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Advanced Local Predictors Based Short-Term Load Forecasting for Unit Commitment Scheduling

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***Abstract* – Theunit commitment (UC) problem is the problem of deciding which electricity generation units should be scheduled economically in a power system in order to meet therequirements of load and spinning reserve.In this paper, the UC problem is solved for an optimum schedule of generating units based on the load data forecasted using advanced local predictors. These local predictors are local support vector regression (LSVR) and local radial basis function (LRBF) Low-cost generation is important in power system analysis. Under forecasting or over forecasting will result in the requirement of purchasing power from spot market or an unnecessary commitment of generating units. Accurate load forecasting is the first step to enhance the UC solution. Total costs calculated for the actual load and two different forecasting load data are compared. A 10-units test system is used for this analysis. The results show the importance of accurate load forecasting to UC.**

***Keywords* – Dynamic Programming, Kernel Principal Component Analysis, Load Forecasting, Local Radial Basis Function, Local Support Vector Regression, Unit Commitment.**

I. INTRODUCTION

Short term load forecasting (STLF) is a vital part of the operation of power systems. STLF aims to predict electric loads for a period of minutes, hours, days, or weeks. STLF has always been a very important issue in economic and reliable power systems operation such as unit commitment, reducing spinning reserve, maintenance scheduling, etc. Sophisticated forecasting tools with higher accuracy are necessary to achieve lower operating costs and higher reliability of the electricity supply.

Because of its importance, STLF has been widely researched and a number of models were proposed during the past few decades. These can be classified as either traditional or artificial intelligence (AI) based techniques. The former include time series predictors such as the linear or multiple regression [1], autoregressive moving average exogenous variable (ARMAX) model [2] and Kalman filtering [3]. These methods are based on a linear regression model and cannot always represent the nonlinear characteristics of complex loads [4].

Various AI techniques were used for STLF, such as artificial neural networks (ANNs) [5], expert systems [6], radial basis function (RBF) [7] and fuzzy-neural models [8]. These are very suitable because of their ability not only to learn time series load curves but also to model an unspecified nonlinear relationship between the load and its influencing factors [4].

Recently, SVR [9], [10] has also been applied successfully to STLF. SVR replaces the empirical risk minimization which is generally employed in the classical methods such as ANNs, with a more advantageous structural risk minimization principle. SVR has been shown to be very resistant to the over fitting problem and give a high generalization performance in forecasting problems [11].

All the above techniques are known as global predictors in which a predictor is trained using all data available but give a prediction using a current data window. The global predictors suffer from some drawbacks which are discussed in our previous work [12], [13]. To overcome these drawbacks, the local RBF(LRBF) and the local SVR (LSVR) predictors are proposed in our previous work [12]–[14] and used to solve the short term load forecasting problem.

Unit commitment problem (UC) is a nonlinear, mixed integer combinatorial optimization problem. The UC problem is the problem of deciding which electricity generation units should be scheduled economically in a power system in order to meet the requirements of load and spinning reserve. It is a difficult problem to solve in which the solution procedures involve the economic dispatch problem as a sub-problem. Since UC searches for an optimum schedule of generating units based on load forecasting data, the improvement of load forecasting is first step to enhance the UC solution [15].

In this paper, we propose UC method to reduce the production cost by combining load forecasting with UC problem. First, short-term loads are forecasted using LSVR, and LRBF models. Then UC problem is solved using the dynamic programming method.

We have chosen the historical data for the South Australia electricity market, which includes the power demand for the period of 2003-2005. Historical weather data was collected from Macquarie University Web Site [16]. Then the forecasted loads are fed into 10-units test system for unit commitment to show the reactions of unit commitment to forecasting errors.

The paper is organized as follows: Section II discusses the STLF based local methods. A review of the UC problem, its formulation and its solution are presented briefly in Section III. Applications and simulations for STLF and UC problem are given in Sections IV and V, respectively. Finally, Section VI concludes the work.

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II. Short Term Load Forecasting Based Local Predictors

A. Phase Space Reconstruction Based on KPCA

Due to the complexity of the historical load data and the uncertainty of the influencing factors such as weather, economical, and random factors, the time series reconstruction technique can be applied to the power load forecasting. The traditional time series reconstruction techniques such as the coordinate delay (CD) method have a serious problem which is discussed in [14], [17]. To overcome this problem, the kernel principal component analysis (KPCA) is used recently to process the nonlinear time series [17].

The main idea of KPCA is first to map the original inputs into a high dimensional feature space via a kernel map, which makes data structure more linear, and then to calculate principal components in the high-dimensional feature space [18].

Suppose there is a set of data $X = \{x_i\}_{i=1}^{N}$ where each $x_i \in \Re^n$ and the mean value E[X] = 0. By mapping x_i into $\Phi\{x_i\}$, KPCA solves the Eigenvalue as following [17]:

$$\lambda_i \upsilon_i = \tilde{C}\upsilon_i, \quad i = 1,2,\ldots,N \tag{1}$$

where, $\tilde{C} = (1/N)\sum_{i=1}^{N}\Phi(x_i)\Phi(x_i)^T$ is the sample covariance matrix of $\Phi\{x_i\}$, λ_i is one of the non-zero Eigenvalues of $\tilde{C}$ and υ_i is the corresponding Eigenvector.

There exist coefficients α_i (i=1,2,…,N) meet:

$$\upsilon_i = \sum_{j=1}^{N}\alpha_i(j)\Phi(x_j) \tag{2}$$

Where, $\alpha_i(j)$ are the components of α_i. Assuming the Eigenvector of $\Phi\{x_i\}$ is of unit length $\upsilon_i \cdot \upsilon_i = 1$, each α_i must be normalized using the corresponding Eigenvalue $\tilde{\alpha}_i = \alpha_i / \sqrt{\alpha_i \lambda_i}$, i=1,2,…,N.

Finally, the principal component for xi, based on $\tilde{\alpha}_i$ can be calculated as following:

$$p_t(i) = \upsilon_i^T \Phi(x_t) = \sum_{j=1}^{N}\tilde{\alpha}_i(j)Q(x_j, x_t), \quad i = 1,2,\ldots,N \tag{3}$$

Where, Q is an $N \times N$ matrix called kernel function. From (3), one can notice that, the maximal number of principal components that can be extracted by KPCA is N. The dimension of p_t can be reduced in KPCA by considering the first several Eigenvectors that is sorted in descending order of the Eigenvalues.

In this paper, we employ the commonly used Gaussian kernel defined as:

$$Q(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right) \tag{4}$$

B. Support Vector Regression (SVR)

The basic idea of SVR is to map the data x into a high dimensional feature space via a nonlinear mapping, and perform a linear regression in that feature space [10] as:

$$f(x) = \langle w, x\rangle + b \tag{5}$$

Where⟨., .⟩denotes the dot product, w contains the coefficients that have to be estimated from the data and b is a real constant. Using Vapink'sε–insensitive loss function [9], the overall optimization is formulated as:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}w^T w + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$$

$$\text{subject to}\begin{cases} y_i - (w^T\phi(x_i) + b) \le \varepsilon + \xi_i^* \\ (w^T\phi(x_i) + b) - y_i \le \varepsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0, \qquad i = 1,\ldots,N \end{cases} \tag{6}$$

where, xi is mapped to higher dimensional space by the function ϕ, ε is a real constant, ξ_i and ξ_i^* are slack variables subject to ε-insensitive zone and the constant C determines the trade-off between the flatness of f and training errors.

Introducing Lagrange multipliers αi and α_i^* with $\alpha_i\alpha_i^* = 0$ and $\alpha_i, \alpha_i^* = 0$ for i=1,…,N, and according to the Karush-Kuhn-Tucker optimality conditions [10], the SVR training procedure amounts to solving the convex quadratic problem:

$$\min_{\alpha,\alpha^*} \frac{1}{2}\sum_{i,j=1}^{N}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) + \varepsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) - \sum_{i=1}^{N}y_i(\alpha_i - \alpha_i^*)$$

$$\text{subject to}\begin{cases} 0 \le \alpha_i, \alpha_i^* \le C \\ \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0, i = 1,\ldots, N \end{cases} \tag{7}$$

The output is a unique global optimized result that has the form:

$$\hat{y} = \hat{f}(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)Q(x_i, x) + b \tag{8}$$

where, $Q(x_i,x)=\phi(x_i)\cdot\phi(x)$. Using kernels, all necessary computations can be calculated directly in the input space, without computing the explicit map $\phi(x)$. Various kernel types exist such as linear, hyperbolic tangent, Gaussian, polynomial, etc. [10]. Here, we employ the commonly used Gaussian kernel as defined by (4).

C. Local Predictors

Local prediction is concerned with predicting the future based only on a set of K nearest neighbors in the reconstructed embedded space without considering the historical instances which are distant and less relevant. Local prediction constructs the true function by subdivision of the function domain into many subsets

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(neighborhoods). Therefore, the dynamics of time series can be captured step by step locally in the phase space and the drawbacks of global methods can be overcome.

The LSVR and LRBF methods can be summarized as follows [12]:

First, reconstruct the time series using KPCA. For each query vector q, the K nearest neighbors$\{z_q^1, z_q^2, \ldots, z_q^K\}$among the training inputs is choosing using the Euclidian distance as the distance metric between the q and each z in the reconstructed time series. Using these Knearest neighbors, train the SVR (or RBF) to obtainsupport vectors and corresponding coefficients. Finally, the output of SVR (or RBF) can be computed.

III. Unit Commitment Problem Formulation

The objective of the UC is to minimize the system operating costs, which are the sum of production and startup costs of all units over the entire study time span, under the generator operational and spinning reserve constraints [19].

Mathematically, the objective function, or the total operating cost of the system can be written as follows [18], [20]:

$$\min_{P_i^t u_{it}} \left(\sum_{t=1}^{T} \sum_{i=1}^{N} u_i^t \left[F_i\left(P_i^t\right) + S_i^t \left(1 - u_i^{t-1}\right)\right]\right) \quad (9)$$

where P_i^t is the output power of unit i at period t, u_i^t is the commitment state of unit i at period t, $F_i\left(P_i^t\right)$ is the fuel cost of unit i at output power P_i^t , S_i^t is the start up price of unit i at period t, N is the number of generating unit and T is the total number of scheduling periods.

The constraints are as follows:

- Power balance:

$$\sum_{i}^{N} u_i^t P_i^t = D^t \quad (10)$$

where D^t is the customers' demand in time interval t.

- Generating limits: These limits definethe region within which a unit must be dispatched.

$$u_i^t P_i^{\min} \le P_i^t \le u_i^t P_i^{\max} \quad (11)$$

- Minimum up time: Once the unit is committed, it must be kept running for certain number of hours, called the minimum up time, before allowing turning it off. This can be formulated as follows:

$$\begin{aligned} &\left(X_{on,i}^{t-1} - T_i^{up}\right)\left(u_i^{t-1} - u_i^t\right) \ge 0 \\ &X_{on,i}^{t} = \left(X_{on,i}^{t-1} + 1\right) u_i^t \end{aligned} \quad (12)$$

where, $X_{on,i}^t$ is the number of hours the unit has been on line and T_i^{up} is the minimum up time.

- Minimum down time: Once the unit is turned off, it is not allowed to be brought online again before spending certain number of hours called minimumdown time. This can be formulated as follows:

$$\begin{aligned} &\left(X_{off,i}^{t-1} - T_i^{down}\right)\left(u_i^t - u_i^{t-1}\right) \ge 0 \\ &X_{off,i}^{t} = \left(X_{off,i}^{t-1} + 1\right)\left(1 - u_i^t\right) \end{aligned} \quad (13)$$

where $X_{off,i}^t$ is the number of hours the unit has been off line and T_i^{down} is the minimum down time.

- Spinning reserve: It can be modeled as follows

$$\sum_{i}^{N} u_i^t P_i^{\max} \ge D^t + R^t \quad (14)$$

where R^t is the spinning reserve requirements.

- Start up cost which can be modeled by the following form:

$$S_i^t = \begin{cases} HS^i, & \text{if } X_{off,i}^t \le T_i^{down} + CH^i \\ CS^i, & \text{if } X_{off,i}^t > T_i^{down} + CH^i \end{cases} \quad (15)$$

where, HS^i, CS^i is the unit's hot/cold start up cost and CH^i is the cold start hour.

Fuel cost functions $F_i\left(P_i^t\right)$ is frequently represented by the following polynomial function:

$$F_i\left(P_i^t\right) = a_i + b_i P_i^t + c_i \left(P_i^t\right)^2 \quad (16)$$

where a_i, b_i, c_i are the coefficients for the quadratic cost curve of generating unit i.

The details of the dynamic programming method which used in this paper can be found in [21], [22].

IV. Forecasting Results

In this paper, the performance of the LWSVR is tested and compared with local SVR and local RBF using hourly load and temperature data in South Australia. The load data used includes hourly load for the period of 2003-2005 for the South Australia electricity market. While the hourly temperature for the same period is collected from Macquarie university web site.

Choosing K is very important step in order to establish the local prediction model. There are some methods used in literatures to find this parameter such as cross validation [23] and bootstrap [24]. In this paper K is calculated using a systematic method which is proposed by us in [13]:

$$K = \text{round}\left(\frac{\alpha}{N \times k_{\max} \times D_{\max}} \sum_{i=1}^{N} \sum_{k=1}^{k_{\max}} D_k(x_i) \right) \quad (17)$$

where, N is the number of training points, k_{max} is the maximum number of nearest neighbors, $D_k(x_i)$ is the distance between each training point x and its nearest neighbors while D_{max} is the maximum distance, $\frac{1}{N \times k_{\max} \times D_{\max}} \sum_{i=1}^{N} \sum_{k=1}^{k_{\max}} D_k(x_i)$ is the average distance around the points which is inversely proportional to the local densities and α is a constant. The two constants k_{max} and α are very low sensitivity parameters.k_{max} can be

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chosen as a percentage of the number of training points (N) for efficiency while α can be chosen as a percentage. In this paper, k_{max} and α are always fixed for all test cases at 70% of N and 95, respectively.

In addition, the parameters of the KPCA algorithm which are the number of principal components (n_c) and σ^2 in the Gaussian kernel function are computed using the cross validation method. The values of these parameters are 13 and 1.05, respectively.

We quantified the prediction performance with the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). They can be defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|A(i) - F(i)\right| \tag{18}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|A(i) - F(i)\right|}{A(i)} \times 100 \tag{19}$$

where, A and F are the actual and the forecasted loads, respectively, n is the testing dataset size, and i denotes the test instance index.

To make results comparable, the same experimental setup is used for the three predictors. That is the week of February 15-21, 2005 has been used as attesting week. The available hourly load and temperature data (for the period of 2003-2005) are used to forecast the testing week.

First, we calculate the MAE and MAPE of each day during the testing week. Then the average MAE and MAPE values of each method for the testing week are calculated. The results are shown in Table I.

Table I : Forecasting Results

	LRBF	LSVR
MAE (GW)	0.0314	0.0213
MAPE (%)	2.3	1.55

These results show that, the LSVR method outperforms LRBF. It improves the MAE over LRBF by 32.2%. Whereas, it improves the MAPE over LRBF by 32.6%.

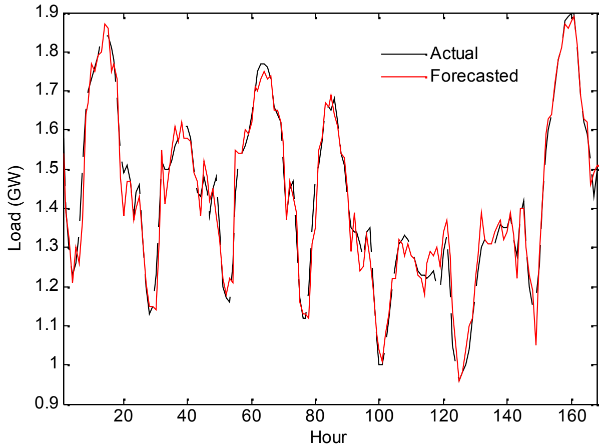

Fig.1. Forecasted and actual hourly load from 15th to 21st February 2005 using LRBF

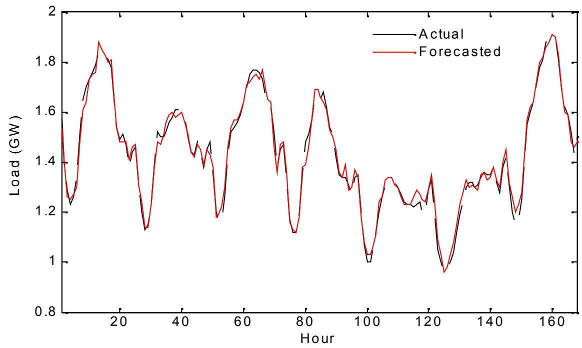

Fig.2. Forecasted and actual hourly load from 15th to 21st February 2005 using LSVR

Figs. 1-2 show the actual load and forecasted load values using LRBF and LSVR, respectively for the testing week. Theseresults show that the LSVR gives a better prediction performance than LRBF. However the forecasted values of both of them are very close to the actual values.

V. Forecasting Results In Unit Commitment

The results of load forecasting are fed into a 10-units system [25] which is selected as a test system. Table II shows the test system data. The spinning reserve is assumed to be 10% of the demand. The actual loads (24 hour) as well as the forecasted loads are given in Table III. Feasible unit combination and total cost (TC) values of the 10 units test system using dynamic programming method for load values and forecasting load values are given in Table IV. It is clear that accurate load forecasting is very important for the UC solution. The total cost of the forecasting load values for LRBF method is more than that of actual load values by $13140.6. Additionally, the total cost of the forecasting load values for LSVR is more than that of actual load values by $5016.

VI. Conclusion

In this paper, since high accuracy of the load forecasting for power systems improves the security of the power system and reduces the generation costs, the next day load forecasting using LWSVR method firstly made for solving the UC problem, for 10 units test system. Dynamic programming method is used for solving the UC problem. Total costs are calculated for load data which is taken from South Australia electricity market and forecasting load data computed by local RBF, local SVR and LWSVR, separately. Comparing these total costs show that accurate load forecasting is important for UC. Over-prediction of STLF wastes resources since more reserves are available than needed and, in turn, increases the operating cost. On the other hand, under-prediction of STLF leads to a failure to provide the necessary reserves which is also related to high operating cost due to the use of expensive peaking units.

Table II: Test System Data

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P^{max} (MW)	455	455	130	130	162	80	85	55	55	55
P^{min} (MW)	150	150	20	20	25	20	25	10	10	10
a ($/h)	1000	970	700	680	450	370	480	660	665	670
b ($/MWh)	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
c ($/MWh^2)	0.00048	0.00031	0.0020	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
T_i^{up} (h)	8	8	5	5	6	3	3	1	1	1
T_i^{down} (h)	8	8	5	5	6	3	3	1	1	1
HS	4500	5000	550	560	900	170	260	30	30	30
CS	9000	10000	1100	1120	1800	340	520	60	60	60
CH	5	5	4	4	4	2	2	0	0	0

Table III: Actual Load of 10 units 24 Hour Test System and the Forecasted Loads Using LRBF and LSVR

Hour		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Loads (GW)	Actual	1.33	1.19	1.05	1.00	0.96	0.98	1.00	1.04	1.12	1.19	1.24	1.30	1.32	1.32	1.30	1.31	1.34	1.36	1.35	1.35	1.38	1.32	1.28	1.38
	LRBF	1.37	1.28	1.14	1.05	0.96	0.98	1.04	1.10	1.12	1.23	1.28	1.39	1.32	1.31	1.31	1.34	1.36	1.37	1.32	1.34	1.39	1.33	1.22	1.40
	LSVR	1.35	1.24	1.09	1.03	0.96	0.98	1.03	1.08	1.15	1.23	1.28	1.33	1.30	1.31	1.30	1.29	1.35	1.36	1.33	1.34	1.38	1.33	1.30	1.40

Table IV: Feasible Unit Combination of Test System for Actual Load and Forecasting Load Values Using LRBF and LSVR

Hour	Feasible UC (Actual load)	Feasible UC (Local RBF)	Feasible UC (Local SVR)
1	1 1 1 1 1 0 1 0 0 0	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 0 0 1 1 0
2	1 1 1 1 1 0 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 0 0 0 0 0
3	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0
4	1 1 0 0 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0
5	1 1 0 0 1 0 0 0 0 0	1 1 0 0 1 0 0 0 0 0	1 1 0 0 1 0 0 0 0 0
6	1 1 0 0 1 0 0 0 0 0	1 1 0 0 1 0 0 0 0 0	1 1 0 0 1 0 0 0 0 0
7	1 1 0 0 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0
8	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0
9	1 1 0 1 1 0 0 0 0 0	1 1 0 1 1 0 0 0 0 0	1 1 1 1 1 0 0 0 0 0
10	1 1 1 1 1 0 0 0 0 0	1 1 1 1 1 0 0 0 0 0	1 1 1 1 1 0 0 0 0 0
11	1 1 1 1 1 0 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
12	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 0 0 0
13	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
14	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
15	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
16	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
17	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 0 0 0
18	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 1 0 0
19	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 1 0 0
20	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
21	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 0 1 0 0
22	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
23	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0	1 1 1 1 1 1 0 0 0 0
24	1 1 1 1 1 1 0 1 0 0	1 1 1 1 1 1 1 0 0 0	1 1 1 1 1 1 0 1 0 0
TC	$ 606165.3	$ 619305.9	$ 611181.5

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