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# An Efficient Short-Term Electric Power Load Forecasting Using Hybrid Techniques

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***Abstract*: The power system plays an essential part in the transmission of electricity. Generation, transmission and distribution are the main parts of electricity consumption, and day to day, the demand for electricity increases. So, the prediction of price and load is significant in the power system. The short term load forecasting (STLF) predicts the load 24 hours ahead or a week ahead. This paper investigates the effect of price and load on short term load forecasting with two hybrid techniques (HT). The first hybrid technique consists of wavelet as well as Generalized Autoregressive Conditionally Heteroscedastic (GARCH) analysis methods and the second hybrid technique consists of GARCH, EGARCH, GJR models and Particle swarm optimization (PSO). The first hybrid technique (FHT) is analyzed by taking the Price from the Ontario grid and the second hybrid technique (SHT) is diagnosed by taking the load from the Xintai power plant. The prediction of Price and load depends on input data. The results are significant and its accuracies are effective. The analysis of two hybrid techniques clearly defines its work and the ability to produce the result. In the first HT, the wavelet decomposes the data and the GARCH models analyze the decomposition data. In the second HT, the GARCH, EGARCH, GJR models are executed the input data and PSO brings the smoothness of the result. The forecasting price results and load calculation indicates less error and it is essential for short term load forecasting.***

***Keywords*:** Short term load forecasting (STLF), Hybrid technique (HT), Wavelet, GARCH, Particle swarm optimization (PSO).

## I. Introduction

In the power system, short term load forecasting (STLF) plays an important for its operation like unit commitment, economic load dispatch, maintenance scheduling, hydro-thermal scheduling, etc. It also helps in load switching operation and load management for an electrical utility. As compared to the regulated areas, STLF is very important in the deregulated electricity market because the profit of the electricity market is involved. The amount of electricity is bid by an energy bidder depending on STLF in the deregulated market. An accurate STLF improves the accuracy of price forecasting. But the prediction of the exact load is challenging due to its nonlinearity and the factors influence the load like time, weather and price of the electricity. Different researchers have applied other methods for predicting the exact load and the accuracy of the STLF is improved by research. STLF is investigated by various old methods [4], [5] like linear regression [6], time series [7], pattern recognition [8], Kalman filter model [9]. But these methods are unable to solve the problem of the nonlinearity of load. So, new approaches are investigated on STLF like GARCH model [9], wavelet [10], PSO [11], expert system [12], ANN method [13]-[15], fuzzy logy [16], hybrid wavelet-Kalman filter [17], etc. because of its excellent output result.

The most useful method is the GARCH model. It has been used for price forecasting and STLF. In this manuscript, we have worked on price forecasting and load forecasting in two separate subsections.

Now a day, the GARCH model is essential for price forecasting and STLF. In this manuscript, we have applied a combined model of GARCH and wavelet for price forecasting and GARCH, EGARCH, GJR and PSO for STLF. In FHT, GARCH is a symmetrical model which is newly using for the control of Price in STLF as it is bringing success in price forecasting and wavelet helps to carry the information of data like trends, discontinuities in higher-order derivatives as well as self-similarities where other techniques are not able to do this. It is also helping in decompose the signal [18].

In SHT, GARCH, EGARCH, GJR models are used to reconstruct the data and PSO brings STLF. The PSO technique is a machine learning technique which is proposed by

Eberhart and Kennedy in 1995. It can apply in all emergency area for real-time optimization [19], [20] like quantum PSO using radial basis function (RBF) [21], load forecasting using RBF and PSO [22] and PSO for inertia weight factor and chaos [23], etc.

The research gap found by studying the literature review is:

- The shallow neural network is used in the past for forecasting, which degrades the forecasting accuracy
- The collection of noisy real-time data and extraction of various features found in load demand makes modeling of an accurate STLF model challenging. There always remains a research scope to develop a robust STLF scheme for precise estimation of future load demand pattern that helps the system in maintaining area generation control and resource dispatch.
- There is always a need for fast and robust forecasting method as in the past, the researchers have examined the forecasting with slow and sensitive schemes.
- The methodologies provided for STLF are either very complicated or have included fewer variables impacting the load variation in the short-term horizon. Most of the time, climate variables such as humidity, the dew point is excluded from modeling a less complicated forecasting model. Therefore, there has always been a research scope for developing an STLF model, which can assess these climate variables impact on load variation and design a less complicated model.

In this paper, the research gap is fulfilled by proposing two-hybrid accurate, robust schemes which include a greater number of variables impacting the load variation in a short time horizon. For the first time, the impact of Price and load in STLF is analyzed, which is also the main contribution in this paper.

This manuscript is arranged in the following ways: Section 2 gives the work of a hybrid approach, Section 3 represents the case study, Section 4 presents results and discussion, and Section 5 concludes the entire work.

## II. The Hybrid Techniques

*A. First hybrid technique (FHT):-*

This first HT is developed by working of wavelet and GARCH (1, 1) with the Monte-Carlo simulation result, as shown in Figure 1. The following steps are carried out.

Step-1: Wavelet is applied to the decomposition of the original data.

Step-2: GARCH (1, 1) is used in the analysis of decomposing data.

Step-3-Monte-Carlo simulation is applying for the prediction of the Price.

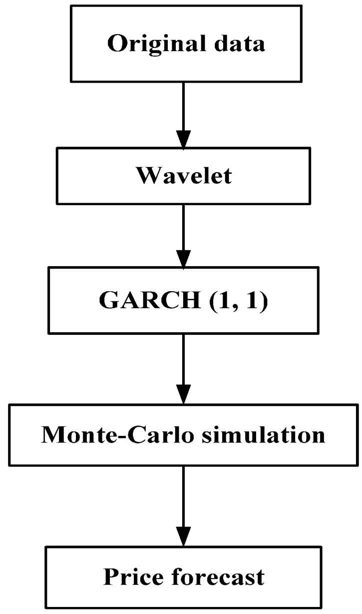


**Figure 1.** Schematic of the proposed model

*1) Wavelet*

The signal of significant restriction of time interval consisting of zero mean value is known as a wavelet. It decomposes the original waveform is shifted way as well as scale type. Low and high pass filters allow the decomposition signal, as shown in Figure 2 [18].

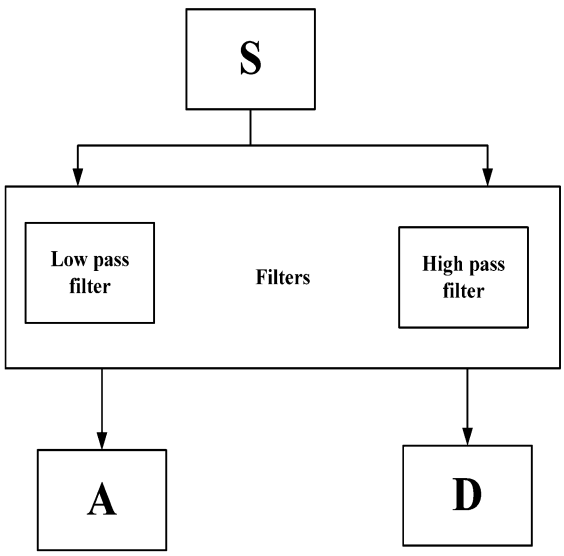


**Figure 2.** Signal formation

Figure 2 shows that the original signal S is passing through the low and high pass filters and the signal from filters is represented by A & D, respectively. Then the signals A & D are passing through the down sampling for further decomposition, as shown in Figure 3.

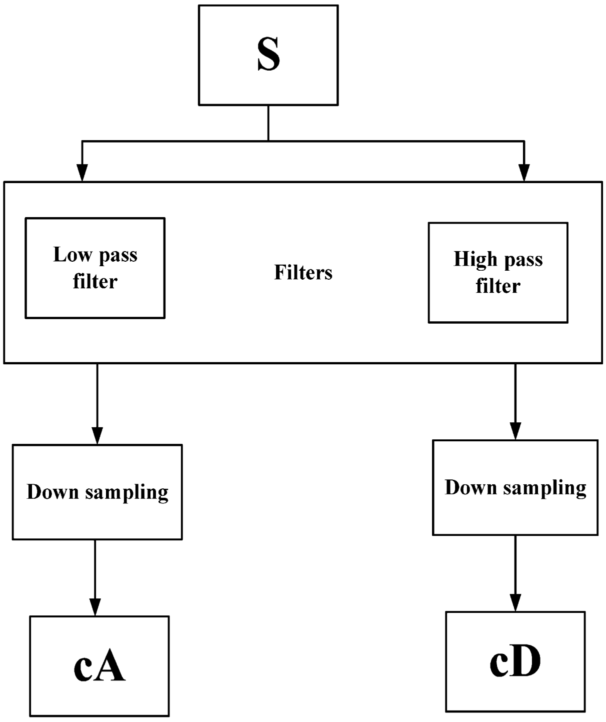


**Figure 3.** Decomposition of signal

Figure 3 shows that the decomposing signals cA and cD are produced by down sampling, which reduces the length of data, and this process produces the discrete wavelet transform coefficients. It is used by wavelet for the propose of discretely sampling.

*2) GARCH*

The vital characteristic of the GARCH model is conditional variance and the conditional distribution is allowing by sequential based on the conditional variance of the original. The work of GARCH (1, 1) is similar to normal autoregressive moving-average (ARMA). But it allows the more explanation in many conditions [24]. The standard form GARCH (p,q) is expressed as Eq. 1.

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \sigma_{t-i}^2 + \sum_{j=1}^{p} b_j \sigma_{t-j}^2 \quad (1)$$

Where,

$p$ = GARCH method order

$q$ = ARCH method order

$a_0, a_i, b_j$ = Constants

$\sigma_t^2$ = Conditional variance

In this manuscript, we are using GARCH (1, 1) instead of GARCH (2, 2), which may apply. So the GARCH (1, 1) is as Eq. 2.

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_1 \sigma_{t-1}^2 + \sum_{j=1}^{p} b_1 \sigma_{t-1}^2 \quad (2)$$

After the calculation of GARCH (1, 1) value, The Monte-Carlo technique is used for the finding of valuable coefficients of GARCH (1, 1) using as Eq. 3 [25].

$$\bar{X} = \frac{1}{N} \sum_{i=1}^{N} f(X^i) \qquad (3)$$

Where,

$\bar{X}$ = Random number fluctuating around the theoretically expected value

$N$ = number of expected value

$X$ = Expectation value

*B. Second hybrid technique (SHT): -*

This second HT is developed by working of GARCH, EGARCH, GJR, and PSO models, as shown in Figure 4. The following steps are carried out.

Step-1: GARCH, EGARC, GJR are defined.

Step-2: Each model is applied to require data sample for forecasting propose

Step-3: Finally, PSO will be used for the smoothness of the required forecasting result.

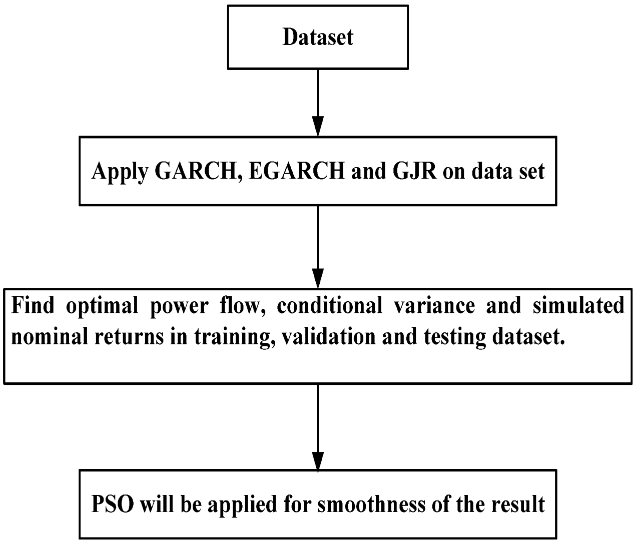


**Figure 4.** Schematic of the proposed model

*1) GARCH*

The conditional variance is significant in autoregressive as well as moving average structure, which is calculated by the application of the GARCH model. In this model, the constraints factor is limited to 1.

The GARCH model is defined as Eq. 1. This model allows the present and past conditional variance with past returns, calculated by the GARCH model. This model is also extended with the addition of some other factors.

*2) EGARCH*

This model is the difference from the GARCH model because it is the logarithm of conditional variance, which simulates the asymmetries between positive as well as negative shocks, and it will make the exponential effect of leverage.

In this model, there is no limit of parameters, and the conditional variance is straightforward as the standardized shocks have finite values. It is defined as Eq. 4.

$$\ln(\sigma_t^2) = a_0 + \sum_{i=1}^{q} a_i \frac{|\sigma_{t-i}| + c_i \sigma_{t-i}}{\sigma_{t-1}} + \sum_{j=1}^{p} b_j \ln(\sigma_{t-j}^2) \quad (4)$$

Where,

$p$ = Order of GARCH process

$q$ = Order of ARCH process

$a_0, a_i, b_j$ = Constants

$c_i$ = Leverage parameter

$\sigma_t^2$ = Conditional variance

*3) GJR*

It is used to solve the asymmetric problem by present conditional variance, which is used for past positive and negative returns.

GJR will be defined in Eq. 5 & Eq.6

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i \sigma_{t-i}^2 + \sum_{j=1}^{p} b_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \eta_i \sigma_{t-i}^2 l_{t-i} \quad (5)$$

Where,

$p$ = GARCH method order

$q$ = ARCH method order

$a_0, a_i, b_j$ = Constants

$\eta_i$ = Leverage parameter

$$l_t = Dummy\ \mathrm{var}\,iable = \begin{cases} 1, if\ \sigma_{t-i} < 0 \\ 0, otherwise \end{cases} \quad (6)$$

$\sigma_t^2$ = Conditional variance

*4) PSO*

The characteristic of this model is determined by a group of birds as well as educate of fishes. The self-speed and neighbor's speed are calculating the factors of individual birds in a swarm.

By this behavior, the particles are reaching to a suitable position. The speed, as well as the place of the particle, is determined as Eq. 7 and Eq. 8.

$$v_{ij}^{t+1} = wv_{ij}^t + c_1 r_{1j}^t (p_{ij}^t - x_{ij}^t) + c_2 r_{2j}^t (p_{gj}^t - x_{ij}^t) \quad (7)$$

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \quad (8)$$

Where,

$v$ = Speed of the particle

$x$ =Place of particle

$w$ = The constraint of Inertia weight

$c_1$ = Cognitive coefficient

$c_2$ = Social coefficient

$r_{1j}, r_{2j}$ = Random quantities whose value lies between 0 and 1.

$p_{ij}$ = Position of $i^{th}$ particle for $j^{th}$ dimension

$p_{gj}$ =Global Position of particle for $j^{th}$ dimension

*C. The proposed hybrid modeling techniques*

*1) First hybrid technique (FHT): -*

This approach consists of a wavelet that decomposes the original data, GARCH (1, 1) process the decomposition data, and then the Monte-Carlo technique is using for finding out the GARCH coefficients. The following steps describe the detail work.

1. Step-1: - The wavelet analysis is applied to break the first sample of data.
2. Step-2: - The decomposition data is processed through the GARCH (1, 1) model.
3. Step-3: - GARCH (1, 1) coefficient is found by the Monte-Carlo technique.
4. Step-4: - Forecasting result is found by random permutation and algorithms of the first sample of data.
5. Step-5: - Second sample of data is seen by the repetition of Step-1 to Step-4.

*2) Second hybrid technique (SHT): -*

This approach consists of GARCH, EGARCH, GJR and PSO. The training process founds the forecasting result. The training process founds the forecasting result and its accuracy is defined by mean absolute error (MAE) as well as root mean square error (RMSE) [26]. The following steps describe the detailed work.

1.Step-1: - Each model is defining.
2. Step-2: - Each model is tested with data samples.
3. Step-3: -Forecasting result is obtained.
4. Step-4: PSO acquires -Smoothness of forecasting result.
5. Step-5: - The result is found by the repetition of Step-1 to Step-4.

*D. Forecasting accuracy evaluation*

The MAE (mean absolute error) and RMSE (root mean square error) as Eq. 9 and Eq. 10, respectively, are using to find out the error.

$$MAE = \frac{1}{T}\sum_{i=1}^{T} |y_i - \hat{y}| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T} (y_i - \hat{y}_i)^2} \quad (10)$$

Where,

$y_i$ =Actual price / load

$\hat{y}_i$ = Forecasted price/ load

$T$ = Number of forecasting

## III. Case Study

*A. Forecasting results of FHT*

The required technique is used in Ontario dataset to design the wavelet-GARCH method for price forecasting in STLF. The actual prices and forecasted prices are given in Table 1(a) for Figures 5(a-c) and 6(a-c). The forecasted prices are excellent as compared to other techniques [27], which is using ANN, fuzzy logic, and a combination of both techniques for the price forecasting as given in Table 1(b).

*Table 1(a). Comparisons between actual and forecasted prices*

| Time (hr.) | Actual Price (Rs.) | Forecasted Price (Rs.) |
|---|---|---|
| 1 | 93.25 | 9.2117 |
| 2 | 44.14 | 21.1437 |
| 3 | 40.26 | -84.2634 |
| 4 | 38.58 | 87.5299 |
| 5 | 67.65 | -87.4012 |
| 6 | 44.99 | -2.7660 |
| 7 | 45.49 | 24.0553 |
| 8 | 51.07 | 12.8356 |
| 9 | 57.47 | -13.727 |

| | | |
|---|---|---|
| 10 | 53.3 | 53.3442 |
| 11 | 39.56 | -43.2401 |
| 12 | 39.43 | 160.4599 |
| 13 | 56.43 | -10.0248 |
| 14 | 39.47 | 8.3737 |
| 15 | 38.26 | 78.4054 |
| 16 | 42.85 | 0.3745 |
| 17 | 37.14 | -17.6981 |
| 18 | 49.18 | -36.0279 |
| 19 | 58.28 | 83.1318 |
| 20 | 48.36 | 28.0095 |
| 21 | 42.08 | -13.4893 |
| 22 | 57.51 | 65.7122 |
| 23 | 44.55 | -5.2766 |
| 24 | 47.63 | -61.7319 |
| 25 | 42.8 | 84.9926 |
| 26 | 43.67 | 27.8619 |
| 27 | 45.08 | -49.1221 |
| 28 | 44.42 | -56.9905 |
| 29 | 57.42 | -72.0425 |
| 30 | 41.47 | 121.0806 |

The negative sign in forecasted Price indicates the reduction of Price.

*Table 1(b). Comparisons between actual and forecasted prices*

| Time (hr.) | Actual Price ($) | Forecasted Price ($) |
|---|---|---|
| 55 | 990 | 200 |
| 75 | 420 | 100 |
| 212 | 820 | 220 |
| 225 | 790 | 220 |
| 250 | 420 | 220 |
| 375 | 320 | 100 |
| 450 | 390 | 100 |
| 475 | 730 | 100 |

During this peak period, the forecasted prices are significantly less than the actual price because of the outage of the generator and new bidding strategies of market participants.

*B. Simulation environment*

The simulation environment is performed by MATLAB 2010a software. The whole investigation has been carried out by developing vital optimization programs and testing real-time forecasted data. Table 1 and Table 9 present the actual and forecasted values of Price and load, respectively.

*C. Simulation results of FHT*

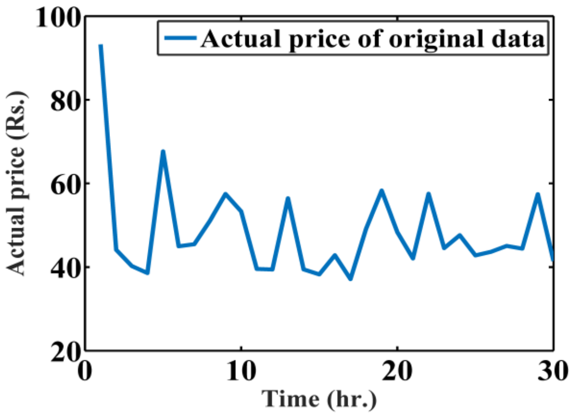


**Figure 5(a).** Actual prices of original data

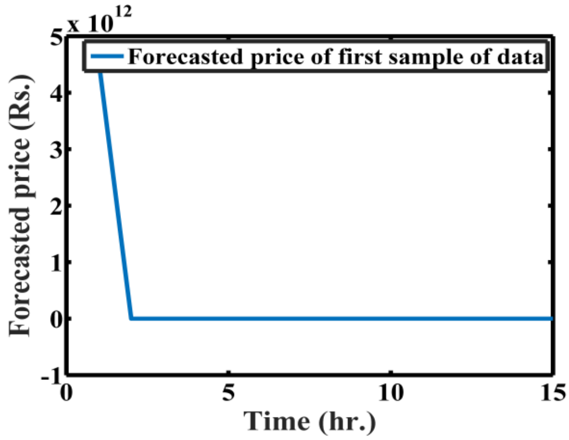


**Figure 5(b).** Forecasted prices of the first sample of data

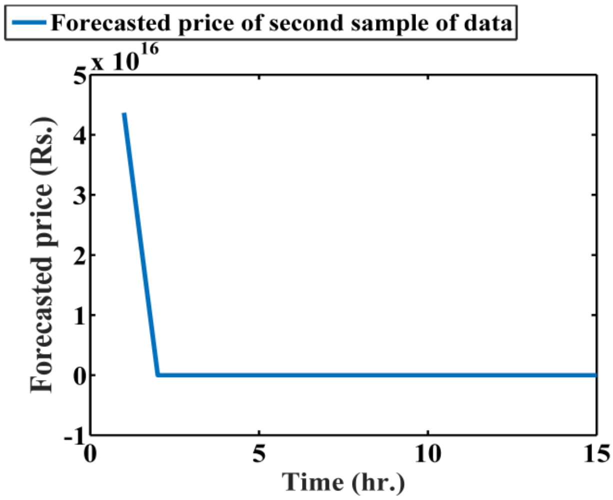


**Figure 5(c).** Forecasted prices of the second sample of data

Figure 5(a) gives a variety of actual Price concerning time and these values help in the prediction of future Price in the Ontario power plant. Figures 5(b) and 5(c) give the control of price in the predicted value by liner increasing and decreasing for the first and second halves of 15 samples of the actual Price. In Figures 5(b) and 5(c), the forecasted prices are simultaneously decreasing because it depends on the utilization of electricity by consumer needs.

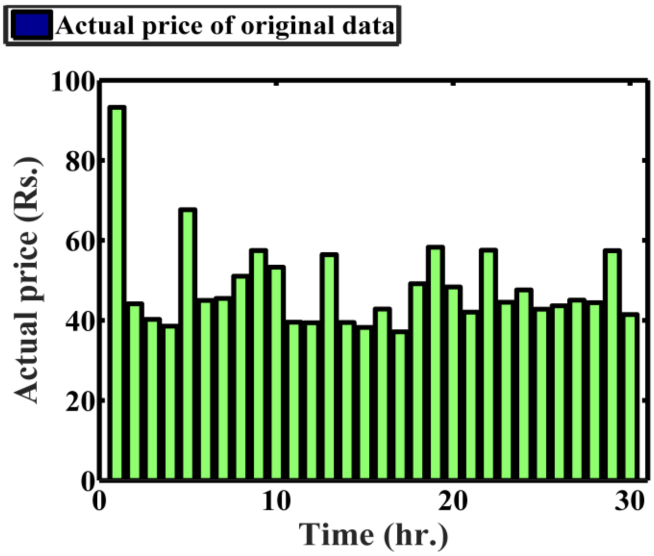


**Figure 6(a).** Actual prices of original data

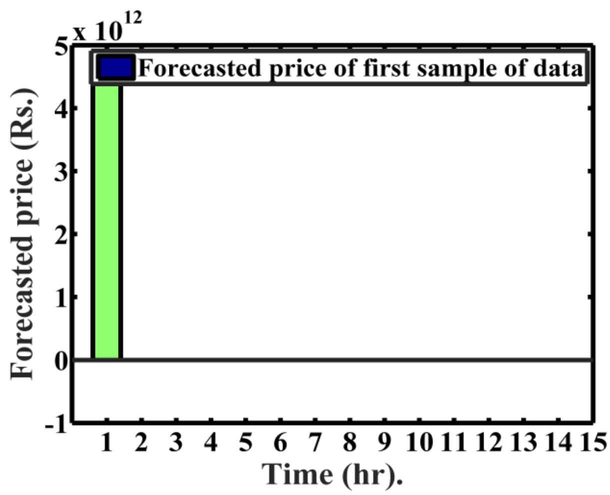


**Figure 6(b).** Forecasted prices of the first sample of data

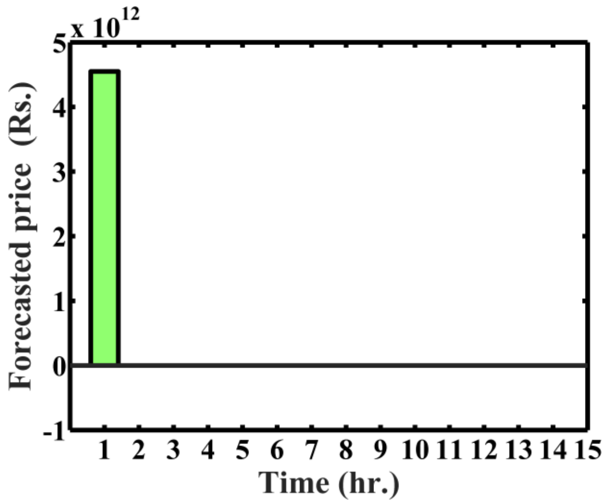


**Figure 6(c).** Forecasted prices of the second sample of data

The trend of the histogram in Figure 6(a) shows the operation of the Ontario power plant with actual price value in bar form. Figure 6(b) and Figure 6(c)'s histogram trend indicates the control of Price in the predicted value for the first and second halves of 15 samples of the actual Price. The forecasted price value depends on the utilization of electricity by consumer needs. So the predicted price is less in Figure 6(b) and more in Figure 6(c).

*D. Forecasting results of SHT*

The Xinati power plant is placed in the Hebei territory of China, where we are considering the hourly basis load and weather data. These data are used for determining the effectiveness of load in STLF.

These data, as given in Table 2, are considering from 10th June 2006 t0 30th June 2006, which is called as historical data sample. The three segments classify these information samples, i.e., initial, checking, and confirmatory information samples.

*Table 2. Data sample*

| DATE(2016) | POWER LOAD (MW) | WEATHER LOAD |
|---|---|---|
| 6.10 | 897 878 826 830 824 854 1037 1094 1176 1272 1300 1317 1281 1304 1286 1287 1286 1178 1034 | 0.2385 0.2125 0 |
| 6.11 | 930 892 890 846 832 890 1059 1136 1181 1273 1331 1359 1321 1250 1223 1259 1299 1336 1364 1343 1354 1383 1271 1131 | 0.2152 0.2101 0 |
| 6.12 | 1025 982 944 921 916 987 1142 1246 1277 1359 1408 1441 1460 1380 1342 1322 1378 1379 1390 1389 1408 1345 965 796 | 0.2415 0.1027 0 |
| 6.13 | 750 733 703 697 718 716 820 937 976 1048 1115 1165 1153 1006 957 949 959 1023 1052 1066 1074 1055 937 843 | 0.2421 0.1423 0 |
| 6.14 | 776 788 750 754 766 785 956 1052 1139 1240 1273 1335 1321 1254 1241 1274 1333 1345 1349 1346 1351 1338 1237 1096 | 0.2154 0.1212 0 |
| 6.15 | 970 930 901 898 882 968 1129 1238 1272 1344 1400 1412 1427 1337 1285 1333 1362 1395 1432 1388 1379 1371 1283 1134 | 0.2523 0.3124 0 |
| 6.16 | 1044 998 959 952 975 1075 1276 1316 1381 1448 1498 1559 1549 1456 1407 1437 1506 1509 1518 1445 1453 1440 1338 1194 | 0.2103 0.2126 0 |
| 6.17 | 1066 1028 983 981 1000 1080 1305 1398 1438 1534 1559 1583 1583 1515 1498 1512 1547 1589 1611 1623 1589 1587 1493 1315 | 0.2156 0.2470 0 |
| 6.18 | 1223 1154 1122 1087 1099 1199 1386 1466 1515 1594 1620 1678 1619 1565 1512 1537 1591 1628 1649 1613 1647 1650 1568 1391 | 0.2380 0.2416 0 |
| 6.19 | 1250 1194 1175 1122 1085 1215 1395 1453 1513 1612 1672 1723 1698 1657 1608 | 0.2351 0.3215 0 |

| | | |
|---|---|---|
| | 1600 1567 1627 1608 1513 1486 1477 1420 1304 | |
| 6.20 | 1169 1136 1070 1060 1057 1137 1330 1408 1470 1541 1595 1640 1566 1550 1533 1564 1580 1572 1585 1567 1509 1493 1406 1244 | 0.2419 0.2780 0 |
| 6.21 | 1144 1096 1039 983 938 1016 1222 1358 1443 1539 1570 1571 1518 1443 1408 1470 1511 1532 1517 1519 1440 1380 1290 1129 | 0.2411 0.2801 0 |
| 6.22 | 1039 985 977 934 944 1037 1227 1332 1461 1548 1597 1625 1571 1453 1429 1477 1526 1528 1514 1478 1411 1377 1307 1138 | 0.2512 0.2456 0 |
| 6.23 | 1056 991 982 949 938 1033 1243 1322 1430 1536 1587 1622 1544 1447 1408 1451 1540 1567 1565 1548 1501 1480 1374 1224 | 0.2123 0.1476 0 |
| 6.24 | 1102 1039 990 951 947 1037 1249 1353 1419 1543 1608 1591 1549 1423 1392 1432 1504 547 1580 1486 1400 1373 1251 1095 | 0.2416 0.2134 0 |
| 6.25 | 996 948 925 881 908 984 1227 1317 1410 1513 1578 1566 1525 1449 1369 1430 1471 1442 1384 1287 1261 1311 1224 1077 | 0.2751 0.2347 0 |
| 6.26 | 994 938 939 901 912 991 1182 1310 1356 1488 1513 1533 1490 1435 1384 1444 1497 1581 1576 1551 1474 1448 1379 1252 | 0.2415 0.2556 0 |
| 6.27 | 1135 1079 1033 999 988 1091 1290 1392 1445 1557 1608 1599 1557 1465 1401 1434 1501 1579 1561 1585 1537 1520 1441 1326 | 0.2315 0.2647 0 |
| 6.28 | 1196 1104 993 821 760 728 729 800 838 934 973 1047 1069 1018 1013 1079 1092 1116 1083 1096 1060 1112 1036 954 | 0.2372 0.2502 1 |
| 6.29 | 861 828 800 798 787 799 845 912 982 1090 1122 1181 1174 1122 1092 1151 1199 1204 1207 1167 1177 1238 1168 1033 | 0.2134 0.2199 0 |
| 6.30 | 943 914 907 875 873 872 931 976 1062 1144 1213 1263 1231 1196 1150 1190 1212 1231 1223 1228 1245 1317 1214 1081 | 0.2385 0.2125 0 |

As given in Table 3 and the data samples are normalized within the range of [0,1] for better results for Figs. 7-15 and Tables 4-9.

*Table 3.Classification of information samples*

| Information | Date (June 2006) |
|---|---|
| Initial | 10th to 21st |
| Checking | 22nd to 28th |
| Confirmatory | 30th |

*E. Simulation results of SHT*

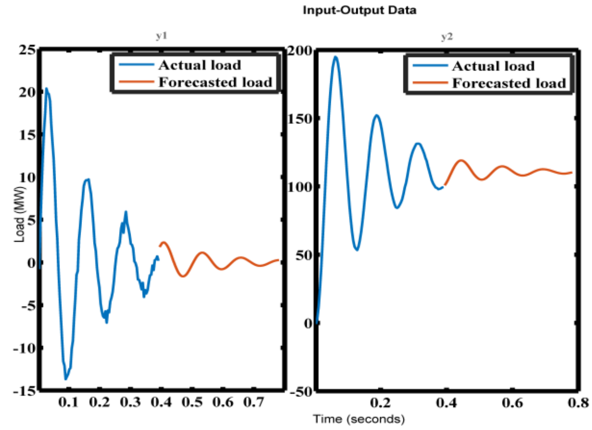


**Figure 7.** Comparison of optimal power flow with input and output data

Figure 7 shows the flow of power for input and output data respectively, where some disturbances are present in input data. These disturbances are controlled in output value with the help of a simulation technique during the running of the Xintai power plant.

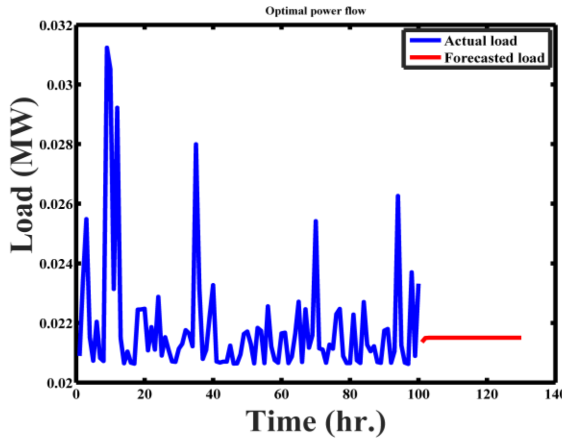


**Figure 8.** Optimal power flow using GARCH model

Figure 8 shows the control of power from decreasing in forecasted value concerning actual value using the GARCH model, which helps to bring a good result.

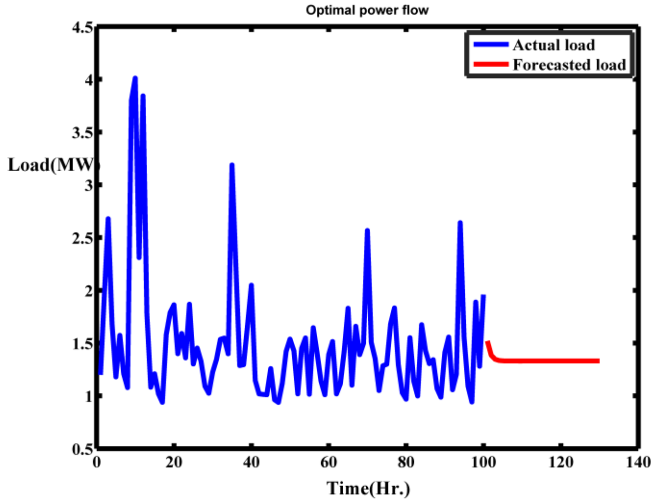


**Figure 9.** Optimal power flow using EGARCH model

Figure 9 shows the control of power in forecasted value using the EGARCH model. This trend indicates increasing in power.

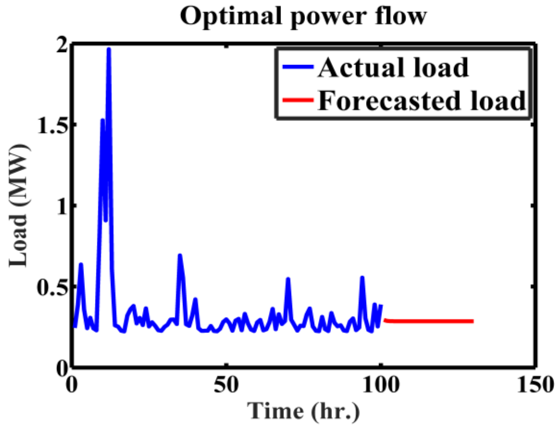


**Figure 10.** Optimal power flow using GJR model

In Figure10, the trend shows the control of power in forecasted value and it can be noticed from the trend that by using the GJR model, fluctuation of power is removed.

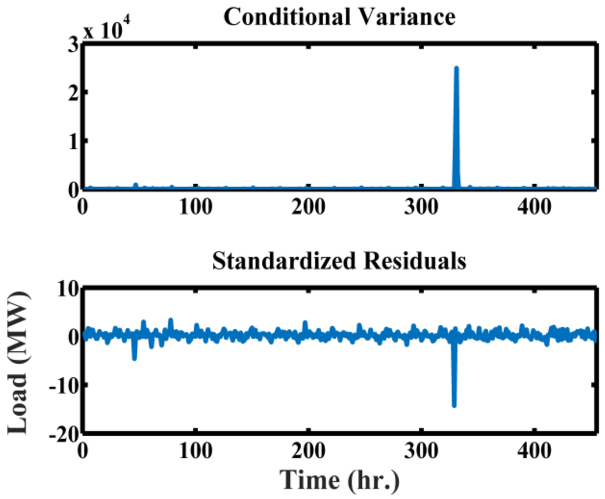


**Figure 11.** Calculation of conditional variance and standardized residuals during the training process

In Figure 11, the trend of the curve shows the accurateness of predicted value by the selection of conditional variance and standardized residuals value during the training of the data. The load is sudden with rise and fall in the time of 330 hrs because of some external factors like sunny day, winter day and cloudy day which in turn affects the load. This is removed by the calculation of conditional and standardized residual values.

*Table 4. GARCH (0, 1) model of conditional variance*

| Parameter | Value | Standard error | t statistic |
|---|---|---|---|
| Constant | 21.1043 | 3.35604 | 6.28845 |
| ARCH{1} | 0.426346 | 0.139877 | 3.04801 |
| DoF | 3.7281 | 0.455675 | 8.1815 |

Table 4 gives the parameter value of the GARCH (0, 1) model for optimal power flow by the selection of constant, ARCH and DoF values during the calculation of conditional variance.

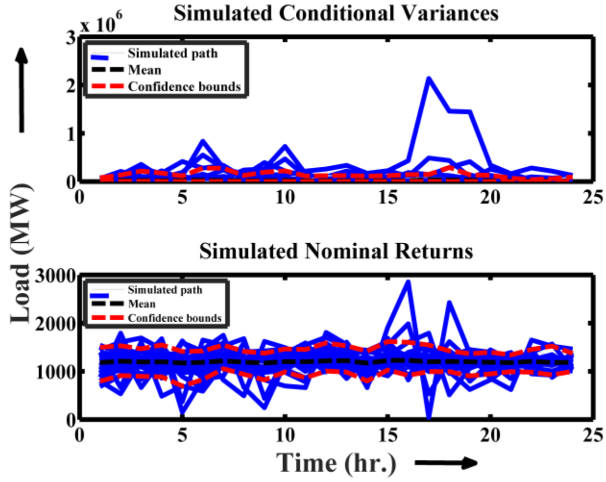


**Figure 12.** Calculation of simulated conditional variance and simulated nominal returns during the testing process

Figure 12 shows the paths of optimal power flow using the simulated approach, mean and conditional bounds during the simulation of conditional variance and nominal return in the testing of data.

*Table 5. GARCH (1, 1) model of conditional variance*

| Parameter | Value | Standard error | t statistic |
|---|---|---|---|
| Constant | 906.807 | 1776.13 | 0.510551 |
| GARCH {1} | 0.220487 | 0.309414 | 0.712594 |
| ARCH{1} | 0.741176 | 0.882933 | 0.839448 |
| Offset | 1195.86 | 13.7879 | 86.7331 |

Table 5 also gives the design value of the parameter for optimal power flow by selecting constant, GARCH, ARCH and offset values during the calculation of conditional variance in the GARCH (1, 1) model.

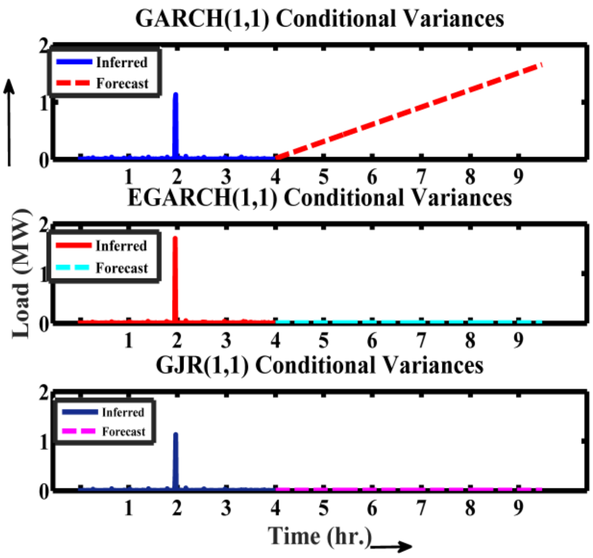


**Figure 13.** Calculation of conditional variance with GARCH, EGARCH, and GJR during the testing process

In Figure 13, the trend shows a reduction of fluctuation of load by calculation of conditional variance during the testing operation. It also indicates a decrease in errors.

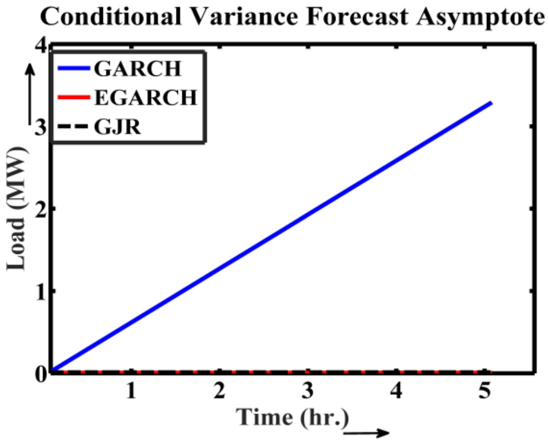


**Figure 14.** Effect of load with GARCH, EGARCH, and GJR during the training process

Figure 14 indicates the noise-free curve of the loads acquired during the training of data using GARCH, EGARCH and GJR model.

*Table 6. GARCH (0, 1) model of conditional variance*

| **Parameter** | **Value** | **Standard error** | **t statistic** |
|---|---|---|---|
| Constant | 0.00327603 | 0.000445629 | 7.35148 |
| ARCH{1} | 1 | 0.182348 | 5.48403 |

*Table 7. EGARCH (1, 1) model of conditional variance*

| **Parameter** | **Value** | **Standard error** | **t statistic** |
|---|---|---|---|
| Constant | -4.42063 | 0.93212 | -4.74256 |
| GARCH {1} | 0.128253 | 0.178401 | 0.7189 |
| ARCH{1} | 1 | 0.182348 | 5.48403 |
| Leverage{1} | 0.458658 | 0.0820929 | 5.58706 |

*Table 8. GJR (0, 1) model of conditional variance*

| **Parameter** | **Value** | **Standard error** | **t statistic** |
|---|---|---|---|
| Constant | 0.00364592 | 0.000397661 | 9.1684 |
| ARCH{1} | 1 | 0.159196 | 6.28157 |
| Leverage{1} | -0.0671856 | 0.126273 | -5.32068 |

Tables 6, 7, and 8 give the design value of the parameter model for optimal power flow in GARCH (0, 1), EGARCH (1, 1) and GJR (0, 1) models respectively during the calculation of conditional variance with the choice of constant, ARCH, GARCH and Leverage values.

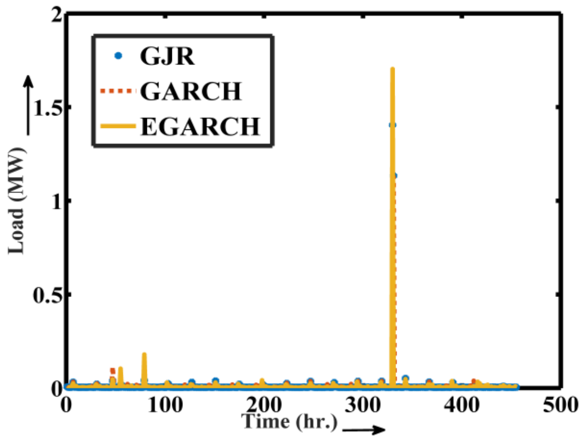


**Figure 15.** The smoothness of result using PSO

Figure 15 shows the accurateness of predicted load and smoothness of the result using PSO for GARCH, EGARCH and GJR models.

*Table 9. Load forecasting results of different models*

| **Time (hr.)** | **GARCH** | | **EGARCH** | | **GJR** | |
|---|---|---|---|---|---|---|
| | **Actual load (MW)** | **Fore cast load (MW)** | **Actual load (MW)** | **Fore cast load (MW)** | **Actual load (MW)** | **Fore cast load (MW)** |
| 1 | 0.012 | 0.02 | 0.006 | 0.02 | 0.009 | 0.02 |
| 50 | 0.003 | 0.18 | 0.003 | 0.18 | 0.003 | 0.18 |
| 100 | 0.003 | 0.02 | 0.002 | 0.02 | 0.003 | 0.02 |
| 150 | 0.009 | 0.03 | 0.014 | 0.03 | 0.009 | 0.03 |
| 200 | 0.004 | 0.01 | 0.005 | 0.01 | 0.005 | 0.01 |
| 250 | 0.007 | 0.01 | 0.008 | 0.01 | 0.007 | 0.01 |
| 300 | 0.003 | 0.01 | 0.004 | 0.01 | 0.004 | 0.01 |
| 350 | 0.005 | 0.01 | 0.004 | 0.01 | 0.004 | 0.01 |
| 400 | 0.003 | 0.01 | 0.004 | 0.01 | 0.004 | 0.01 |
| 450 | 0.003 | 0.01 | 0.003 | 0.01 | 0.003 | 0.01 |

Table 9 shows the predicted load concerning actual load and the MAE (Mean absolute error) of GARCH, EGRCH, and GJR is 0.0258, 0.0257, 0.0259, and the RMSE of GARCH, EGARCH, and GJR is 0.0568.

## IV. Result and Discussion

The wavelet calculates the forecasting prices and GARCH model using Monte-Carlo simulation, and the forecasting prices are compared with actual prices as given in Table 1(a). Here, the Monte-Carlo simulation predicts the Price sensitively with the decomposition of data and its analysis by wavelet and GARCH model, respectively, in FHT. Figure 5(a) explains the actual price flow of the Ontario power plant, which helps to predict Price in-terms two half of sample data. Figure 5(b) gives the first half of 15 sample data of the expected price, and the forecasted price is more, and Figure 5(c) gives the second half of 15 sample data of the predicted price, and the forecasted price is less. These two figures, Figure 5(b) and Figure 5(c), bring the expected price value of the Ontario plant, which reduces the cost of electricity. Figure 6(a) gives the actual value of Price in bar form for which the Ontario power plant operates. Figures 6(b) and 6(c) describe the predicted Price with the help of wavelet and GARCH models in bar form for the control of Price.

In SHT, the actual load is tested by GARCH, EGARCH, and GJR models, as given in Table 2. After that, the tested load is run by PSO for smoothness, which brings good results in the predicted value, as shown in Table 9. Figure 7 gives the load flow of input and output data during the running of the Xintai power plant. The GARCH model represents the reduction of the variation of the load from decreasing to constant in Figure 8. In Figure 9, the predicted load is constant by the decrease in the fluctuation of the load from increasing with the help of the EGARCH model. The GJR model helps to control the change of the predicted load in Figure 10. Figure 11 brings good results in the expected load by the help of conditional variance and standardized value of data during the training period. Figure 12 describes the path of simulated conditional variance and simulated nominal returns during the testing of data where the simulated approach, mean, and conditional boundary removes the unwanted data for the accurateness of the result. In Figure 13, the conditional variance of testing data reduces the fluctuation of the load. While Figure 14 describes the noise-free of load during the training period. Figure 15 brings smoothness of the predicted load and gives accurateness in the result. Tables 4 and 5 help in the design of the parameters for the optimal power flow by the GARCH model concerning the Figures 12 and 13, respectively. Similarly, Tables 6, 7, and 8 also describe the design value of GARCH, EGARCH, and GJR model for the smoothness of the power flow.

## V. Conclusion

This manuscript explains the development of the model for the effect of Price and load on STLF using hybrid techniques (HT). In this study, we concluded that in the first hybrid technique (FHT), the original data is decomposed by wavelet. Then GARCH (1,1) is estimated using decomposition data as well as the Monte-Carlo technique is using for the calculation of GARCH (1, 1) coefficients. In the second hybrid technique (SHT), each model is defined with specific conditions, and each model helps process the data sample. Then the output of the model is optimized through PSO for smoothness of the result. Finally, the random permutation and algorithm are used to find out the forecasting result. These hybrid techniques (HT) are the best methods for predicting Price, and load in STLF is seen from the result.

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