Multiobjective Optimization Applied to Maintenance Policy for Electrical Networks

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***Abstract*—A major goal for managers of electric power networks is maximum asset performance. Minimal life cycle cost and maintenance optimization becomes crucial in reaching this goal, while meeting demands from customers and regulators. This necessitates the determination of the optimal balance between preventive and corrective maintenance in order to obtain the lowest total cost.**

The approach of this paper is to study the problem of balance between preventive and corrective maintenance as a multiobjective optimization problem, with customer interruptions on one hand and the maintenance budget of the network operator on the other. The problem is solved with meta-heuristics developed for the specific problem, in conjunction with an evolutionary particle swarm optimization algorithm.

The maintenance optimization is applied in a case study to an urban distribution system in Stockholm, Sweden. Despite a general decreased level of maintenance (lower total maintenance cost), better network performance can be offered to the customers. This is achieved by focusing the preventive maintenance on components with a high potential for improvements. Besides this, this paper displays the value of introducing more maintenance alternatives for every component and choosing the right level of maintenance for the components with respect to network performance.

***Index Terms*—Asset management, component reliability importance, maintenance, multiobjective optimization, power distribution systems.**

I. Introduction

MAXIMUM asset performance is one of the major goals for electric power system managers. To reach this goal, minimal life cycle cost and maintenance optimization becomes crucial while meeting demands from customers and regulators. Consequently one of the fundamental objectives is to relate maintenance to system reliability performance in an efficient and effective way. This is the aim of several maintenance methods such as the reliability centered maintenance method [1] and its further developed methods, such as the reliability centered asset management [2]. In this context, it becomes crucial to find a solution to the problem of optimal balance between corrective and preventive maintenance (the maintenance problem). In the literature, a number of methods exist, e.g., [3]–[5], that focus on capturing the optimal level of maintenance with respect to a specific objective, such as minimizing a specific interruption index while meeting a budget constraint.

This paper takes the concept of these methods further by applying the methods of multiobjective optimization to the maintenance optimization. This is done using a similar approach to that in the distribution system development planning described in [6], where a multiobjective approached is utilized. The difference is that the proposed focuses on maintenance instead of planning. Furthermore, this method has been developed to deliver optimal solutions for computational-intense reliability calculations that are based on simulations. This is an attribute that allows for detailed modeling of the studied network. The multiobjective approach puts the customer interruption on the one side and the maintenance budget of the distribution system operator (DSO) on the other. Thus, the proposed method provides a span of optimal solutions that the decision maker can choose among, each with different expected outcomes for maintenance budget and customers.

II. Optimization Problem, Method

The approach of this paper is a maintenance policy optimization, which results in a number of interesting solutions. The solutions are developed by utilizing component reliability importance indices, derived from Monte Carlo reliability simulations. The method is divided into five essential concepts:

1) reliability Monte Carlo simulations;
2) component reliability importance indices;
3) multiobjective approach;
4) optimization heuristics;
5) selection of optimum (results).

The merit of this paper lies in the combination of these concepts, presented below in their respective subsections.

A. Event Driven Monte Carlo Simulation

The Monte Carlo simulation method is based on an event-driven approach, i.e., a simulation with variable time steps, where the time between significant events is identified. In this context, significant events are state changes of components. Minimal cut-sets are used to calculate the system behavior as a result of component status. In the current setup, the simulation runs for a specified number of cycles. At the simulation start, we assume that all components are functional. The next step is to generate the time-to-failure for every component. Time-to-failure is based on the component's failure rate, which in turn is based on component parameters, e.g., level of maintenance and inherent failure rate. We then move forward in time to the first event, in our case a failed component. The changed status of the failed component is then recorded along with the effects of the failure. The list of coming events is consequently

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updated with the generated repair time for the failed component. This is followed by the identification of the next event in the simulation, probably the repair of the failed component but not impossibly an occurrence of another failed component and its consequences (e.g., a second-order minimal cut-set failure). By recording the effects of the different system states and their durations, we obtain reliability data, such as the utilized component importance index, and more traditional reliability data, such as customer interruption costs and SAIFI and SAIDI [7]. The simulation approach and its implementation into the reliability analysis tool RADPOW is presented in [8].

Simulations compared to analytical calculations render the optimization more complicated. This is because Monte Carlo simulations to a certain degree deliver stochastic output and in general can be said to require more calculation time per reliability calculation. However, the simulations do allow us to implement more complicated model behaviors.

B. Component Reliability Importance Index

Component reliability importance indices provide the connection between component and system reliability performance [9]. The component reliability importance index used in this paper, I^M [10], corresponds to the expected total customer interruption cost caused by the studied component over a specific time interval (usually one year). The index, which was developed for calculation by simulation [10], is calculated by accumulating the total interruption cost caused by every interruption to the finally causing component over all simulated years. The accumulated cost for every component is then divided by the total simulation time in order to obtain an expected interruption cost per time unit. The index is defined as follows:

$$I_i^M = \frac{K_i}{T} \quad [€/\mathrm{yr}] \tag{1}$$

where K_i is the total accumulated customer interruption cost over the total simulated time T for component i. The index gives an indication of which components should be prioritized for preventive maintenance actions (or in some cases redesigns of the structures that result in the high value of I^M). Moreover, I^M gives information on components that do not incur much interruption cost for the network. It might, for example, be beneficial to reduce preventive maintenance for these components. However, to reach the best possible solution, this information needs to be adequately combined with knowledge about available maintenance actions, their costs, and estimated effects.

C. Multiobjective Approach to the Optimization Problem

The task of finding the optimal balance of preventive and corrective maintenance is approached as a multicriteria/multiobjective optimization problem. On one hand, we have the customers' demands for power delivery, and on the other hand, we have the maintenance cost for the DSO. In this study, we have chosen to use the total customer interruption cost as the measure of network performance from the customer perspective. The maintenance costs are closely related to the analyzed network, its components, structure, and available resources.

It is possible to extend the multiobjective approach by studying every load point's availability as an individual objective. Some cases might, for example, call for pure Pareto improvements [11], where all customers are viewed separately, i.e., improvements that reduce costs or at least keep costs at current levels for all parties involved. To study all customers independently while requiring Pareto improvements narrows down the feasible solution space. Furthermore, with more objectives, the solution space quickly becomes difficult to grasp with the increasing number of load points.

It is interesting to note that the two objectives (customer interruption cost and cost of maintenance) do not entirely point the solution in two different directions since the cost of corrective maintenance to a certain degree correlates with the customers' inconvenience.

D. Heuristic Optimization Approach: AGEBOM—Approximate Gradient Evaluation Bi-Criteria Optimization Method

The proposed optimization is based on an aggregated auxiliary objective function that incorporates the two objectives: the customer interruption cost and the maintenance cost of the network (both corrective and preventive).

1) Objective Function: A scaling between the customer interruption cost and the maintenance cost of the network is introduced. This scaling is varied in order to obtain a number of nondominated solutions with specific tradeoff between customers and DSO. The objective function of the optimization is presented in

$$\min s * C^{\mathrm{IC}} + C^{\mathrm{CM}} + C^{\mathrm{PM}} \quad [€/\mathrm{yr}] \tag{2}$$

where C^{IC} [€/yr] is the expected yearly system customer interruption cost, C^{CM} [€/yr] the cost of corrective maintenance, C^{PM} [€/yr] the cost of preventive maintenance, and s is the scale factor (tradeoff). The unit of the scale factor, s, becomes DSO money per unit of customer money. The scale factor constitutes a translation of the expected customer interruption costs into terms of DSO costs. C^{IC} is obtained from simulations [10] and depends on the maintenance strategy. The values of C^{CM} and C^{PM} are based on the maintenance strategy; see the case study for an example. The three different costs in the objective function depend on the network and its components. They constitute component failure rates, repair times, and network structure and operation. In addition, the simulation delivers the component reliability importance index, I^M [€/yr], for every component [10]. The index I^M corresponds to the average yearly customer interruption cost caused by the specific component. How C^{PM} and C^{CM} are calculated depends largely on the network under study; for this paper, these costs are presented in the case study. C^{IC} is calculated according to [12]

$$C^{\mathrm{IC}} = \sum_L \lambda_L (k_L P_L + c_L P_L r_L) \quad [€/\mathrm{yr}] \tag{3}$$

where C^{IC} is the total expected yearly customer interruption cost for the system, P_L [kW] average power, λ_L [f/yr] and r_L [h/f] are reliability indices for every load point L, and k_L [€/f, kW] and c_L [€/kWh] are cost constants representing the customer types and composition for every load point L.

2) Workflow of Optimization: Since the reliability calculations of customer interruption costs and component importance are derived from simulations, the optimization approach is pushed toward a method that requires few calls on calculation of objective function and other outputs. Another aspect is that the simulations constitute a "black box" that an optimization routine cannot see through. However, the concept of component reliability importance indices allows for a certain degree of visibility into the "black box."

It is assumed that the caused interruption cost is linearly dependant on the failure rate of the component, when no other data are changed, that is, assuming that a relative change in failure rate results in the same relative change in customer interruption cost. Given maintenance actions and estimates of failure rate changes and maintenance cost/savings caused by these, a cost-benefit ratio can be developed. This is the ratio between the change in interruption cost and the cost/savings of the investigated action. By doing this for all available actions for all components, the available actions can be ranked.

The optimization, which can be described as a steepest descent method, commences with a *leap*. The leap introduces the best cost-benefit ratio actions for each component into the solution. This is done despite violating the assumption above. The leap is followed by a stepwise approach that does not violate the above assumption. In other words, all available maintenance actions are evaluated, but only the most profitable one is selected, given that it is expected to result in a better objective function. The optimization is illustrated in Fig. 1.

The start condition for the optimization is that all components are at their initial (current) state. Then a reliability calculation (simulation) is performed. The index, I^M, which is an output from the simulation, is used in order to estimate the impacts on the objective of all maintenance actions available; see (4). The estimates are then used to select *all* seemingly beneficial maintenance actions (this is the leap). This is done despite the fact that every maintenance action is evaluated individually, neglecting the consequences of all the other actions. This approach does not warrant a local optimum being reached, and therefore, we proceed with more cautious "steps," i.e., we continue with a new simulation based on the maintenance actions chosen from the previous step/leap. As before, we evaluate all available maintenance actions, but here only select the most beneficial maintenance action (hence, this is called a step). The steps and reliability calculations are then performed until no more improvements are found. The achieved optimal point is stored. One optimization cycle is then accomplished and the scale, s, is incremented. The calculation continues with a leap starting from the previous optimum. This is continued until there are no more scales to optimize for.

In both *leap* and *step*, the following approximate evaluation of each individual maintenance alternative is made:

$$P_{i,j} \approx \Delta\lambda_{i,j} C_i^{\mathrm{CM}} + \Delta C_{i,j}^{\mathrm{PM}} + s\Delta\lambda_{i,j}\frac{I_i^M}{\lambda_i}[€/\mathrm{yr, action}] \quad (4)$$

where $P_{i,j}$ is the expected change of the objective function if maintenance alternative j is implemented for component i, s is the scale factor of customer interruption costs, λ is the component failure rate, and Δ denotes the change from the current maintenance policy in the optimization process. C_i^{CM} corresponds to the expected corrective maintenance cost that a failure of component i incurs for the DSO. ΔC^{PM} depends on the cost difference of introducing the studied maintenance action compared to the current policy. Equation (4) is approximate since

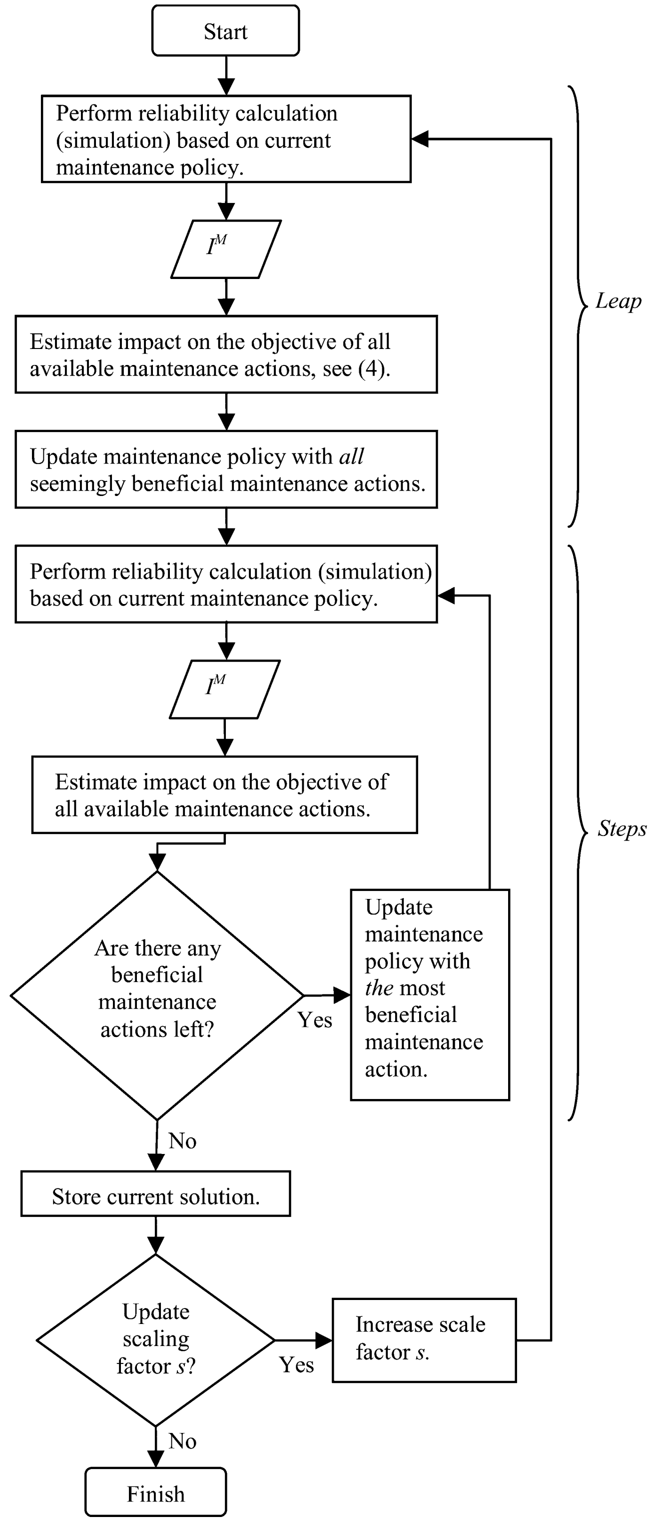

Fig 1. Flowchart for the optimization process.

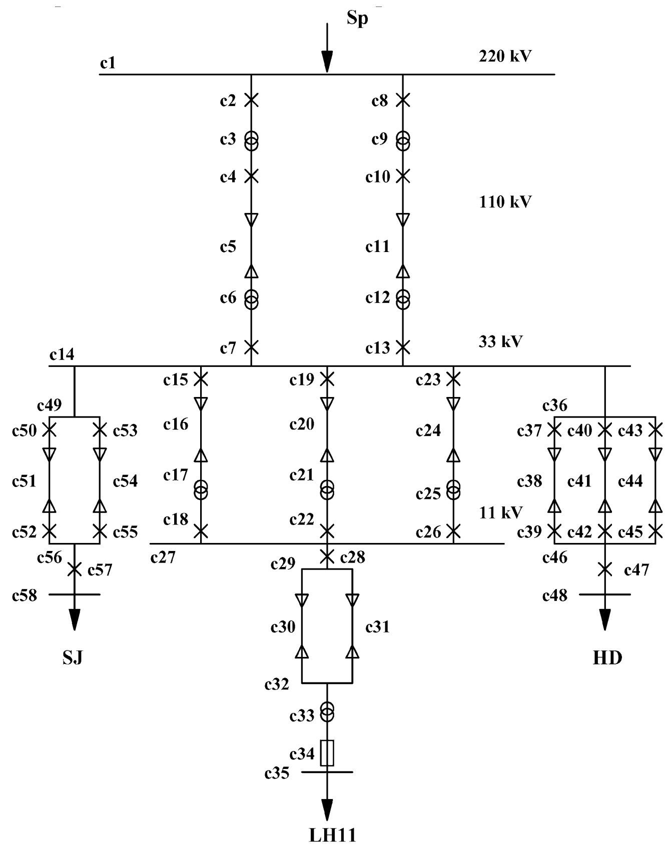

Fig 2. Studied system [13].

the last term is an approximation of how the customer interruption cost will change. For each component in the *leap*, the lowest value of P is chosen for the next simulation. In the *steps*, only one action is chosen, i.e., based on the lowest value, given that this value is below zero.

E. Results and Selection of Optimum

Given that the method has not found local optima, the suggested approach will deliver a number of optimal points, exemplified in the case study below. These points will be located on the Pareto border and are all optimal from a specific point of view. The solution that is selected by the decision maker depends on many factors such as the current status and behavior of the network. The different solutions provide the decision maker with important information on the expected consequences of the different maintenance policies.

III. Case Study

A. Network, the Birka System

The Birka system is located in the southern parts of Stockholm. The name is derived from the former Birka Energi AB, of which the presented network was a part. Birka Energi is now a part of the Fortum consortium. The system (see Fig. 2), which is thoroughly presented in [13] and [14], includes a 220/110-kV station (Bredäng) and one 110/33-kV, 33/11-kV station (Liljeholmen). These two stations are connected with two parallel 110-kV cables. From the Liljeholmen station, there are two outgoing 33-kV feeders, Högalid (HD) and Railway (SJ); there are also 32 outgoing 11-kV feeders (LH11), here represented by one average set of components (28–35). The model includes 178 components, numbered 1–58, with 16 copies of component 28–35. The components are divided into five types: circuit breakers (e.g., c2), cables (e.g., c5), transformers (e.g., c3), bus bars (e.g., c1), and fuses (e.g., c34). In the network, every component has a specific failure rate and repair rate. In total, this network serves approximately 38 000 customers where the load point SJ consists of one customer, that is, the railway. The load point LH11 represent one average load point of 32 actual outgoing feeders, which in total serve 14 300 customers. The load point HD feeds approximately 23 400 customers [14]. In the model, we have assumed piecewise constant failure and repair rates for every component, based on investigations of the network [14]. Note that the constant failure rates should be interpreted as population average values for the specific type of component population, averages that can be modified by selected maintenance policies for the individual. Furthermore, the components are assumed to be independent.

B. Maintenance

In this application study, the maintenance actions are modeled on an aggregated level, i.e., if the components should be maintained as of today or if the preventive maintenance should be increased or decreased. This is modeled as if there were three different preventive maintenance alternatives for each component in the network.

1) *Keep current preventive maintenance level; average failure rate is assumed to remain unchanged; no change in cost for preventive and corrective maintenance.*
2) *Improve the preventive maintenance; the average failure rate is assumed to be halved for the studied component; the additional cost of this is one cost unit.*
3) *Decrease the preventive maintenance; the average failure rate is assumed to be doubled for the studied component; cost savings: one cost unit.*

Furthermore, it is assumed that the cost of one corrective maintenance action is β cost units. In the basic case, β is set at 10 cost units. Here, the cost of corrective maintenance is chosen in relation to the maintenance effects in order to introduce incentives into the operator's maintenance budget to perform preventive maintenance. Studies have been performed for other values of β; see the sensitivity study section of this paper. The relationship between changes in failure rate and cost of corrective maintenance is expressed as

$$\Delta C^{\mathrm{CM}} = \beta \sum_{\mathrm{i}} (\lambda_i^{\mathrm{new}} - \lambda_i) \tag{5}$$

where i denotes component number. The change in preventive maintenance is calculated according to the formula

$$\Delta C^{\mathrm{PM}} = \mathrm{sum}(\mathrm{incr\ maint}) - \mathrm{sum}(\mathrm{decr\ maint}) \tag{6}$$

where sum(incr maint) corresponds to the number of components with increased preventive maintenance actions and sum(decr maint) is the number of components with decreased maintenance.

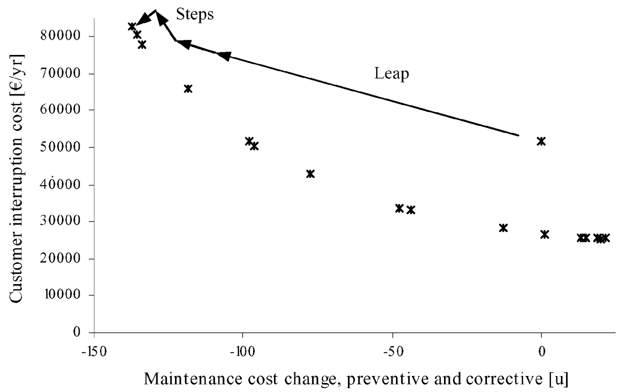

Fig. 3. Optimal solutions calculated. The x-axis corresponds to changes in maintenance budget in comparison to today's budget. Note the starting point for the optimization (not an optimum), located at (0, 51 912). The arrows illustrate the optimization process to one optimum.

TABLE I
OPTIMIZATION RESULTS

Meas. / Solution	C^{IC}_{LH11} [€/yr]	C^{IC}_{HD} [€/yr]	C^{IC}_{SJ} [€/yr]	**ΣC^{IC}** [€/yr]	**C^{PM}** [units]	***Σcomp. failures*** [f/yr]	*SAIFI* [int/yr]	*SAIDI* [h/yr]
Org.	47009	4283	620	**51912**	**n/a**	**4.01**	0.144	0.271
1, 2, 3	73734	8049	1160	**82943**	**-144**	**4.66**	0.211	0.451
4	72103	7204	1046	**80353**	**-142**	**4.64**	0.192	0.434
5	70612	6302	909	**77823**	**-140**	**4.63**	0.175	0.416
6	58492	6361	917	**65770**	**-124**	**4.57**	0.174	0.356
7	46181	4726	788	**51695**	**-87**	**2.91**	0.121	0.280
8	45589	4225	725	**50539**	**-85**	**2.90**	0.113	0.271
9	39038	3398	727	**43163**	**-66**	**2.86**	0.104	0.227
10, 11	29930	3147	694	**33771**	**-33**	**2.57**	0.098	0.178
12	29449	2934	698	**33081**	**-29**	**2.56**	0.092	0.174
13	24767	2929	701	**28397**	**3**	**2.43**	0.089	0.151
14, 15	23763	2495	515	**26773**	**17**	**2.42**	0.079	0.141
16	23242	2232	409	**25883**	**30**	**2.35**	0.074	0.135
17	23052	2213	344	**25609**	**32**	**2.33**	0.074	0.134
18	23116	2091	347	**25554**	**36**	**2.31**	0.073	0.133
19	23042	2095	307	**25444**	**37**	**2.30**	0.073	0.133
20	23170	2068	306	**25544**	**39**	**2.28**	0.073	0.133

"Org." represents the non-optimized original solution, i.e. maintenance policy as of today. Data used in the optimization process are marked in bold. A number of solutions are identical; these are presented in the same row. C^{PM} corresponds to the net change of preventive maintenance units.

Note that the assumed maintenance alternatives in general "punish" relocation of maintenance resources in terms of total number of component failures. Consider the example of two components, both with the same initial failure rate, λ, and both being at alternative 1. By moving maintenance resources, i.e., moving one component to alternative 2 and the other to alternative 3, this results in the sum 2 1/2 λ (compared to 2λ, before maintenance reallocation).

C. Results

The result of the optimization routine is a number of optimal points (solutions) which are all optimal from a specific point of scale. In Fig. 3, a number of optimal points are displayed, as well as the starting point (present situation). Note that since every optimization is built on results from a separate simulation, some of the optimal points are dominated by other optimal points. A point is dominated when another point exists that is better in respect of at least one criterion without being worse in any other criteria. The existence of these points is explained by the fact that every optimization is based on one or more (individual) simulations. In the preceding work of this paper, it has been seen that with more iterations in each simulation, the number of dominated points decreases. In Table I, more details are found for the solutions presented. Solutions 7–13 all dominate the "initial point." Even when considering SAIDI and SAIFI, solutions 8–13 dominate the initial point, despite SAIDI and SAIFI not being directly included in the optimizations. Solutions 7–13 are probably more interesting than the others, since they do not aggravate the situation for any of the two parties involved. This is, however, only true if we look at the total customer interruption cost. If we study every load point separately, it can be seen in Table I that the interruption cost for node SJ is higher for solution 1–13 than for the starting point. One approach to this somewhat problematic situation might be to state that solutions 7–13 constitute Pareto improvements from a system perspective, which implies that we utilize our resources for the common good of the customers. Another approach might be to put constraints on the optimization, ensuring that the reliability offered to customers does not fall below current levels, or to penalize customer node interruption costs that are above today's level. If we want to investigate this issue further, we need to split up the utilized customer objective into three new objectives, i.e., one measure for every load point. It is noteworthy that such an approach will most likely be less efficient from a global perspective. In this paper, we recognize the possibility of approaches that consider individual constraints on customer nodes. Nevertheless, we continue the study with the focus on the common good, i.e., lowest total cost.

D. General Discussion of Results

If we study the optimization problem from the perspective of the DSO, one approach is to see how much we can decrease the maintenance budget, without decreasing the service to the customers. This is achieved by identifying the solution with the nearest lower customer interruption cost compared to the solution of today (0, 51 912). The maintenance cost difference between the starting point and the optimal point now reached gives us an estimate of today's maintenance policy inefficiency,[1] that is, how much it is possible to save on today's maintenance policy without reducing average customer service. This approach suggests solution number 7 for the case study, which would significantly reduce the cost of preventive maintenance. Likewise, we can perform this operation in reverse by going down from today's (0, 51 192) solution to the Pareto border in order to localize the point that, given today's budget, will give us the lowest customer interruption cost. This approach suggests solution 13. According to Table I, this solution, with the utilized

[1]Since the studied example is based on partially fictive data, no definite conclusions can be drawn about the current management of the studied network.

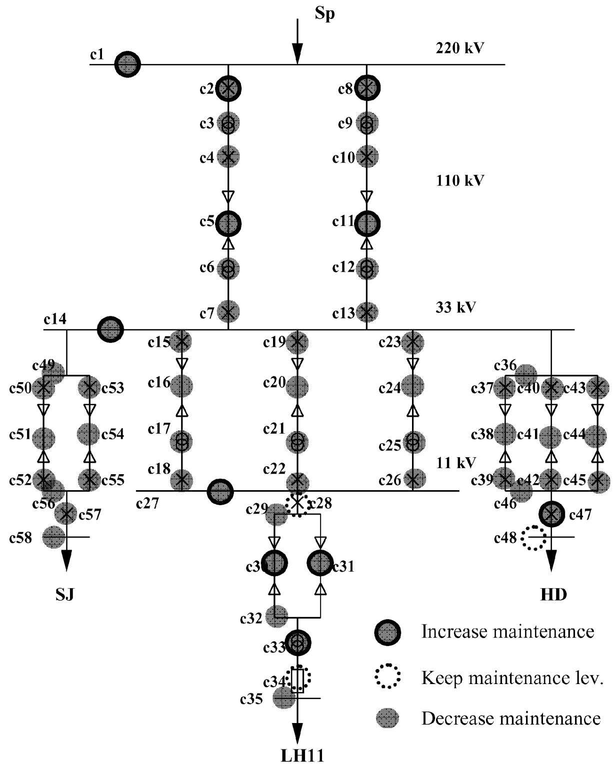

Fig. 4. Illustration of optimum number 10.

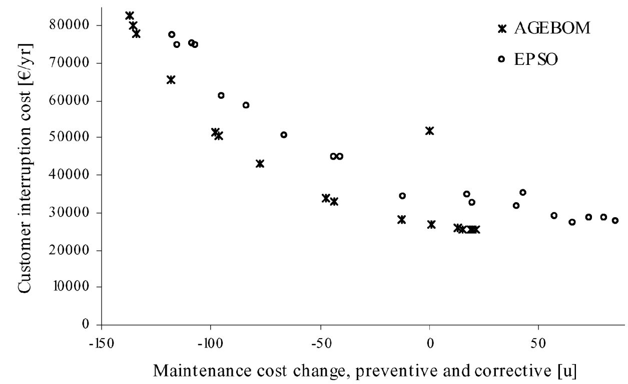

Fig. 5. Calculation results for EPSO (o) and AGEBOM (x). Note that the solution at (0, 51 912) corresponds to today's maintenance policy.

assumptions, would result in an almost halved customer interruption cost. While the preventive maintenance is increased for this solution, the cost of corrective maintenance is lowered, resulting in a slightly lower maintenance cost than that of today.

E. Results Continued for One Optimum (Number 10)

In this section, we study one of the reached optima in more detail, namely, optimum number 10, to exemplify a specific solution. Normally, the DSO should choose a suitable solution. In this case, we continue and assume that the DSO chooses solution number 10. This might be motivated by the fact that this point has a suitable combination of lowered customer interruption costs and lowered maintenance cost. One additional advantage of this point is that the interruption cost for node 3 is relatively close to the starting value.

The resulting maintenance plan stipulates that the preventive maintenance level should be increased for 56 components while being decreased for 89 components and kept the same for 33 components. Fig. 4 presents an illustration of the suggested actions for optimum number 10 applied to the network.

IV. Validation and Sensitivity Analysis

A. Validation of Optimization Method

The optimization problem has been approached with an additional tool, the evolutionary particle swarm optimization (EPSO) algorithm, developed at INESC Porto [15].

The EPSO algorithm can be described as a combination of evolutionary algorithms [16] and the particle swarm optimization algorithm (PSO) [17]. Put simply, EPSO works with a number of solutions (called particles) in the problem space. These particles have properties of position, inertia, and memory. Each particle generates new particles (offspring) that "move" according to a combination of where the other particles are located (cooperation), inertia, and memory (of the best point ever visited for the specific particle). Every particle in the offspring is evaluated by an objective function. Based on this evaluation, through selection using elitism (or stochastic tournament), good descendants of each particle have a higher chance to survive and stay in the process than the less "good" particles. The surviving particles serve as a new generation of particles, replacing their ancestors. When producing offspring, the method automatically mutates the weights of the different movement aspects (inertia, cooperation, and memory). The mutation of the weights corresponds to a self-tuning of parameters in a particle swarm optimization. Basically the most notorious difference between PSO and EPSO is that EPSO removes bad particles with inferior combination of weights and updates, through mutation, the movement weights. A comparison between EPSO and PSO may be found in [18].

The AGEBOM algorithm results were compared with the results from EPSO. Since EPSO to a certain degree utilizes a random approach and investigates several solutions simultaneously, the method is not as prone as AGEBOM to get stuck in local optima. Therefore, we investigated whether the AGEBOM algorithm's solutions could be improved. No indications of improvements could be found, which indicates that the given problem formulation is without local optima in which the AGEBOM gets stuck.

Since the AGEBOM algorithm requires relatively few calls to the objective function and the objective function in this case is based on simulations, the method becomes fast compared to the more intricate approach of the EPSO algorithm.

Fig. 5 shows the effectiveness of the developed AGEBOM algorithm compared to EPSO. The interpretation of this result is that the AGEBOM is well adapted to the problem under study. More complex problems may result in better relative performance by the EPSO algorithm.

B. Sensitivity Analysis

One might argue that the above assumptions on how the failure rate changes with changes in maintenance are somewhat

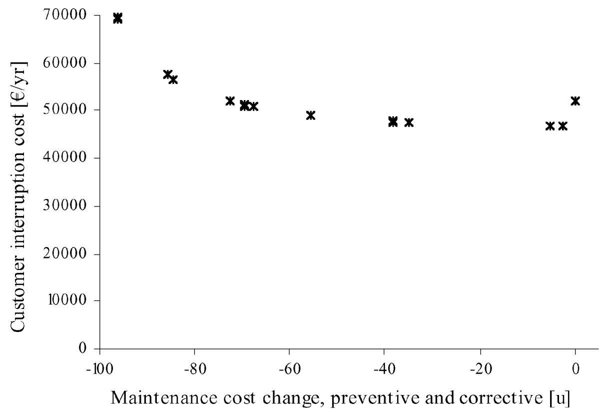

Fig. 6. Illustration of optimal points for expensive corrective maintenance and big losses in reallocation of maintenance resources. Note that the solution at (0, 51 912) corresponds to the present maintenance policy.

optimistic. Therefore, we look at an example of reduced efficiency in the allocation of preventive maintenance resources and a more expensive corrective maintenance. In this scenario, the cost of corrective maintenance is tenfold compared to the first studied case ($\beta = 100$). Increased preventive maintenance results in only 10% reduction of the failure rate, and decreased preventive maintenance results in 100% increased failure rate (as before).

Despite the effects of the changes presented above, the process produces improvements, for example, where we are capable of reducing the customer interruption costs by approximately one fifth while keeping within today's maintenance budget. See Fig. 6 for an illustration of the results.

It can be seen in this section that there is still a value in optimizing the maintenance despite large "penalties" in reallocating maintenance resources. The benefits do not become as significant as with the basic assumptions, but they are still present. This is an effect of providing an existing solution (today's policy) with more alternatives that we optimize over. What is actually shown in this section is more an illustration of how the results may vary within an actual outcome. It also shows that there is probably some value in introducing more maintenance policies for every component and in choosing the right level of maintenance for each component with respect to network performance. For a more extensive sensitivity analysis, where, for example, only the reallocation of resources is penalized harder, see [19].

V. Discussions and Potential Improvements

A. More Parties

This paper only studies the problem of maintenance from two perspectives, i.e., customers and DSOs. This is somewhat of a simplification since there are more parties involved in the process, such as regulatory authorities and third-party maintenance providers. Regulatory issues can be accumulated within a widened definition of maintenance budget. For example, penalties that the DSO has to pay because of too low reliability in one area and/or increased/decreased maximum allowed charge per kWh can be incorporated into the model. Third-party maintenance providers may also complicate the optimization further, but in this paper, they are considered to perform specified policies and their impact is not further analyzed here.

B. Network Performance From Customer View

Using customer interruption costs as a performance measure may seem somewhat farfetched but carries a number of advantages. Among these is the possibility of incorporating the effects of both short power failures (kW) and longer interruptions (kWh) in one measure. Additionally, it is possible to include concepts of power quality and the importance of different customers into a customer cost perspective. Furthermore, money is a measure that is possible to communicate throughout organizations and to people, all the way from the customers to the board of the DSO as well as regulating authorities. It is completely possible to establish values for interruption costs; this has been accomplished in a number of studies, e.g., [20] and [21]. Furthermore, this aggregated measure is quite widely used in the process of network performance assessments. In Sweden [22] and Norway [23], the regulation of DSOs is partly based on interruption costs. Many companies use the customer interruption cost in investment planning. It is, however, perfectly possible to replace the proposed measure with another measure in the optimization, for example, a weighted index based on SAIDI and SAIFI, as proposed in [3]. A modification in network performance measure requires a new component importance index, to replace (1). The conclusion is that the proposed customer network performance measure is adequate but that it may be replaced/modified for situation- specific reasons, e.g., a regulation based on SAIDI and SAIFI.

VI. Conclusion

The results from the maintenance optimization are interesting. Despite a general decreased level of maintenance (lower total maintenance cost), better network performance can be given to the customers. This is achieved by focusing the preventive maintenance on components with a high potential for improvement in system performance. In the end, this shows that there is value in introducing more maintenance policies for every component and in choosing the right level of maintenance for every component. Here we have proposed a tool for this selection process.

The case study requires more data in order to demonstrate the true benefits of the maintenance policy optimization. Data on costs of corrective and preventive maintenance and estimates of how preventive maintenance affects the components are needed. However, in the less optimistic sensitivity analysis, we still show a possibility of improving the maintenance by use of the proposed method. The optimization method is based on time-efficient heuristics, which include a risk of getting stuck in local optima in more complicated problem formulations. Here is the strength of using the EPSO algorithm in the optimization apparent. Although more costly in terms of computation time, it is a tool that may prove very useful when optimizing more complicated problems.

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