An Adaptive Dynamic Grid-based Approach to Data Distribution Management[a]

Azzedine Boukerche[1], YunFeng Gu[1], Regina B. Araujo[1,2]
[1]PARADISE Research Laboratory
SITE, University of Ottawa, Canada
[2]Federal University of Sao Carlos, Brazil
Emails: {boukerch,yungu}@site.uottawa.ca, regina@dc.ufscar.br

Abstract

This paper presents a novel Adaptive Dynamic Grid-based Data Distribution Management (DDM) scheme, which we refer to as ADGB. The main objective of our protocol is to optimize DDM time through matching probability (MP) and federates' performance. A Distribution Rate (DR) along with MP are used as part of the ADGB method to select, throughout the simulation, from different devised advertisement schemes, the best scheme to achieve maximum gain with acceptable network traffic overhead. As opposed to previous protocols, the novelty of our ADGB scheme is its focus on improving overall performance, an important goal for DDM strategy. In this paper, we present our scheme and highlight its performance analysis.

1. Introduction

For large scale distributed simulations, Data Distribution Management (DDM) plays a key role on traffic volume control [7,8,10,11,12,13]. In recent years, several solutions have been devised to make DDM more data filtering efficient and adaptive to different traffic conditions. Examples of such systems include the Region-Based(RB), Fixed Grid-Based(FGB), Hybrid and Dynamic Grid-Based schemes(DGB) [3][4][6]. However, less effort has been made to improve the overall processing performance of DDM techniques. This paper presents a novel DDM scheme, based on the DGB approach, which focus on improving the overall processing performance through DDM time analysis. The scheme, named *Adaptive Dynamic Grid-Based (ADGB)*, uses an adaptive advertising method, in which information on a target cell involved in the process of *matching* subscribers to publishers is known in advance. This adaptive mechanism uses the concept of *DR,* which represents the relative processing load and traffic volume generated at each *Fed* as well as *MP* to select different control schemes that achieves maximum gain with acceptable network traffic overhead.

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2. Analysis for Potential DDM Optimizations

Due to the DGB DDM scheme's ability to combine most of the advantages of the other DDM schemes, this method was chosen to have its performance evaluated for potential optimizations.

Three main factors are described as important to evaluate the overall performance of the DGB DDM scheme: the *DDM Time*, the *DDM Messages* and the Multcast Groups (*MGRP*) *used* [3]. In this paper, we focus on how to optimize the *DDM Time* which includes: the *propagation delay(Prop)* of Publishing(Pub) or Subscribing (Sub) to a cell; the *allocation time(Alloc)* for creating an *MGRP;* the *processing time(Proc)* for updating all necessary tables; the *Prop* for triggering publishers or subscribers and making them join the appropriate *MGRP*s; and the *join MGRP time(Jon)*.

2.1 DDM time analysis for the DGB approach

In order to analyze *DDM Time* in detail, certain assumptions and notations are made as follows: (1) *DDM Time* is denoted by T; (2) The same *Prop* for *DDM Messages* is experienced between each source-destination pair of nodes (*Fed*s), denoted by T_{prop} ; (3) The *Alloc* for *MGRP* is constant, denoted by T_{alloc}; (4) The *Proc* (*matching*, updating all necessary tables, etc.) at the owner of a target cell is constant, denoted by T_{proc}; (5) The *Jon* consists of the *Proc* at the triggered entity, the *Prop* for the update message sent back to the owner of the target cell and the *Proc* at the owner, denoted by T_{join}; and (6) *Matching* condition is satisfied when there is at least one pair of publisher and subscriber from different *Fed*s interested in the same target cell.

DDM Time processing procedure: *DDM Time* is categorized into two cases: (A) *DDM Time before matching,* the time that it takes for a subscriber/publisher to request to a target cell currently not yet in the *matching* process; (B) *DDM Time after matching,* the time used when a subscriber/publisher requests to a target cell currently already in the *matching* process. The main difference between *DDM Time before matching* and *after matching* is the *Alloc* for the MGRP.

Considering that a target cell has at least one publisher, at the time of the first subscription, for both of the above *DDM Time* cases, the owner of target cell might be one of

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the following:

(A) For *DDM Time before matching*

- A.1 One of the existing publishers is the owner:

$$T_{A1} = T_{prop} + T_{proc} + T_{alloc} + T_{prop} + T_{join}$$
$$= 2T_{prop} + T_{proc} + T_{alloc} + T_{join}$$

- A.2 Prospective subscriber is the owner:

$$T_{A2} = T_{proc} + T_{alloc} + T_{prop} + T_{join}$$

- A.3 Owner of the target cell is none of the above:

$$T_{A3} = 2T_{prop} + T_{proc} + T_{alloc} + T_{join} = T_{A1}$$

(B) For *DDM Time after matching*

- B.1 One of the existing publishers is the owner:

$$T_{B1} = T_{prop} + T_{proc} + T_{prop} + T_{join} = T_{A1} - T_{alloc}$$

- B.2 Prospective subscriber is the owner:

$$T_{B2} = T_{proc} + T_{join} - T_{prop} = T_{A2} - T_{alloc} - 2T_{prop}$$

- B.3 Owner of target cell is none of the above:

$$T_{B3} = T_{prop} + T_{proc} + T_{prop} + T_{join} = T_{A1} - T_{alloc}$$

2.2 DDM time analysis for optimization

(a) Potential optimization on DDM time. For *DDM Time* after *matching*, if we assume that the prospective subscriber has the immediate knowledge of any information about the target cell, then, in case B.1 above, we have

$$T_{B1}' = T_{join} = T_{B1} - 2T_{prop} - T_{proc}$$

Similarly, we can compute all the other cases:

$$T_{B2}' = T_{proc} + T_{join} - T_{prop} = T_{B2}$$
$$T_{B3}' = T_{join} = T_{B1} - 2T_{prop} - T_{proc}$$

But, for *DDM time before matching*, the following results are given directly, since it is very easy to verify. $T_{A1}' = T_{A1}$, $T_{A2}' = T_{A2}$, and $T_{A3}' = T_{A3}$.

From the analysis above, an important observation on *DDM Time* is derived:

Efficiency can only be achieved on DDM Time after matching if information on the target cell is known in advance.

(b) Average DDM Time. Suppose we use a fully randomized cell ownership distribution algorithm. Let the number of *Fed*s in a simulation be N_{fed}, and *MP* be γ, then the probability(Prob) of case A.2 or B.2 is given as:

$$\Pr[A.2] = \Pr[B.2] = \Pr[owner] = 1/N_{fed} = \eta$$

and

$$\Pr[A.1] + \Pr[A.3] = \Pr[B.1] + \Pr[B.3] = 1 - \Pr[owner]$$
$$= 1 - \eta$$

Thus, the average *DDM Time* can be written as:

$$E(T) = \{T_{A1}(1 - \Pr[owner]) + T_{A2}\Pr[owner]\} \times (1 - \Pr[matching])$$
$$+ \{T_{B1}(1 - \Pr[owner]) + T_{B2}\Pr[owner]\} \times \Pr[matching]$$
$$= \{T_{A1}(1-\eta) + T_{A2}\eta\}(1-\gamma) + T_{B2}\eta\gamma + T_{B1}(1-\eta)\gamma \quad \text{....... (2.1)}$$

If we let

$$T_U = T_{A1}(1 - \Pr[owner]) + T_{A2}\Pr[owner]$$
$$T_M = T_{B1}(1 - \Pr[owner]) + T_{B2}\Pr[owner]$$

The average *DDM Time* for the *DGB* approach is:

$$E(T) = T_U(1-\gamma) + T_m\gamma \quad \text{...... (2.2)}$$

Since efficiency can only be obtained on *DDM time after matching*, if we let

$$T_m' = T_{B1}'(1 - \Pr[owner]) + T_{B2}'\Pr[owner]$$

then, we have the average *DDM time* for an optimized scheme:

$$E(T') = T_U(1-\gamma) + T_m'\gamma \quad \text{...... (2.3)}$$

(c) Maximum gain (μ). If we denote the average *DDM Time* difference between the original and the optimized scheme as:

$$E(\Delta T) = E(T) - E(T')$$

then, maximum gain can be described as:

$$\mu = \frac{E(\Delta T)}{E(T)}$$

Thus,

$$\mu = \frac{(T_m - T_m')\gamma}{T_u(1-\gamma) + T_m\gamma} \quad \text{......(2.4)}$$

Let $\boldsymbol{T_{join} = T_{prop} + 2 \cdot T_{proc}}$, ((5) in 2.1.1) and for simplicity the *Proc* is ignored compared to the *Prop*, thus:

$$E(\Delta T) = E(T) - E(T') = 2T_{prop}(1-\eta)\gamma$$

then, maximum gain (*MG*) would be:

$$\mu = \frac{2T_{prop}(1-\eta)\gamma}{T_{prop}[3 - \eta(1+2\gamma)] + T_{alloc}(1-\gamma)} \quad \text{....... (2.5)}$$

From equation (2.5), we can see that, for a large of $\boldsymbol{N_{fed}}$ ***(η ->0)***, and an idealized *MP* (*γ->1*), *MG* may reach up to ***2/3***. From the discussion made above, it is clear that DGB *DDM time after matching* can be improved. Thus, a new optimized scheme, named *Adaptive Dynamic Grid-based* (ADGB) was devised that is based on knowledge in advance about the target cell. From equation (2.5), we can notice that the gain on performance is highly related to the *federate*s number and *MP*. For the purpose of balancing the tradeoff between cost and gain of the ADGB new scheme, an adaptive scheme is necessary. For that, a detailed study on the behavior of the *Sub*/*Pub* and *matching* processes, based on the probability analysis of a fully randomized simulation, is carried out in the next section. This study will serve as a basis for the design of the ADGB scheme to be presented later.

3. Performance analysis of ADGB

Consider that in a fully randomized simulation running in a grid routing space, each *Fed* (a physical node running in the simulation) has a certain number of *object*s (players of the simulation). In this routing space, an *object* moves by subscribing to a number of cells centered at its position and publishing to a number of cells centered at another random point. At the beginning of the simulation, *Fed*s distribute their *object*s across the routing space randomly, then each *object* moves towards one of four possible directions (East, West, South and West). An *object* can change its direction after a certain time of moving, and stop at the border of the routing space until a different moving direction is chosen.

In the scenario described above, the possibilities of each decision made are evenly likely distributed to all of its possible choices. To simplify our analysis, the routing space is considered as a *2-D* space in this paper, but our results can be extended and applied to a routing space of any dimension. Since both Sub and Pub behaviors of objects are fully randomized, we will focus only at the Sub behavior in the following section, however, the result can be applied to both of them.

3.1 Subscribing/Publishing Probability

3.1.1 Federate Sub/Pub Probability. Depending on the scope of our considerations, the concept of ***Sub/Pub Probability*** (***SP/PP***) may refer to one of the following two definitions: the Prob of a cell being subscribed(Sub) or published(Pub) by an object (***OSP or OPP***) or the Prob of a cell being Sub or Pub by a *Fed* (***FSP or FPP***). If we let ***n*** be number of objects(*obj*) managed by *Fed* ***i***, the relationship between ***FSP*** and ***OSP*** at *Fed* ***i*** can be expressed as:

$$\begin{aligned}&\Pr[\text{cell k be Sub by Fed i}]\\&=\Pr[\text{cell k be Sub by at least one obj at Fed i}]\\&=1-\Pr[\text{cell k not Sub by any obj at Fed i}]\\&=1-\prod_{j=1}^{n}(1-\Pr[\text{cell k be Sub by obj j at Fed i}])\end{aligned}$$

If we use α_i, β_i to denote ***FSP*** and ***FPP*** at *Fed* ***i***, and p_j to denote ***OSP*** or ***OPP*** of *object* ***j*** at *Fed* ***i***, then:

$$\alpha_i,\beta_i=1-\prod_{j\in obj}(1-p_j) \quad \text{...... (3.1)}$$

3.1.2 Object Sub/Pub Probability. In the expression above, ***FSP*** is given in terms of ***OSPs*** at that *Fed.* Since a Sub area of an object is centered at the position of that object, if we let $p_{j,k}$ be the Prob of cell ***k*** being Sub by *object* ***j***, then:

$$\begin{aligned}p_{j,k}&=\Pr[\text{cell k be Sub by obj j}]\\&=\Pr[\text{obj j in a Sub area centered at cell k}]\\&=\sum\Pr[\text{obj j in cell q}]\end{aligned}$$

(where q is in the set of actually subscribed cells)

In a fully randomized simulation, the Prob of an object moving to any cell is uniformly distributed. Thus,

$$p_{j,k}=\frac{\text{Actually subscribed cells at cell k}}{\text{Total cells in Routing Space}} \quad \text{...... (3.2)}$$

From the result obtained above we can see that the Sub cells by an object depend on the position of that *object.* Thus, ***OSP*** is actually an average value of the Prob of a cell being Sub by an object. If we let the ***Sub Rate*** (***SR***) be defined as the rate of the actually Sub cells by an object over the maximum Sub cells, and use r_k representing ***SR*** at cell ***k*** and ***r*** representing the overall ***Average Sub Rate*** (***ASR***). Also, let $C=c\times c'$ be the routing space grid, $S=s\times s'$ be the Sub region grid, $S'=(s+1)\times(s'+1)$ be the maximum Sub cells, and S_k' denotes the actually Sub cells when object is in cell ***k*.** Thus, ***ASR*** can be expressed as:

$$r=(\sum_{k=1}^{C}r_k)\frac{1}{C}=\sum_{k=1}^{C}\frac{S'_k}{S'}\frac{1}{C} \quad \text{...... (3.3)}$$

thus

$$\begin{aligned}p_j&=\sum_{k=1}^{C}p_{j,k}\frac{1}{C}=\sum_{k=1}^{C}(\frac{S'_k}{C})\frac{1}{C} \quad \text{by ......(3.2)}\\&=\sum_{k=1}^{C}\frac{S'_k}{S'}\frac{1}{C}\frac{S'}{C}\end{aligned}$$

by substituting for equation (3.3), we have

$$p_j=r\frac{S'}{C}=r\frac{(s+1)(s'+1)}{cc'} \quad \text{...... (3.4)}$$

3.2 Average Sub rate (ASR)

In this section, we will focus on ***ASR*** and derive out the final equation for computing ***OSP***. In order to give a relatively simple view of the logical relation between ***ASR*** and ***OSP***, the notations used in 3.1 are simplified as follows: (1) the square routing space grid $C=c\times c$; (2) the square Sub region grid $S=s\times s$; (3) ***c*** is integral times of ***s***.

Although a simplified scheme is being used, it can be shown that a more general situation can be derived from it and that the conclusions are not affected by this simplification.

If we let r_C, r_S and r_{CT} denote ***ASR*** at corner region (CR), side region (SDR) and central region (CTR) respectively, then

$$\begin{aligned}ASR=r&=\sum_{k=1}^{C}r_k\frac{1}{C}=\sum_{k=1}^{C}r_k\frac{1}{M\cdot S} \qquad (m=c/s)\\&=\frac{1}{M}\{\sum_{k\in CRs}\frac{r_k}{S}+\sum_{k\in SRs}\frac{r_k}{S}+\sum_{k\in CTRs}\frac{r_k}{S}\}\\&=\frac{1}{M}\{4r_C+4(m-2)r_S+(m-2)^2r_{CT}\}\end{aligned}$$

Since $r_{CT}=1$ and $M = m\times m$:

$$ASR = r = \frac{4r_C + 4(m-2)r_S + (m-2)^2}{m^2} \quad ......(3.5)$$

and by simplification

$$ASR = r = (1-\frac{s+1}{4c})^2 + [1+(-1)^s]\times$$
$$[\frac{1}{4c(s+1)} - \frac{1}{16c^2} + \frac{1}{32c^2(s+1)^2}] \quad .....(3.13)$$

where c/s = m $\in \boldsymbol{N}$

Notice that when ***c*** and ***s*** are large, thus, we have

$$r \approx r_{odd} = (1-\frac{s+1}{4c})^2 \quad ......(3.14)$$

where c/s = m $\in \boldsymbol{N}$

3.3 Matching Probability (MP)

When a *Fed* ***i*** has all ***FSP*** and ***FPP*** (α_j and β_j***)*** from other *Fed*s in hand, it is ready to have an overall view of the *MP* of the simulation. If we use ***F*** to denote the total number of *Fed*s of a simulation, the process of obtaining the overall *MP* is straightforward, as shown below

The Prob of a cell having at least one subscriber can be denoted as:

$$\Pr[\text{a cell be subscribed}] = 1-\prod_{j=1}^{F}(1-\alpha_j)$$

where ***F*** = # of *Fed*s

Similarly, the Prob of a cell having at least one publisher can be denoted as:

$$\Pr[\text{a cell be published}] = 1-\prod_{j=1}^{F}(1-\beta_j)$$

The Prob of a cell being Sub & Pub by only one *Fed*:

Pr[a cell be published and subscribed by only one Fed]

$$= \sum_{i=1}^{F}\alpha_i\beta_i\prod_{j\neq i}^{F}(1-\alpha_j)(1-\beta_j)$$

A *matching* condition can be satisfied when there is at least one pair of Subscriber and Publisher from different *Fed*s. Thus, if we let γ denotes the *MP,* then

$$\gamma = \Pr[\text{a cell be Sub}]\cdot\Pr[\text{a cell be Pub}]$$
$$-\Pr[\text{a cell be Sub and Pub by only one Fed}]$$

Thus

$$\gamma = [1-\prod_{j=1}^{F}(1-\alpha_j)][1-\prod_{j=1}^{F}(1-\beta_j)] - \sum_{i=1}^{F}\alpha_i\beta_i\prod_{j\neq i}^{F}(1-\alpha_j)(1-\beta_j) \quad ......(3.16)$$

4 The Design of The ADGB Scheme

The study given above will serve as a foundation for the design of our ADGB scheme to be presented in the next section.

4.1 Control schemes used in ADGB

In what follows, we shall discuss 4 basic schemes we investigate.

(1) Fixed MGRP(FMG) - This control scheme is equivalent to the FGB DDM, since each *MGRP* is bounded to a fixed cell, and all *Fed*s have complete knowledge of the mapping between *MGRP*s and cells. In this case, no advertising is necessary at all.

(2) Piggyback(PG) - With piggyback control, advertising messages are grouped along with normal *DDM messages*. For efficiency reasons, an advertising message might have to wait to be grouped with other advertising messages

(3) Direct Advertising(DA) – In this control scheme, advertising messages are sent directly to other *Fed*s. Lower Class of Service (CoS) can be applied to this scheme.

(4) First Sub/Pub(1st SP) - In this control scheme, once the first registration request from a *Fed* to the owner of target cell has been acknowledged back, *matching* information of that cell is automatically shared among all the objects managed by that *Fed*.

4.2 Principles for the design of ADGB

The main concern related to the design of ADGB is how to achieve efficiency with acceptable communication overhead. Thus, ADGB should be invoked with the complete knowledge of the overall simulation status. This mainly include: existing traffic condition, *MPerf* and processing load at each *Fed*. Based on the discussions in section 4.1.3, we know that ***DR*** is a simple and straightforward parameter directly related to this knowledge.

If we set two thresholds $1 > \gamma_H > \gamma_L > 0$ for *MP* (γ), and one threshold δ for ***DR*** (δ), the guideline for the design of ADGB can be described as shown in Fig. 5-1.

4.3 Achievable gain (μ')

While maximum gain can only be achieved when ***FMG*** is applied, in most cases, the *MP* can not get so high, thus, other advertising schemes have to be used for efficiency matters. Because the ADGB approach combines different advertising schemes that can be selected according to existing traffic condition, *Mperf* and processing load at each *Fed*, it can achieve the desired gain.

Suppose a new *matching* can be advertised to all *Fed*s within an average of Δt unit time. If we let

```
if γ ≥ γ_H
  Fixed MGRP is enabled
else
  Piggyback and First Sub/Pub are enabled
  if γ ≥ γ_L
    if δ_i at source federate i > δ'
        Direct Advertising is disabled at source
    else
        Direct Advertising is enabled at source
        for all other destination federate j and j != source{
          if δ_j at destination federate > δ'
              Direct Advertising to federate j is disabled
          else
              Direct Advertising to federate j is enabled
          endif // end if δ_j
        } // end for loop
    endif // end if δ_i
  endif // end if γ ≥ γ_L
endif // end if γ ≥ γ_H
```

Figure 5-1 Design Principle of ADGB Control Scheme

$T_u = T_{A1}(1-\Pr[owner]) + T_{A2}\Pr[owner]$

$T_m = T_{B1}(1-\Pr[owner]) + T_{B2}\Pr[owner]$

$\sigma = \Pr[\text{got advertisement}]$

$p_\Delta = \Pr[\Delta t] = \Pr[\text{Sub/Pub request within } \Delta t \text{ unit time}]$

$p_k = \Pr[\text{Sub/Pub with knowledge of matched cell}]$

by equation (2.1), average *DDM time* for original approach is

$E(T) = T_u(1-\gamma) + T_m\gamma$

For maximum gain, efficiency could be achieved directly on T_m to T_m' once *matching* is met (section 2.2). However, for the achievable gain, this can only be obtained when a potential subscriber or publisher has knowledge of the matched cell in advance. Thus, average *DDM Time E(T'')* for ADGB is

$$\begin{aligned} E(T'') = {} & T_u(1-\gamma) + T_m\gamma p_\Delta(1-p_k) + T_m'\gamma p_\Delta p_k \\ & + T_m\gamma(1-p_\Delta)(1-\sigma)(1-p_k) \\ & + T_m'\gamma(1-p_\Delta)(1-\sigma)p_k \\ & + T_m'\gamma(1-p_\Delta)\sigma \end{aligned}$$

Thus,

$$\begin{aligned} E(T'') = {} & T_u(1-\gamma) \\ & + T_m\gamma[p_\Delta(1-p_k) + (1-p_\Delta)(1-\sigma)(1-p_k)] \\ & + T_m'\gamma[p_\Delta p_k + (1-p_\Delta)\sigma + (1-p_\Delta)(1-\sigma)p_k] \end{aligned}$$

for $\boldsymbol{p_k}$, since it is equivalent to

p_k=Pr[Fed in MGRP of the matched cell]

=Pr[Fed Sub to matched cell]

+Pr[Fed Pub to matched cell]

+Pr[Fed Sub and Pub to matched cell]

then

$p_k = \alpha_i(1-\beta_i) + (1-\alpha_i)\beta_i = \alpha_i + \beta_i - \alpha_i\beta_i$

thus, the achievable gain could be computed as:

$$\mu' = \frac{E(T) - E(T'')}{E(T)}$$

Finally

$$\mu' = \frac{(T_m - T_m')\gamma[p_\Delta p_k + (1-p_\Delta)\sigma + (1-p_\Delta)(1-\sigma)p_k]}{T_u(1-\gamma) + T_m\gamma} \qquad \text{......(5.1)}$$

6. Conclusion

In this paper, we have presented a novel DDM scheme which focuses upon improving the *DDM Time*. We have shown that *DDM Time* could be improved after *matching* if the information on the target cell was known in advance. Thus, an adaptive control mechanism was devised, as part of the ADGB scheme, which provides four different advertising types that can be selected according to the simulation situation to provide maximum gain with acceptable communication costs. We have presented our schemes and we have discussed their performance analysis.

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