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Optimization of Energy Supply Networks using Ant Colony Optimization

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Abstract

The planning of an energy supply network has to take into account the consumers' demand and location as well as the production and location of potential plants and the necessary network structure to connect both. Usually this planning process is done in two steps, choosing the plants first, and constructing the optimal network secondly. With the usage of regenerative energies, the choice of the location of these plants which depend heavily on regional environmental conditions and hence the resulting network becomes increasingly important. This paper introduces an approach for combining the choice of plants and the choice of a network structure in the same process using the meta-heuristic Ant Colony Optimization. The results of the implemented algorithm are illustrated in a test scenario.

1. Introduction

The rising demand of energy consumption and the electrification of developing countries require the planning of new energy supply structures. The consideration of renewable energies converted by power plants like wind turbines or PV converters increases the complexity of the planning process. While single conventional base load power plants have usually a capacity of several hundred MW, single renewable energy based power plants have much less capacity which furthermore depends on local environmental conditions. So, in the planning process of an electricity grid based on renewable energies an optimal set of power plants and the optimal network structure for connecting the plants with consumers have both to be determined on a much more detailed level. The main objective is the minimization of financial effort, where the investment cost and maintenance cost for plants and grid have to be included.

In this paper, we investigate a scenario of a region with potential locations for power plants and fixed locations of energy consumers. The plants, e.g. coal-fired, wind, or solar power plants, can differ in type, power output or other attributes, which makes it hard to select the best plants. In addition, the region contains various consumers (villages), which have to be supplied with electrical energy. The objective of the optimization is to select the optimal power plant locations and the best supply network, so that the costs of the energy supply system are optimal. The costs of setting up a grid for electric power transmission depend on the lines' routes which itself depend on the choice and assignment of power plants. So, the cost for connecting a consumer to a set of power plants depends on the costs of the plants as well as on the network's structure.

This paper describes the results of a Diploma thesis (Warner 2008) which investigated whether a solution of the problem is possible using the meta-heuristic "Ant Colony Optimization" (ACO). In the next section, we will describe related research activities for solving the energy supply network construction and for the more general problem of capacitated plant location planning. Section 3 gives a short summary of Ant Colony algorithms. The given problem is described by a model in section 4. Afterwards, we present

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the adaptation of the ACO algorithm to the problem and some results which could be obtained for our test scenarios.

2. Related Work

Electrification is an essential topic for ensuring improvement in developing countries where in particular rural areas often do not have access to electricity. The connection of remote locations to a centralized net often is too expensive and leads to severe dependency on increasing commodity prices. So, the construction of optimal energy networks which also takes decentralized sustainable supply structures with renewable energies gains increasing importance.

The problem of constructing optimal power grids in rural areas of developing countries has been researched in (Baur, 2000). In his dissertation, Baur observes that the main methodological challenge consists in the fact that the individual villages can not be treated independently as the cost for connecting such a consumer depend on the connection status of neighbored consumers. He develops algorithms for determining whether a connection to a centralized network is more efficient than a decentralized power generation. He constructs optimal power grids using a mixed integer programming approach which due to the NP-hard nature of the problem was only applicable for small problem sizes. He also introduces a heuristic approach which is based on graph theoretical analysis of the consumers and their topology. This heuristics connects villages in an iterative algorithm to so called conglomerates which are connected to the network if a decentralized solution would be more expensive. So, this heuristic presupposes that there is already a given centralized network. In a case study he applies his graph-theoretical approach to a region in Marokko, which contains 67 villages as consumers. The result of his optimization process consists of the decision whether (and how) a village should be connected to the existing network or whether it should be supplied by a decentralized network.

Another related approach is the class of Capacitated Plant Location Problems (CPLP): Given a set of potential plants with different locations and fixed costs and capacities and a set of customers with demands for fixed amounts of goods supplied from these plants. The task is to find a subset of plants which can supply the demands of all customers and causes minimal production and transportation costs. The CPLP is known as strongly NP-hard (Ghiani et al. 2002) and has been extensively studied in clustering and location theory. There are various solution to this problem using exact methods (e.g. Branch and Bound) or meta-heuristics (e.g. by Lagrange heuristics (Sridharan, 1991)). These approaches rely on a fixed transportation infrastructure and try to determine a set of optimal, closed routes for distributing the goods, after the optimal choice of plants is done. In the current approach, however, a complex network structure, i. e. a set of acyclic subgraphs, has to be determined. The network cost can be crucial for the optimal result. So, the choice of plants and the choice of network connection will not treated as separate problems.

3. Ant Colony Optimization

The meta-heuristics Ant Colony Optimization (ACO) has been introduced by Dorigo (Dorigo and Stützle, 2004). It can be used to solve static as well as dynamic combinatorial optimization problems. They use an artificial ant colony to solve discrete optimization problems and are inspired by the foraging behavior of real ants. For discovering the shortest path to a food resource, ants cooperate and communicate by depositing pheromones on their path which can be interpreted by other ants. The evaporation of pheromones and the random choice of paths allow the exploration of alternatives. The deposition of pheromones has to be configured so that a better path leads to a higher pheromone concentration which itself causes a higher probability, that this path is chosen by other ants. So, the overall process can be seen as a positive feedback loop. As a result, the collective is able to solve much more complex problems as it would be possible by the sum of the individual abilities of each ant. This behavior is also known as swarm intelligence.

The ACO meta-heuristics use artificial ants, which are searching the best path on a graph. There are diverse variants of ACO algorithms which have been successively applied to routing, assignment, scheduling, subset, machine learning, and bioinformatics problems. In our approach, we adapt the idea of ant colony algorithms for solving the combination of the choice of an optimal subset (of power plants at given locations) and the determination of the best network structure.

For solving a given task, a given number of iterations are performed. In each iteration, a number of ants searches independently for a solution of the given problem. Each ant explores the surrounding space, which is usually given by the neighbored vertices of the problem graph, and builds a partial solution based on a local heuristic which depends usually on annotations on the arcs to the neighbored vertices and the existing pheromones trails but also include random influences. At the end of each iteration cycle, i.e. when all ants have determined a solution to the problem, pheromone evaporation of the old trails and after that the new artificial pheromones are laid. The pheromone evaporation phase decreases all pheromone trails to smooth the influence of old routes and to allow new routes to be established. According to (Dorigo and Stützle, 2004), pheromone evaporation helps in avoiding rapid convergence of the algorithm towards a sub-optimal region.

For the newly laid pheromone trails, the intensity of the pheromone trails on an arc depends on the quality of the ant's solution. Dorigo (Dorigo and Stützle, 2001) suggests different methods for choosing the ants who are allowed to lay pheromones: In the Ant System (AS), each ant lays 1/C on each arc of its solution, where C is the overall cost of its solution. The Ellitist Ant System (EAS) extends the pheromone update process of the ant system by intensifying the best solution found so far. The Rand-Based Ant System (AS_{rank}) ranks all solutions by its overall costs. Only ants with a high rank are allowed to lay pheromones and the amount of pheromones increases with its rank. (Bullnheimer et al. 1997) observed that AS rank usually perform more efficiently than the EAS and clearly better than the AS.

4. Model of the Energy Supply

For a first approach of a problem specific ACO algorithm, the complexity of the optimization scenario has been reduced by abstracting from real world details. Similar to the approach of Jörg Baur mentioned above, the simplified optimization scenario consists of three components: the potential plants, the consumers and the power supply grid.

A **potential plant** is characterized by its location, its capacity and its costs, which aggregate investment cost and production cost. Fluctuating power output, which occurs in particular in connection with renewable energy sources, is abstracted to a constant value. This means, every type of plant is assigned to an average amount of energy, which it produces annually. So, if P is the set of potential plants, and R is the set of positive real numbers, the function $production\colon P \rightarrow R$ returns the energy production of a plant. In addition, different types of costs, like production costs or investment costs, were combined to an annual value.

Each **consumer** aggregates the consumption of a bigger unit, e.g. a village, and is described by its location and demand for energy. The consumer's energy consumption is also reduced to an average annual consume, which is unrelated to daily or other fluctuations. If C is the set of all consumers, the function $demand\colon C \rightarrow R$ returns the demand of a consumer.

The **power supply grid** consists of connection between plants and consumers. For sake of simplicity, we do not differentiate between the voltage levels and do not evaluate the grid infrastructure inside a village. Connections can be drawn between consumers and plants but as well between two consumers. The (annual) cost of a power line depends on various factors, such as Euclidean distance, altitude, regional ground characteristics and technical aspects like capacity.

Detailed proposals for computing the annual costs of plants and power lines can be found in (Baur, 2004). The approach presented here can be extended by these more refined cost models without influencing the general design of the algorithms.

These components can be modeled as a graph (V, E) with two types of vertices $V = P \cup C$, $P \cap C = \emptyset$, which are either power plants P or consumers C. The set of (undirected) edges E consists of all possible connections, i.e. $E = V \times V$. If $G' = (V', E')$ is a sub-graph of G with $V = P' \cup C$ and $E' \subseteq V' \times V'$, G' represents a feasible solution of the problem, if the energy demand of all consumers can be fulfilled, i.e. if $G_{comp} = (V_{comp}, E_{comp})$ denotes a connected component of the graph:

$$\forall G_{comp} \subset G' : \sum_{c \in C} demand(c) \leq \sum_{p \in P_{comp}} production(p)$$

The problem to be solved is to determine an optimal subset $P' \subseteq P$ and an optimal subset of edges $E' \subseteq V' \times V'$ with $V' = P' \cup C$, so that in the resulting graph $G' = (V', E')$ each consumer's demand is fulfilled and the costs are minimal. With

$$\text{cost}(G') = \sum_{p \in P'} \cos t(p) + \sum_{e \in E'} \cos t(e)$$

the optimization criterion can be described as follows:

$$\text{opt}(G) = \min \{cost(G') \mid G' \textit{ feasible solution}\}$$

5. Adaptation of ACO

Some well-known ACO applications to NP-hard problems are similar to the given problem:

- Similar to the TSP (Dorigo and Stützle, 2001), we are looking for cost-optimal connections between vertices of a graph. But in the TSP problem all vertices have to be connected while here we have to find the optimal subset of (producer) vertices. Besides, an optimal network usually results in a graph and can not be restricted to be a route.
- The Bin Packing Problem (Ducatelle, 2001) treats the question of finding a partition of objects with a minimal number of bins, where the volume of each bin is restricted. This can be compared to the determination of connected components of the graph, but it does not handle the minimization of the connection costs.
- The vehicle routing problem (VRP), in particular the capacitated vehicle routing problem (Mazzeo and Loiseau, 2005), minimizes the number of vehicles and the duration of the routes. Deviant from the VRP where each node belongs to exactly one route, the connecting network in our problem will be branched, i.e. there is a m : n relation between consumers and power plants.

So, for fulfilling all demands of our energy supply network problem, the meta-heuristic ACO has been adapted in an evolutionary process to treat the following problems

- The ants must be enabled to collect "energy" from a producer's node and allocate it to consumer.
- Each consumer must be supplied with the demanded amount of energy.
- Ants may return to an already visited node in the current connected component (in particular to a plant's node) to allow branched networks.

5.1 Optimization process

In advance to the optimization process, the constraint

$$\sum_{c \in C} demand(c) \leq \sum_{p \in P} production(p)$$

is checked to ensure that a feasible solution exists. If the condition holds, the optimization process is started and the graph G = (V, E) is constructed. For evaluation purposes, in the test scenarios the costs of arcs are determined by Euclidean distances between connected nodes. Additionally, the costs of a plant j will be considered with the cost of the first connecting arc (i,j) which lead to it.

The ACO optimization performs in a predetermined number of iteration cycles. Initially, the pheromone values of the arcs are set to the same value. In each iteration cycle t of the ACO algorithm, all ants search independently from each other for a path which represents a solution for the optimization problem.

At each plant node of the graph, one ant starts and initially collects the energy of this plant node j, i.e. each ant has an energy storage which is initially set to the energy production of this plant: So, if ant k starts at time step s=0 in plant node j, it is set

```
energy_k(k, 0)     = production(j);
production(j,0)    = 0;
```

In order to build a feasible connected component of the graph, the ant tries to move to consumers to this plant and connects them. The next node is chosen randomly: The ant decides first, if it chooses a plant or a consumer node as next node where the probability for either kind is based on the relation between average pheromone trails on the arcs to the neighboured consumers and plants. The attractiveness of an arc is determined by its pheromone trail and its connection costs. So, to balance cost vs. pheromones we calculate the attractiveness of arc (i,j) by

$$\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta},$$

where

- $\eta_{ij}(t)$ represent the cost of the arc $(i,j) \in E$.
- $\tau_{ij}(t)$ describe the pheromones on arc (i,j) in iteration cycle t.
- α, $\beta \geq 0$ are weights of the pheromone trail and the path costs, resp..

If N^i is the set of possible consumer or plant neighbours of an ant at node i, the probability that ant k chooses node j as a next node if it current position is at node j is calculated by the ratio of the attractiveness of arc (i,j) to the sum of all neighbour attractiveness values:

$$p_{ij}(t) = \frac{(\tau_{ij}(t))^{\alpha} (\eta_{ij}(t))^{\beta}}{\sum_{n \in N^{k,i}} (\tau_{in}(t))^{\alpha} (\eta_{in}(t))^{\beta}}$$

In our experiments we restricted the neighbourhood to all neighbours within a certain distance. If a node j has already been visited by an ant, the ant evaluates whether the old or the new connection is cheaper and uses the lower cost. At a consumer node i at time step s, the ant assigns energy to this node and updates the node's demand and its energy storage:

```
d                  = min( demand(i,s) , energy(k,s) );
energy(k, s+1)     = energy(k,s) -d;
demand(i, s+1)     = demand(i,s) -d;
```

At a plant node j at time step s of iteration cycle t, the ant k loads new energy:

```
d                  = production(j,s);
energy (k, s+1)    = energy(k,s) + d;
production(j,s+1)  = 0;
```

If the connection of a new node allows for cheaper connections inside the current connected component, the costs of the cheapest connection are used. When the ant has energy left and 'moves' from one node to consumer node, these nodes are assumed to be connected and the new node is supplied with the needed amount of energy. As long as the ant has energy left, which can be used to supply more consumers, the ant is free to connect other consumers to the current connected component of the graph. To ensure a complex network structure, the ant can also "jump" to another node of the current connected component, after having connected at least one new consumer. If it has no energy left, the ant has to jump to another plant, which still possesses energy. Plants can only be visited by 'jumps': Before leaving the current connected component of the graph by a jump, the ant's energy level is reassigned to the last visited plant node. With the connection of a plant to another connected component, the ant inherits all energy which is produced in this component, but has not been assigned yet. After all consumers are supplied, the ant jumps to its starting node and the next ant begins to search a path from another producer node.

In the process, we have to differentiate between arcs which represent power lines and arcs which describe "jumps" and are only necessary to describe the ant's route. The latter describe changes to another connected component of the graph – their costs are set to 0.

At the end of each iteration cycle, a defined percentage ρ of pheromones evaporate on each arc according to the Ant-Cycle algorithm (Dorigo et a., 1996)

$$\forall (i,j) \in E : \tau_{ij} \leftarrow (1-\rho)\tau_{ij}$$

Furthermore, the pheromones on the arcs are increased: In analogy to Rank-Based Ant Systems (Dorigo and Stützle, 2001), the amount of deposited pheromones is determined by the rank of the found solution. The change in the pheromone trails is based on the cost G_k of the solution for each ant k, i.e. the aggregated costs of the visited plants and the resulting network. These cost contribute to the new pheromone on arc (i.,j) by

$$\Delta\tau_{ij} = \sum_{ant\ k} \frac{Q}{G_k}$$

where Q>0 is a predefined constant. Hence, an arc which is used in more and good solutions gets a high pheromone trail, and consequently is highly attractive in the next iteration cycle. All the paths found by the ants are evaluated and the solution with minimal costs is determined as new best solution. Afterwards, a new iteration cycle starts, until the desired number of iterations is done. When all the iteration is done, the final solution is determined as the solution with minimal cost.

5.2 Example Scenario and Evaluation

The presented ACO algorithm uses predefined constants for balancing the attractiveness of arcs (α, β), for the pheromone evaporation (ρ), and for the pheromone update (Q). The quality of an ACO algorithm's solutions and its speed of convergence usually highly depend on these parameter settings.

Plant	1	2	3	4	5	6	7	8	9	10
Production	70	70	70	20	70	70	70	20	20	70
Cost	5000	4900	5000	3000	5000	4900	4900	3000	4900	4900

Tab. 1: Plant parameters in the test scenario

For determining optimal parameters, a test scenario has been constructed which consists of 10 potential plant locations, and 17 consumer locations. The scenario allowed to check whether the ants were able to decide on situations, where plants differ by one or more of the characteristics “amount of energy production”, “distance to consumers”, and “annual costs”.

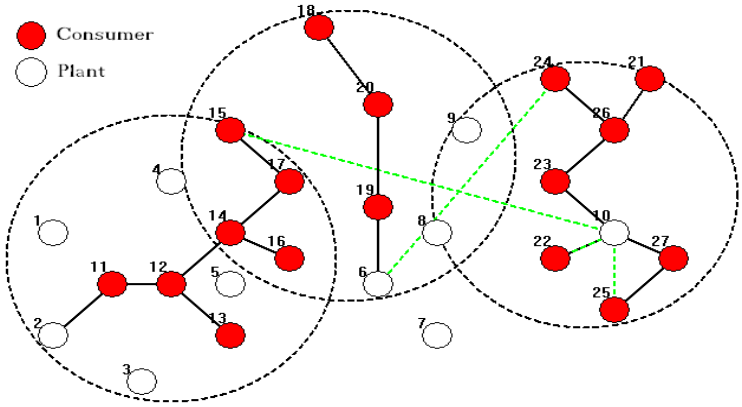

Figure 1: Final solution of the Test Scenario after 100 iterations using 20 ants

The energy production (in abstract energy units) and the annual cost of the plants are given in table 1. Each consumer was instantiated with the same energy demand of 10 energy units. The overall energy production of the plants highly exceeds the demand, so that diverse solutions are possible. The pheromone update factor Q was depending on the expected overall costs. The optimization process has been performed for all 32 qualitatively different combinations of varying α, $\beta \in \{0, 1, 3, 5\}$, $\rho \in \{0.1, 0.01, 0.001\}$, which have been run 5 times with 100 iteration. The results recommended a parameter setting of α=1, β=3, and ρ=0.1 and confirmed the recommended parameter setting in other ACO applications. The evaluation of the diverse methods for pheromone update has shown that the rank-based update leads to the best results. Figure 1 shows a solution which has been found using the recommended parameter settings.

In an evaluation of the optimization process we analyzed the development of the pheromone annotations on the arcs. The final solution usually contains the arcs with the highest pheromone rank. We noticed that the pheromone values of all arcs in the final solution are increased compared to their initial values. The evaluation of the development of the ants’ paths shows that the pheromone trails eliminates unnecessary loops in the pheromone trail quite early in the optimization process.

One mayor drawback of the implemented optimization process is the fact that ants are not allowed to connect plants. This restriction was introduced to limit the solution space of possible network structures. But test cases can be constructed where it impedes the determination of an optimal solution.

5.3 Implementation

A prototypical experimentation tool has been implemented to allow the research of different parameter settings and diverse scenarios for the ACO attempt to the given problem. The optimization algorithm and the graphical user interface have been implemented in the object-oriented dynamic programming language Python.

The tool discriminates between scenario and experiments. A scenario consists of all producer nodes and all consumers together with its essential parameters, the costs of each arc. Scenarios are stored persistently in xml-files. An experiment combines a scenario, its optimization parameters and settings and the results of the optimization process. The graphical user interface allows administrating scenarios and experiments, to navigate through a scenario and to manipulate scenarios and experiments by adding or modifying plant or consumer nodes, arcs' costs and setting optimization parameters. Besides, it visualizes the optimization process and its results.

6. Conclusions and Further Work

In this paper we studied an approach for the construction of optimal energy supply networks which consists of determining an optimal choice of plants and their location as well as a construction of the connecting network. The search for an optimal grid has been done by adapting the ACO meta-heuristic. The implemented algorithm produces encouraging results for the developed test scenarios.

As this approach seems to be worth of further investigation, we will develop a general, extensible and efficient framework for ACO as an experimentation base for our further work. The presented algorithms will be redesigned to overcome the mentioned restrictions and to allow a better evaluation of its characteristics, i.e. the ants' behavior and the algorithms' performance and quality. Besides, some decision have been made during the design process of the current approach to ensure that the resulting algorithm is very close to existing ACO applications, e.g. that the path of a single ant should represent a complete solution. It will be interesting to see, whether a direct cooperation of ants could lead to better results.

Furthermore, the case study used in (Baur, 2000) will be adapted to analyze the quality of the results that our approach can achieve in a real world scenario.

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