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Accurate Hybrid Method for Rapid Fault Detection, Classification and Location in Transmission Lines using Wavelet Transform and ANNs

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Abstract: The present paper presents an accurate hybrid framework capable to rapidly detect, classify & locate short-circuit faults on transmission lines. The proposed algorithm has employed the values resulted from each three- phase currents wavelet transform in order to obtain instantaneous fault detection. Singling out short-circuit faults based on the measured voltage waveforms and three-phase current is done when fault events occur in power transmission lines. The energy derived from three-phase currents and three-phase voltages wavelet transform has been used as the classification algorithm input .Then fault location has been activated as the result of fault classification method. Combining the methods such as multilevel wavelet transform, multilayer perceptron neural network in a set has been utilized to determine short-circuit fault type and location at the moment of occurrence. The accuracy and superiority of the present paper derived results due to the fundamental wavelet transform concepts as an excellent feature extractor have been compared with those of another paper exploiting Fourier transform.

Keywords— Transmission lines, Fourier transform, Wavelet transform, Multilayer perceptron neural network, Fault detection, Fault classification, Fault location.

I. Introduction

One of the basic components of every power system is its transmission lines. The main task of these lines is to transfer the produced power by the power stations (power supply facilities) to the consumption centers (end users). Every disturbance in conducting this task will incur substantial losses to the producers & the consumers, concurrently. Of the main disturbances occurring in power systems & on the transmission lines are different short-circuits happening for different reasons. Because power transmission lines have been expanded in long distances, to locate fault in case of using inspection procedures, it takes a lot of time while it is possible for the transmission lines to pass various geographic areas (uneven mountainous areas & wilderness) and or it is possible for the inspection & searching happen under adverse weather conditions often the time when lines faults occur accompanying lots of problems for the repair team.

Thus in order to accelerate the operations transmission lines repair, utilizing some methods and using some devices able to determine fault location rapidly & accurately enough seem necessary for the system operators & repairmen. Such devices are called fault distance detectors & the algorithms used in them are known as fault locating algorithms. Recently, artificial neural networks (ANNs) have gained some achievements in power system applications [1]. Diverse algorithms have been reported for transmission lines fault detection, and classification location. Most papers are about the methods employing time-dependent differential equations solution related to transmission lines for fault locating [2-3].There are many papers that use other methods such as wavelet transform [4], neural network [5-6] and travelling waves [7-8] for fault location.

In this paper, an accurate method has been used for short-circuit fault detection, classification & location in transmission lines by analyzing the results in a two-machine system. The efficiency & results gained in this research have been compared with those from another study using Fourier transfer as feature extraction & has been employed in multilayer perceptron neural network for fault classification & location [9].

II. Proposed Algorithms

II.1. Wavelet Transform

Wavelet Transform is a more general form of Fourier transform. Fourier transform is applied for waveforms stationary over time. But the signals not stationary over time & have no iterative feature, either, rather they are transient waveforms that may occur in a signal several times are categorized as non-persistent signals and therefore, Fourier transform cannot be used for frequency-time isolation, about this case, the transform is applicable that includes time factor along with frequency factor where wavelet transform possesses this feature [10].

II.2. Artificial Neural Network

ANNs have are based on a rather simple model of a neuron [11-12-13-14]. An ANN is built by many neurons & special synthetic model integration. Every neural network is made up of one input layer, one output layer and one or more hidden layers.

In this paper, Levenberg- Marquarlt Method has been employed.

III. Proposed Model Structure

III.1. The proposed Combined (Hybrid) Set

In the present paper, base frequency 60 Hz has been considered for designed power system in PSCAD/EMTDC software. Sampling rate 20 KHz (333 samples /cycle is measured by power measuring units) has been selected for signals extraction from transmission lines. Measurement units for getting three-phase current & voltage have been installed in the origin bus. Then, the acquired data for fault analysis in fault detection,

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classification & location algorithms are transferred to MATLAB software. The proposed set includes three steps: fault detection, classification & location. The set first step is able to calculate the exact fault occurrence time in power system. If no fault is detected, the remaining parts of the module will get activated.

When a fault has been detected, discrete wavelet transform at one level is used to extract feature on post-fault occurrence three-phase voltages .Signals feature is obtained by estimating current values energy & voltage waveforms transform partial factors. After that, the obtained features have been used as input to back propagation algorithm for detecting the short-circuit faults type occurred in power system .And at the end, after fault type determination, fault location module including back propagation, receives the new input from the features second normalization step & locates fault.

III.2. Proposed Power System Model

The study system in this work is due to a two machine three-phase power system of 400 KV simulated for transmission line fault detection, classification and location. The single circuit transmission line of 100 km length has been surveyed in this paper. The study system single (circuit) line diagram has been illustrated in Fig.1 and its parameters have been mentioned in table 7(appendix). Sources No.1 & 2 is in the same size, δ (phase difference between Source1 & Source2) equals 30°, thus Source1 is viewed as the main one (leading).

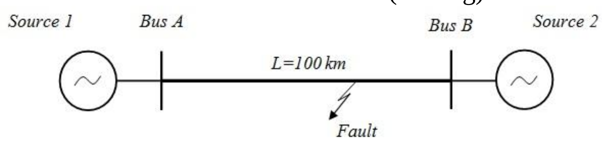

Fig.1: Simulated Power System Model

IV. Proposed Algorithm Synthetic Framework

IV.1. Fault Detection Model

In the current study, discrete wavelet transform has been employed for hidden data extraction in current waveforms when a fault occurred in the transmission lines and after that, it has changed appropriately for fault effect extraction & the faults specifications. Through a discrete wavelet decomposition filter for high pass frequencies, three-phase currents are isolated. Choosing the mother wavelet is very significant in detecting, classifying & locating different types of transient faults. Usually the suitable mother wavelet used for protection applications is wavelet Daubechies (db). Some studies have been conducted to analyze the accuracy of 4 different types of mother wavelets db1, db2, db3 and db4. The results are given in table 1 and finally, mother wavelet db4 with higher accuracy relative to the other wavelets under study has been applied that has been executed as high-pass filter of finite impulse response.

Table 1: db4 wavelets test accuracy for fault detection

Row	Mother wavelet type	Fault detection accuracy
1	db1	99.76
2	db2	99.97
3	db3	99.49
4	db4	99.99

Filter output includes high frequency details resulting high frequency detail coefficients HFR, HFS, HFT by down sampling of second order at a level .Fig.2 depicts wavelet transform effect on the samples due to SG single-phase fault. The 1st column shows current samples, the 2nd one depicts approximation & the 3rd shows the current partial factors.

If the first high frequency detail coefficients difference absolute value is higher than a threshold value; the disturbance is detected in one current signal phase. This logic has been shown for each of the three phases R, S & T as the following.

$$D_R(n) = \begin{cases} 1, & if\left|\left(HF_R(n) - HF_R(n-1)\right)\right| > Th_d \\ 0, & otherwise. \end{cases}$$
$$D_S(n) = \begin{cases} 1, & if\left|\left(HF_S(n) - HF_S(n-1)\right)\right| > Th_d \\ 0, & otherwise. \end{cases} \quad (5)$$
$$D_T(n) = \begin{cases} 1, & if\left|\left(HF_T(n) - HF_T(n-1)\right)\right| > Th_d \\ 0, & otherwise. \end{cases}$$

If a disturbance in detected in each of the three-phase currents, signal Detect goes up (the number gets 1):

$$Detect(n) = OR(D_R, D_S, D_T) \quad (6)$$

The threshold value Th_d can be determined based on the max analog input limit to the signal pre-processor, sampling frequency & selected wavelet. The threshold value Th_d in this paper has been set 1×10^{-2} in this effect. The required time for disturbance detection is 25ms.

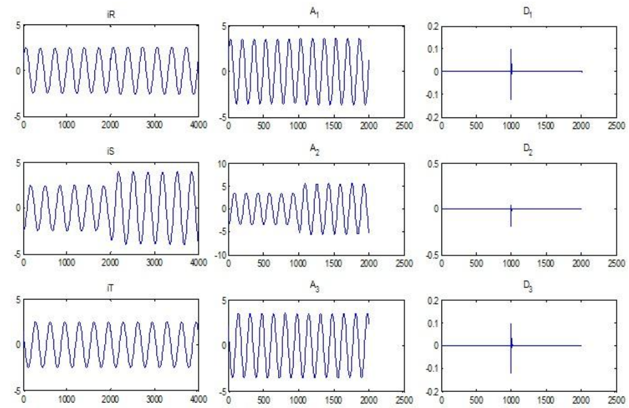

Fig.2: mother wavelet db4 related current signal approximation & detail coefficients

IV.2. Fault Classification Model

In this paper, the discrete wavelet transform has been utilized for hidden data extraction in voltage waveforms when a fault occurred in the transmission lines, then it has been changed appropriately for effect extraction & faults features in order to be used in multilayer perceptron neural network .

In this article, post-fault voltage normalized wavelet energy & post-fault current normalized energy are utilized as input to back propagation algorithm. The general procedure to obtain input features using discrete wavelet can be described as it follows:

- Transient voltages & currents are registered in the designed measurement bus.
- The registered Transient voltages & currents in measurement units are sampled with frequency FS = 4 kHz (64 samples/cycle) in a quarter of cycle after fault occurrence.

- The ground mode (component 0) of voltages & currents is gained via the following formula.
$V_0 = V_R+V_S+V_T$ (7)
$I_0 = I_R+I_S+I_T$
- The discrete wavelet transform is used for all three-phase & ground mode voltage for achieving wavelet coefficients using db4 as the mother wavelet.
- The wavelet transform coefficients at a level (Level-1) are squared (WTC^2).
- Each signal wavelet energy is calculated by summing WTC^2 on a quarter of cycle after fault detection (E_k) k = R, S, T, 0.
- The currents energy for a quarter of cycle is calculated after instantaneous fault (I_k) k = R, S, T, 0.
- The calculated wavelet energy of transient voltage and energy of the phase currents are normalized as:

$$E_{N_i} = \frac{E_i}{E_R+E_S+E_T+E_0} \; for\, i = R,S,T \quad (8)$$
$$I_{N_i} = \frac{I_i}{I_R+I_S+I_T+I_0} \; for\, i = R,S,T$$

In order to classify different fault types, 4 multilayer perceptron neural network (MLP_{Ck}) (k=1... 4) have been used and to detect if there is a fault in the phase or not, each neural network has been trained. So that MLP_{C1} has been trained for fault detection in phase R & MLP_{C2} for fault detection in phase S and MLP_{C3} for fault detection in phase T & MLP_{C4} for detecting that if fault has been to ground or not?
The output of each MLP_{Ck} (k = 1, .., 4) is -1 0r +1. For the first three classifiers +1 means fault has occurred in the questioned phase and -1 means it isn't in that phase. For the last classifier +1 means fault has occurred to ground. The input features refer to each three-phase normalized wavelet energy & voltages ground mode in addition to the post-fault three-phase currents normalized energy. Therefore the processed features in a training matrix are stored in dimensions 2× N. The input to each classifier neural network is training matrix & a pre-labeled classifier vector (1×N) (classifier label, includes each train data). The algorithm operation schema is displayed in Fig.3.

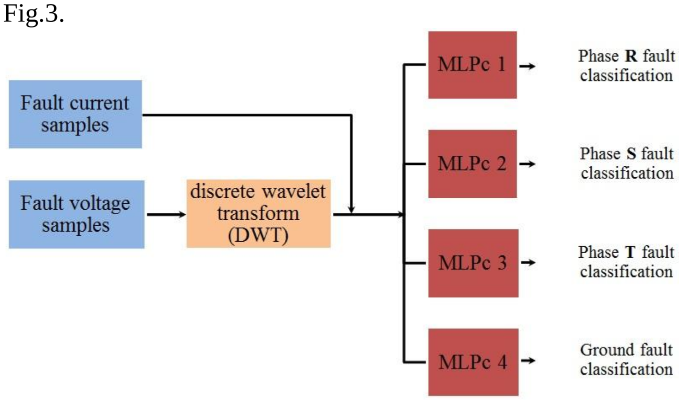

Fig.3: fault classification & location models structure

IV.3. Fault Location Model

As seen in Fig.4, after fault detection & fault type determination using MLP_{Ck} algorithms, the proposed set using MLP_{Li} algorithms, it will be possible to locate fault exactly.

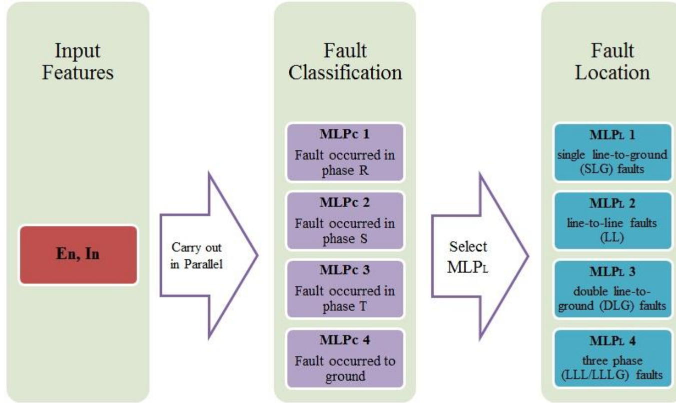

Fig.4: fault classification & location models structures

Training process in back propagation algorithm is accompanied to estimate fault location by generalizing the input features used in the classifier neural network training process. In locator neural network training process, training samples, every voltages three-phase normalized wavelet energy are along with post-fault three-phase currents normalized energy from the second normalization step (input features) and their corresponding fault location. In order to minimize numerical problems risk, the 2nd normalization is done through the following equation [15]:

$$\tilde{x}_i = \frac{(x_i-\mu_i)}{\sigma_i} \quad (9)$$

Where x̃i is normalized feature value , μi & σi stand for mean and standard deviation based on all feature training samples i^{th} and the samples number is 6. Training samples & their corresponding fault location are first obtained by computer assisted simulated power system measurement units that post-processing, the training samples are stored in a matrix in dimension 6×N and their corresponding location in another matrix in dimensions 1×N.

V. Simulation Results

The proposed synthetic algorithm has been run on two-machine system model. Various fault scenarios have been simulated in the system under the fault resistance extensive variations (R_f) and fault locations (L). The following values have been used in this research:

- Fault distance: 0 ≤ L ≤ 100km with ΔL=5km, that means faults are different in 21 locations.
- Fault resistance: 0 ≤ R_f ≤ 80 Ω with ΔL=5 km, that means 17 different fault resistances for each fault.

Back propagation algorithm has been utilized with Levenberg optimizing method for locator multilayer perceptron neural network training & testing. For the above mentioned scenario, all the 11 single-phase, two-phase, two-phase to ground, three-phase & three-phase to ground faults (RG, SG… RST, RSTG) have been taken into account. Given the fault resistance number R_f, 17 scenarios & the locations under the effect of fault are 21 cases, therefore, 357 training samples have been generated for each one of the 11 fault types. Voltages & currents in Bus 1 have been registered with sampling frequency f_s = 20 kHz. And ultimately, the results achieved in this research have been compared with a an identical study where instead of using

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wavelet transform, Fourier transform has been benefitted from for the feature extraction mechanism from voltage & current values as the input to the multilayer perceptron neural network (MLP) with back propagation.

V.1. Classifier Algorithm

Out of 3927 data related to each of the phases R,S,T & 3570 data related to fault to ground according to table 2 have been selected randomly & used as training & testing data set for classifier neural network .In table 2, the data use rate & the classifier algorithm hidden layers number WT-MLP & the similar method FFT-MLP [9] are depicted .

Table 2: data use rate & the classifier algorithm hidden layers number WT-MLP compared to the similar method FFT-MLP

Algorithms	Train Ratio%	Validation Ratio%	Test Ratio%	Hidden layer WT-MLP		Hidden layer FFT-MLP [9]	
Classifier_R	20	15	65	T	15	T- L	1-2
Classifier_S	40	15	45	T	10	T- L	1-2
Classifier_T	20	15	65	T	10	T- L	1-2
Classifier_G	40	15	45	T	20	T- L	1-2

The classifier algorithm accuracy for each of the 4 classifier neural network is calculated as it follows:

$$\%accuracy = \frac{Number\ of\ correct\ fault\ type\ classified}{Number\ of\ test\ cases} \times 100$$

(10)

The results from the classifier algorithm have been given in table 3. Thus from table 3, it is seen that the proposed method's accuracy has been desirable for fault classification. In the present paper (WT-MLP) method, all 11 types of fault (single-phase, two-phase, two-phase to ground, three-phase & three-phase to ground have been applied in the classifier algorithm training & testing steps .While in the similar method FFT-MLP [9], three-phase to ground fault data haven't been used in training process. In other words, 10 types of fault types have been utilized in training & testing steps.

Table 3: comparing accuracy & results from the classifier algorithm performance in this paper using similar method through FFT-MLP

Fault type	Samples tested	True fault classifications	No. of misclassifications	WT-MLP accuracy (%)	FFT-MLP [9] accuracy (%)
R	2553	2553	0	100	100
S	1767	1767	0	100	100
T	2553	2553	0	100	100
G	1607	1589	18	98.88	100
Total	8480	8462	18	99.72	100

4 classifier algorithms have been run in parallel, for instance, if the output MLP_{Ck} is this way: MLP_{C1}=1, MLP_{C2}=1, MLP_{C3}=0, MLP_{C4}=, it means DLG fault including R & S phases to ground have occurred. The demographic results of training & test samples for back propagation neural network have been displayed for fault detection on R phase in Fig.5.

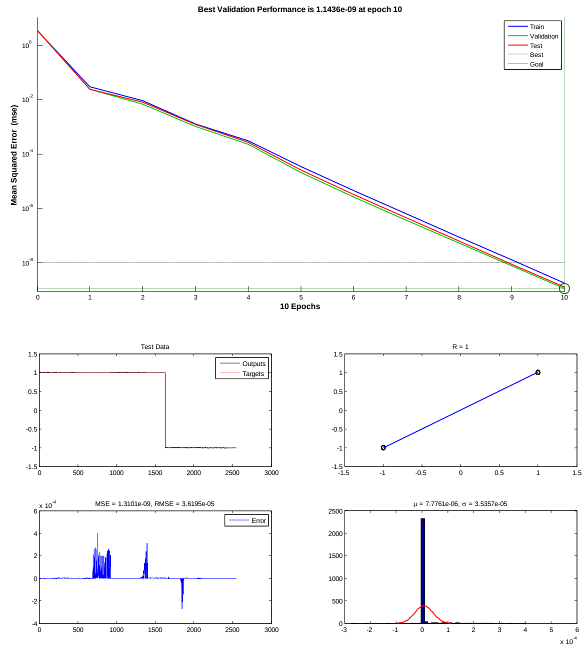

Fig.5: R phase classification regarding training & test samples

V.2. Locater Algorithm

From the data about each of the single-phase, (LG), two-phase (LL) and two-phase to ground (LLG) faults & 714 data about three-phase & three-phase to ground faults (LLL/LLLG) according to table 4, the data have been chosen randomly and used as train & test data set for locator algorithm WT-MLP. In table 4, the rate of using data & the locator algorithm WT-MLP hidden multilayer number & the identical method FFT-MLP have been presented.

Table 4: Rate of using data & the locator algorithm WT-MLP hidden multilayer number compared with identical method FFT-MLP

Algorithms	Train Ratio%	Validation Ratio%	Test Ratio%	Hidden layer WT-MLP		Hidden layer FFT-MLP [9]	
Locator_LG	20	15	65	T-T	40-25	T-T-T-L	10-8-8-1
Locator_LL	40	15	45	T-T	35-21	T-T-T-L	8-8-8-1
Locator_LLG	20	15	65	T-T	42-31	T-T-T-L	10-8-8-1
Locator_ LLL/LLLG	40	15	45	T-T	35-21	T-T-T-L	10-10-8-1

The demographic results of training & test samples for locator neural network for three-phase & three-phase to ground faults have been depicted in Fig.6.

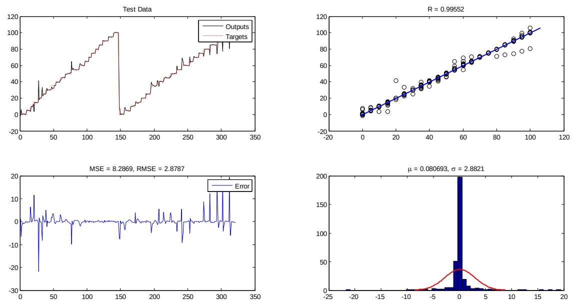

Fig.6: estimating three-phase & three-phase to ground faults considering training & test samples

The index for the locator algorithm performance evaluation is defined through the following equation:

$$\%Error = \frac{|Actual\ fault\ location - MLP\ output|}{Length\ of\ the\ line} \times 100 \qquad (11)$$

Minimum & maximum test fault in the locator algorithm for both methods WT-MLP & FFT-MLP have been given in table 5. It is clear from the table 5 that the maximum fault location algorithm WT-MLP is less than that of FFT-MLP.

Table 5: comparing fault due to locator algorithm performance of WT-MLP & FFT-MLP

Type of fault	Min. error		Max. error	
	WT-MLP	FFT-MLP [9]	WT-MLP	FFT-MLP [9]
LG	27×10^{-6}	6.0711×10^{-4}	0.031	0.026964
LL	8.3×10^{-6}	1.0716×10^{-5}	0.034	0.042846
LLG	28×10^{-6}	3.9771×10^{-4}	0.038	0.058261
LLL/LLLG	15×10^{-6}	8.8926×10^{-4}	0.021	0.33

In table 6, the results of 4 cases of fault with various location conditions with train points (out of train & test samples) have been taken into account.

Table 6: locator algorithm performance result for 4 test fault samples

Fault type	Test fault real location (km)	WT-MLP		FFT-MLP [9]	
		Test fault estimation location (km)	Error %	Test fault estimation location (km)	Error %
LG	82	82.1271	0.1271%	81.668	0.3324%
LL	37	37.0063	2.2516%	36.986	0.0135%
LLG	64	63.9878	0.0121%	64.025	0.0253%
LLL/ LLLG	14	14.147	0.9031%	14.493	0.4925%

The location results show the sufficient accuracy of the locator algorithm .In this paper, it is possible for fault location to be located in case of each of these 11 types of faults occurrence while in the similar method, according to the authors' statement, it is possible for 10 fault types to be located.

VI. Conclusion

An accurate method for short-circuit fault detection, classification & location over power transmission lines has been presented. Discrete wavelet transform has been used as the main factor in feature extraction from post-fault occurrence three-phase current & voltage signals and in the continuation, via applying some changes in high frequency detail components, they are utilized as input to the proposed algorithms.

The significant features of the proposed method are:

1) Only one db4 high-pass mother wavelet filter has been used for each phase; 2) For fault detection, classification and location, there is no need for complicated energy computations, only squaring and summing operation of the samples are required; 3) The threshold limit estimation has been used for fault detection being very easy to be executed.

In fault classification, discrete wavelet transform (DWT) at a level (Level-1)has been employed for data extraction in a quarter of cycle of the phases R, S & T and zero sequence of the post-fault voltage signals registered in measurement units. The fault stricken phases have been defined employing multilayer perceptron neural network with back propagation train algorithm & Levenberg optimizing method. The post-fault voltage signals normalized detail components energy & post-fault current signals normalized energy have been applied as input to the classifier neural network & post-fault voltage signals ground mode normalized wavelet detail components energy have been used for fault detection to ground. Daubechies-4 (db4) wavelet transform has been used as the mother wavelet & analysis has been done at one level, that is, Level-1.

In fault location, the features used in the classifier network have been normalized for the second time and they have been employed along with fault locations as input for the locator neural network. Accordingly, it has been displayed that the proposed short-circuit fault detection, classification& location (FDCL) operations are rapid, very reliable and safe.

Appendix

Table 7: study power system parameters

Transmission line positive & negative sequence impedance (ohm/km)	$3.26 + j36.743\,[\Omega/km]$
Transmission line zero sequence impedance (ohm/km)	$32.15 + j111.753\,[\Omega/km]$
Source positive sequence impedance(ohm)	$15.057\angle 85^\circ = 1.31 + j15\,[\Omega]$
Source zero sequence impedance (ohm)	$26.702\angle 85^\circ = 2.33 + j26.6\,[\Omega]$
Apparent power(MVA)	$685\,[MVA]$
Rated voltage (KV)	$400\,[kV]$
Source 1 phase angle(degree)	$30\,[deg]$
Source 2 phase angle(degree)	$0\,[deg]$
Frequency (hertz)	$60\,[Hz]$
Transmission line length (km)	$100\,[km]$

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