Parallel Tabu Search Algorithm for Data Structure Composition

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Abstract. In this paper we propose a parallel tabu search algorithm to solve the problem of the distributed database optimal logical structure synthesis. We provide a reader with information about the performance metrics of our parallel algorithm and the quality of the solutions obtained in comparison with the earlier developed consecutive algorithm and other methods.

Keywords: Neural networks, tabu search, parallel programming, distributed databases.

1 Introduction

The problems of optimal composition of complex data structures play an extremely important role in many critical applications varying from cloud computing to distributed databases (DDB) [1]. In later class of applications that problem is usually formulated as synthesis of optimal logical structure (OLS). In accordance with [2] it consists of two stages. The first stage is a composition of logical record (LR) types from a set of atomic data elements (DE). The second stage is irredundant allocation of LR types among nodes in the computing network (CN). For each stage various domain-specific constraints are introduced as well as optimum criteria are specified.

From mathematical point of view the specified problem is a NP-complete non-linear optimization problem of integer programming. So far different task-specific approaches were proposed such as branch-and-bound method with a set of heuristics (BBM) [3], probabilistic algorithms, etc. However not many of them exploit benefits of parallel processing and grid technologies [4], [5], [6], [7].

In previous works the authors developed the exact mathematical formalization of the OLS problem in terms of neural networks and offered the sequential modified Tabu Search (TS) algorithm which used as a state transition mechanism by different Tabu Machines (TM) for each stage of the solution [8], [9]. The constructed algorithm produced solutions with good quality, but it was computationally efficient for small mock-up problems only.

In the present article we propose a new distributed model of TM (DTM) and a computationally efficient parallel algorithm for solution of complex OLS problems. The article has the following structure. In Section 2 we outline critical elements of TM. For the sake of consistency Section 3 briefly presents formal definition of OLS problem and our previous proposals of that problem mapping onto the consecutive TM. In Section 4 general description of newly proposed DTM-algorithm is given and Section 5 specifies it in details. Section 6 describes evaluation of the proposed parallel algorithm. Overview of the results in Section 7 concludes the article.

2 Short Overview of Tabu Machine Model and Dynamics

In our work we use the generic model of TM as it was specified by Minghe Sun and Hamid R. Nemati [10] with the following important constituents.

$S = \{s_1, ..., s_n\}$ is the current state of the TM, it is collectively determined by the states of its nodes.

$S_0 = \{s_1^0, ..., s_n^0\}$ is the state of the TM with the minimum energy among all states which are obtained by the current moment within the local period (or within the short term memory process (STMP)).

$S_{00} = \{s_1^{00}, ..., s_n^{00}\}$ is the state of the TM with the minimum energy among all states which are obtained by the current moment (within both the STMP and the long term memory process (LTMP)).

$T = \{t_1, ..., t_n\}$ is a vector to check the tabu condition.

$E(S)$ is the TM energy corresponding to the state S.

$E(S_0)$ is the TM energy corresponding to the state S_0.

$E(S_{00})$ is the TM energy corresponding to the state S_{00}.

k is the number of iterations (i.e. the number of neural network (NN) transitions from the one state to another) from the outset of the TM functioning.

h is the number of iterations from the last renewal the value of $E(S_0)$ within the STMP.

c is the number of the LTMPs carried out by the current moment.

The following variables stand as parameters of the TM-algorithm:

l is the tabu size,

β is the parameter determining the termination criterion of the STMP,

C is a maximum number of the available LTMPs inside the TM-algorithm.

The state transition mechanism of the TM is governed by TS and performed until the predefined stopping rule is satisfied. Let's name this sequence of state transitions as a work period of the TM. It is advisable to run the TM for several work periods. It is better to begin a new work period of the TM using information taken from the previous work periods, from a "history" of the TM work by applying LTMP. In such a case TS algorithm finds a node which has not changed its state for the longest time among all neurons of the TM. And then this node is forced to switch its state.

3 A Consecutive TM-Algorithm for OLS Problem

As [2] states, the general problem of DDB OLS synthesis consists of two stages.

1. **Composition of logical record (LR) types** from data elements (DE) using the constraints on:
    a. the number of elements in the LR type;
    b. single elements inclusion in the LR type;
    c. the required level of information safety of the system.

    In addition, LR types synthesis should take into account semantic contiguity of DEs
2. **Irredundant allocation of LR types** among the nodes in the CN using the constraints on:
    a. irredundant allocation of LR types;
    b. the length of the formed LR type on each host;
    c. the total number of the synthesized LR types placed on each host;
    d. the volume of accessible external memory of the hosts for storage of local databases;
    e. the total processing time of operational queries on the hosts.

The objective of OLS synthesis is to minimize the total time needed for consecutive processing of a set of DDB users' queries. Such problem has an exact but a very large mathematical formalization. So, we provide it in the Appendix I and Appendix II of this paper due to its limited size and should refer to [2], [3], [8], [9] for further details.

In our previous work [9] we have offered a new method for formalization of the described problem in the terms of TM and have constructed TMs' energy functions as follows. TM for the first stage consists of one layer of neurons, connected by complete bidirectional links. The number of neurons in the layer is equal to I^2, where I is the number of DEs. Each neuron is supplied with two indexes corresponding to indexes of DEs and LRs. For example, $OUT_{xi}=1$ means, that the DE x will be included to the i-th LR. All outputs OUT_{xi} of a network have a binary nature, i.e. accept values from set $\{0,1\}$. The following TM energy function for LR composition was proposed:

$$E=-\frac{1}{2}\cdot\sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{x=1}^{I}\sum_{y=1}^{I}\left[-A_1\cdot\delta_{xy}\cdot\left(1-\delta_{ij}\right)+B_1\cdot\delta_{ij}\cdot\left(1-\delta_{xy}\right)\cdot\left(2\cdot a_{xy}^{g}-1\right)-D_1\cdot\delta_{ij}\cdot\right.$$
$$\left.\cdot\left(incomp\_gr_{xy}+incomp\_gr_{yx}\right)\right]\cdot OUT_{xi}\cdot OUT_{yj}+\sum_{i=1}^{I}\sum_{x=1}^{I}\left[\frac{B_1}{2}\cdot\sum_{\substack{y=1\\y\neq x}}^{I}\left(a_{xy}^{g}\right)^2+\frac{C_1}{2\cdot F_i}\right]\cdot OUT_{xi} \quad (1)$$

Here $w_{xi,yj} = -A_1 \cdot \delta_{xy} \cdot (1-\delta_{ij}) + B_1 \cdot \delta_{ij} \cdot (1-\delta_{xy}) \cdot (2 \cdot a_{xy}^g - 1) - D_1 \cdot \delta_{ij} \cdot (incomp\_gr_{xy} + +incomp\_gr_{yx})$ are weights of neurons, $T_{xi} = \left(\frac{B_1}{2} \cdot \sum_{\substack{y=1 \\ y \neq x}}^{I} \left(a_{xy}^g \right)^2 + \frac{C_1}{2 \cdot F_i} \right)$ are neurons' thresholds.

The quality of logical record types composition is estimated by the value of N_q parameter defined by the following formula

$$N_q = \frac{\sum_{i=1}^{I} \sum_{x=1}^{I} \sum_{\substack{y=1 \\ y \neq x}}^{I} OUT_{xi} \cdot \left(OUT_{yi} - a_{xy}^g \right)^2}{I \cdot (I-1)} \cdot 100\% \ . \quad (2)$$

The best value for N_q is zero. The values of N_q parameter for mock-up problems solutions are shown in Table 1.

Table 1. The values of N_q parameter (%) for mock-up problems solutions.

	$I = 10$	$I = 20$	$I = 40$
	BBM		
	15,6	36,3	18,3
	NN-GA-algorithm		
	2,2	31,6	16,3
	TM-algorithm		
Maximum %	35,6	36,3	12,6
Average %	16,1	34,8	12,5
Minimum %	4,4	28,4	12,2

For the second stage of irredundant LR allocation we offered TM with the same structure as TM for LR composition, but the number of neurons in the layer is equal to $T \cdot R_0$, where T is the number of LRs, synthesized during LR composition, R_0 is the number of the hosts available for LR allocation.

As a result of constraints translation into the terms of TM the following TM energy function for the LR allocation was obtained:

$$E = -\frac{1}{2} \cdot \sum_{r_1=1}^{R_0} \sum_{r_2=1}^{R_0} \sum_{t_1=1}^{T} \sum_{t_2=1}^{T} \left[-A_2 \cdot \delta_{t_1 t_2} \cdot (1-\delta_{r_1 r_2}) \right] \cdot OUT_{t_1 r_1} \cdot OUT_{t_2 r_2} + \sum_{r_1=1}^{R_0} \sum_{t_1=1}^{T} \left[\frac{B_2 \cdot \psi_0}{2 \cdot \theta_{t_1 r_1}} \cdot \right. \quad (3)$$

$$\left. \cdot \sum_{i=1}^{I} \left(x_{it_1} \cdot \rho_i \right) + \frac{C_2}{2 \cdot h_{r_1}} + \frac{D_2 \cdot \psi_0}{2 \cdot \eta_{r_1}^{EMD}} \cdot \sum_{i=1}^{I} \left(\rho_i \cdot \pi_i \cdot x_{it_1} \right) + \frac{E_2 \cdot \left(t_{r_1}^{srh} + t_{r_1} \right)}{2} \cdot \sum_{p=1}^{P_0} \left(\frac{SN_{pt_1}}{T_p} \right) \right] \cdot OUT_{t_1 r_1}$$

Here $w_{t_1r_1,t_2r_2} = -A_2 \cdot \delta_{t_1t_2} \cdot (1 - \delta_{r_1r_2})$ are weights of neurons, $T_{t_1r_1} = \frac{B_2 \cdot \psi_0}{2 \cdot \theta_{t_1r_1}} \cdot \sum_{i=1}^{I} (x_{it_1} \cdot \rho_i) + \frac{C_2}{2 \cdot h_{r_1}} + \frac{D_2 \cdot \psi_0}{2 \cdot \eta_{r_1}^{EMD}} \cdot \sum_{i=1}^{I} (\rho_i \cdot \pi_i \cdot x_{it_1}) + \frac{E_2 \cdot (t_{r_1}^{srh} + t_{r_1})}{2} \cdot \sum_{p=1}^{P_0} \left(\frac{SN_{pt_1}}{T_p} \right)$ are neurons' thresholds. Here the I is the number of DEs, $z_{pr_1}^{t_1} = OUT_{t_1r_1} \cdot SN_{pt_1}$ and SN_{pt_1} is introduced as a normalized sum, i.e. $SN_{pt_1} = \begin{cases} 1, \text{ if } \sum_{i=1}^{I} w_{pi}^{Q} x_{it_1} \geq 1 \\ 0, \text{ if } \sum_{i=1}^{I} w_{pi}^{Q} x_{it_1} = 0 \end{cases}$, where w_{pi}^{Q} is the matrix of dimension $(P_0 \times I)$. That matrix shows which DEs are used during processing of different queries.

In [9] we also compared the developed TM-algorithm with other methods like [10] to estimate an opportunities and advantages of TS over our earlier approaches based on Hopfield Networks [11] or their combination with genetic algorithms (NN-GA-algorithm) [2]. Using a high-dimensional mock-up problem we found that TM solutions overcome solutions received by NN-GA-algorithm in terms of average quality on 8,7%, and overcome the quality of solutions received by BBM on 23,6% (refer to Fig. 1). CPU time for LR composition was on average 36% less that the same spent by the Hopfield Network approach. So, our TM is able to produce considerable better solutions. However this algorithm is time consuming on high-dimensional tasks, and therefore we need to construct a parallel TM-algorithm in order to validate our approach on the high-dimensional tasks and increase the performance. Moreover, the parallel algorithm helps us to reveal the influence of the tabu parameters on the tasks' solution process and to determine the dependency between tabu parameters and characteristics of our problem in order to obtain better solutions faster.

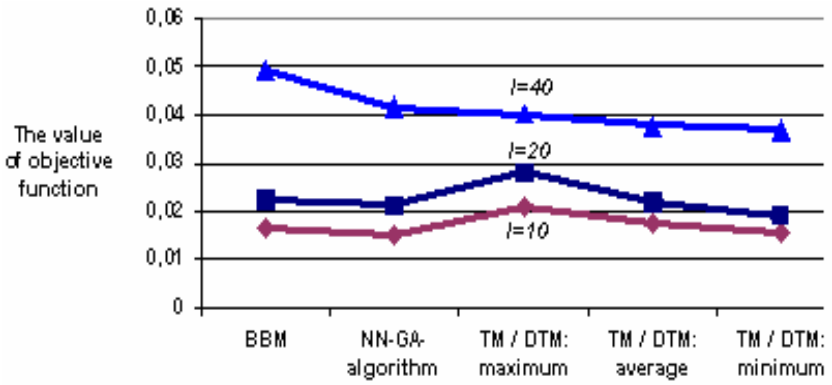

Fig. 1. The value of objective function on mock-up problems solutions.

4 A General Description of DTM Functioning

The newly proposed parallel algorithm of TM exploits parallelization capabilities of the following procedures:

1. finding a neuron to change its state;
2. changing the value of $\Delta E(S_i)$ of neurons for using it on the next iteration;
3. calculation of energy function value;
4. calculation of values of auxiliary functions used in aspiration criteria of TM;
5. transition from one local cycle to the other.

For the case of the homogeneous computational parallel cluster with multiple identical nodes the following general scheme of new parallel functionality is proposed. The set of neurons of the whole TM is distributed among all nodes' processors according to the formula $N_p = \begin{cases} n_1 + 1, \text{ if } p < n_2 \\ n_1, \text{ otherwise} \end{cases}$, where $n_1 = \left\lfloor \frac{N}{P} \right\rfloor, n_2 = N \bmod P$, N is the number of neurons in the whole TM, $p = \overline{0,(P-1)}$ is the index of processor, P is the number of processors. The number of Tabu sub-machines (TsMs) is equal to the number of available processors. So, one TsM is located on each processor and TsM with index p consists of N_p neurons. During the initialization stage neural characteristics are set to each neuron. The scheme of DTM is depicted on Fig. 2.

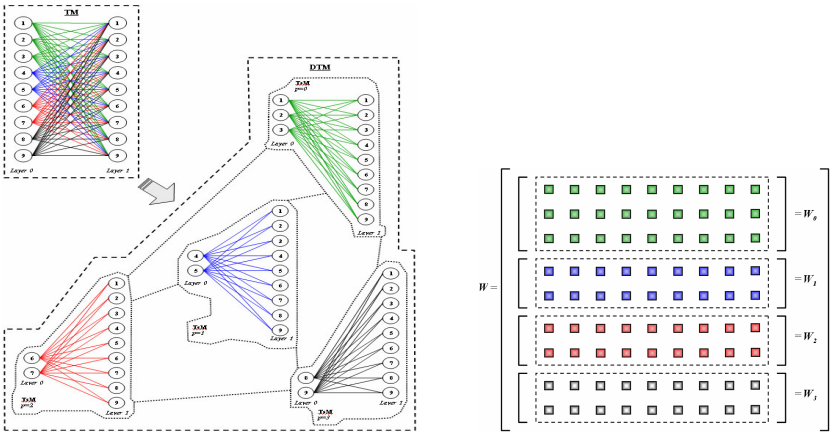

Fig. 2. DTM scheme (*left*) and method of W_p construction from the whole matrix W (*right*) for the case with $N = 9$ and $P = 4$.

The same figure shows how the weight matrix of each TsM $W_p = \left\{ w_{ij}^p; i = \overline{1, N_p}; j = \overline{1, N} \right\} = \left\{ w_{ij}; i = \overline{\sum_{k=0}^{p-1} N_k + 1, \sum_{k=0}^{p} N_k}; j = \overline{1, N} \right\}$ is constructed from the weight matrix $W = \left\{ w_{ij}; i, j = \overline{1, N} \right\}$ of the whole TM. When the optimal state of DTM is

achieved, the results from all TsMs are united. For the proposed method of the whole TM decomposition the proposition that the energy of the whole TM is additive on the energies of TsMs including in the DTM, i.e. $E = E_0 + E_1 + \ldots + E_{P-1} = \sum_{p=0}^{P-1} E_p$, is formulated and proofed by authors but due to lack of the space is omitted in that article.

Let's consider a common implementation of DTM taking into account a parallel implementation of foregoing procedures.

Initialization. This stage assumes the construction and initialization of TsMs including into the DTM. These procedures are conducted following the mentioned above scheme of distribution of DTM neurons among the set of available processors. After the structure of each TsM is defined, TsMs are provided with the following characteristics: the matrix of neurons weights, vector of neurons thresholds, and vector of neurons biases. Thus, on the current stage we have the set of TsMs, and the elements of this set are

$$subTM_p = \{W_p, I_p, T_p, In_p\}, \quad p = \overline{0,(P-1)} \ , \tag{4}$$

where $subTM_p$ is p-th TsM, W_p is the matrix of its neurons weights, I_p is the vector of neurons biases, T_p is the vector of neurons thresholds, and In_p is the vector of initial states of TsM's neurons. Matrixes W_p and vectors I_p and T_p are defined according to the following formulas:

$$W = \{w_{ij}; i, j = \overline{1,N}\} = \begin{bmatrix} W_0 \\ W_1 \\ \vdots \\ W_{P-1} \end{bmatrix} = \begin{bmatrix} \{w_{ij}^0; i = \overline{1,N_0}; j = \overline{1,N}\} \\ \{w_{ij}^1; i = \overline{1,N_1}; j = \overline{1,N}\} \\ \vdots \\ \{w_{ij}^{P-1}; i = \overline{1,N_{P-1}}; j = \overline{1,N}\} \end{bmatrix} = \begin{bmatrix} \{w_{ij}; i = \overline{1,N_0}; j = \overline{1,N}\} \\ \{w_{ij}; i = \overline{N_0+1,N_0+N_1}; j = \overline{1,N}\} \\ \vdots \\ \left\{w_{ij}; i = \overline{\sum_{k=0}^{P-2} N_k + 1, \sum_{k=0}^{P-1} N_k}; j = \overline{1,N}\right\} \end{bmatrix} \tag{5}$$

$$I = \{i_j; j = \overline{1,N}\} = \begin{bmatrix} I_0 \\ I_1 \\ \vdots \\ I_{P-1} \end{bmatrix} = \begin{bmatrix} \{i_j^0; j = \overline{1,N_0}\} \\ \{i_j^1; j = \overline{1,N_1}\} \\ \vdots \\ \{i_j^{P-1}; j = \overline{1,N_{P-1}}\} \end{bmatrix} = \begin{bmatrix} \{i_j; j = \overline{1,N_0}\} \\ \{i_j; j = \overline{N_0+1,N_0+N_1}\} \\ \vdots \\ \left\{i_j; j = \overline{\sum_{k=0}^{P-2} N_k + 1, \sum_{k=0}^{P-1} N_k}\right\} \end{bmatrix} \tag{6}$$

$$T=\left\{t_j;\, j=\overline{1,N}\right\}=\begin{bmatrix} T_0 \\ T_1 \\ \vdots \\ T_{P-1} \end{bmatrix}=\begin{bmatrix} \left\{t_j^0;\, j=\overline{1,N_0}\right\} \\ \left\{t_j^1;\, j=\overline{1,N_1}\right\} \\ \vdots \\ \left\{t_j^{P-1};\, j=\overline{1,N_{P-1}}\right\} \end{bmatrix}=\begin{bmatrix} \left\{t_j;\, j=\overline{1,N_0}\right\} \\ \left\{t_j;\, j=\overline{N_0+1,N_0+N_1}\right\} \\ \vdots \\ \left\{t_j;\, j=\overline{\sum_{k=0}^{P-2}N_k+1,\sum_{k=0}^{P-1}N_k}\right\} \end{bmatrix} \quad (7)$$

Vector In of initial states of the whole TM neurons is random generated, and then cut on P parts. Each part (i.e. In_p) corresponds to the concrete TsM.

The local cycle of the TM. Let's consider the local cycle of DTM.

Choose the neuron-candidate for the next move. The first step of the TM local cycle is the search of the neuron for each TsM which should change its state on the current iteration. The criterion to choose such a neuron is defined as the following:

$$\Delta E_p(S_j)=\left\{\min\left\{\Delta E_p(S_i)\mid i=\overline{1,N_p}\right\}\ :\ k-t_j\le l\ \vee\ E_p(S)+\Delta E_p(S_j)<E_p(S_0)\right\}_{p=\overline{0,(P-1)}}. \quad (8)$$

Thus, the search of neurons satisfied to the condition (8) is performed in parallel on the hosts of CN.

The comparison of found neurons. After the neuron satisfied to the condition (8) is found on each host, the search with help of STMP reduce operations defined by authors for MPI_Allreduce function is performed within the whole DTM to find the neuron j^*, such that $\Delta E(S_{j^*})=\min\left\{\Delta E_p(S_j)\mid p=\overline{0,(P-1)}\right\}$.

Change the energy value of neurons. After the required neuron j^* has been found, and each TsM has information about it, each neuron of $subTM_p$, $p=\overline{0,(P-1)}$ changes its $\Delta E(S_i)$ value. The calculation of DTM energy function change is done in parallel on each $subTM_p$. Further the cycle is repeated following described scheme until the condition of exit from the local cycle of the TM is satisfied.

The global cycle of the TM. We select neuron, that didn't change its state longest, on each TsM. The number j of this neuron on each $subTM_p$ is defined according to the following criteria:

$$\left(t_j\right)_p=\min\left\{t_i\mid i=\overline{1,N_p}\right\},\quad p=\overline{0,(P-1)}\,. \quad (9)$$

The search of $\left(t_j\right)_p$ is done on the available processors in parallel according to the formula (8).

The comparison of found neurons. After the neuron satisfied to the condition (9) is found on each host, the search with help of LTMP reduce operations defined by authors for MPI_Allreduce function is performed within the whole DTM to find the neuron j^*, such that $t_{j^*} = \min\left\{\left(t_j\right)_p \mid p = \overline{0,(P-1)}\right\}$.

Change the energy value of neurons. After the required neuron j^* has been found, and each TsM has information about it, each neuron of $subTM_p$, $p = \overline{0,(P-1)}$ changes its $\Delta E(S_i)$ value. The calculation of DTM energy function change is done in parallel on each $subTM_p$. Further the cycle is repeated following described scheme until the number of LTMP calls will exceed $C : C \in Z^+, C \geq 0$ times. After that the search is stopped and the best found state is taken as the final DTM state.

5 The Algorithm of DTM Functioning

Let's try to represent the general description as an algorithm outlined step by step. We will use the following notations: N is the number of neurons in the DTM, i.e. $|S| = |S_0| = |S_{00}| = N$; N_p is the number of neurons including into the TsM $subTM_p$, where $p = \overline{0,(P-1)}$; P is the number of processors on which DTM operates.

Step 1. Construct TsMs $subTM_p$ and randomly initialize initial states of its neurons. Define the tabu-size l of DTM. Let $h = 0$ and $k = 0$ are counters of iterations in the frame of the whole DTM. Let $c = 0$, and $C \geq 0$ is the maximum number of LTMP calls in the frames of the whole DTM. Let $\beta > 0$ is defined according to inequality $\beta \cdot N > l$ in the frames of the whole DTM too.

Step 2. Find the local minimum energy state S_0. Calculate $E(S_0)$ and

$$\Delta E(S) = \begin{bmatrix} \Delta E(S_1) \\ \Delta E(S_2) \\ \vdots \\ \Delta E(S_N) \end{bmatrix} = \begin{bmatrix} \Delta E_0(S_i),\ i = \overline{1, N_0} \\ \Delta E_1(S_i),\ i = \overline{N_0 + 1, N_0 + N_1} \\ \vdots \\ \Delta E_{P-1}(S_i),\ i = \overline{\sum_{k=0}^{P-2} N_k + 1, \sum_{k=0}^{P-1} N_k} \end{bmatrix}, \quad i = \overline{1, N}. \tag{10}$$

The values of $E_p(S_0)$ and $\Delta E_p(S_i)$ for $p = \overline{0,(P-1)}$ are calculated in parallel on P processors. Let $S_{00} = S_0$ is the best global state, and $E(S_{00}) = E(S_0)$ is the global minimum of energy. Let $S = S_0$ and $E(S) = E(S_0)$. Let $t_i = -\infty, \forall i = \overline{1, N}$.

Step 3. In the frames of each $subTM_p$ choose the neuron j with $\Delta E_p(S_j)$ satisfied to $\Delta E_p(S_j) = \left\{\min\left\{\Delta E_p(S_i) \mid i = \overline{1, N_p}\right\} : k - t_j \leq l \ \vee\ E_p(S) + \Delta E_p(S_j) < E_p(S_0)\right\}, p = \overline{0,(P-1)}$.

Step 4. Using STMP reduce operations defined by authors, form the set $\{j^*, \Delta E(S_{j^*}), s_{j^*}\}$, where j^* is the index of neuron (in the frames of the whole DTM) changing its state at the current moment, $\Delta E(S_{j^*})$ is the change of DTM energy function value after the neuron j^* has changed its state, s_{j^*} is a new state of neuron j^*.

Step 5. If $subTM_p$ contains the neuron j^*, then $t_{j^*} = k$, $s_{j^*} = 1 - s_{j^*}$.

Step 6. Let $t_{j^*} = k$, $k = k + 1$, $h = h + 1$, $S = S_{j^*}$, $E(S) = E(S) + \Delta E(S_{j^*})$ in the frames of the whole DTM.

Step 7. Update $\Delta E(S)$ using (10). The values of $\Delta E_p(S_i)$ are calculated in parallel on P processors.

Step 8. Determine if a new state S is a new local and / or global minimum energy state: if $E(S) < E(S_0)$, then $S_0 = S$, $E(S_0) = E(S)$ and $h = 0$; if $E(S) < E(S_{00})$, then $S_{00} = S$ and $E(S_{00}) = E(S)$ in the frames of the whole DTM.

Step 9. If $h < \beta \cdot N$, go to **Step 3.**, else go to **Step 10.**

Step 10. If $c \geq C$, then the algorithm stops. S_{00} is the best state. Else, in the frames of each $subTM_p$ choose in parallel the neuron j with $(t_j)_p$ satisfied to $(t_j)_p = \min\{t_i \mid i = \overline{1, N_p}\}$, $p = \overline{0, (P-1)}$. Using LTMP reduce operations defined by authors, form the set $\{j^*, \Delta E(S_{j^*}), s_{j^*}\}$, where j^* is the index of neuron (in the frames of the whole DTM) changing its state at the current moment, $\Delta E(S_{j^*})$ is the change of DTM energy function value after the neuron j^* has changed its state, s_{j^*} is a new state of neuron j^*. Let $S_0 = S_{j^*}$ and $E(S_0) = E(S) + \Delta E(S_{j^*})$, $c = c + 1$ and $h = 0$. Go to **Step 6.**

It's worth mentioning that on the **Step 10.** a new state of local energy minimum $E(S_0)$ is set without any auxiliary checks, i.e. it can be worse than the previous S_0. Exploiting this technique we exclude stabilization in local energy minimums and expand areas of potential solutions.

6 Performance Evaluation

In order to evaluate the performance of constructed DTM the set of experiments on mock-up problems with DTM consisting of $N = 100$, $N = 400$ and $N = 1600$ neurons were done on multi-core cluster. 372 trial solutions were obtained for each mock-up problem depending on the values of $< l, C, \beta >$ parameters of DTM.

We proposed to use an average acceleration as the metric to evaluate efficiency of DTM. The dependency of average acceleration on the number of processors for mock-up problem with $N = 1600$ is depicted on Fig. 3. DTM gives a linear acceleration.

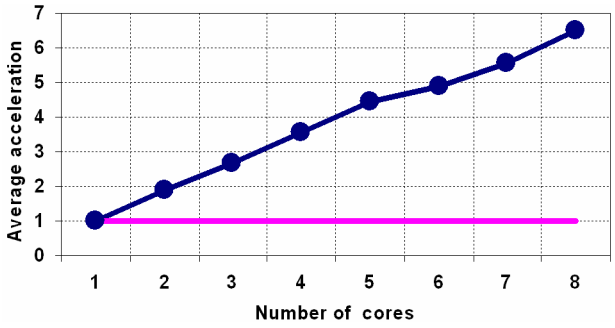

Fig. 3. Average acceleration for mock-up problem with $N = 1600$.

7 Conclusion

In this paper we proposed parallel TM-algorithm for DDB OLS synthesis problem. The constructed DTM was validated and compared with the sequential TM. As expected, both approaches give the same results with the solutions quality higher than the quality of solutions received by NN-GA-algorithm [2], [8] on average 8,7% and by BBM [3] on average 23,6% on mock-up problem with higher dimension.

DTM was applied to recomposition of logical record types for the database used by human resource management tool in the international IT-company. The result set of logical record types takes the semantic contiguity of DEs on 7,5% better than the currently existing structure.

It is worth mentioning that during the DTM cycles intensive data communication between processors is carried out in the proposed algorithm. DTM provides a linear acceleration. Therefore, we can speak about the significant increasing of DTM performance in compare with its consecutive analogue for the high-dimensional problems. This statement is not contrary to our objectives, because the problem of DDB OLS synthesis is important today in view of high dimensionality.

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Appendix I: Formal Characteristics of the Subject Domain

The name	The designation
Characteristics of a DDB structure	
The set of data elements	$\mathbf{D^G} = \{d_i^g / i = \overline{1, I}\}$
The vector of elements lengths	$\boldsymbol{\rho} = \{\rho_i\}$
The vector of data element's instantiation numbers	$\boldsymbol{\pi} = \{\pi_i\}$
The matrix of a semantic contiguity of data elements	$\mathbf{A^G} = \|a_{ii'}^g\|$, where $a_{ii'}^g = 1$ if there is a semantic connection between the i-th and i'-th elements, $a_{ii'}^g = 0$ – otherwise
Characteristics of user's queries	
The set of user's queries	$\mathbf{Q} = \{q_p / p = \overline{1, P_0}\}$
The matrix of data elements usage during processing of queries	$\mathbf{W^Q} = \|w_{pi}^Q\|$, where $w_{pi}^Q = 1$ if query p uses (during processing time) the i-th element, $w_{pi}^Q = 0$ – otherwise

The name	The designation
The matrix of frequencies of queries used by the users	$\mathbf{\Lambda^Q} = \left\|\xi_{kp}^{Q}\right\|$, where ξ_{kp}^{Q} is the frequency of the usage of the p-th query by the user k
Characteristics of the users	
The set of the users	$\mathbf{U} = \left\{u_k \,/\, k = \overline{1, K_0}\right\}$
The matrix of an attachment of the users to hosts in the computing network	$\boldsymbol{\nu} = \left\|\nu_{kr}\right\|$, where $\nu_{kr} = 1$ if the k-th user is attached to host r of computing network, $\nu_{kr} = 0$ – otherwise
The matrix of queries usage by the DDB users	$\mathbf{\Phi^Q} = \left\|\varphi_{kp}^{Q}\right\|$, where $\varphi_{kp}^{Q} = 1$ if user k uses query p, $\varphi_{kp}^{Q} = 0$ – otherwise
The matrix of an attachment of the queries to client hosts	$\mathbf{\Lambda^Q} = \left\|\delta_{pr}^{Q}\right\|$, where $\delta_{pr}^{Q} = 1$ if $\sum_{k=1}^{k_0} \nu_{kr}\varphi_{kp}^{Q} \geq 1$; $\delta_{pr}^{Q} = 0$ if $\sum_{k=1}^{k_0} \nu_{kr}\varphi_{kp}^{Q} = 0$
Characteristics of the set of computing network's hosts	
The characteristics of the set of computing network's hosts	$\mathbf{N} = \left\{n_r \,/\, r = \overline{1, R_0}\right\}$
The vector of memory volumes on servers of computing network, accessible to the user	$\boldsymbol{\eta}^{\mathbf{EMD}} = \left\{\eta_r^{EMD}\right\}$, where η_r^{EMD} is the value of accessible external memory on server at host r in the computing network
Average initial time characteristics	
The average time of assembly of the data block at formation of queries' data array	t^{ass}
The average time of one query formation	t^{dis}
The average time of a route choice, establishment of logic (virtual) connections between the client-host (r_1) and server-host (r_2)	$t_{r_1 r_2}^{ser}$
The average time of transfer of one data block (logical record) of query or transaction from the client-host (r_1) on the server site (r_2) on the shortest way	$t_{r_1 r_2}^{trf}$
The average time of access to LDB files and search in them of required logical records	t^{srh}
The average time of processing of one logical record on the server-host (r_2), dependent of productivity of the server	t_{r_2}

$x_{it} = 1$ if the i-th data element (DE) is included into the t-th logical record (LR) type; $x_{it} = 0$, otherwise.

$y_{tr} = 1$ if the t-th LR type is allocated to the server of the r-th host in the computing network; $y_{tr} = 0$, otherwise.

$z^t_{pr_2} = 1$ if $\sum_{i=1}^{I} y_{tr_2} w^Q_{pi} x_{it} \geq 1$; $z^t_{pr_2} = 0$ if $\sum_{i=1}^{I} y_{tr_2} w^Q_{pi} x_{it} = 0$. Variable $z^t_{pr_2}$ defines types of LRs used by the p-th query on the server of the r_2-th host in the computing network.

$z_{pr_2} = 1$ if $\sum_{t=1}^{T} \sum_{i=1}^{I} y_{tr_2} w^Q_{pi} x_{it} \geq 1$; $z_{pr_2} = 0$ if $\sum_{t=1}^{T} \sum_{i=1}^{I} y_{tr_2} w^Q_{pi} x_{it} = 0$. Variable z_{pr_2} defines a set of LDB server-hosts to which the p-th query addresses. T is a number of LRs types synthesizing in the solution process.

Appendix II: Mathematical Statement of the Problem

The general task of DDB OLS synthesis by criteria of a minimum of total time needed for consecutive processing of a set of DDB users' queries is formulated in the following way:

$$\min_{\{x_{it}, y_{tr}\}} \sum_{k=1}^{K_0} \sum_{p=1}^{P_0} \xi^Q_{kp} \cdot \varphi^Q_{kp} \cdot \left\{ \sum_{r_1=1}^{R_0} \nu_{kr_1} \cdot \left[\sum_{r_2=1}^{R_0} z_{pr_2} \cdot \left(t^{dis} + t^{ser}_{r_1 r_2} + t^{trf}_{r_1 r_2} \cdot \left(1 + \sum_{t=1}^{T} z^t_{pr_2} \right) \right) + t^{ass} \right] + \sum_{r_2=1}^{R_0} \sum_{t=1}^{T} z^t_{pr_2} \cdot \left(t^{srh}_{r_2} + t_{r_2} \right) \right\}$$

subject to

1. the number of elements in the LR type $\sum_{i=1}^{I} x_{it} \leq F_t, \forall t = \overline{1,T}$, where F_t is maximum number of elements in the record t;
2. single elements inclusion in the LR type $\sum_{t=1}^{T} x_{it} = 1, \forall i = \overline{1,I}$;
3. the required level of information safety of the system $x_{it} x_{i't} = 0$ for given d_i and $d_{i'}$;
4. irredundant allocation of LR types $\sum_{r=1}^{R_0} y_{tr} = 1, \forall t = \overline{1,T}$;
5. the length of the formed LR type $\sum_{i=1}^{I} x_{it} y_{tr} \rho_i \psi_0 \leq \theta_{tr}$, $\forall t = \overline{1,T}, \forall r = \overline{1,R_0}$, where θ_{tr} is the greatest allowable length of the record t determined by characteristics of the server r;
6. the total number of the synthesized LR types placed on the server r: $\sum_{t=1}^{T} y_{tr} \leq h_r, \forall r = \overline{1,R_0}$, where h_r is the maximum number of the LR types supported by the local database management system of the server-host r;

7. the volume of accessible external memory of servers $\sum_{t=1}^{T}\sum_{i=1}^{I}\psi_0\rho_i\pi_i x_{it} y_{tr} \le \eta_r^{EMD}, \forall r = \overline{1, R_0}$ for storage of local databases;
8. the total processing time of operational queries on servers $\sum_{r=1}^{R_0}\sum_{t=1}^{T} z_{pr}^{t} \cdot (t_r^{srh} + t_r) \le T_p, \forall p = \overline{1, P_0}$ for given $Q_p \in Q$, where T_p is the allowable processing time of p needed for search.