Reduction Of Power Losses in Electrical Power Systems Using Nonlinear Regression Techniques

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ABSTRACT

Operators of electrical power systems (EPS) are always faced with the most important problem, how to minimize the transmission and distribution additional power losses. Reduction of power losses and cost increases the efficiency of the power system and provides a significant reduction in energy consumption. This paper proposes a way to achieve this goal. In order to minimize the operational cost it is necessary to maintain EPS close to optimal mode. A mathematical model as optimization problem is developed for minimizing additional power losses and operational costs incurred due to the absence of the optimal correction in EPS. The model determines the relation between additional losses/costs and the control parameters of online tap changer transformers (OLTC). The prediction of the relation is established by means of statistical nonlinear regression models. The regression technique requires statistical data which has been obtained by performing power flow for the EPS with numerous configurations of OLTCs and transformation ratios. The software used for power flow is NETDRAW program. The developed model is applied to a test network. The results show the effectiveness of the model in substantial savings in power and cost as well. The research work would be very useful for supporting the procedures in central control center and energy management system in order to let the EPS working in optimal operation.

Key Words: Power losses, Optimization, Nonlinear regression, Power Systems.

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تخفيض مفاقيد الاستطاعة في منظومات القدرة الكهربائية باستخدام تقانة الارتباط اللاخطي

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الملخص

يواجه المشغل في مركز التنسيق مسألة بالغة الأهمية تتعلق بكيفية تخفيض مفاقيد الاستطاعة في منظومة القدرة الكهربائية. إذ إنّ هذا التخفيض من شأنه رفع مردود المنظومة، وترشيد استهلاك الطاقة الكهربائية. اقترح البحث طريقة لتحقيق هذا الهدف مما يقرب المنظومة من العمل وفق نمط التشغيل الأمثل. يقدم البحث نموذجا رياضيا يمثل تأثير محددات التحكم للمحولات متغيرة المآخذ تحت الحمل OLTC في مفاقيد النظام ومن ثمّ في كلفتها. تُستخدم تقانة تحليل الارتباط غير الخطي للتنبؤ بتلك العلاقة. تقتضي هذه التقانة تحضير معلومات إحصائية اختبارية تم تأمينها من خلال إجراء جريان حمولة للمنظومة عدداً من المرات، ولنسب تحويل متعددة للمحولات باستخدام النظام البرامجي NETDRAW. طُبّقت الخوارزمية المطورة على أساس النموذج الرياضي المنجز باستخدام شبكة نموذجية. وبيّنت النتائج الحاسوبية فعالية الطريقة المنجزة في تحقيق وفر بنسبة ملحوظة في المفاقيد والكلفة.

تبرز أهمية البحث في إمكانية استخدام نتائجه في تعزيز إجراءات إدارة الطاقة في مركز التحكم والتنسيق لمنظومة القدرة الكهربائية؛ بهدف الاقتراب –ما أمكن– من نمط التشغيل الأمثل.

الكلمات المفتاحية: مفاقيد الاستطاعة، منظومات القدرة، تقانة الارتباط اللاخطي.

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1. INTRODUCTION

The main function of an EPS is to supply the customers with reliable electrical energy with high quality and minimum cost [1]. Today’s EPSs strive to meet three requirements: very high reliability, low cost [2], and, increasingly since the 1970s, reduced environmental impacts [3].

In general, energy losses are estimated from the discrepancy between energy produced (as reported by power plants) and energy sold to end customers; the difference between the generated power and consumed power constitutes transmission and distribution power losses. Energy losses are the power losses over a period of time. Reduction of system power losses is a fundamental key. Studies have shown that losses in the distribution system approach 8 to 10%. In USA, the transmission and distribution losses were estimated at 6.6% in 1997 and 6.5% in 2007 [4, 5].

While the near daily growth of world energy resources prices continue, less improvement has been achieved in the financial aspects for electrical companies. It is urgent to create and find out new methods to minimize the electrical energy costs. Obviously, the optimal running mode of EPSs requires the integration of: management, control, monitoring, and maintenance, which leads to minimizing the cost of electrical energy.

The cost minimizing choice of inputs depends on two essential sets of parameters: the given output level and the given price factor. It is obvious that if we change relative price factor, the cost-minimizing choice of the inputs would change. The cost function and its analysis are due largely to the famous research of [6, 7]. The analysis of the cost function in EPSs can be achieved by global analysis of the EPSs regulating devices (RD) and modes.

Generally, the optimal operation mode of an EPS is defined, with regard to voltage and current behavior, as the ideal optimal situation that in practice can only be approximately achieved [8]. The most important reasons of deviation from the ideal optimal mode can be summarized as follows [9]:

- Network configuration variations, in proximity to loads: for example, frequent inserting and disconnecting operations of loads, or opening and closing operations of distribution networks due to local requirements or operation of protection systems (e.g., with stormy weather)
- Load variations: for example, those caused by intermittent operating cycles (traction systems, rolling mills, tooling machines, excavators, welding machines, etc.)
- The physical dissymmetry of the electrical part of the system: for example, in lines, transformers and mostly in loads (as single-phase loads), which can be amplified by anomalous connections (e.g., the disconnection of a phase or an unsymmetrical short-circuit)
- The nonlinearities of the electrical part, with reference to the instantaneous values of voltages, currents, magnetic fluxes, etc.: for example, saturations and magnetic hysteresis and granular effects due to winding distribution and slots in the machines; electrical characteristics of arc furnaces, fluorescent lights, thyristor controlled converters, static compensators, etc.
- Finally, the interconnections between very large systems (e.g., neighboring countries)

Regarding the above-mentioned hypotheses, the operator at the dispatch control, as responsible decision maker, has to improve this situation by keeping the system at the optimal operating condition within minimum and convenient operating costs [10]. The operator activity has to take the system to the optimality as far as the decision is right [11], and involves continuous monitoring and interaction with archived and real-time data using a typical number of dispatch means [12].

2. ELECTRICAL POWER SYSTEM COSTS

Power losses have a considerable effect on the active power generation and consequently on the electricity cost. It is essential for economic efficiency of the electric energy market to allocate this cost fairly among the power system agents. As the operational cost model evolves over time, any impact or change to the operation can easily be incorporated into the model with effects to the operation accurately forecasted.

Operational cost modeling of the electrical systems is not a one-time event, but rather an iterative process that continues to be refined over time until one has a finely tuned model of operation. It depends mainly on the load flow problem which is specifying the loads in MW and MVAr to be supplied at certain buses of a transmission system [13]. Any change to the operation can then be applied to the model and the impact on cost, time, main power requirements and service levels can be accurately predicted. The costs are generally known as the average cost and its marginal cost.

The general cost function for an electrical power station according to [14], is given by the equation:

$$\mathbf{C} = \sum_{\mathbf{j}=\mathbf{1}}^{\mathbf{q}} \mathbf{C_j\, P_{Gj} dt} \ \rightarrow \mathbf{min} \qquad (1)$$

Or

$$\mathbf{C} = \sum_{\mathbf{j}=\mathbf{1}}^{\mathbf{q}} \mathbf{B_j C_u\, P_{Gj} dt} \ \rightarrow \mathbf{min} \qquad (2)$$

where:

C_j – Fuel costs to generate power

P_{Gj} – Generated power in the j–station

B_j – Consumption fuel consuming in j station

C_u – Cost of consumed fuel in j station

The $C_j = B_j C_u$ is a nonlinear function for the active power P_{Gj}. When transmission distances are very small and density is very high, transmission losses are neglected and the optimal dispatch of generation is achieved with all plants operating at equal incremental production cost [15].

In a large interconnected network where power is transmitted and distributed over long distances, losses are a major factor and affect the optimum dispatch of generation. One common practice for including the effect of transmission and distribution losses is to express the total losses as a quadratic function of the generator power outputs P_L.

$$P_L = \sum_{i=1}^{n_g} \sum_{j=1}^{n_g} P_i B_{ij} P_j \qquad (3)$$

A more general formula containing a linear term and a constant term (Korn`s loss formula) [14, 9] is:

$$\mathbf{P_L} = \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{n_g}} \sum_{\mathbf{j}=\mathbf{1}}^{\mathbf{n_g}} \mathbf{P_i B_{ij} P_j} + \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{n_g}} \mathbf{B_{0i} P_i} + \mathbf{B_{00}} \qquad (4)$$

The coefficients B_{ij} are called losses coefficients and they are assumed constants. Reasonable accuracy can be expected provided the actual operating conditions are close to the base case, where the B-constants are, were computed. There are various ways to obtain these B-constants. The optimal economic dispatching problem is to minimize the overall generating costs C_{Total} (Eq. 1) as a function of plant output, subjected to the constraints that generation should equal total demands and losses.

$$\sum_{i=1}^{n_g} \mathbf{P_i} = \mathbf{P_D} + \mathbf{P_L} \qquad (5)$$

where P_i should satisfy the minimum and maximum generating limits.

The network equations can be formulated systematically in a variety of forms. The resulting equations are known as the power flow equations and mostly solved by iterative techniques. Power flow studies are the backbone of power system analysis and design. It is also required for planning, operation, economic scheduling and exchange of power utilities, transient stability analysis and contingency studies. The optimal dispatch can be estimated and found out using mainly the Lagrange multiplier.

3. THE INFLUENCE OF THE CONTROL DEVICES ON THE ELECTRICAL POWER SYSTEM LOSSES

The influence of control on power system losses is a postulate logic issue. This situation is explained by an example describing the relationship between active power losses ΔP and the control parameters U_i in a power system (Figure 1), where curve (a) and curve (b) belong to m- load mode and m + 1 load mode respectively. The first mode optimal parameters of RD are fulfilled? With $U_{iO}^{(m)}$ and active power losses $\Delta P_O^{(m)}$.

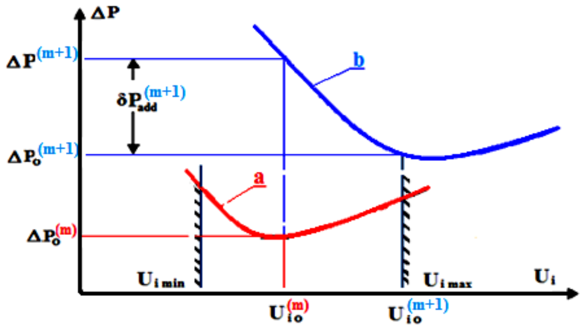

Figure 1. Active power losses versus tap-changer sittings (curve a for m- mode, curve b - for m+1 mode).

During normal load variations (demand), the current and the power flow also changed and there is a great need to keep the regime in the optimal minimum operating power losses zone which theoretically corresponds with the minimum costs. This can be achieved by using different RD during operation in the system such as: Classical control with On-Load Tap Changer (OLTC) and controlled compensators.

To get $\Delta P_O^{(m+1)}$ position, during the transition from (m) load mode to (m-1) load mode throw variations, we must change the parameters of the RD from $U_{iO}^{(m)}$ to $U_{iO}^{(m+1)}$. The active power losses may differ from $\Delta P_O^{(m+1)}$ to $\Delta P^{(m+1)}$. If the correction is absent, this will lead to additional active power losses (which could be avoided by continuous corrections and regulations):

$$\boldsymbol{\delta P_{add}^{(m+1)} = \Delta P^{(m+1)} - \Delta P_O^{(m+1)}} \qquad (6)$$

These additional losses depend on the rate between the running operating mode and the optimal mode. In general, the additional losses can be formulated as:

$$\boldsymbol{\delta P_{addi} = f(U_i)} \qquad (7)$$

Where,

U_i The operating parameter of the RD or regulating margin,

i The corresponding correction step.

Figure 2, which is derived from Fig. 1 by shifting the origin of coordinates to the optimal losses $\Delta P_O^{(m+1)}$, shows that each step of RD parameters in a range $(U_{iO}^{(m)} - U_{iO}^{(m+1)})$ corresponds to its own value of additional losses.

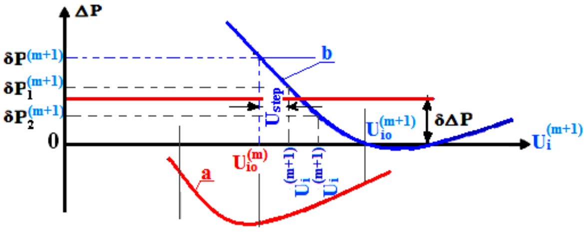

Figure 2. Add-on power losses versus tap-changer sittings (curve a for m mode and curve b for m+1 mode).

Nevertheless, the equilibrium operation previously defined corresponds to an ideal situation which in practice can only be approximately achieved. Regarding the above-mentioned hypotheses (and assuming that stability holds), the most important reasons for deviation from the ideal behavior are mentioned in section 1 of this paper.

4. MODELING THE ADDITIONAL OPERATIONAL COSTS

The additional Operational costs for a group of the electrical system are given by equation 8:

$$\mathbf{C_{add}^{(m+1)} = \sum_{i=1}^{k} C_{addi}^{(m+1)}} \qquad (8)$$

where, C_{addi} is the additional costs incurred due to the absence of correction in the electrical systems modes. These costs C_{addi} are depending on the additional active power losses, the time period and the power losses costs. Equation 8 can be performed as:

$$\mathbf{C_{add\,i}^{(m+1)} = \delta P_{add\,i}^{(m+1)} T_{(m+1)} b_o} \qquad (9)$$

where,

$\delta P_{add\,i}^{(m+1)}$ – Additional active power losses incurred due to absent correction in the electrical system at the $(m-1)$ load mode i^{th} RD.

$T_{(m+1)}$ – The time period of the (m-1) load mode for the i^{th} part of the power system

b_o – The losses costs in USD/kWh

Obviously there is a clear relation between additional operational costs C_{add} and the number of steps regulating switch gears n_{sg} for the correction operation of the power system. This relation can be reflected in mathematical forms by means of statistical analysis.

The regression function classic statistical problem is to try to determine the relationship between two random variables **X** and **Y**. Linear regression attempts to explain this relationship with a straight line fit to the data. The linear regression model [16] postulates that:

$$\mathbf{Y = a + bX + e} \qquad (10)$$

where, the residual (e) is a random variable with mean zero. The coefficients (a) and (b) are determined by the condition that the sum of the square residuals is as small as possible.

The regression analysis for curve fitting is defined on the basis of graphical practical results. The relation $\delta P_{addi} = f(U_i)$ can be explained as the additional losses in terms of a switchgear number for the equipment of the electrical system ("Figure 3" 1st curve), where n'_{i0} for every i^{th} equipment is:

$$\mathbf{n'_{i0} = \left| \frac{U_{iO}^{(m)} - U_{iO}^{(m+1)}}{U_{step\,i}} \right|} \qquad (11)$$

Where, U_{step} is regulation step of transformation ratio for the i^{th} transformer (for example)? The time period

$T^{(m+1)}$ for i^{th} step is characterized by the daily load profile (load demand) and does not depend on the n_{sg}. The b_0 losses costs in USD/kWh directly depend on the configuration topology of the electrical network. Consequently, the interdependency of the additional costs C_{addi} on the n_{sg} can be reflected by taking corresponding coordinate`s of δP_i and the relation $\delta P_i = f(n_i)$ Figure 3.

A better model can be obtained if a nonlinear regression model is used. Therefore the $C_{addi} = f(n_i)$ regression pattern will be used as it shown in Figure 4 curve 2. For any configuration of the electrical network system, the curves can be contrived by the experimental results of the load flow calculations and analysis. When the model function is not linear in the parameters, the sum of squares must be minimized by an iterative procedure. This introduces many complications which are summarized by the differences between linear and non-linear least squares. Regression models predict a value of the (**y**) variable given by known values of the (**x**) variables. If the prediction is to be done within the range of values of the (**x**) variables where they are used to construct the model it is known as interpolation [17, 18].

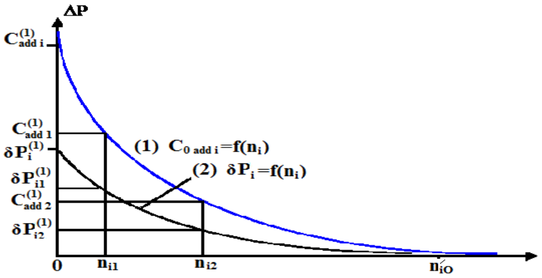

Figure 3. Add-on costs and power losses versus number of tap-changer sittings.

Once a regression model has been constructed, it is important to confirm the goodness of fit of the model and the statistical significance of the estimated parameters. A number of N experimental steps on the curve $C_{addi} = f(n_i)$ (Figure 4), shows the different steps. In Table 1, a different types of the regression function are shown. The general form is $\hat{C}_{addi} = \varphi(n_i)$ where, $\widehat{C}_{addi}$, is regression function weight distances between the variables of C_{addi} and n.

The standard deviations for $\left|\hat{C}_{addi} - C_{addi}\right|$ are used, together with the assumption that the errors belong to a normal distribution, to determine confidence limits for the parameters. The choice of the regression function can be perspicuous by using the flowing steps:

- Using the input data as a result of the N experiments for the electrical system to find the approximation coefficients for the regression function $\widehat{C}_{add\,i} = A_i n_i^{\alpha i}$. For which the deviation $\left|\hat{C}_{addi} - C_{addi}\right|$ used for the same points.
- The experimental relation (function) of the running and maintenances costs on the switchgear numbers with acceptable accuracy can be $\hat{C}_{add\,i} = A_i n_i^{\alpha i}$ with the condition $A_i > 0, n_i > 0,\ \alpha_i < 0$.

Table 1: Regression functions and its standard deviations

No. Experiment	Regression function typ	Deviations $\left|\hat{C}_{add\,i} - C_{add\,i}\right| \times \%$
1	$\hat{C}_{add\,i} = a_i n_i + b_i$	$\leq 10\%$
2	$\hat{C}_{add\,i} = \dfrac{1}{a_i n_i + b_i}$	$\leq 20\%$
3	$\hat{C}_{add\,i} = A_i n_i^{\alpha i}$	$\leq 5\%$

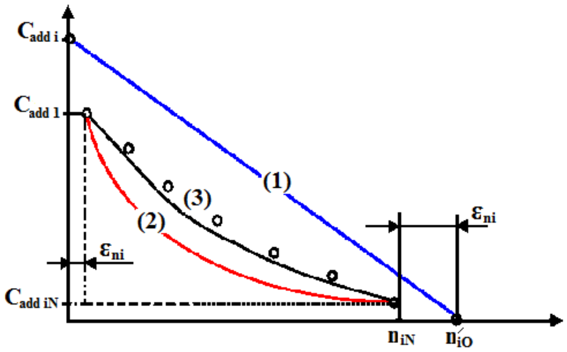

Figure 4. General type regression function which fulfill with the Cadd i = f(ni) approximation

THE REGRESSION MODEL COEFFICIENTS

The regression coefficients, representing the amount of the dependent variable $\widehat{C}_{addi}$ changes when the corresponding independent changes 1 unit (step) for ith part of the power system, have the form:

$$\hat{\mathbf{C}}_{\mathbf{addi}} = \mathbf{A_i n_i^{\alpha_i}} \qquad (12)$$

The equation is nonlinear by the time dependence, so using the least squares regression partially is not recommended. This function $\hat{C}_{addi} = A_i n_i^{\alpha i}$ should be linearized by the natural logarithms [17, 18]. Logarithmic regression model equation generally can be presented as:

$$\mathbf{\ln \hat{C}_{addi} = \ln A_i + \alpha_i \ln n_i} \qquad (13)$$

This can be transformed as: $\mathbf{\ln \hat{C}_{addi} = Z_i;\quad \ln A_i = D_i;\quad \ln n_i = X_i}$

Eq. (13) takes a linear form

$$\mathbf{Z_i = D_i + \alpha_i X_i} \qquad (14)$$

In this case the least squares regression can be represented as:

$$\begin{cases} \sum_{j=1}^{N} \mathbf{D_i} + \alpha_i \sum_{j=1}^{N} \mathbf{X_{ij}} = \sum_{j=1}^{N} \mathbf{Z_{ij}} \\ \sum_{j=1}^{N} \mathbf{X_{ij} D_i} + \alpha_i \sum_{j=1}^{N} \mathbf{X_{ij}^2} = \sum_{j=1}^{N} \mathbf{X_{ij} Z_{ij}} \end{cases} \qquad (15)$$

where, N- is the simulation experiment number from which the X and Z are defined.

The last system can be retransformed as:

$$\begin{cases} \mathbf{N \ln A_i + \alpha_i \sum_{j=1}^{N} \ln n_{ij} = \sum_{j=1}^{N} \ln C_{addij}} \\ \mathbf{\sum_{j=1}^{N} \ln n_{ij} \ln A_i + \alpha_i \sum_{j=1}^{N} \ln n_{ij}^2 = \sum_{j=1}^{N} \ln n_{ij} \ln C_{addij}} \end{cases} \qquad (16)$$

Eq. 15 can be solved with boundary conditions as in Figure 4:

$$\mathbf{n_{ij} = \varepsilon_{ni};\quad C_{addij} = f(n_{ij});}$$

$$\mathbf{n_{iN} = n'_{i0} - \varepsilon_{ni};\quad C_{addiN} = f(n_{iN})}$$

where, ε_{ni} is the given accuracy for the switch gear numbers n_i that are discrete.

The regression coefficients from Eq. 16 for approximation properties of Eq. 12 for i^{th} part of the power system are weighted. The weights estimate the relative predictive power of each independent, controlling for all other independent variables in the equation for a given model. The standardized version of the coefficients is the weights and the ratio of the coefficients is the ratio of the relative predictive power of the independent variables. Associated with multiple regression, multiple correlation, which is the percent of variance in the dependent variable explained collectively by all of the independent variables [19].

The convenient model should be tested to assure that the residuals are dispersed randomly throughout the range of the estimated dependent.

The model convenient criterion:

$$\mathbf{F_I^* \le F_\alpha} \qquad (17)$$

Where, F_I^* is the relation of the chosen disperse s_{2i}^2 and s_{1i}^2 or q_{2i}^2, q_{1i}^2 and s_{1i}^2. Depends on the number of degrees of freedom f_{2i} and f_{1i} of the variables. F_α-table standard (criteria) Poisson distribution for count data. The disperse s_{2i}^2 and s_{1i}^2 or q_{2i}^2, q_{1i}^2 and q_{1i}^2 is a sum of square difference for i^{th} part of the EPS, if it is a linear regression.

However, this is not strictly valid because linear regression is based on a number of assumptions. In particular, one of the variables must be fixed experimentally and/or precisely measurable [19]. So, the simple linear regression methods can be used only when we define some experimental variable and test the response of another variable to it [20]. So the s_{2i}^2 and s_{1i}^2 or q_{2i}^2, q_{1i}^2 are defined experimentally with dependence on the number of degrees of freedom:

$$\mathbf{f_{2i}\left(f_{2i}^{for\ S_1^2}\right) = N;\ f_{2i}\left(f_{2i}^{for\ q_1^2}\right) = N-1} \qquad (18)$$

The weights for the interaction of nonlinear regression based on minimum sum of square difference in the logarithmic and not on sum of square difference:

$$\begin{aligned}
\mathbf{s_{1i}^2} &= \frac{\sum_{j=1}^{N} \ln\left(C_{add(ij)}/\bar{C}_{add(ij)}\right)^2}{N};\\
\mathbf{q_{1i}^2} &= \frac{\sum_{j=1}^{N} \ln\left(C_{add(ij)}/\bar{C}_{add(ij)}\right)^2}{N-1}\\
\mathbf{s_{2i}^2} &= \frac{\sum_{j=1}^{N} \ln\left(C_{add(ij)}/\hat{C}_{add(ij)}\right)^2}{N-2};\\
\mathbf{q_{2i}^2} &= \frac{\sum_{j=1}^{N} \ln\left(C_{add(ij)}/C_{add(ij)}\right)^{\sim}}{N-2}
\end{aligned} \qquad (19)$$

If the conditions (17) are not realized, the approximation of the Equation 12 should be changed for another more accurate experimental method. Finally, the relationship between the additional operational costs and the absent of the optimal corrections as a function was demonstrated as a mathematical model companioned with its algorithm.

Despite of the interesting results, we have left unanswered important questions about the functions of the derivative. For instance, it would be interesting to know the control plan strategy for a certain electrical system in both normal and contingency working mode. Another problem is to find an optimal schedule that minimizes the long-run average cost per time slot with special case studies for electrical systems [21]. Never the less, such problems can be topics for further research. Future research can be built on the broad-based framework by including uncertainty and dynamic quality management decisions. Such extensions would help to address the following issues: What variables (both financial and non financial) can be measured? How can the measured variables be used to provide information (estimates) of latent variable?.

5. CASE STUDY

5.1 TEST NETWORK

The electrical network used in this study is given in Figure 5. It consists of 16 buses, 16 branches and 8 transformers three of which are equipped with OLTCs. The input data are summarized in Table2, Table3, and Figure4.

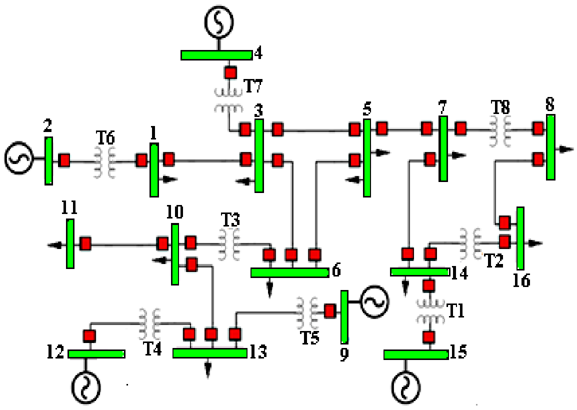

Fig. 5. The electrical network used in this study

Table 2. Input data of tested network.

No	Bus i	Bus j	Type	R Ω	X Ω	TR
1	1	3	Line	1.500	7.850	-
2	3	5		0.950	6.200	-
3	5	6		0.350	2.400	-
4	10	11		0.700	1.600	-
5	5	7		1.150	6.650	-
6	7	14		2.400	15.500	-
7	8	16		2.240	26.100	-
8	1	2	T 6	0.250	34.250	20/230
9	3	4	T 7	0.240	7.000	20/230
10	6	10	T 3	0.200	12.500	230/132
11	9	13	T 5	0.770	16.700	15.8/132
12	12	13	T 4	0.250	7.400	10.5/132
13	7	8	T 8	0.800	35.000	230/33
14	14	15	T 1	0.200	6.250	10.5/230
15	14	16	T 2	0.800	35.00	230/132

Table 3 Bus data

us	Type	P_{load} MW	Q_{load} MVAR	P_G MW	Q_G MVAR	V kV	δ [Deg]
1	PQ	86.0	20.0	0.0	0.0		
2	PV	0.0		125.0		20	
3	PQ	64.0	9.0	0.0	0.0		
4	Slack					20	0
5	PQ	47.0	35.0	0.0	0.0		
6	PQ	92.0	30.0	0.0	0.0		
7	PQ	61.0	8.0	0.0	0.0		
8	PQ	29.0	18.0	0.0	0.0		
9	PV	0.0		100.0		15.8	
10	PQ	31.0	18.0	0.0	0.0		
11	PQ	34.0	20.0	0.0	0.0		
12	PV	0.0		60.0		10.5	
13	PQ	14.0	8.0	0.0	0.0		
14	PQ	7.0	3.0	0.0	0.0		
15	PV	0.0		15.0		10.5	
16	PQ	31.0	18.0	0.0	0.0		

Table 4. Data of the transformers and modes losses

Transformer No	1	2	3	4	5	6	7	8
U_{step}	0.0015	0.0015	0.004	-	-	-	-	-
$U_{step\ 0}$	0.068	0.091	0.50	0.09	0.5	0.5	0.09	0.068
$U_{step\ 1}$	0.0695	0.0925	0.504	-	-	-	-	-
$U_{step\ 2}$	0.071	0.094	0.508	-	-	-	-	-
$U_{step\ 3}$	-	-	0.512	-	-	-	-	-
$U_{step\ 4}$	-	-	0.516	-	-	-	-	-
$U_{step\ 5}$	-	-	0.52	-	-	-	-	-
Mode 1 (Optimal)								
$U_{Optimal}$	0.068	0.091	0.50	0.09	0.5	0.5	0.09	0.068
ΔP_0 MW				54.78				
Mode 2 (Peak)								
U_i	0.068	0.0925	0.50	0.09	0.5	0.5	0.09	0.068
ΔP MW				9.17				
OLTC: n_{step}	2	2	5	-	-	-	-	-

Figure 6 shows I–optimal mode and II peak load mode power losses in MW, without correction the parameters of the RD.

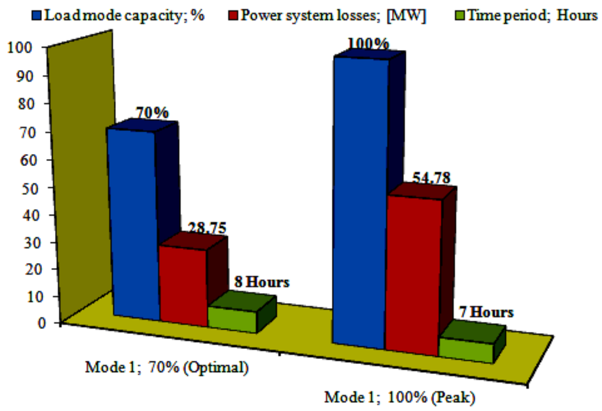

Figure 6. Power Losses of Load modes m and m+1

5.2 ALGORITHM STEPS

There are several steps involved in finding the optimal load mode to minimize additional losses and costs in a transmission and distribution system**.** The single and multiple factor test scenarios will be performed for load mode 2 based on load mode 1.

From the single factor scenarios we have calculated the regression relationships between add-on power losses cost and all 8 transformers settings ($C_{addi} = f(n_i)$) using eqs 12-16 considering the weights in eq. 19. It is found that the transformers 4 to 8 have negligible effect on add-on costs, while transformers 1, 2, and 3 are considered as critical components. Therefore, we check the multi-factor scenarios of transformers 1, 2 and 3 as shown in Table 5.

Table 5. Single-Factor Test Scenario for Load Mode 2

Scenarios	T1 TC setting	T2 TC setting	T3 TC setting
1	0	1	1
2	1	1	1
3	2	1	1
4	1	0	1
5	1	1	1
6	1	2	1
7	1	1	0
8	1	1	1
9	1	1	2
10	1	1	3
11	1	1	4
12	1	1	5

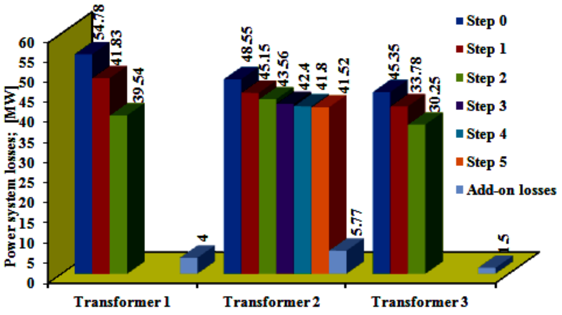

Fig. 7. Power system losses of single-factor test scenarios

Table 6. Multifactor Test Scenario for Load Mode 2

Scenarios No;	T1	T2	T3
1	**Step 0**	**Step 0**	**Step 0**
2	**Step 2**	**Step 0**	**Step 0**
3	**Step 2**	**Step 2**	**Step 0**
4	**Step 2**	**Step 2**	**Step 5**
5	**Step 0**	**Step 2**	**Step 5**
6	**Step 0**	**Step 0**	**Step 5**
7	**Step 0**	**Step 2**	**Step 0**
8	**Step 2**	**Step 0**	**Step 5**

5.3 RESULTS AND DISCUSSION

From Figures 8 and 9, and based on Table 6, it is obvious that scenario 4 gives the minimum additional power losses of 1.4 MW and consequently the lowest add-on operational cost (784 $). The minimum losses are about 8% of the additional power losses for base scenario (1). Thus, the optimal OLTC settings of transformers1, 2, and 3 are found to be 2, 2 and 5 steps respectively.

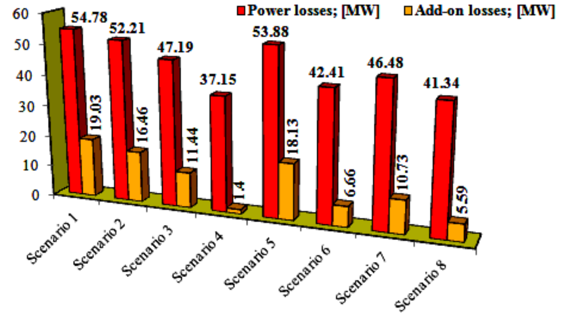

Fig. 8. Simulation Results of multi-factor Tests for Load Mode II

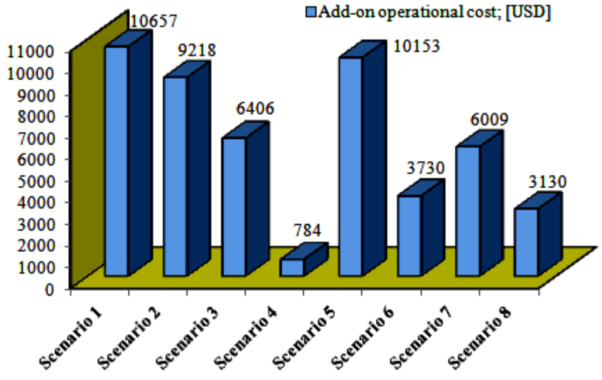

Fig. 9. Additional costs of multi-factor test scenarios

CONCLUSIONS

Reducing the additional embedded power losses and costs in electrical power systems by the control center will lead to overall running cost minimizing.

This study raised and discussed the importance of adjusting and control of online tap changer transformers in the electric power system so that the dispatch operator can avoid the additional embedded operating losses and costs by continuous optimization according to the developed nonlinear regression model based on experimental power flow simulations carried out by Netdraw program [22].

The performed case study shows that substantial power and cost savings can be obtained justifying the effectiveness of the developed model.

The model can be enhanced by future research considering other control parameters such as reactive power allocation and use flexible AC transmission units (FACTS).

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