TRANSMISSION EXPANSION PLANNING IN THE NORDIC SYSTEM FOR WIND POWER INTEGRATION BASED ON ANT COLONY OPTIMIZATION

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Summary – This paper presents a transmission expansion algorithm based on ant colony optimization. It was developed and tested on a model for the Nordic area. The main focus of this work was to build a transmission expansion planning tool able to cope with the new challenge of large wind power integration. Thus, the optimization uses hourly time steps to include wind and load variations. Nevertheless, the overall simulation time to find good solutions is quite fast using heuristic information. The ant colony optimization method proved to be flexible and delivered reasonable results for the calculated scenario of wind power integration for 2030.

Keywords: transmission expansion, hydro power system, wind power integration, ant colony optimization, computational intelligence, parallel computing

NOMENCLATURE

B^{con}	The R branches which are congested most of the time of a year in the reference case
$C^{\mathrm{S}}_{k,h}$	System cost for feasible hour h for solution k
$C^{\mathrm{P}}_{k,h}$	Penalty cost for infeasible hour h for solution k
$C^{\mathrm{S_{total}}}_{k}$	Total system costs for one whole year for solution k
$C^{\mathrm{S_{total,ref}}}$	Total system costs for one whole year for the reference case (without any reinforcements)
$C^{\mathrm{I_{annuity}}}_{k}$	The annuity of total investment costs for the chosen reinforcement
E	Index for the outer iterations, called expedition
E	Maximal number of expeditions (outer iterations)
H	Index for hours [1…8760]
I	Branch number
K	Index for an arbitrary solution [1…K]
K	Maximal number of possible solutions
M	Index for the inner iteration, called mission
M	Maximal number of missions (inner iterations)
n	Number of branches which can receive reinforcements
q_k	Solution quality of solution k
R	Maximal number of branches chosen for one solution S_k
S	Consists of all possible combinations of the branches s_i which can receive reinforcements
S_k	Solution k consisting of R branches s_i
s_i	Partial solution branch i belonging to S_k
S^{best}	Best solution among several S_k
φ^{local}	Local pheromone reduction rate (0…1]
$\varphi^{\mathrm{global}}$	Evaporation rate (global pheromone reduction rate)
$\tau_{i,m}$	Amount of pheromone for branch i in m
$\tau_{i,e}$	Amount of pheromone for branch i after one expedition e is finished
τ^{quant}	Pheromone quant, the smallest unit of pheromone
$\Delta\tau_{i,e}$	Amount of new pheromone for branch i received in e
$\Delta\tau^{\mathrm{start}}_{i}$	Amount of pheromone distributed for the branches with the highest Lagrange multipliers in the base case

1 INTRODUCTION

Traditionally there has been a strong connection between power generation and power transmission expansion. The transmission system was primarily built to transport electricity from power plants to demand areas. After the liberalization of power markets, the transmission system operators (TSO) and planners faced a new challenge in transmission expansion planning (TEP). A significant number of new methods for TEP have been proposed and tested by researchers and TSO. It is still a task to meet particular challenges with TEP problems, especially when it comes to coordinate new transmission lines for wind power integration. The planning, permitting and construction of a transmission line may take 5…10 years, while a wind project needs only 2…3 years. This situation is setting up a scheduling conflict, since a remote wind project cannot be financed until the transmission access is provided, and the transmission line cannot be built with cost recovery certainty until the need for service from the wind plant is shown [1]. The successful large scale wind power integration requires a redesign of TEP scheduling. For this the TSO needs improved TEP tools including the nature of wind power integration.

The work of this paper concentrates on the development of an algorithm for transmission expansion based on ant colony optimization (ACO). The flexibility of the method allows a higher grade of detail when including wind power integration into TEP modelling.

Through several studies in different institutions the challenge of wind power integration has been analyzed from various angles. In the TradeWind project the European model Power System Simulation Tool (PSST) has been developed at SINTEF Energy Research with the aim to investigate large wind power integration in Europe [2]. Within TradeWind and later studies done by the Norwegian Research Center for Offshore Wind Technology the focus concerning transmission capacities was on interconnections between countries and boundaries [3]. The goal for the present paper is to implement a new algorithm for TEP on a national level, which shows good and fast computational performance. Later it can be implemented in PSST allowing broader studies of wind power integration in Europe, investigating both national and international transmission capacities, including onshore transmission expansion as well as offshore interconnections.

For this paper an ACO algorithm was implemented in a model for the Nordic area (former Nordel) including eastern Denmark, Finland, Norway and Sweden. The system simulation is done by a DC optimal power flow using Matpower/Matlab.

The paper starts with a description of the used metaheuristic method and provides the mathematical background for the implemented algorithm. The next section presents the problem formulation and introduces the algorithm developed during this work. The following section describes the Nordic model which is used to test the proposed algorithm. Finally the results are presented and a conclusion is made for the performance of the algorithm.

2 ANT COLONY OPTIMIZATION

The ACO algorithm has been developed in 1992 [4]. It belongs to the group of swarm intelligence optimizations among computational intelligence methods, which is receiving increased attention with the growing availability of parallel computing. ACO algorithms show a positive feedback in solution recovery. They are based on a distributed computation, which avoids premature convergence and use a constructive heuristic to find acceptable solutions in an early stage of the search process.

2.1 Inspiration from nature

The idea behind the ACO is the behaviour of ants in an ant colony. When a single ant finds food, it travels back to the nest and leaves a serum called pheromone on its path. Thus, other ants find the way to the food source by following the pheromone path. Due to evaporation of the pheromone the following ants will not exactly walk the same path as the first ant. After a certain time interval there will be several paths with different pheromone concentration levels. Subsequently the shortest path will be travelled by most ants and hence receive the highest pheromone concentration. Finally all ants travel the shortest path between food source and nest.

2.2 Mathematical formulation of the method

The main characteristic for an ACO is that the pheromone values of the solution are updated after each iteration, according to the quality of the solution. The amount of pheromone is related to a probability value for each possible solution in the solution set. The pheromone update can be done in different ways, depending on the versions of ACO. Ever since the first ant colony algorithm was published in 1992, the method has been improved continuously providing various versions of ACO. The ant colony system (ACS) shows the best performance for solving different computationally intensive combinatorial problems thus was chosen for this work [5].

The ACS consists of two pheromone update rules. The local pheromone update rule has the main aim to diversify the search performed by subsequent ants during iterations. This is achieved by pheromone reduction on the local, but not on the global level. After one mission m has been successfully fulfilled by one ant forming a solution S_k, the pheromone reduction rule is applied to any partial solution s_i that was chosen by that ant:

$$\tau_{i,m+1} = \begin{cases} \varphi^{\text{local}} \cdot \tau_{i,m} & \text{if } s_i \in S_k \\ \tau_{i,m} & \text{otherwise} \end{cases} \tag{1}$$

where $\tau_{i,m}$ is the pheromone amount at s_i and φ^{local} is the local pheromone reduction rate.

The global, also called offline, pheromone update rule is applied for the best solutions found during the iteration. This can be done in several ways e.g. update the iteration-best or the best-so-far solution. If s_i is part of the best solution S^{best}, it receives pheromone according to the following rule:

$$\tau_{i,e+1} = \begin{cases} \varphi^{\text{global}} \cdot \left(\tau_{i,e} + \Delta\tau_{i,e}\right) & \text{if } s_i \in S^{\text{best}} \\ \varphi^{\text{global}} \cdot \tau_{i,e} & \text{otherwise} \end{cases} \tag{2}$$

where φ^{global} is the global pheromone evaporation rate and $\Delta\tau_{i,e}$ is the amount of pheromone received in iteration e.

Controlling the amount of pheromone used for the update is one of the main challenges when developing ACO algorithms. When ants walk paths the amount of pheromone grows faster on shorter paths, only because more ants manage to walk shorter paths during the same time periods as on longer path. This effect is represented by determining the solution quality, e.g. difference in path length, time or cost savings.

At the end of each iteration the pheromone of every s_i is multiplied by the evaporation rate, which represents the fact that pheromone disappears over a certain time period. From a mathematical point of view this means that solutions which are not visited anymore will acquire a decreasing probability to be chosen.

2.3 *Analogy for transmission expansion planning*

For TEP the following analogies can be constituted. The paths being walked by ants represent the branches which receive reinforcements. The path length from nest to food, being the objective to minimize, is represented by the sum of system and investment costs for the TEP. The system costs are a result from the DC optimal power flow with the implemented reinforcements on the chosen transmission lines.

The path length defining the solution quality is represented by the saving of system costs through expanding transmission capacity.

The values of pheromone for each branch are multipliers of the smallest pheromone unit, here called pheromone quant, which are defined by the number of branches in the model.

3 PROBLEM FORMULATION

In the following section the TEP problem formulation is explained. The methodology used in this work is described and the total algorithm is presented and visualized in Fig. 1.

3.1 *Transmission expansion planning problem*

The calculation process of heuristic optimization methodologies is characterized by finding arbitrary solutions, test their feasibility and define a quality of the solution which is used as information to find more and better solutions. In the transmission expansion problem the solution matrix S consists of all possible combinations of the R branches s_i which can receive reinforcements. For one solution candidate S_k each branch s_i can only be chosen one time to receive reinforcement and the maximal number of allowed reinforcements is R.

$$S = \left[S_1 \quad \cdots \quad S_k \quad \cdots \quad S_K \right] \tag{3}$$

K is the number of possible combinations, defining all potential solution candidates. It is determined by the number of branches n and the number of allowed reinforcements R in the following way

$$K = \begin{pmatrix} n+R-1 \\ R \end{pmatrix} \tag{4}$$

The number K can become tremendously large. Considering even a medium sized problem with 44 branches and allowing 8 reinforcements K reaches over 636 million possible combinations. This large number shows that a classical approach of calculating all possible solutions and comparing them is not accomplishable in a reasonable time.

After M solution are chosen in each iteration, an evaluation of the solution feasibility and quality is performed by a DC optimal power flow based on linear programming. The general mathematical formulation can be found in [6].

The DC optimal power flow is run for every hour in a whole year. The total system cost $C_k^{\mathrm{S_{total}}}$ is the sum of system costs for every feasible hour $C_{k,h}^{\mathrm{S}}$ plus a penalty cost $C_{k,h}^{\mathrm{P}}$ for the hours where the DC optimal power flow could not find a solution, i.e. that the suggested reinforcement plan cannot meet the required capacity during that hour.

$$C_k^{\mathrm{S_{total}}} = \sum \begin{cases} \sum\limits_h C_{k,h}^{\mathrm{S}} & \text{if } h \text{ is feasible} \\ \sum\limits_h C_{k,h}^{\mathrm{P}} & \text{else} \end{cases} \tag{5}$$

The system cost for one hour is defined as the sum of the production of all generators multiplied with their marginal costs.

Further results from the DC optimal power flow are the Lagrange multipliers associated with each constraint, especially those according to branch constraints. A high value means reinforcing in the corresponding line would give an equivalent good improvement of the system power flow and so a lower system cost. These multipliers calculated from the base case (without any reinforcements) are used as heuristic information for the ACO algorithm. They define the vector of start pheromone values leading the search in the most significant direction.

The optimization function is defined by the minimization of the total system costs $C_k^{\mathrm{S_{total}}}$ for the whole year and the annuity of total investment costs $C_k^{\mathrm{I_{annuity}}}$ for the chosen reinforcement:

$$Min\, f(k) = C_k^{\mathrm{S_{total}}} + C_k^{\mathrm{I_{annuity}}} \tag{6}$$

The objective of minimizing system costs can be seen as a regulatory authority viewpoint. Minimizing investment costs can represent the system operator viewpoint. Thus, a combination of both would reflect a system with a regulated TSO monopoly.

3.2 *Proposed methodology*

The complete optimization algorithm for finding the best transmission expansion plan consists of two separate optimization procedures: The ant colony system that is searching for solution candidates and the DC optimal power flow that verifies the feasibility and quality of each candidate.

During the optimization process the ACO algorithm uses different heuristic information to determine the search for solutions. The heuristic information is given by the DC optimal power flow results. The optimal power flow of the base case (system without any reinforcements) delivers the reference value for the system cost $C^{S_{\text{total,ref}}}$ and the Lagrange multipliers for the branch constraints. These multipliers are used to define the pheromone start value in the following way:

$$\tau_i = \begin{cases} \tau^{\text{quant}} + \Delta\tau_i^{\text{start}} & \text{if } i \in B^{\text{con}} \\ \tau^{\text{quant}} & \text{else} \end{cases} \tag{7}$$

B^{con} are the branches which are congested most of the time of a year. $\Delta\tau_i^{\text{start}}$ refers to a standardized value representing the number of hours of a year, where the corresponding branch i is congested.

After each expedition consisting of M missions, when the ACO has chosen a set of solutions, a DC optimal power flow is performed and the system cost for the corresponding solution is calculated. The difference of the reference system cost $C^{S_{\text{total,ref}}}$ and the calculated system cost $C_k^{S_{\text{total}}}$ for a solution k defines the solution quality q_k and thus the amount of pheromone update.

$$q_k = \begin{cases} \left(C^{S_{\text{total,ref}}} - C_k^{S_{\text{total}}}\right) & \text{if } C^{S_{\text{total,ref}}} > C_k^{S_{\text{total}}} \\ 1 & \text{else} \end{cases} \tag{8}$$

and the amount of pheromone update is defined as:

$$\Delta\tau_{i,e} = \tau^{\text{quant}} \cdot q_k \quad \forall\ i \in S^{\text{best}} \tag{9}$$

There are two different types of update rules which can be used, as mentioned earlier. The iteration-best rule updates the best solution of the solution set after each iteration while the best-so-far rule updates the best solution found so far during all iterations done up to that point. The iteration-best update rule avoids early convergence and delivers better results [7]. A probability vector is calculated from the amount of pheromone received, which defines the likelihood for the branch to be chosen during the next expedition. The ACO algorithm is established according to the following steps (compare Fig.1):

(i) Until the maximum number M of solutions, being chosen during one mission m, is reached, do the following: One ant picks a solution S_k consisting of r branches to reinforce. The local pheromone update rule is applied according to Eq. (1).

(ii) For h=1…8760 calculate a DC optimal power flow of each S_k found in (i) and find the best solution S^{best} of that expedition e.

(iii) While $e<E$ do the global update rule for all s_i according to Eq. (2) and start (i) again, else finish the algorithm and present results.

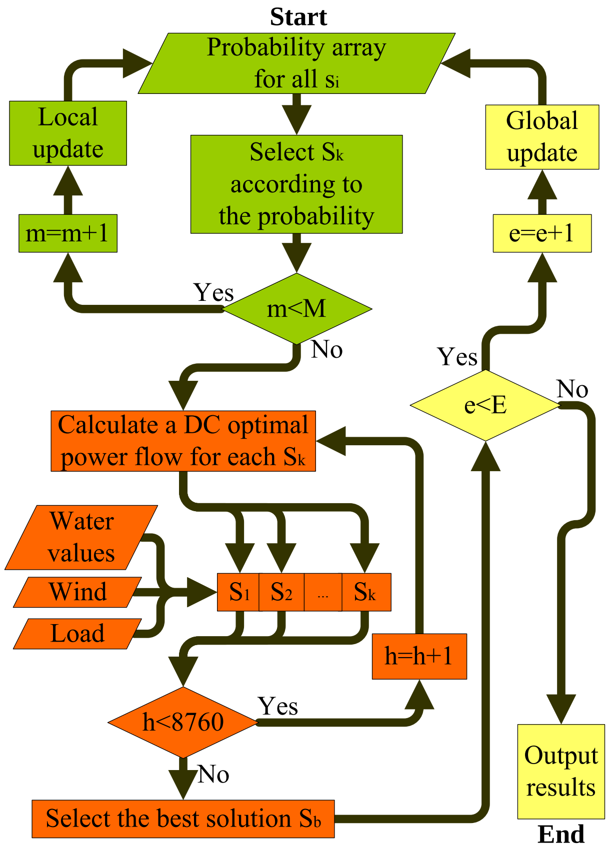

Figure 1: Flow chart of the total algorithm with step (i) in green, step (ii) in orange and step (iii) in yellow.

The flexibility of the algorithm allows the use of parallel computing which leads to an enormous reduction of calculation time. The DC optimal power flow, meaning the whole step (ii) in Fig.1, can be calculated simultaneously for every S_k found in step (i), since the input in each single optimal power flow is independent of the output of the other power flows.

4 TEST SYSTEM

The Nordic area was chosen for developing and testing the ACO algorithm. The primary reason for this choice is the motivation to develop the algorithm for specific requirements for that particular system in order to be able to do more extensive case studies later. Another and important reason was the availability of data and information as well as the access to other transmission expansions studies for the Nordic system. This gives the possibility to compare results and define the quality of the performance of the ACO algorithm.

4.1 Case description

The Nordic area model has 36 buses, 38 generators, 44 branches, 15 transformers and two voltage levels. The generation is dominated by hydro power. An overview over generation types, number, size and marginal cost intervals can be found in Table 1.

Generator type	Number	Aggregated capacity (GW)	Marginal cost range (€/MWh)
Hydro	15	45.8	35…66
Fossil	3	22.3	25…60
Nuclear	4	11.9	10...15
Wind	16	21.9	0.5
Total	**38**	**101.9**	**0.5…66**

Table 1: Generators in the Nordic model

The optimal power flow uses the generators with lowest marginal costs first. One of the goals of the simulation is a maximum wind power penetration. Thus, wind generators are modeled with very low marginal costs. The hydro generators are simulated with marginal costs according to the weekly average of their water values from 1949 to 1999 related to the northern Europe system [8], [9]. This represents an average year for the hydro power plants and their reservoir level. All generation costs are linear cost functions.

Figure 2 shows the location of buses, branches and wind power cluster for the Nordic area model. The offshore wind power generators from the scenario 2030 are connected radial to the closest and most adequate buses.

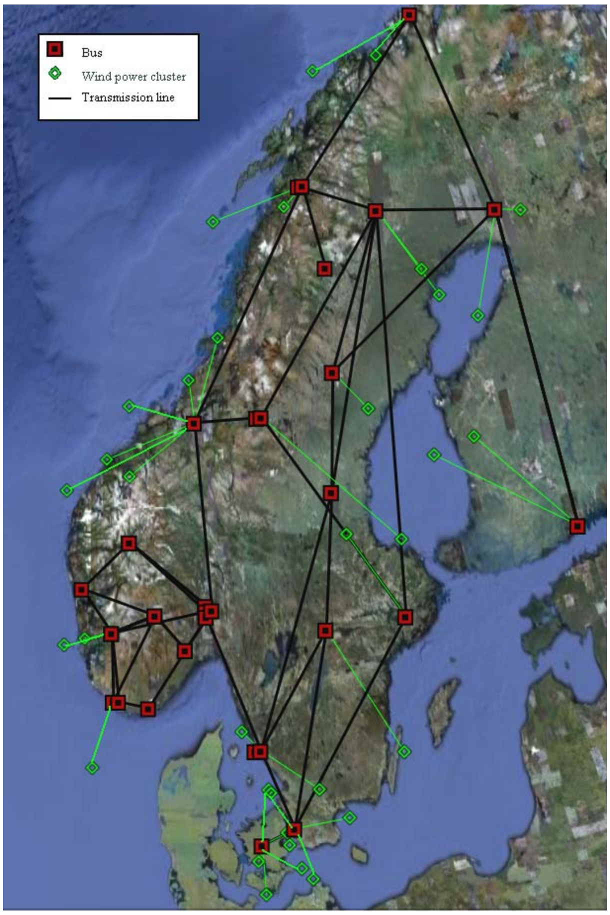

Figure 2: Nordic area model with buses, transmission lines and on- and offshore wind power cluster for the medium scenario of the year 2030; Google Earth maps under "© 2010 Google"

When a branch is chosen to receive reinforcement it can be extended to its double maximal capacity, however the minimal capacity expansion is 500 MW. The investment costs depend on the voltage level, the added capacity and a factor defining the infrastructure quality of the branch location receiving reinforcements. Thus, the cost range for the reinforcements lays between 225 and 1000 k€/km. The annuity for the total investment is calculated with standard parameters, i.e. the amortization time is set to 20 years and the interest rate is set to 5 percent.

4.2 Scenario description

To test and demonstrate the performance of the ACO algorithm a simple scenario for 2030 was chosen. The annual load increase was set to 0.5 percent calculated from load data of 2007 according to prognosis done by Statnett [10].

The installed wind power capacity was taken from the medium wind scenario for 2030 [11]. Based on the COSMO EU data set the wind power production is calculated individually for each wind power production facility in the modelling area [12].

The following model settings were used as test cases: For the first case, further on referred to as Wi75Nu0, the wind generators are forced to run at 75 percent of the wind power production, while all other generators can be adjusted arbitrarily by the optimal power flow. In the second case, referred to as Wi100Nu20, the total wind power production has to be used, meaning the optimal power flow has to include 100 percent of the wind power production. Additional the nuclear power plants are set to a minimum production of 20 percent of their capacities, which refers to a more realistic situation than in the first case.

5 RESULTS

In this section the simulation results of the TEP problem for the Nordic area solved with the ACO algorithm developed during this work are presented and discussed. The main focus is on the performance of the ACO algorithm. The algorithm was implemented in Matlab R2010a, using Matpower 4.0b4. All calculations are done with a 64-bit Intel(R) Xeon(R) with 8 CPU of 2.27GHz each.

5.1 Presentation

The parameters for the ACO are set to the following values as shown in Table 2. The smallest amount of pheromone update, the pheromone quant, must be dependent on the system size, in particular on the number of branches. A reasonable number is 10 percent of the number of branches. The number of reinforcements is set to maximal 8, meaning that the algorithm can choose to expand any number between 0 and 8.

Parameter	Value
Pheromone quant τ_q	4.5
Reduction rate φ_l	0.8
Evaporation rate φ_g	0.8
Number of reinforcements r	8
Number of missions M	8
Number of expeditions E	50

Table 2: ACO parameters

The evaporation rate reduces the pheromone after every expedition, causing a limit in the maximal reachable amount of pheromone. It can be observed that branches being part of the best solution after each expedition, converge to that equilibrium limit of pheromone.

Table 3 presents the main figures of the results for the two cases. The total length refers to the sum of the length of all reinforced lines. Infeasible hours refer to hours where the DC optimal power flow does not find a solution satisfying all constraints before the stopping criteria. It was observed that infeasible hours occur mainly during high load times or high wind power production hours. Especially in Wi100Nu20, where the wind power production is used to 100 percent, it can be seen that there are still infeasible hours after the reinforcement. The number of allowed reinforcements must be set to a higher value to dispose of these infeasible hours.

	Wi75Nu0	Wi100Nu20
Number of reinforcements	8	8
Total length (km)	1679	1895
Total investment cost (m€)	495	606
Number of infeasible hours before reinforcements	35	2099
Number of infeasible hours after reinforcements	0	151
System cost (m€/year)	6200	6329
System cost saving (m€/year)	279	1238
Calculation time (h)	8.3	11.8

Table 3: Key figures of the results

Figure 3 shows the location of the reinforced lines in the system. In Wi100Nu20 it was not enough to reinforce 8 branches to guarantee zero infeasible hours. The infeasible hours are due to high wind conditions. The congestions occur on the two branches leading to the most northern bus. The system cost in Table 3 for Wi75Nu0 is lower then in Wi100Nu20, which can be explained by the remaining infeasible hours in Wi100Nu20 causing penalty costs included in the system costs.

The system cost saving is the difference between the system cost before and after reinforcement. The saving for Wi100Nu20 is particular high. The reason for this is the high number of infeasible hours before reinforcements, leading to high penalty costs.

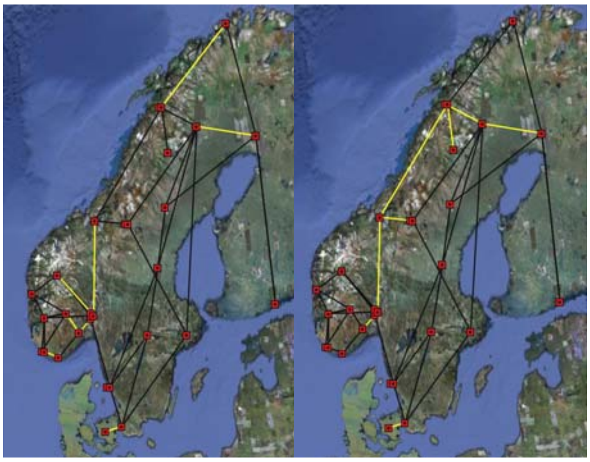

Figure 3: Transmission expansion planning solutions for the Nordic Area. The branches receiving reinforcements are highlighted yellow. On the left hand: Wi75Nu0. On the right hand: Wi100Nu20; Google Earth maps under "© 2010 Google"

5.2 Discussion

The algorithm delivers good results in both cases. The solution contains the branches which are maximal congested during the base case. This is expected according to the dominance of the system costs in the objective function in Eq. (6). When two branches have similar Lagrange multipliers, meaning they would make the same gain in system cost reduction when reinforced, the algorithm converges to the one with lower investment cost, according to the second term in the objective function. It can be observed that the system cost in the objective function dominates the investment cost annuity, which can be changed easily by weighting the cost elements. It is also possible to add or remove a cost component or add other objectives without having to change the rest of the algorithm. Hence it is possible to adjust the objective for a power producer, consumer, transmission operator or regulator viewpoint.

Running the ACO with 8 missions and 50 expeditions means the algorithm tests maximal 400 solution candidates, which is only 0.00006 percent of the potential solution candidates according to Eq. (4). By using heuristic information about the base case with the given parameters, i.e. the Lagrange multipliers for the most congested branches in the base case, it is possible to reduce the number from 636 million potential solutions to 6435 candidates with the highest impact to the objective function. Hence, by running 400 solutions, the algorithm calculates 6 percent of the most relevant solution candidates.

These facts show the enormous potential of using heuristic information for leading the search in the right direction. The flexibility of the algorithm allows an easy implementation of any heuristic information in almost any step of the calculation procedure, which makes it very attractive for further development, e.g. a dynamic version of the optimization algorithm.

The main part of the calculation time occurs during the run of the DC optimal power flow for each hour of one whole year. It is therefore important to reduce the number of necessary optimal power flows to a minimum. This can be done by including additional features, e.g. tabu search [13]. It can be observed that during calculations with a large number of infeasible hours, the calculation time increases, due to the stopping criteria rule for the DC optimal power flow in Matpower [6]. Further on it is possible to increase the calculation speed by using different solvers for the DC optimal power flow, which has not been focused, yet. Finally the hourly dissolution of the algorithm can be changed to a weekly one, or a Monte Carlo choice of a predefined number of hours could be used for the feasibility check of the chosen reinforcement, which additionally would lead to an enormous reduction of calculation time.

6 CONCLUSION

During this work a first version of an ACO algorithm was successfully developed and tested on a model for the Nordic area. The methodology shows good computational qualities and high potential in finding good solutions with very view iterations. There is still a broad capability to reduce the calculation time significantly, though a balance between accuracy and dissolution has to be found.

The flexibility and ability to include any heuristic information makes it an attractive tool for implementation into more comprehensive power system models. Nevertheless it needs a detailed analysis of how the ACO parameters have to be adjusted for larger power systems, since there was found a dependency of the power system size, i.e. particularly the number of branches, and the necessary settings of the ACO parameters to achieve convergence and good solutions.

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