 15 degree
theExcellFileName='Nt_2to8_PF_1st_Scenario_WFLOP.xls';
%% all the number of turbines are tried at one run
for ii=1:10;
    The_Run=strcat('The_Run_is_',int2str(ii),'_');
for Nt=2:8  %number of turbines
N=250; % number of particles
%% randomly turbine locations generating between the farm region
Farm=rassalNt(Nt,r,R);
Farm1=Farm;
for i=1:Nt
    TotFarm1(Nt,i,1)=Farm1(i,1);
    TotFarm1(Nt,i,2)=Farm1(i,2);
end
%% Theoritical power
for i=1:Nt
    for l=1:Nteta+1
        Wel_Def_c(i,l)=SCN1(l,4);
    end
end
[P TP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
```

```
for i=1:Nt
    TotP(Nt,i)=P(i);
end
TotTP(Nt)=TP;
%% Computing velocity deficites and Computing powers after wake
Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);
[uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
%% storing initial efficiency
best1=uTP;
Totbest1(Nt)=best1;


%% Partical Filtering Optimization Algorithm starts here
[Farm founditer timeis best
Biter]=Particle_Filter(maxiter,Nt,Nteta,Farm,SCN1,R,Ck,Ct,Nv,lambda,
Prated,Nu,P,TP,N,r);


%% Finally it is shown the results
for aa=1:maxiter
    Convergence(aa,Nt)=Biter(aa,Nt);
end
for i=1:Nt
    TotFarm(Nt,i,1)=Farm(i,1);
    TotFarm(Nt,i,2)=Farm(i,2);
end
Totbest(Nt)=best;
improvement=best-best1 %% final improvement
Totimprovement(Nt)=improvement;
%TP
Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);
[uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
%uTP
for i=1:Nt
    TotuP(Nt,i)=uP(i);
end
TotuTP(Nt)=uTP;
difference=TP-uTP
Totdifference(Nt)=difference;
efficiency=(uTP/TP)*100 %% final efficiency
Totefficiency(Nt)=efficiency;
```

```
Totfounditer(Nt)=founditer;
Tottimeis(Nt)=timeis;

%% Graphing final farm
graphh(The_Run,(Nt-1),Farm,Nt,r,R);
%% Writing the data to excell

TheExcel_Cell1=0;
for iii=2:Nt
    TheExcel_Cell1=TheExcel_Cell1+iii;
end
    TheExcel_Cellc=TheExcel_Cell1-1;
    StrNt=int2str(Nt);
    TheExcel_Cell2=int2str(TheExcel_Cell1);
    TheExcel_Cella=strcat('a',TheExcel_Cell2);
    TheExcel_Celld=strcat('d',TheExcel_Cell2);
    TheExcel_Celli=strcat('Initial_', int2str(Nt),'_Turbines');
    TheExcel_Cellf=strcat('Final_', int2str(Nt),'_Turbines');
for i=1:Nt
    Writing_Farm1(i,1)=TotFarm1(Nt,i,1);
    Writing_Farm1(i,2)=TotFarm1(Nt,i,2);
    Writing_Farm(i,1)=TotFarm(Nt,i,1);
    Writing_Farm(i,2)=TotFarm(Nt,i,2);
end
xlswrite(theExcellFileName, Writing_Farm1, The_Run,TheExcel_Cella);
xlswrite(theExcellFileName, Writing_Farm, The_Run,TheExcel_Celld);
xlswrite(theExcellFileName, {TheExcel_Celli,' ',' ',
TheExcel_Cellf,''}, The_Run, int2str(TheExcel_Cellc));


xlswrite(theExcellFileName, TotP, The_Run, 'a44');
xlswrite(theExcellFileName, TotuP, The_Run, 'a53');
xlswrite(theExcellFileName, TotTP, The_Run, 'a62');
xlswrite(theExcellFileName, TotuTP, The_Run, 'a64');
xlswrite(theExcellFileName, Totdifference, The_Run, 'a66');
xlswrite(theExcellFileName, Totefficiency, The_Run, 'a68');
xlswrite(theExcellFileName, Totbest1, The_Run, 'a70');
xlswrite(theExcellFileName, Totimprovement, The_Run, 'a72');
xlswrite(theExcellFileName, Totfounditer, The_Run, 'a74');
xlswrite(theExcellFileName, Tottimeis, The_Run, 'a76');
```

```
xlswrite(theExcellFileName, {'Ideal power of each Turbines',' '}, The_Run, 'a43');

xlswrite(theExcellFileName, {'Optimized power of each Turbines',' '}, The_Run, 'a52');

xlswrite(theExcellFileName, {'Ideal power of Wind Farm',' '}, The_Run, 'a61');

xlswrite(theExcellFileName, {'Optimized power of Wind Farm',' '}, The_Run, 'a63');

xlswrite(theExcellFileName, {'Power losses of the Wind Farm',' '}, The_Run, 'a65');

xlswrite(theExcellFileName, {'Efficiency of the Wind Farm',' '}, The_Run, 'a67');

xlswrite(theExcellFileName, {'Optimized power of the Wind Farm at initial solution',' '}, The_Run, 'a69');

xlswrite(theExcellFileName, {'Improvement of the algorithm',' '}, The_Run, 'a71');

xlswrite(theExcellFileName, {'Iteration number that the optimized layout was found',' '}, The_Run, 'a73');

xlswrite(theExcellFileName, {'Termination time of the algorithm',' '}, The_Run, 'a75');


end

end
```

A4.3.2 The Function 'Particle Filter'

```
function [Farm founditer timeis best Biter]=Particle_Filter(maxiter,Nt,Nteta,Farm,SCN1,R,Ck,Ct,Nv,lambda,Prated,Nu,P,TP,N,r)
%Particle Filtering Optimization starts here
tic;
founditer=0;
iter=1;
Fark=zeros(Nt,1);
alpha=0.375;
betha=0.25;
gama=0.375;
for i=1:Nt
    ProbNt(i)=1;
end
while maxiter-iter+1~=0
    TFark=0;
    Wel_Def_c=WelDefc(Nt,Nteta,Farm,SCN1,R,Ck,Ct);
    [uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
    best=uTP;
    for i=1:Nt
        Fark(i)=P(i)-uP(i); % the power loss of the ith turbine
        TFark=TFark+Fark(i); % the power loss of the Farm
    end

    if TFark>0 % Filtering proces is strating here
        Tfilter=FilteredT(Nt,N,ProbNt);
        for i=1:Nt
            MFarm=Farm;
            for a=1:Tfilter(i)
                MFarm(i,1)=-r + (2*r).*rand;
                MFarm(i,2)=-r + (2*r).*rand;
                MFarm=AFarm(i,Nt,MFarm,R,r); %checking the new farm coordinates if they are in the farm or not and etc
                Wel_Def_c=WelDefc(Nt,Nteta,MFarm,SCN1,R,Ck,Ct);
                [uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
                for ia=1:Nt
                    Fup(i,a,ia)=uP(ia);
                    Prob_i_ia_a(i,a,ia)=(1-(uP(ia)/P(i)));
```

```
                end
                FuTP(i,a)=uTP;
                Prob_i_a(i,a)=(1-(uTP/TP));
                for ia=1:Nt
                    FilterFarm(i,a,ia,1)=MFarm(ia,1);
                    FilterFarm(i,a,ia,2)=MFarm(ia,2);
                end
            end
            a_best(i)=FuTP(i,1);
            f_i_a_index(i)=1;
            for k=2:Tfilter(i);
                if FuTP(i,k)>a_best(i)
                    a_best(i)=FuTP(i,k);
                    f_i_a_index(i)=k;
                end
            end
        end
        for i=1:Nt
            for a=1:Tfilter(i)
                Prob_i_ia(i,i)=sum(Prob_i_ia_a(i,:,i))/Tfilter(i);
            end
            Prob_i(i)=sum(Prob_i_a(i,:))/Tfilter(i);
% the observation function
ProbNt(i)=gama*ProbNt(i)+alpha*Prob_i_ia(i,i)+betha*Prob_i(i);
        end
        i_best=a_best(1);
        f_i_index=1;
        for k=2:Nt;
            if a_best(k)>i_best
                i_best=a_best(k);
                f_i_index=k;
            end
        end
        for ia=1:Nt

F_Farm(ia,1)=FilterFarm(f_i_index,f_i_a_index(f_i_index),ia,1);

F_Farm(ia,2)=FilterFarm(f_i_index,f_i_a_index(f_i_index),ia,2);
        end
        Wel_Def_c=WelDefc(Nt,Nteta,F_Farm,SCN1,R,Ck,Ct);
```

```
        [uP uTP]=Power(Nt,Nv,Nteta,SCN1,lambda,Prated,Nu,Wel_Def_c);
        if best<uTP
            Farm=F_Farm;
            Farm=F_Farm;
            best=uTP;
            founditer=iter;
        end
    else
        Biter(iter,Nt)=(best/TP)*100;
        iter=maxiter;
    end
   Biter(iter,Nt)=(best/TP)*100;
   iter=iter+1;
end
timeis=toc;
```

A4.3.3 The Function 'FilteredT'

```
% Assigning the particle numbers for the turbines
function Tfilter=FilteredT(Nt,N,ProbNt)
for i=1:Nt
Tfilter(i)=1+floor(ProbNt(i)*N);
end
```