Loss Evaluation and Total Ownership Cost of Power Transformers—Part II: Application of Method and Numerical Results

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***Abstract*—The numerical results detailed in this paper reflect on a method proposed to accurately appraise the energy and the demand component of the cost of losses for evaluating the total ownership cost of power transformers. Specifically, the proposed method is evaluated on a small-scale real system, by incorporating realistic financial data and system characteristics through appropriate technoeconomic models as well as statistical evaluations. The calculated loss components of this paper are compared to the methodology detailed in IEEE C.57.120-1991.**

***Index Terms*—Demand component of losses, energy component of losses, risk assessment and forecasting, system cost parameters, total cost of losses.**

I. Introduction

A METHOD for evaluating the life-cycle losses of new power transformers is detailed in a companion paper [1]. Hence, the proposed method is numerically evaluated in this paper, offering a thorough real-case application. Toward completing this work, system characteristics and financial data (concerning capital and operating expenditure) are obtained from the Cyprus Power System (CYPS). This system constitutes an example where the transformers user (Electricity Authority of Cyprus) possesses its own generation and transmission facilities.

To address the impact of escalated fuel prices in life-cycle loss evaluations of power transformers, this paper has adopted a widely used approach in economics (Markov-regime switching models) [2], which allows escalation rates to switch between a mixture of constant rates, where the weight attributed to each constant term is purely determined by relevant historical data. The application of the method pertains to the calculation of projected fuel prices per the specific fuel used (or would be used) in the generation mix of the system under study. A numerical evaluation of the method and a benchmarking against the IEEE C.57.120-1991[3] method are also provided.

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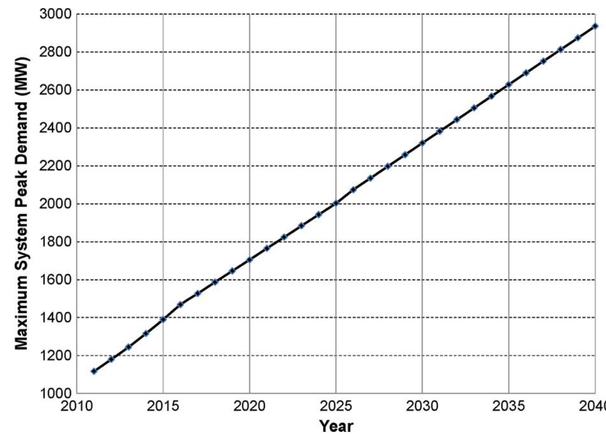

Fig. 1. Forecasted maximum system peak demand (MW).

II. Load and Energy Forecasts

Per the methodology detailed in the companion paper [1], it is necessary to obtain forecasts of the system's peak demand and energy generation over the transformer life cycle (e.g., 30 years). The CYPS relevant forecasts are utilized [4] in this work. In particular, Fig. 1 illustrates the CYPS's peak demand (MW) forecast for a 30-year horizon.

Fig. 2 illustrates the forecasted energy requirements from CYPS-planned facilities. In particular, these planned facilities (peaking generation additions) will mainly include CCGTs. It is worth noting that these generation additions would use Diesel LSFO until 2015. At 2016, it is expected to switch to liquid natural gas (LNG). This scenario has been incorporated in our analysis, as illustrated by Fig. 3 which illustrates the calculated fuel consumption (FuC) [1] by the planned peak generation units. The calculated fuel consumption (FuC) in MT is the converted MWh energy (UG) illustrated by Fig. 2, by following the methodology detailed in the companion paper [1]. This conversion assumes net calorific values (NCV) of 41 MJ/MT and 49 MJ/MT for Diesel LSFO and LNG fuels, respectively. It further assumes 27% efficiency (n_{ef}) for the machines burning diesel LSFO and 50% efficiency for the machines that will burn LNG [5], [6].

III. Forecasted Energy Prices

Predictions of any fuel-dependent energy prices over the life cycle of a power transformer should be carried out in loss evaluation endeavours. The methodology found in IEEE C57.120-

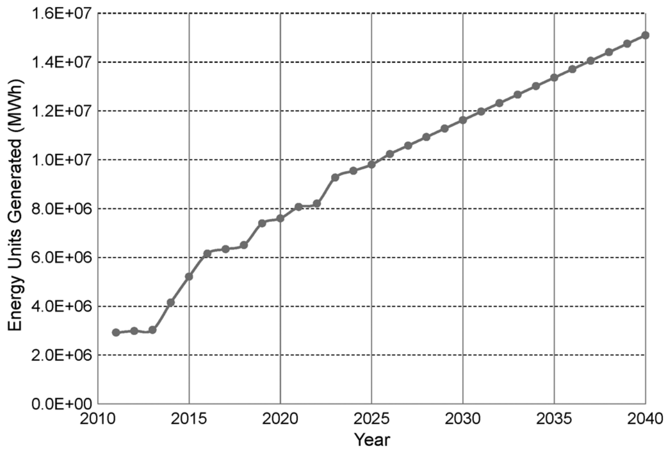

Fig. 2. Forecasted energy generation by peaking generation additions—UG (MWh).

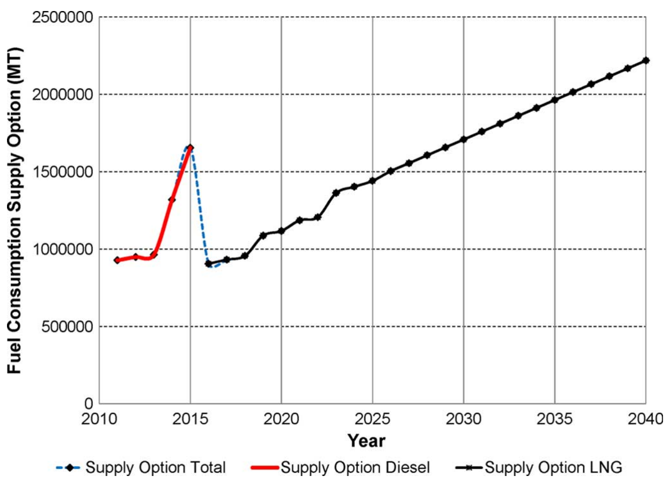

Fig. 3. Forecasted fuel consumption from "peaking generation additions" generating units (FuC).

1991 [3] models the changes in the underlying variable by a constant trend every year (1)

$$F_v = P(1+i)^N \tag{1}$$

where P is the present value of energy (fuel component), F_v is the future value of energy (fuel component), N is a future year, and i is a given escalation rate. In other words, changes in the underlying variable P from period to period are constant.

A. Brent Oil Price Forecasts

In this paper, projections of the cost of production attributable to the price of oil are based on projections of the price of Brent oil for the following 30 years. Prices of Brent oil (also known as London Brent or Brent Blend) are used for the period starting from January 1978 until March 2011 (399 monthly observations) in U.S.$/barrel. The data are transformed to Euros/barrel and then adjusted for inflation as illustrated in Fig. 4. It is evident from Fig. 4 that if a constant increase was assumed from year to year, after year 2000, the predicted value would almost always be underestimated. In this paper, the current practice (1)

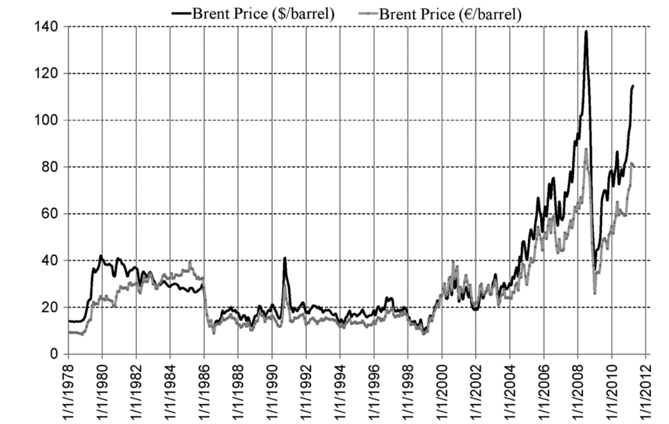

Fig. 4. Historical record of Brent oil price (U.S.$/barrel) adjusted for inflation.

is improved by adopting a two-step approach. First, the underlying variable is assumed to follow a geometric Brownian motion (GBM), where the (log of) changes of the underlying variable are not only assumed to be constant but also associated with a constant standard deviation.

Hence, the GBM approach introduces the effect of estimated volatility in future forecasts. Our model adds another layer of flexibility to the estimation of future prices, by allowing the underlying variable to switch between two GBM processes, where the amount of time spent in each process is determined by a hidden, homogeneous Markov chain [7].

Hence, two models are used to produce price forecasts: 1) a single GBM and 2) a regime-switching model of two geometric Brownian motions (RSGBM2). The GBM assumes that log changes in the price of oil are distributed normally. The RSGBM2 is a generalization of the GBM model as it uses a hidden Markov chain to allow log changes in price to alternate between two GBMs and, hence, accommodating non-normality characteristics in log-changes in price. Regime switching models were introduced in [2], improved in [8] and [9], and have been widely used in econometrics for more than 50 years to model the nonstationary time series (i.e., when the mean and/or variance of a series is not constant). Estimation is performed using maximum-likelihood estimation, and the best model is chosen using goodness-of-fit tests, such as the likelihood ratio test, the Akaike, and the Schwarz–Bayes information criterion.

More specifically, on any given month t, Brent petroleum prices (Brent_t) are denoted by S_t, and their logarithmic changes by $Y_t = \log(S_t/S_{t-1})$. Y_t is assumed to follow a regime switching model with two states; $\rho_t = j$ or k. A hidden Markov chain with a constant transition probability matrix P in (2), determines where the process lies on a month t

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{2}$$

where $p_{jk} = \Pr[\rho_{t+1} = k | \rho_t = j]$ represents the probability that the process is in regime j on month t and it will switch to regime k on month $t+1$ ($j = 1, 2$ and $k = 1, 2$). Each state represents a GBM, which implies that log changes in prices follow a normal distribution. Therefore, the general form of the RSGBM2 model is $Y_t|\rho_t \sim N(\mu_\rho, \sigma_\rho^2)$ with parameters μ_1, σ_1, μ_2, σ_2, p_{11}, and p_{22}. In the case of a single GBM, only

TABLE I
GOODNESS OF FIT BETWEEN GMB AND RSGBM2

	Akaike	Schwartz Bayes	LL Test
GBM	342.30	338.32	344.30
RS-GBM	388.81	376.85	394.81
LR Test	-	-	101.02
***p*-value**	-	-	0.0000
Best Model:	RSGBM2	RSGBM2	RSGBM2
LL: Log-likelihood value; LR Test: Likelihood Ratio Test			

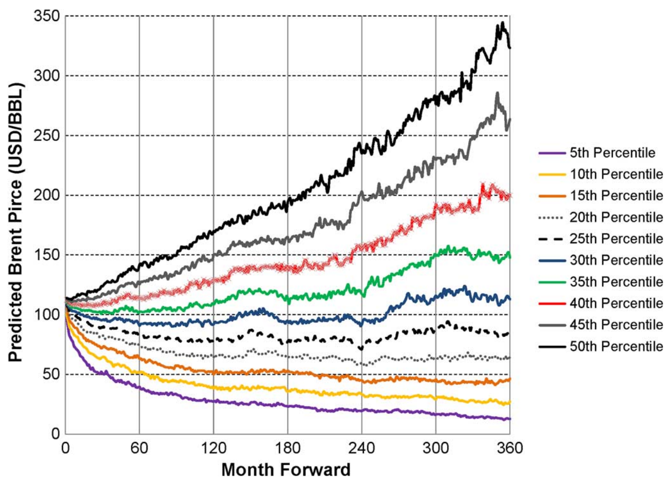

Fig. 5. The 5th–50th percentiles of nominal predicted Brent oil price $\mathrm{FFP}_{\mathrm{Brent},t}$.

two parameters are needed (μ, σ). Both models are fitted using maximum-likelihood estimation by Hamilton and Susmel [10]. The three goodness-of-fit tests illustrated by Table I show strong evidence for the use of RSGBM2 in modeling historical prices of Brent petroleum.

Consequently, forecasts $(\mathrm{FFP}_{\mathrm{Brent},t})$ for a 360-month horizon are produced using the estimated parameters of the RSGBM2 model:$\mu_1 = 0.86\%$, $\sigma_1 = 11.91\%$, $\mu_2 = -0.26\%$, $\sigma_2 = 3.25\%$, $p_{11} = 96.67\%$, and $p_{22} = 92.30\%$. These parameters show that log changes in prices are more persistent in regime 1 since $p_{11} > p_{22}$, where there exists an overall monthly average increase in log prices of 0.86% per month and a volatility of 11.91%. A number of forecasted scenarios are generated for the 360 months ahead of 2011, assuming that all factors affecting prices in the estimation period will continue to hold in the forecasting period. Fig. 5 illustrates the 5th through 50th percentile of all forecasts $(\mathrm{FFP}_{\mathrm{Brent},t})$. The prices that are shown do not include inflation—2% is assumed.

For example, the 40th percentile $\mathrm{FFP}_{\mathrm{Brent},t}$ shows that 40% of all future forecasts are less than or equal to the values displayed.

B. Application of Methodology for CYPS Particulars

As detailed in Section II, the "peaking generation additions" for the CYPS would use Diesel LSFO until 2015. At 2016, it is expected to switch to liquid natural gas (LNG). However, given the long history of data for Brent oil prices and several episodes of changes in world supply and demand over the past 30 years,

TABLE II
REGRESSION ANALYSIS (1995–2011)

	Diesel	LNG
R_squared	0.9807	0.4162
Intercept (κ_1, κ_2)	-0.0305	2.5728
Brent Coefficient (μ_1, μ_2)	1.1668	0.3112

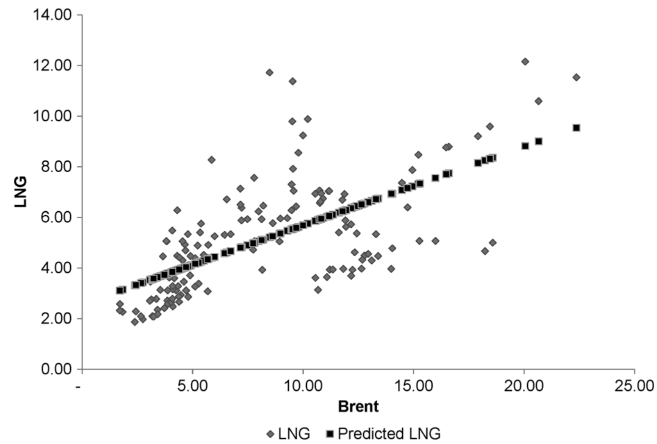

Fig. 6. Linear regression between Brent oil and LNG prices from 1997 to 2011.

the forecasted prices of Brent oil are used as a benchmark to estimate future prices of diesel LSFO and LNG. The necessary assumptions to be made are that the relationship that exists between Brent oil and diesel LSFO and LNG will continue to hold in the period ahead. To estimate the price of the two fuels used in the CYPS, historical prices (from 1995–2011) of diesel LSFO and LNG were used [11]. All prices were quoted/transformed in U.S.$/GJ. Since the used models rely on the statistical properties of historical data obtained from [11], linear regressions of the historical price of diesel and LNG on the price of Brent oil are obtained per

$$\mathrm{FFP}_{\mathrm{Diesel}_t} = \kappa_1 + \mu_1 \times \mathrm{FFP}_{\mathrm{Brent}_t} + \varepsilon_{diesek,t}$$
$$\mathrm{FFP}_{\mathrm{LNG}_t} = \kappa_2 + \mu_2 \times \mathrm{FFP}_{\mathrm{Brent}_t} + \varepsilon_{\mathrm{LNG},t}. \quad (3)$$

The results of the regressions are given in Table II. On a similar note, Fig. 6 illustrates the results of the linear regression between the Brent oil and LNG prices. In the interest of space, only the relation between Brent oil and LNG is presented since the relation between Brent oil and diesel behaves similarly. In particular, κ_1 and κ_2 are the intercept coefficients, μ_1 and μ_2 are the coefficients for Brent oil prices, and $\varepsilon_{\mathrm{diesek},t}$ and $\varepsilon_{\mathrm{LNG},t}$ are the zero-mean error terms for the regressions of diesel and LNG, respectively.

In our analysis, it is assumed that the relation between the diesel LSFO or LNG to Brent oil will be similar whether the underlying units are in U.S.$/GJ or Euros/GJ. Therefore, the coefficients obtained from (3) are expected to hold when either Diesel (LSFO) or LNG are regressed on Brent oil prices. The GJ units can be converted either to megawatt-hours of electricity or to corresponding fuel consumption (MT) by using appropriate calorific values and machines' efficiencies as explained in the companion paper [1].

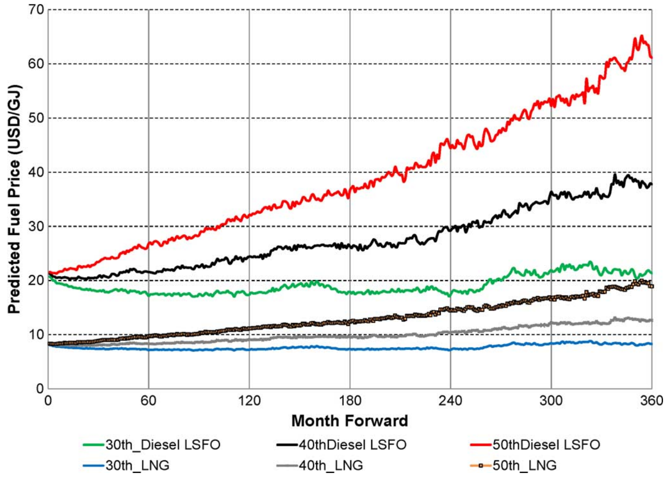

Fig. 7. The 30th, 40th, and 50th percentiles of nominal forecasted diesel LSFO ($\mathrm{FFP}_{\mathrm{Diesel}}$) and LNG prices ($\mathrm{FFP}_{\mathrm{LNG}}$).

C. Diesel and LNG Price Forecasts

The aforementioned analysis shows that diesel (LSFO) prices behave similar to those of Brent oil. The coefficient of Brent oil is 1.1668 (p value < 0.01) but the intercept is not statistically different than zero (p value <0.91). The conclusion is that for every unit increase in the price of Brent oil, diesel prices increase by 1.1668 (4). This coefficient is intuitively correct since diesel is a refined version of Brent oil; hence, any coefficient over 1.0 is justified

$$\mathrm{FFP}_{\mathrm{Diesel}_t} = -0.0305 + 1.168 \times \mathrm{FFP}_{\mathrm{Brent}_t}. \quad (4)$$

Furthermore, LNG prices are also positively related to those of Brent oil. The positive relationship is shown in Fig. 6 and the regression results in Table II. The coefficient of Brent oil is 0.3112 (p value < 0.01) and the intercept is 2.5728 (p value < 0.01). Hence, 41.62% of the variation in LNG prices is explained by Brent oil prices. The conclusion is that for every unit increase in the price of Brent oil, LNG prices increase by 0.3112 plus an additional constant increase of 2.5728 irrespective of the price of Brent oil

$$\mathrm{FFP}_{\mathrm{LNG}_t} = 2.5728 + 0.3112 \times \mathrm{FFP}_{\mathrm{Brent}_t}. \quad (5)$$

Therefore, for each forecasting scenario of the Brent oil price generated in Fig. 5, a corresponding forecast for diesel LSFO ($\mathrm{FFP}_{\mathrm{Diesel},t}$) and LNG ($\mathrm{FFP}_{\mathrm{LNG},t}$) can be calculated by utilizing (4) and (5). Fig. 7 illustrates the calculated prices for Diesel (LSFO) and LNG for the 30th, 40th, and 50th percentiles for a 360-month forward horizon.

IV. Weighted Multiplying Factors

The methodology detailed in the companion paper [1] is adopted to weigh an operating expenditure to its corresponding demand and energy component of the cost of losses. Therefore, the "weighted multiplying factors" associated with operation costs and repair and maintenance costs are reflected in Table III.

TABLE III
Allocation of Weight Factors

Cost Item	Demand Component (%)	
Operation	$cc_o = \dfrac{1}{1+0.38\times LF}$	84 % (*LF:0.518*)
Repairs & Maintenance	$cc_{rm} = \dfrac{1}{1+0.876\times LF}$	69 % (*LF:0.518*)
	Energy Component (%)	
Operation	$ec_o = 1 - cc_o$	16% (*LF:0.518*)
Repairs & Maintenance	$ec_{rm} = 1 - cc_{rm}$	31% (*LF:0.518*)

TABLE IV
Example of Fuel and Energy Data

Year	Sent Out Energy Units (MWh)	Fuel Consumption for Sent Out Units (MT)	Sum of machines running hours for zero load losses (hours)	Zero Load Fuel Consumption (MT)
2002	3535	1194	32.9	29.3
2003	13848	4485	129.3	114.8
2004	23371	7800	218.2	193.7
2005	38846	14846	393.8	349.6
2006	17495	6577	250.2	222.2
2007	40648	13532	286.4	254.3
2008	26972	10401	214.3	190.3
2009	29647	11178	214.9	190.8
2010	9334	3481	87.1	77.4
	E: 22633		*F*: 203	

For CYPS, $\varepsilon \times \tau = 0.38$ for operation costs and $\varepsilon \times \tau = 0.876$ for repairs and maintenance costs, per the load factors (LF) tabulated.

A. Allocation of Weighted Factors to Fuel Costs

The calculation example that follows pertains to generating units consuming diesel LSFO [4]. Both recorded and estimated data tabulated in Table IV relate: 1) to "sent out" energy units (MWh) from a generating plant and their corresponding fuel consumption (MT) and 2) to the sum of machines' running hours to provide the zero load losses and their corresponding fuel consumption (MT).

Fig. 8 illustrates the plotted recorded data for "Sent Out Energy" (MWh) and the corresponding fuel (diesel LSFO) consumption (MT) for each year per Table IV. A straight line is fitted between the plotted points using the method of least squares. The slope of this line results in the incremental fuel rate for the generating plant's machines burning diesel LSFO fuel. For this particular example, the incremental fuel rate INFR is 0.3624 MT/MWh.

Furthermore, Fig. 9 illustrates the plotted recorded data for the machines' running hours to provide the zero load losses and the corresponding zero-load fuel consumption. A straight line is fitted between the points and the slope of this line yields the zero-load fuel rate (ZRFL). The ZRFL for the machines burning diesel LSFO fuel is calculated at 0.8879 MT/h (Fig. 9). By evaluating (6) as detailed in the companion paper [1], the calculated

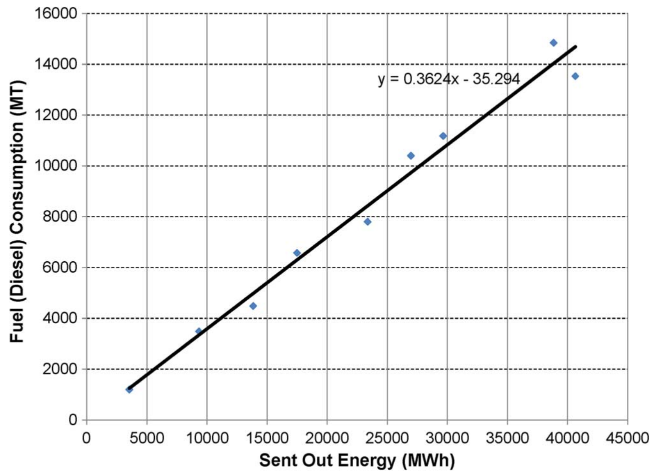

Fig. 8. Incremental fuel-rate calculation for machines burning diesel LSFO.

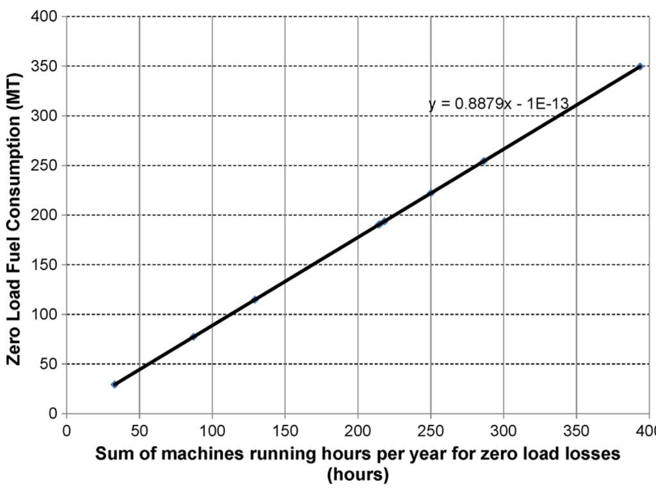

Fig. 9. ZRFL calculation for machines burning diesel LSFO.

% demand and energy component weight factors for the machines burning diesel LSFO are shown in (6) at the bottom of the page.

V. Demand Component of the Cost of Losses

A. Demand Component Attributed to Operating Costs

Table V tabulates the financial parameters necessary to determine the demand component of the cost of losses attributed

TABLE V
REPAIRS AND MAINTENANCE (GENERATION) COSTS, INFLATION, AND SYSTEM DEMAND

Year	Cost of Repairs and Maintenance (€)	Inflation Rate Per Annum (%)	System Peak Demand (MW)
2005	5,305,000	2.60	855
2006	4,579,000	2.50	903
2007	3,926,000	2.40	1035
2008	4,696,000	4.70	1003
2009	10,044,000	0.30	1098
2010	7,602,000	-	1118

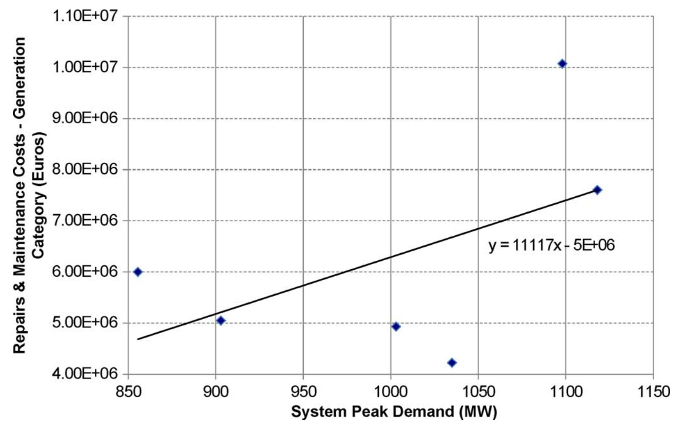

Fig. 10. Incremental cost Euros/MW—repairs and maintenance—generation.

to the repair and maintenance costs that are classified under the generation category of the CYPS.

Using these data, the deinflated costs are plotted against the system's maximum demand (MW) of each corresponding year as illustrated in Fig. 10.

Once the incremental cost value is determined (i.e., the slope of the graph (a_{g_RM})), the annual demand component of the cost of losses attributed to the repairs and maintenance costs (D_{gop_RM}) for the generation category is evaluated by

$$\begin{aligned} D_{gop\_RM} &= SFcc_g \times cc_{rm} \times a_{g\_RM} \\ D_{gop\_RM} &= \left(\frac{2}{3}\times 1.1\right)\times 0.6933 \times 11.117 \\ &= 5.652 \mathrm{Euros/kW} \end{aligned} \tag{7}$$

where cc_{rm} is the percent weighted multiplying factor for the demand component of the cost of losses assigned for repairs and maintenance costs (Table III). $SFcc_g$ is the size factor for the generation's category-related costs, assuming a reserve margin (RM) of 10% (0.1 p.u.) [1].

$$\begin{aligned} \mathrm{DCF_{diesel}} &= \frac{F \times \mathrm{ZRFL}}{E \times \mathrm{INFR} + F \times \mathrm{ZRFL}} \\ &= \frac{203h \times 0.8879(\mathrm{MT/h})}{22633(\mathrm{MWh}) \times 0.3624(\mathrm{MT/MWh}) + 203\mathrm{h} \times 0.8879(\mathrm{MT/h})} \\ &= 0.02165 \\ \mathrm{ECF_{diesel}} &= 1 - \mathrm{DCF_{diesel}} = 0.978 \end{aligned} \tag{6}$$

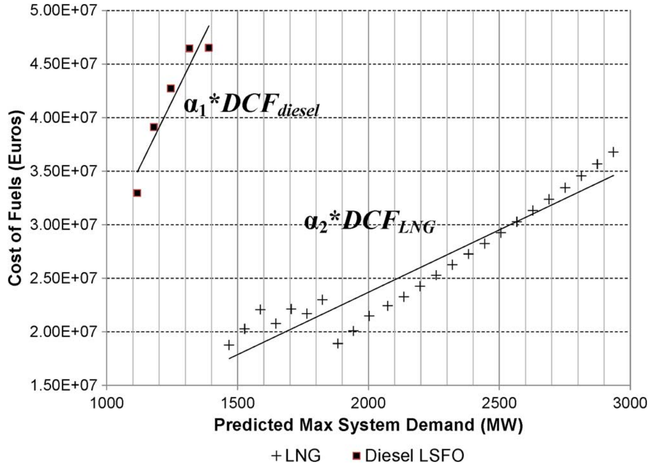

Fig. 11. Demand component for fuel usage and cost.

B. Demand Component Attributed to Fuel Costs

In this evaluation, the 40th percentile prediction has been considered as the benchmark scenario for the corresponding prices of diesel LSFO and LNG fuels. These are the two fuels that will be used in the generation mix of the CYPS in a 30-year horizon. Consequently, Fig. 11 illustrates the application of the methodology [1] to obtain a future cost trend attributed to fuel usage and prices with respect to the forecasted generation demand. The y-axis cost (FC) is determined by multiplying the total predicted fuel consumption (FuC) (Fig. 3) with the 40th percentile scenario of the forecasted fuel prices $(\mathrm{FFP}_{\mathrm{Diesel}}, \mathrm{FFP}_{\mathrm{LNG}})$ per Fig. 7 and the demand component factor for fuels $\mathrm{DCF}_{\mathrm{fuel}}$ [1]. Therefore, the annual demand component (α_F) for the cost of fuels is the weighted average (8) of the two slopes illustrated by Fig. 11

$$\begin{aligned} D_F &= \frac{\mathrm{DCF}_{\mathrm{diesel}} \times n_1 \times \alpha_1 + \mathrm{DCF}_{\mathrm{LNG}} \times n_2 \times \alpha_2}{n_1 + n_2} \\ D_F &= \frac{0.2165 \times 5 \times 1187.74 + 0.02165 \times 25 \times 555.55}{25+5} \\ &= 17.292 \text{ Euros/kW} \end{aligned} \tag{8}$$

where n_1 is the number of years that diesel LSFO will be in use and n_2 is the number of years that LNG will be in use. For this example, a weight factor $(\mathrm{DCF}_{\mathrm{diesel}} = \mathrm{DCF}_{\mathrm{LNG}})$ of 2.16% per (6) has been used. Consequently, by evaluating(8), the demand component of the cost of losses attributed to fuels (D_F) is calculated at 17.292 Euros/kW.

C. Aggregate Demand Component of Losses

The annuitized cost per kilowatt of new peaking generation units (ACPG) is evaluated by assuming a real discount rate (d) of 10%, annuitized over 30 years, an RM of 10% and C_{PG} of 900 Euros/kW. The annuitized cost per kilowatt of planned transmission system installations (ACTS) is found by assuming a real discount rate of (d) 10%, annuitized over 30 years and C_{TS} 164.21 Euros/kW [1]. Consequently, Table VI tabulates the calculated demand component of losses (D) attributed to the capital and operating costs, per the two categories considered. It is noted that all calculated values are based on the methodology described in the companion paper [1] by taking into consideration the appropriate category, size, and weighted allocation factors.

TABLE VI
DEMAND COMPONENT OF THE COST OF LOSSES—EAC SYSTEM

Annuitized Demand Costs per kW	***D_{g_item}***	***D_{t_item}***
ACPG (New Peak Generation Installation)	73.294	N/A
ACTS (Transmission System Installations)	N/A	11.88
Fuel (D_F)	17.292	N/A
Operation	0.0001	31.029
Repairs and Maintenance	5.6520	1.159
Green House Emissions	0.01866	N/A
Sum	D_{g_peak}: 96.248 €/kW	D_{t_peak}: 44.068 €/kW
$D_{peak} = D_{g\ peak} + D_{t\ peak}$	140.316 €/kW	

TABLE VII
OPERATION (TRANSMISSION) COSTS, INFLATION, AND UNITS GENERATED

Year	Operation Costs - Transmission (€)	Inflation Rate Per Annum (%)	Units Generated (MWh)
2005	3,952,000	2.60	4472585
2006	6,935,000	2.50	4735864
2007	9,575,000	2.40	5037688
2008	16,176,000	4.70	5322452
2009	19,161,000	0.30	5565134
2010	25,029,080	-	5950450

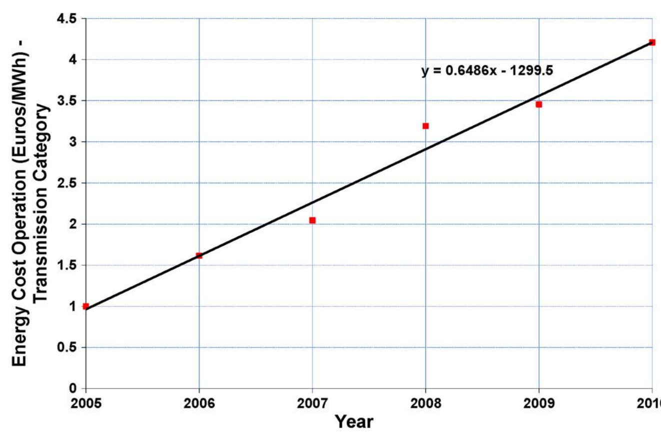

Fig. 12. Increment energy component—operation costs—transmission (Euros/MWh).

VI. ENERGY COMPONENT OF THE COST OF LOSSES

A. Energy Component Attributed to Operating Costs

Table VII presents the historical costs for operation as well as further particulars allocated to the transmission category of the CYPS.

The ratio (Euros/MWh) of the deinflated costs to the total energy generated per year is plotted against each corresponding year as illustrated by Fig. 12.

A straight line is then fitted on the plotted points using the method of least squares following the methodology described in the companion paper [1]. Consequently, the energy component of operation costs allocated under the transmission category is evaluated by

$$\begin{aligned} E_{t_{\mathrm{op}}\_\mathrm{op}} &= (\lambda_{t\_\mathrm{op}} \times Y(\mathrm{Latest\_Year}) + \delta_{t\_\mathrm{op}}) \times ec_{\mathrm{op}} \\ E_{t_{\mathrm{op}}\_\mathrm{op}} &= (0.6486 \times 2010 - 1299.5) \times 0.16 = 067 \text{ Euros/MWh} \end{aligned} \tag{9}$$

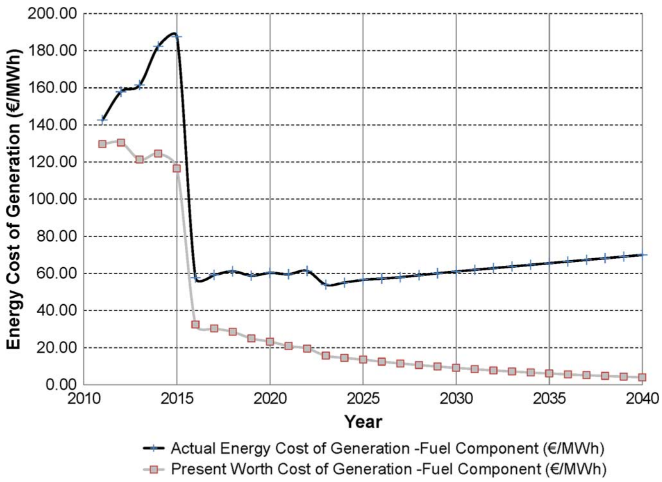

Fig. 13. Annuitized energy component of losses attributed to fuel costs.

where $ec_{\rm op}$ is the percent weighted multiplying factor for the energy component of the cost of losses assigned for operation costs (Table III).

B. Energy Component Attributed to Fuel Costs

This example also incorporates the 40th percentile prediction for diesel LSFO and LNG pricing $(\mathrm{FFP}_{\mathrm{Diesel}}, \mathrm{FFP}_{\mathrm{LNG}})$ per Fig. 7. It further uses an energy component weight factor for fuels $(\mathrm{ECF}_{\mathrm{Diesel}} = \mathrm{ECF}_{\mathrm{LNG}})$ of 97.8% for planned generation [1] and a real discount rate (d) of 10%. Fig. 13 illustrates the application of the methodology on the energy cost (fuel component) of planned generation where LNG is expected to replace diesel LSFO fuel in 2016, as illustrated in Figs. 2 and 3. The annuitized energy component of losses attributed to forecasted fuel prices (AE_F) is calculated at 102.35 Euros/MWh by evaluating >

$$\mathrm{AE}_F = \left[\sum_{j=1}^{4} \frac{\mathrm{EFC}_{\mathrm{Diesel}} \times \mathrm{FC}_j}{\mathrm{UG}_{\mathrm{Diesel}_j}} \times pw_j + \sum_{j=5}^{30} \frac{\mathrm{EFC}_{\mathrm{LNGe}} \times \mathrm{FC}_j}{\mathrm{UG}_{\mathrm{LNG}_j}} \times pw_j\right] \times crf_n. \quad (10)$$

\>

C. Aggregate Energy Component of Losses

Table VIII tabulates the calculated annuitized energy component of losses attributed to all relevant operating costs classified under generation and transmission categories per the specific system's accounts. It is noted that all calculated values are based on the methodology described in the companion paper [1] by taking the appropriate category and weighted allocation factors into consideration. The Green House Emissions costs allocated to the energy component of the cost of losses follow the same calculation principles described for the fuel costs.

VII. Benchmarking of the Proposed Method

To facilitate a valid comparison to the IEEE standard method [3], the calculated $D_{\rm peak}$ is benchmarked against the "Levelized Total System Investment Cost" (LIC). To evaluate the LIC value per [3], a fixed charge rate for generation level (FCRG) of 12% and a fixed charge rate for transmission level (FCRS) [3] of 14% have been assumed, as shown in Table IX. The difference between the two is because $D_{\rm peak}$ includes the fixed portion of the system's operating expenditure.

Furthermore, the calculated $E_{\rm peak}$ is benchmarked against the "Levelized Energy Cost for Load Loss Evaluations" (LECL) [3]. Table X tabulates the corresponding comparison.

The discrepancy is attributed to the fact that [3] proposes the use of constant escalation rates (on a yearly basis) to determine the future energy values over the life cycle of a transformer per (2). The theoretical background of these escalation rates is not defined in the standard's methodology. For evaluating LECL per the IEEE C57.120-1991 method, a constant escalation energy rate of 3% has been assumed until 2016 and a constant escalation energy rate of 1% has been assumed for the 2016–2040 period. The two different escalation rates reflect on the planned fuel usage by CYPS (diesel up to 2016 and LNG from 2016 to 2040). However, the proposed approach offers a globalized statistically based tool for estimating future energy rates (by using the derived fuel price forecasts). The statistically based escalation rates are specifically derived for each fuel used (or would be used) in the generation mix of the system under study.

TABLE VIII
ENERGY COMPONENT OF THE COST OF LOSSES

Annuitized Energy Costs per MWh	$E_{g\ item\ n}$	$E_{t\ item\ n}$
AE_F	102.35	N/A
Operation	1.065	0.670
Repairs and Maintenance	0.420	0.087
Green House Emissions	0.914	N/A
Sum	E_{g_peak}: 104.749 €/MWh	E_{t_peak}: 0.757 €/MWh
$E_{peak} = E_{g\,peak} + E_{t\,peak}$	105.51 €/MWh	

TABLE IX
BENCHMARKING OF THE DEMAND COMPONENT CALCULATION

Evaluation of IEEE C57.120-1991 Method on CY.P.S Characteristics	Evaluation of Proposed Method on CY.P.S Characteristics
$LIC = GIC \times FCRG + SIC \times FCRS$ * $LIC = 900 \times 0.12 + 164.21 \times 0.14 = 130.99$ €/kW * The acronyms used are as defined in [3]	D_{peak}= 140.316 €/kW ** ** As calculated in Table VI

TABLE X
BENCHMARKING OF THE ENERGY COMPONENT CALCULATION METHOD

Evaluation of IEEE C57.120-1991 Method on CY.P.S Characteristics	Evaluation of Proposed Method on CY.P.S System Characteristics
$LECL = SPWECY \times crf_n$ * $LECL = 1029.819 \times 0.106 = 109.24$ €/MWh *The acronyms used are as defined in [3]	E_{peak}= 105.51 €/MWh ** ** As calculated in Table VIII

VIII. Sensitivity Analysis

It is well understood that some form of uncertainty exists with future energy-related price forecasts; uncertainty that increases with longer time horizons. The latter reflected the need to generate and assess a number of cost evaluation scenarios utilizing

TABLE XI
SENSITIVITY ANALYSIS FOR DIFFERENT FUEL PRICE FORECASTS

Fuel Price Percentile Prediction	30^{th}	40^{th}	50th
D_{peak} (€/kW)	124.987	140.316	151.597
E_{peak} (€/kWh)	0.0874	0.1055	0.1265
Deviation from benchmark scenario (D_{peak})	-10.91 %	-	8.05%
Deviation from benchmark scenario (E_{peak})	-17.16 %	-	19.90 %

TABLE XII
DATA FOR EVALUATING TOC OF POWER TRANSFORMERS

Load Factor (Transmission System 2010)	0.518
Calculated Loss Load Factor Equation (E.A.C)	$LLF = 0.1 \cdot LF + 0.9LF^2$
Loss Load Factor –LLF (2010)	0.293
Peak responsibility factor for Step Down Substation Transformer (PRFS)	0.81
Availability Factor (AF)	0.95
Cooling operation per year (FOW)	0.30
Real Discount Rate	10%
Future Inflation Rate	2%
Levelized Annual Peak Load of Transformer as per its life-cycle, for Demand Component (*PQD*)	0.4081
Levelized Annual Peak Load of Transformer as per its life-cycle, for Energy Component (*PQE*)	0.4564
D_{PEAK}	140.316 €/kW
E_{PEAK}	105.51 €/MWh

different fuel pricing forecasting scenarios. Table XI tabulates the sensitivity analysis of incorporating the 30th, 40th (benchmark scenario), and 50th percentile of fuel predictions, on the demand and energy components calculations for cost of loss. It specifically shows that when comparing the % difference of D_{peak} and E_{peak} components by assessing the 40th percentile and the 30th percentile predictions, the % difference is more evident in E_{peak} (-17.16%). This indicates that energy component E_{peak} calculation is more dependent on future forecasting prices rather than demand component D_{peak} $(-10.91\ \%)$ and, therefore, should be interpreted with care.

IX. TOTAL OWNERSHIP COST OF POWER TRANSFORMERS

A numerical example is provided in this section for total ownership cost (TOC) by evaluating (28) found in the companion paper [1]. Table XII tabulates the numerical factors which are utilized to evaluate the TCL of power transformers. The evaluation assumes that $D_{\text{PEAK}} = D_{\text{BASE}}$ and $E_{\text{PEAK}} = E_{\text{BASE}}$ (i.e., base and peak costs are used as if they were the same).

The evaluated TOC equation per the CYPS specifics, tabulated in Table XII, is provided by

$$\text{TOC} = P.P + 1018.46 \times \text{NLL} + 71.75 \times LL + 417.62 \times \text{AUX} \tag{11}$$

where NLL are the no-load losses, LL accounts for the load losses, and AUX are the auxiliary losses of the transformer. It is noted that the loss evaluation factors of (11) should be updated on a case-by-case basis. This is achieved by appropriately updating the data tabulated in Table XII.

The dominant elements in the process of evaluating the loss factors of (11) are the demand $(D_{\text{PEAK}} - \text{Euros/kW})$ and the energy component $(E_{\text{PEAK}} - \text{Euros/kWh})$ of losses. This is because these elements are heavily dependent on the relevant capital and operating expenditures of the utility which may vary substantially. Fig. 14 shows the subdivision of all costs for the two components, per the results tabulated in Tables VI and VIII, respectively.

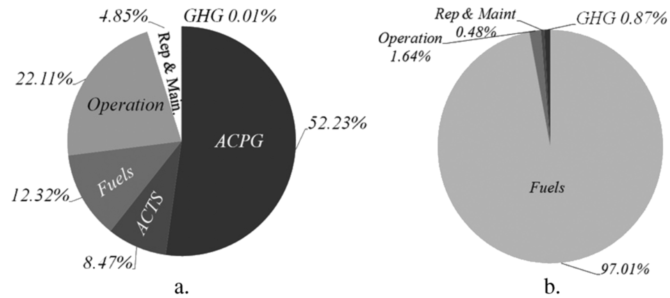

Fig. 14. Percent subdivision of costs establishing demand and energy components. (a) Demand component D_{PEAK}. (b) Energy component E_{PEAK}.

TABLE XIII
SENSITIVITY ANALYSIS FOR LOSS FACTORS

	Assumed Variation	NLL Loss Factor % Change	LL Loss Factor % Change	AUX Loss Factor % Change
LLF	0.3 →0.7	-	51.00 %	-
PRFS	0.5 →1.0	-	21.96 %	-
AF	0.5 →0.95	43.40 %	-	-
FOW	0.2 →0.6	-	-	53.20 %
PQD	0.4 →0.9	-	46.7 %	-
PQE	0.4 →0.9	-	70.22 %	-

Table XIII tabulates the influence of other factors in evaluating the loss factors of (11). For example, if the PRFS factor changes from 0.5 to 1 p.u. then the LL loss factor would increase by $+21.96\%$ while the NLL and AUX loss factors would remain unchanged.

On a final note, [12] tabulates a comparison of loss evaluation figures of several countries. The two key elements acknowledged in [12] that impact the variation of the published loss figures are: 1) different economic conditions and 2) credibility/method of calculation. It should be therefore kept in mind that because the loss factors are of eminent influence in the design/manufacturing and purchasing processes, these should be calculated accordingly and the method of calculation should be disclosed. Transparency in these endeavours could lead to win-win scenarios for the utilities and manufacturers.

X. CONCLUSION

The ultimate purpose of this work is to define a holistic-management approach for utilities to assess the total cost of ownership of power transformers. To achieve this, the elements that should be engaged in the process are: 1) the load characteristics of the system under study in terms of defining the load factor, loss load factor, peak responsibility factor, and coincidence factor; 2) an appropriate discount rate based on the overall financial objectives of the utility should the levelized annual cost method be used; 3) relevant capital and operating expenditures of the utility since they represent the use of human and material resources; 4) the calculation of allocation factors to cost items (e.g., cost of fuels) to weigh each financial item to its capacity and energy component; 5) future system expansion in term of forecasts, appropriate usage of future load, energy demands, and fuel consumptions; and 6) predictions of the relevant fuel prices over the life cycle of the plant under study.

The advancements offered by this paper allow a user who possesses its own generation and transmission facilities to more thoroughly approximate and understand the loss evaluation method based on real facts and its long-term objectives.

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