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Impact of Energy End Use and Customer Interruption Cost on Optimal Allocation of Switchgear in Constrained Distribution Networks

Arild Helseth and Arne T. Holen, *Member, IEEE*

***Abstract*—The introduction of new energy carriers, such as natural gas and district heating, to energy systems dominated by electrical power will certainly relieve stress on the power system. Some of the end uses initially served by the power system will be gradually decoupled and served by alternative energy carriers. As a result, the specific customer interruption costs and load profiles will change. In this paper, we analyze how the optimal level of switchgear in electric power distribution systems is affected by such changes. The proposed optimization method is based on a genetic algorithm and takes into account the constrained network capacity.**

***Index Terms*—Customer interruption cost, genetic algorithms (GAs), network constraints, power distribution protection, power distribution reliability.**

I. Introduction

THE basic function of the power distribution system is to supply customers with electrical energy as economically as possible and with an acceptable degree of reliability. Consequently, obeying the two conflicting objectives of economics and reliability is the main challenge when constructing new or expanding existing distribution systems. Several countries, including Norway, have carried out extensive surveys with the purpose of eliciting the economical losses experienced by different customer groups due to power interruptions. In this way, reliability can be quantified in terms of a monetary value, and the worth of any investment in the power system may be found through a cost-benefit analysis [1].

Electrical power is the dominating energy carrier in the Norwegian energy system. By introducing alternative energy infrastructures, such as natural gas and district heating, some of the energy end uses may be decoupled from the power system. As a result, the electrical load profile will change and the demand for electrical power will decrease.

Will this shift in demand affect the optimal level of investments in reliability-enhancing projects? Intuitively, a relief in demand for electrical power will lead to decreased interruption consequences since less power has to be transported to the customers. Thus, the optimal level of investment in reliability will decrease, compared to the case where electricity serves all end uses. Furthermore, load relief on tightly constrained distribution feeders may improve the ability to restore service through reserve connections in the network, resulting in system reliability improvement without additional investments. On the other hand, consumer surveys reveal that the end use that can only be covered by electricity tends to have a higher associated cost of interruption. These conflicting momentums are all incorporated in an optimization method presented in this paper.

Finding the optimal number and location of switchgear in radial distribution systems is a complex problem which has been approached by several authors [2]–[8]. The problem may be classified as a combinatorial optimization problem having a nonlinear and nondifferentiable objective function. Various techniques have been applied to solve the optimal configuration problem (e.g., dynamic programming [2], binary programming [3], simulated annealing [4], direct search [5], and genetic algorithms (GAs) [6]–[8]).

The presented methodology applies a GA for the purpose of optimizing the number of automated and manual switching devices in a prerouted, radial distribution system. The energy end uses are divided in two categories: those that can only be provided by the power system and those that can be provided by any energy infrastructure. Different interruption costs are applied for these two categories. The impact of reduction in demand and changes in the load profile on the optimization problem is analyzed and discussed. By performing this type of study, a network company may analyze whether the amount and configuration of switchgear is appropriate according to the end-use specific interruption costs and load profiles.

II. Interruption Costs

Different customer sectors apply electricity for different end uses. Surveys from various countries show that each customer sector will evaluate the loss of a service differently, depending on the end uses the customer sector typically covers by electricity and the interruption duration [1]. Customers put more emphasis on the cost and inconvenience associated with the inability to perform their activities due to an interruption rather than the energy which is not supplied.

In Norway, the regulation scheme cost of energy not supplied (CENS) adjusts the revenue of the network companies in accordance with the customers' interruption costs [9]. The expected CENS is calculated as the product of the annual expected energy not supplied (EENS) and a specific interruption cost in NOK/kWh_{ENS} (1 Euro $\approx$ 8 NOK). The applied CENS rate is sector dependent, but independent of interruption duration.

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The authors are with the Department of Electrical Power Engineering, Norwegian University of Science and Technology (NTNU), Trondheim 7491, Norway (e-mail: helseth@elkraft.ntnu.no).

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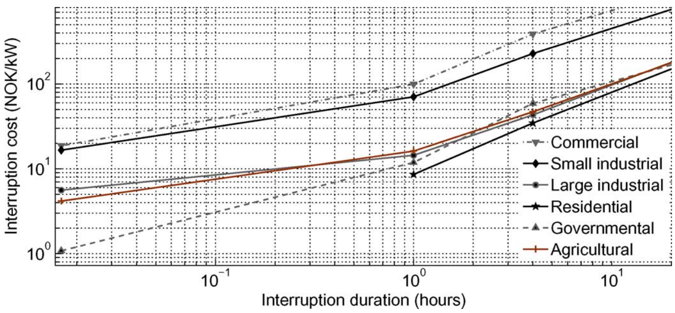

Fig. 1. Sector customer damage functions for Norwegian customers.

TABLE I
RELATIVE CONSUMPTION AND INTERRUPTION COST FOR THE COMMERCIAL CUSTOMER SECTOR

End-use category	Consumption (% of total)	Cost (% of total)
Space heating	26	8
Hot tap water	4	2
Cooling	8	4
Electrical boilers	4	1
Cooking	9	2
Lighting, computers, electric devices etc.	49	83

For more detailed system planning, it is believed that the nonlinear profile of interruption costs as a function of interruption duration should be accounted for. Such profiles are conveniently displayed in sector customer damage functions (SCDFs). SCDFs are created by aggregating the cost functions of individual customers in the same customer sector. The SCDFs for the six different customer sectors used in Norway are shown in Fig. 1, based on an extensive survey conducted by the Institute for Research in Economics and Business Administration (SNF) and SINTEF Energy Research [10]. When studying the SCDFs in Fig. 1, one should keep in mind that the consumers in Norway generally apply electricity to cover all energy end uses.

Additional accuracy may be added by assigning one SCDF for each distinctive end-use category, as represented in (1). Examples on typical end-use categories are shown in the first column of Table I

$$\mathrm{SCDF}_i = \begin{bmatrix} C_{e_1,t_1} & C_{e_1,t_2} & \cdots & C_{e_1,t_n} \\ C_{e_2,t_1} & C_{e_2,t_2} & \cdots & C_{e_2,t_n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{e_m,t_1} & C_{e_m,t_2} & \cdots & C_{e_m,t_n} \end{bmatrix}. \quad (1)$$

Where SCDF_i is the SCDF for customer sector i and $C_{e,t}$ is the cost associated with the inability to serve end-use category e during a period t. In this matrix, m different end-use categories and n different interruption duration periods are displayed. All end-use categories are aggregated in Fig. 1 $(m = 1)$, thus every SCDF_i is represented by a $1 \times n$ vector.

Alternative energy carriers, such as district heating and natural gas, are able to cover some of the same end uses as electrical power. An extensive discussion of the different end uses is not within the scope of this paper; thus, we will aggregate end uses in two major categories

End-use category:	Covered by:
Electricity specific	Electric power system
Flexible	Any energy infrastructure

.

Obviously, the category of flexible end uses contains different services depending on the energy carrier. Natural gas may, for example, be used for cooking, but this end use cannot easily be provided by the district heating system. Furthermore, a low supply temperature in a district heating system may exclude the possibility of serving certain thermal end uses.

In the survey described in [10], respondents of some selected customer sectors were asked to estimate the cost associated with the loss of ability to perform activities in selected end-use categories and the annual energy consumption related to each end-use category. These data refer to non-notified interruptions at a given reference time (weekday in January). Data for the commercial customer group are presented in Table I and will be used in the subsequent sections of this paper. The end-use categories of space heating, hot tap water, and electrical boilers are defined as flexible end uses.

It is evident that the inability to perform electricity specific end uses has a higher associated cost than is the case for flexible end uses for the commercial customer sector. Unfortunately, the survey does not give sufficient information to display the end-use specific interruption costs as a function of interruption duration and present accurate corresponding SCDF_i matrices as described in (1) for the two aggregated end-use categories. However, for the purpose of illustrating the suggested method, some new SCDFs were created. The original SCDFs shown in Fig. 1, are now denoted as $\mathrm{SCDF}_i^{\mathrm{old}}$. Based on $\mathrm{SCDF}_i^{\mathrm{old}}$ and the weighting factors α_i and β_i defined in (2), a new SCDF matrix $\mathrm{SCDF}_i^{\mathrm{new}}$, was constructed from (3). For all values of interruption duration, (4) should be fulfilled

$$\alpha_i = \frac{\mathrm{Cost}_i^{EL}(\%)}{\mathrm{Consumption}_i^{EL}(\%)}$$

$$\beta_i = \frac{\mathrm{Cost}_i^{\mathrm{FLEX}}(\%)}{\mathrm{Consumption}_i^{\mathrm{FLEX}}(\%)} \quad (2)$$

$$\mathrm{SCDF}_i^{\mathrm{new}} = \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \times \mathrm{SCDF}_i^{\mathrm{old}} \quad (3)$$

$$\alpha_i \mathrm{Consumption}_i^{EL} + \beta_i \mathrm{Consumption}_i^{\mathrm{FLEX}} = 100\%. \quad (4)$$

Generally, the services related to the flexible end-use category are less affected by short interruptions than the services related to the electricity specific end use (e.g., due to thermal inertia of buildings and the presence of storage tanks for hot tap water). Consequently, it is likely that the shape of the SCDF for the flexible and electricity specific end-use categories will differ for low values of interruption duration. In order to reflect the differences in shape for the two end-use categories, it is simply assumed that interruptions of the flexible end use having a duration of less than X mins will not be noticeable for the customers.

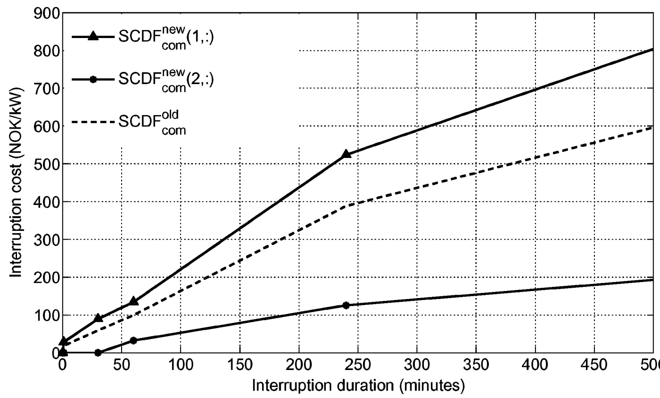

Fig. 2. SCDF for the commercial customer sector.

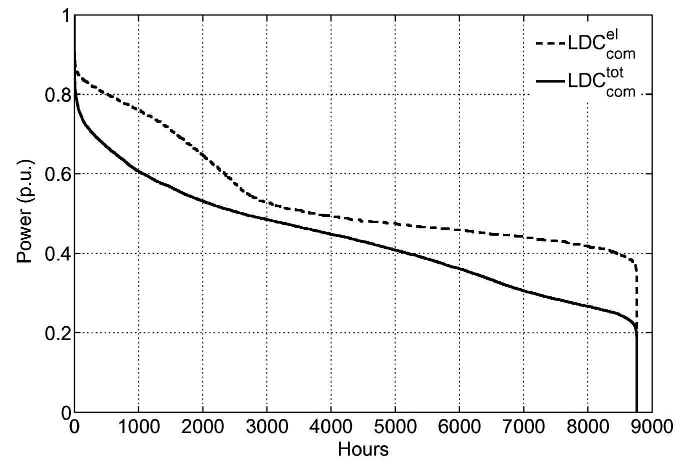

Fig. 3. Load duration curve for the commercial customer sector.

Accordingly, β_i is set to be equal to zero and α_i is changed so that (4) is fulfilled.

A new SCDF matrix for the commercial customer sector $\mathrm{SCDF}^{\mathrm{new}}_{\mathrm{com}}$ was constructed from (3). By using data from Table I, the weighting factors become $\alpha_{\mathrm{com}} = 89/66$ and $\beta_{\mathrm{com}} = 11/34$. $\mathrm{SCDF}^{\mathrm{old}}_{\mathrm{com}}$ and $\mathrm{SCDF}^{\mathrm{new}}_{\mathrm{com}}$ are displayed in Fig. 2, with $X = 30$.

It should be noted that the difference between the electricity specific and the flexible end-use categories shown in Fig. 2 was found to be particularly large for the commercial customer sector and was less evident for the remaining customer sectors.

III. Load Duration Curves

In power distribution networks with constrained capacity, load-flow studies will reveal whether the network constraints are met before system reconfigurations are performed. Estimates of reconfiguration capability are normally based on system peak load and, thus, contributes to a conservative estimate of the reliability of the network. For more detailed reliability studies, load duration curves (LDCs) should be applied. A LDC comprises load data plotted in a descending order of magnitude, where each load level has a corresponding probability of occurrence.

The LDCs for the electricity specific and the flexible end-use categories differ significantly in shape due to different consumption patterns throughout the year. LDCs for the sum of all end uses ($\mathrm{LDC}^{\mathrm{tot}}_{\mathrm{com}}$) and the electricity-specific end uses ($\mathrm{LDC}^{\mathrm{el}}_{\mathrm{com}}$), based on hourly peak load measurements from a typical Norwegian commercial-sector customer, are shown in Fig. 3. In order to analyze the possible influence that the differences in shape have on the optimization problem, two 10-step load duration curves ${}^{10}\mathrm{LDC}^{\mathrm{tot}}_{\mathrm{com}}$ and ${}^{10}\mathrm{LDC}^{\mathrm{el}}_{\mathrm{com}}$ were created based on the data presented in Fig. 3. These curves are used in the subsequent calculations and their corresponding numerical values are shown in Table II.

We now assume that the load duration curve $\mathrm{LDC}^{\mathrm{tot}}_{\mathrm{com}}$ from Fig. 3 is representative for the commercial customers who contributed to the survey in [10].

As previously shown in Table I, the electricity-specific end-use category requires 66% of the total energy demand for the commercial customer group. Assuming that this end-use category adheres to the $\mathrm{LDC}^{\mathrm{tot}}_{\mathrm{com}}$, the maximum power required

TABLE II
Numerical Values for 10-Step Load Duration Curves for the Commercial Customer Sector

Step	Probability	${}^{10}LDC^{el}_{com}$ Electricity specific (p.u.)	${}^{10}LDC^{tot}_{com}$ Total (p.u.)
1	0.0057	1.000	1.000
2	0.1084	0.855	0.755
3	0.1142	0.760	0.605
4	0.1142	0.645	0.531
5	0.1142	0.526	0.484
6	0.1142	0.495	0.448
7	0.1142	0.475	0.410
8	0.1142	0.459	0.360
9	0.1142	0.440	0.305
10	0.0868	0.419	0.268

is 66% as well. However, by using the $\mathrm{LDC}^{\mathrm{el}}_{\mathrm{com}}$ displayed in Fig. 3, the maximum power requirement is only 55% of the total maximum power. Thus, applying the correct load curve may influence the reconfiguration capability of constrained feeders which, in turn, may influence the outcome of the optimization problem.

IV. Problem Formulation

Deciding the optimal level of switchgear in a radial distribution system is a combinatorial optimization problem. The solution space is constrained by the type and amount of switchgear available. We consider two categories of switchgear in this optimization procedure: 1) the automatically operated switch (AOS) and 2) the manually operated switch (MOS). Fuses are also modelled, but their locations have been predefined. The presented optimization procedure treats the switch allocation problem as an independent subproblem, without addressing reinforcement or downsizing of distribution system equipment. It is believed that equipment downsizing should be included for a more detailed analysis, and that this feature may be added modularly to the presented procedure.

A. Switchgear

A short and general description of the functionality of the switchgear applied in the proposed model will follow. An AOS will automatically isolate a faulted section of a distribution circuit once an upstream circuit breaker or recloser has interrupted

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the fault current. An MOS is operated manually by a repair crew and is capable of opening and closing a circuit when negligible current is broken or made. The AOS and MOS have no ability to break fault currents; thus, they will not impact the frequency of interruptions experienced by the customers [11]. Fuses are overcurrent protection devices which are usually located at the beginning of distribution laterals. Once a fuse has melted and operated due to a downstream fault, it requires replacement before the protected lateral can carry load again.

B. Assessing Load-Point Reliability

An analytical simulation approach is applied to assess load-point reliability [12]. Radial distribution systems may be modelled as tree data structures comprising a set of nodes and branches. The failure of each system component is simulated and interrupted load points are classified in distinctive classes depending on interruption time. A two-stage restoration strategy is modelled, as described in [13]. First, a limited set of load points is restored by using the available AOSs. These load points experience an interruption of duration equal to the automatic sectionalizing time and belong to class A. Second, additional load points are restored by using MOSs. These load points experience an interruption duration equal to the manual sectionalizing time and belong to class B. Load points which are not restored before the faulted component has been repaired or replaced belong to class C. In case node voltages drop below a preset minimum level ($V_{\min}$) due to reconfiguration, the solution is rejected and alternative switch operations are sought. This procedure is repeated for all load levels and all contingencies.

The reliability assessment procedure is based on the following assumptions:

- the distribution system is radially operated;
- only first-order contingencies are considered;
- all switchgear is 100% reliable;
- all switchgear is properly coordinated;
- temporary failures are not considered;
- a circuit breaker is always located at the root of each tree (i.e., at the substation of the distribution system).

C. Illustrative Example

The following example illustrates the logic of a two-stage restoration strategy. Furthermore, a discussion on the impact of introducing alternative energy carriers on reliability is given.

Consider the simple radial shown in Fig. 4, comprising five busbars (bb1–bb5), branches (B1–B5), load points (L1–L5), switches (S1–S5), and a circuit breaker (CB). Assume that switches S2, S4, and S5 are AOSs and the remaining switches are MOSs, that S1–S4 are normally closed and that S5 is normally open. The reserve connection through feeder 2 (F2) is capable of supplying L4 and L5 at the given load level. Both flexible and electricity specific end uses are served by the power system.

In case of a permanent fault on branch B2, the restoration algorithm will first request that CB and S2 open to isolate B2. The intention is then to close S5, establish the reserve connection through feeder F2, and restore supply to load points L3–L5. However, due to the feeder constraints, the load-flow study will reveal that the suggested operations result in violated feeder constraints and the algorithm will search for the next AOS downstream S2, which is S4. No constraints are violated this time; thus, CB and S4 are opened to isolate B2 and restore service to L5. Subsequently, the second stage of the restoration is initiated, requesting that the MOSs S1 and S3 open and that CB and S4 close to further limit the isolated area. Again, the network constraints are not violated, and L1 and L4 are restored by performing the requested operations. Load points L2 and L3 will not be restored until B2 has been repaired. Consequently, load point L5 belongs to class A, L1 and L4 to class B, and L2 and L3 to class C.

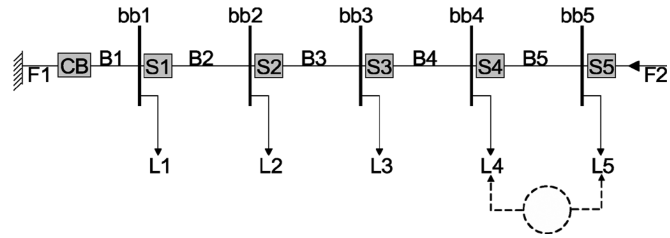

Fig. 4. Simple distribution system radial.

Assume that the flexible end uses of load points L4 and L5 are detached from the power system and served by a local heat supplier. There is now the possibility that, after a permanent fault on B2, S2 can open so that L3–L5 are restored without violating feeder constraints. Load points L3 and L4 will then belong to class A and, thus, experience improvement in reliability. Both the explicit load reduction and the change in aggregated profile of the feeder load are factors that may trigger the change in reconfiguration capability.

D. Genetic Algorithms

GAs are search algorithms based on the mechanics of natural selection and natural genetics. A GA does not rely on the assumption of linearity, differentiability, continuity, or convexity of the objective function.

A simple binary GA was defined for this optimization problem by using the Java package JGAP [14]. Initially, the GA randomly creates a population of feasible solutions. Each solution is a string of binary variables in which each bit represents the presence (1) or absence (0) of switchgear in a predefined location in the distribution network. The possible locations of switchgear are predefined according to a set of rules. Branches are divided in two types: 1) primary and 2) terminal branches. Terminal branches are directly connected to the load points and are equipped with fuses at their sending ends. Primary branches are not directly connected to load points. A switch may be allocated at the sending end of each primary branch. In Fig. 5, switch S1 on branch B1 is represented by the bits {1,0}. The first bit indicates the presence of the switch and the second bit is the absence of automatic control. Similarly, S2 is present and is controlled automatically. Thus, the primary branches B1 and B2 in Fig. 5 have the presence of an MOS and AOS, respectively.

The next generation of solutions is chosen based on the rules of probability theory and the fitness (objective function) of each

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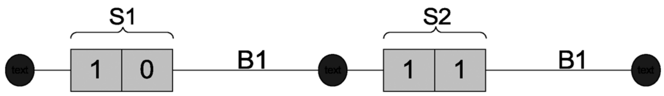

Fig. 5. Possible locations of switchgear on two primary branches.

solution. The further search for an optimal solution is governed by the three basic operators of reproduction, crossover, and mutation. A thorough description of the basic operators of the GA may, for example, be found in [15].

The expected customer outage cost (ECOST) relates the reliability of each solution (s) to a monetary value

$$\mathrm{ECOST}(s) = \sum_{i}^{ni}\sum_{j}^{nj}\sum_{k}^{nk} P_i\lambda_j \Big[\gamma_k^1 \mathrm{LDC}_{i,k}^{\mathrm{tot}}\mathrm{SCDF}_k^{\mathrm{old}}(r_{jk}) + \gamma_k^2 \mathrm{LDC}_{i,k}^{el}\mathrm{SCDF}_k^{\mathrm{new}}(1, r_{jk})\Big]. \quad (5)$$

ni	number of steps on the LDC;
nj	number of components;
nk	number of load points;
P_i	probability of load step i;
λ_j	average failure rate for component j;
γ_k^1, γ_k^2	Boolean variables for load point k;
$\mathrm{LDC}_{i,k}^{\mathrm{tot}}$	total load at step i of the 10-step LDC for load point k;
$\mathrm{LDC}_{i,k}^{el}$	electricity specific load at step i of the 10-step LDC for load point k;
$\mathrm{SCDF}_k^{\mathrm{old}}(r_{jk})$	specific outage cost related to all end uses for the customer group at load point k given the outage time r_{jk};
$\mathrm{SCDF}_k^{\mathrm{new}}(1, r_{jk})$	specific outage cost related to the electricity specific end use for the customer group at load point k given the outage time r_{jk}.

In case all end uses are covered by electricity at a load point k, $\gamma_k^1 = 1$ and $\gamma_k^2 = 0$ in (5). Conversely, if only the electricity specific end use is covered by electricity, $\gamma_k^1 = 0$ and $\gamma_k^2 = 1$. The optimization procedure can be represented as in (6), where ICOST is the total annualized capital cost for switchgear

$$\mathrm{Minimize}(\mathrm{ECOST} + \mathrm{ICOST}). \quad (6)$$

It should be noted that the GA has no convergence guarantee in arbitrary problems. In order to improve the convergence properties, hybrid GA schemes incorporating local search techniques may be constructed. In this study repeatability of the results was used as a convergence guarantee.

V. System Studies

In order to test the suggested optimization procedure and the impact of shifts in SCDFs and LDCs, the radial distribution

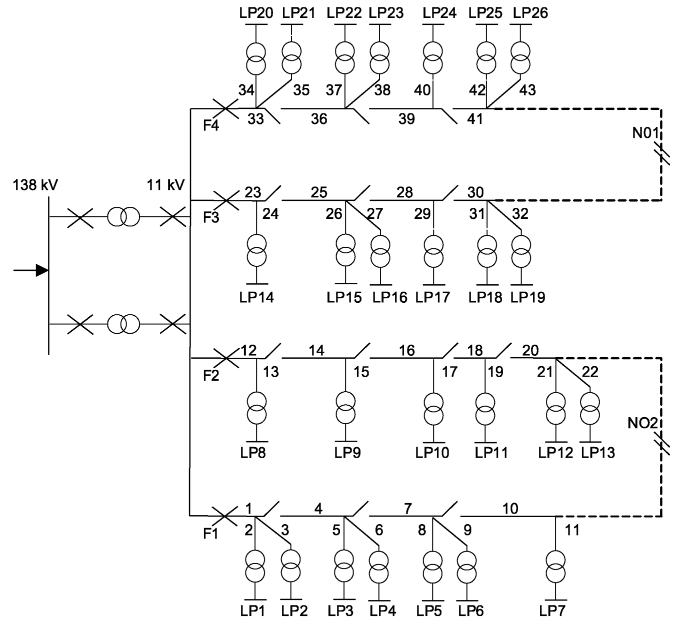

Fig. 6. Distribution system for RBTS bus 5.

system connected to bus 5 of the Roy Billinton Test System (RBTS) was designated as a test system [16], [17]. Failure rates and repair times are given in [16]. Customer data, feeder lengths, and load data are given in [17]. Manual and automatic switching time was set to 1 h and 1 min, respectively. The peak loads given in [17] were all increased by 40%. The annualized capital cost for an AOS and an MOS was set to 12 000 and 8000 NOK/year, respectively. Fig. 6 shows the original version of the test system, where feeders (F1–F4), load points (LP1–LP26), branches (1–43), and normally open switches (NO1–NO2) are labeled.

The system was tested for five different combinations of SCDFs and LDCs. For all simulations, the minimum voltage $(V_{\min})$ was set to 0.95 p.u. Case 1, which is the base case, assumes that the power system supplies all load. The remaining four cases assume that all of the commercial customers (load points 7, 14, 18, 22, and 24 in Fig. 6) have their flexible end use provided by other energy carriers than electric power. The SCDFs and LDCs used for the commercial customer sector were displayed in Fig. 2 and Table II, respectively. All other load points were associated with the SCDFs shown in Fig. 1 and they were assumed to follow the ${}^{10}\mathrm{LDC}_{\mathrm{com}}^{\mathrm{tot}}$ from Table II.

Table III shows the results of the optimization procedure for the different combinations of SCDFs and LDCs. The character a following the switch number indicates the selection of an AOS, while b indicates an MOS. The corresponding ECOSTs and ICOSTs are shown in Fig. 7.

As expected, the results indicate that the ECOST decreases when the commercial customer–sector load is decoupled from the power system. By using the nonadjusted SCDF and LDC for the commercial customer sector in case 2, this decrease is 15.1%. A further comparison between cases 1 and 2 reveals that although the selected locations of switches in the two cases are essentially the same (except from the switch at branch 41), the number of AOSs is considerably higher in the base case.

TABLE III
OPTIMAL ALLOCATION OF SWITCHGEAR FOR THE PRESENTED CASES

Case	Type of SCDF	Type of LDC	Optimal solution
1	$SCDF_{com}^{old}$	$^{10}LDC_{com}^{tot}$	7b, 10a, 20a, NO1a, 25a, 28b, 30a, 39a, 41b, N02a
2	$SCDF_{com}^{old}$	$^{10}LDC_{com}^{tot}$	7b, 10b, 20b, NO1b, 25b, 28b, 30a, 39a, N02a
3	$SCDF_{com}^{old}$	$^{10}LDC_{com}^{el}$	7b, 10b, 20b, NO1b, 25b, 28a, 30b, 39a, N02a
4	$SCDF_{com}^{new}(1,:)$	$^{10}LDC_{com}^{tot}$	7b, 10a, 20a, NO1a, 25a, 28b, 30a, 39b, 41a, N02a
5	$SCDF_{com}^{new}(1,:)$	$^{10}LDC_{com}^{el}$	7b, 10a, 20a, NO1a, 25b, 28a, 30b, 39a, 41b, N02a

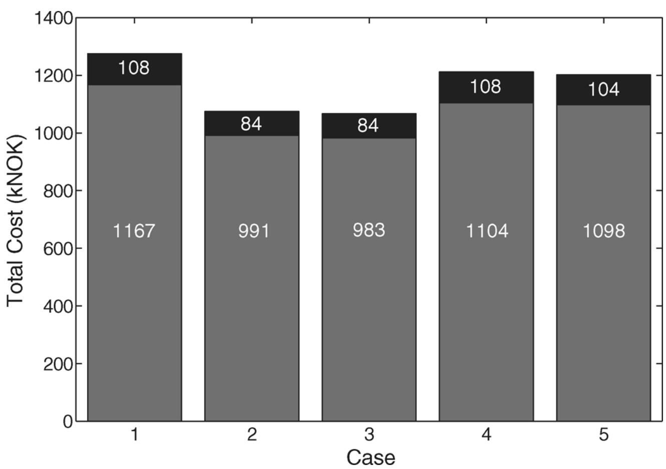

Fig. 7. ECOST (gray) and ICOST (black) for the presented cases ($1\ \mathrm{kNOK} = 1000\ \mathrm{NOK}$).

Marginal changes in ECOST and switch configurations were found when changing the LDC for the commercial customers from case 2 to case 3. The reduction in ECOST, shown in Fig. 7, is a result of the improvement in reconfiguration capability. We also note that the AOS on feeder F3 has changed its location from branch 30 to branch 28.

The optimal allocation and selection of switches is clearly affected by the choice of SCDF. As shown in Table III, the total number of selected switches and the number of AOSs in case 4 is similar to the base case. Taking the final step to case 5, where both the SCDF and LDC have been adjusted, we see that the ECOST decreases compared with case 4, again due to the increased reconfiguration capability. A similar pattern as found when going from case 2 to case 3 is seen from 4 to 5; AOSs are now located more centrally on feeders F3 and F4. By adjusting the SCDF and LDC, the decrease in ECOST from case 1 to case 5 is 5.9%, which is considerably less than the decrease found from case 1 to case 2.

Table IV presents the average annual outage time at some selected load points for the optimal configurations found in cases 1, 2, and 5. It is evident that most load points will experience a reliability improvement in terms of lower expected annual outage time, when going from nonadjusted data in case 2 to adjusted data in case 5.

TABLE IV
AVERAGE ANNUAL OUTAGE TIME FOR SOME SELECTED LOAD POINTS

Load Point	**Case 1** (hr/yr)	**Case 2** (hr/yr)	**Case 5** (hr/yr)
7	3.53	3.64	3.53
12	3.44	3.57	3.44
14	3.53	3.60	3.56
23	3.64	3.64	3.64
26	3.59	3.71	3.58

VI. CONCLUSION

The presented method makes it possible to analyze how the optimal allocation of switchgear in electric distribution systems is affected by decoupling the flexible end use from the system. In particular, the changes in customer interruption costs and load profile have been studied, and it is shown how they influence the optimal allocation of switchgear. This method is useful for configuration studies of distribution networks in areas where alternative energy carriers and sources replace electricity as providers of thermal energy services.

The amount of switchgear allocated in the presented test system was reduced when the flexible end use was decoupled. However, by using customer interruption costs and load duration curves adjusted according to the electricity specific end use, the reduction was not as evident as found when using aggregated data. The test study showed that the choice of SCDF has a more significant impact on the optimization problem than the choice of LDC. In less constrained networks, the impact of adjusting the LDC may be neglected.

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REFERENCES

[1] CIGRE TF 38.06.01, Methods to Consider Interruption Costs in Power System Analysis, CIGRE Publ. 191, 2001.
[2] V. Miranda, A. do Vale, and A. Cerveira, “Optimal emplacement of switching devices in radial distribution networks,” in *Proc. CIRED*, Liège, Belgium, 1983, vol. 13, pp. 1–5.
[3] F. Soudi and K. Tomsovic, “Optimized distribution protection using binary programming,” *IEEE Trans. Power Del.*, vol. 13, no. 1, pp. 218–224, Jan. 1998.
[4] R. Billinton and S. Jonnavithula, “Optimal switching device placement in radial distribution systems,” *IEEE Trans. Power Del.*, vol. 11, no. 3, pp. 1646–1651, Jul. 1996.
[5] P. Wang and R. Billinton, “Demand-side optimal selection of switching devices in radial distribution system planning,” *Proc. Inst. Elect. Eng., Gen., Transm. Distrib.*, vol. 145, no. 4, pp. 409–414, 1998.
[6] G. Levitin, G. Mazal-Tov, and D. Elmakis, “Optimal sectionalizer allocation in electric distribution systems by genetic algorithm,” *Elect. Power Syst. Res.*, vol. 31, no. 2, pp. 97–102, 1994.
[7] R. E. Brown, S. Gupta, R. D. Christie, and S. S. Venkata, “A genetic algorithm for reliable distribution system design,” in *Intelligent Systems Applications to Power Systems*. New York: IEEE, 1996, pp. 29–33.

[8] L. G. W. da Silva, R. A. F. Pereira, and J. R. S. Mantovani, "Allocation of protective devices in distribution circuits using nonlinear programming models and genetic algorithms," *Elect. Power Syst. Res.*, vol. 69, no. 1, pp. 77–84, 2003.

[9] G. Kjolle, A. T. Holen, K. Samdal, and G. Solum, "Adequate interruption cost assessment in a quality based regulation regime," presented at the IEEE Porto Power Tech Conf., Porto, Portugal, 2001.

[10] K. Samdal, G. Kjolle, O. Kvitastein, and B. Singh, Sluttbrukeres kostnader forbundet med avbrudd og spenningsforstyrrelser (in Norwegian) SINTEF Energy Res., 2003.

[11] E. Lakervi and E. J. Holmes*, Electricity Distribution Network Design*, ser. IEE Power Series. Stevenage, U.K.: Peregrinus, 1995, vol. 2.

[12] G. Kjolle and K. Sand, "RELRAD—An analytical approach for distribution system reliability assessment," *IEEE Trans. Power Del.*, vol. 7, no. 2, pp. 809–814, Apr. 1992.

[13] R. E. Brown and A. P. Hanson, "Impact of two-stage service restoration on distribution reliability," *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 624–629, Nov. 2001.

[14] JGAP—Java Genetic Algorithms Package. [Online]. Available: http://www.jgap.sf.net.

[15] D. E. Goldberg*, Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

[16] R. N. Allan, R. Billinton, I. Sjarief, L. Goel, and K. S. So, "A reliability test system for educational purposes—Basic distribution system data and results," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 813–820, Apr. 1991.

[17] R. Billinton and S. Jonnavithula, "A test system for teaching overall power system reliability assessment," *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1670–1676, Nov. 1996.

Arild Helseth received the M.Sc. degree in energy and environmental engineering from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 2003, where he is currently pursuing the Ph.D. degree in electrical power engineering.

Arne T. Holen (M'91) received the M.Sc. and Ph.D. degrees from the Norwegian Institute of Technology (NTH), Trondheim, Norway, in 1963 and 1968, respectively.

He is a Professor in the Department of Electrical Power Engineering, Norwegian University of Science and Technology (NTNU), Trondheim.

Dr. Holen is a member of the Power Engineering Society and of the Society of Reliability Engineers.