Developing Model-Driven Quality-Aware Data Warehouses with a UML Profile

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Abstract

Nowadays, Model-Driven Architecture (MDA) is playing a major role in today's system's development methodologies. Data Warehouse (DW) researchers try to apply MDA standard on DW development project. After surveying the related literature, we found that the main focus of MDA and DW is not as much on performance aspects of DW as on database issues. With the aim to facilitate building a quality-aware DW, we present an extension of the Unified Modeling Language (UML) to create performance UML2 profile and its corresponding metamodel. The profile is defined by a set of new stereotypes to enable DW team to elegantly represent the DW performance requirements with MultiDimensional (MD) properties at the conceptual level. The proposed approach is MDA compliant and uses Query-View-Transformation (QVT) and Model-to-Text (MTL) languages for automatic generation of Platform Specific Model (PSM) and the implementation code in target platform. One key advantage of the proposed approach is that the conceptual modeling of quality-aware DWs is we accomplished independently of the DW target platform, allowing the implementation of the regarded DWs on most of commercial database management systems. Finally, this work has been exemplified and validated by developing a case study in which the proposed profile is used. The outcomes from the validation process give clear evidences that the proposed development framework for DWs outperforms other development methods that do not handle performance requirements at early stages of system development.

Keywords: Data warehousing, Model driven Architecture (MDA), Platform Independent Model (PIM). Platform Specific Model (PSM), Common Warehouse Metamodel (CWM), XML Metadata Interchange (XMI)

1. INTRODUCTION

In recent years Data Warehouse (DW) has become known as a powerful technology for integrating heterogeneous distributed operational data sources into a comprehensive analytical system to predict and make decisions for near future business reengineering [PAIM et al. 2002]. Designing such systems is different from the design of the operational systems that supply data to the warehouse. DW team should elicit functional requirements of decision makers and also the structure requirements of the sourceprovider systems that will be used in a complex process of extracting, transforming, and aggregating data. Moreover, DW team should also focused on non-functional requirements manage to deploy a system that precisely, timely integrates with a number of heterogeneous distributed data sources; presents analytical results in a reliable, accurate format; offers flexibility to end users to execute time-efficient ad-hoc queries[PAIM et al. 2002].

Many data warehousing projects fail to provide the needed information in the right time because the performance aspects of the DW project are considered in the final stages of implementation after end users start blaming that the system is not working as expected. So this paper suggests that performance aspects (Non-Functional Requirements) of the DW should be addressed in the early stages of design by modeling them at conceptual level while modeling the user requirements (Functional Requirement) to have a quality-aware system that meet both operational and strategic visions of organization. Hence, both types of requirements have to be wrapped up in a multidimensional model to meet corporative analytical requirements and provide decision-support functionality as well as strong performance constraints [PAIM et al 2002].

To handle DW performance issues we have to follow a methodological approach. One of the current trends in software development that gains more importance is the model-driven approach. The ideas behind the Model-Driven Architecture (MDA) [OMG 2003b] proposal can facilitate and improve the DW performance solutions. Consequently, to solve DW performance problems, a development framework based on the MDA principles could be used. MDA considers models as first class elements during system design and implementation and establishes a separation of the development process in three abstraction levels, namely CIM, PIM and PSM [MARCOS et al. 2008].

One key advantage of using the MDA is the definition of mappings between the models defined in each level, what makes possible the automation of the development process. Another key advantage is that we can accomplish the conceptual modeling of quality-aware DWs independently of the target platform where the DW has to be implemented, allowing the implementation of the regarded DWs on any commercial database management system [EDUARDO et al. 2006a] [MARCOS et al. 2008].

As mentioned by the UML superstructure specification document [OMG 2005b], there are two extension mechanisms for UML 2.0: (1) the profile mechanism, which is not a first-class extension mechanism by which the modification of existing metamodels is not allowed and (2) the first-class extensibility which is handled through Meta Object Facility (MOF) [OMG 2008], in which there are no restrictions on modifying a metamodel. It is possible to add and remove metaclasses and relationships as is necessary [EDUARDO et al. 2006b] [OMG 2005b]. Hence, to achieve the goals of this work that address the performance requirements at early stages of DW system development using MDA standards [OMG 2003b][ANNEKE et al. 2003], an extension of the unified modeling language (UML) has been created using UML profile. This profile uses stereotypes to represent main DW performance concepts such as Materialized View, Bitmap Index, Normal Index, Function-Based Index and Partitioning.

UML [OMG 2009] has been used because UML is widely accepted as standard for Object-Oriented (OO) modeling language known by most of designers and developers which minimizes the learning curve for understanding new notations or methodologies [SERGIO et al. 2006]. On the other hand, UML is an extensible language that help designer to model new concepts for new applications such as web application, business modeling, database application, service oriented architecture (SOA) application, etc. [MARCOS et al. 2008], [CHRISTOF et al. 2007].

The rest of the paper is organized as follow. Section 2 presents the related works. Section 3 presents the new concepts involved in the proposed performance profile. In Section 4, the Platform Independent Model (PIM) UML2 metamodel with its new stereotypes is explained. Section 5 presents the proposed performance RDBMS Platform Specific Metamodel. In section 6 we implement the case study and present the validation results. Finally, Section 7 presents the main conclusions and future works.

2. Related Work

This work is a based on a previous comprehensive survey conducted by the authors that targeted the research direction in MDA and DW. Most of MDA-related works that have been conducted on DWs can be classified into the following groups

- 1. Creating CWM-based DW Modeling Tools [KUMPON et al. 2003].
- 2. Specifying Metamodel transformations for DW design [LEOPOLDO et al. 2005].
- 3. Extending UML for MultiDimensional Modeling [SERGIO et al. 2006].
- 4. MDA-related DW frameworks [JOSE-NORBERTO et al. 2005][JOSE-NORBERTO et al. 2008].
- 5. Securing DW using MDA [JUAN et al. 2009a][RODOLFO et al. 2006][EDUARDO et al. 2006a][EMILIO et al. 2007a][EMILIO et al. 2007b][EDUARDO et al. 2006b][EMILIO et al. 2008a] [EMILIO et al. 2008b] [EMILIO et al. 2007b].
- 6. Designing Spatial Data Warehouse using MDA Techniques [OCTAVIO et al. 2008].
- 7. Conceptual OLAP Platform-independent Queries [JESUS et al. 2008].
- 8. MDA Framework for Designing Spatial DWs [OCTAVIO et al. 2009].
- 9. MDA Secure Engineering Process for DWs [JUAN et al. 2009b].

Based on this in-deep study and to the best of our knowledge, none of the previous works addresses modeling the DW performance aspects at conceptual level using MDA. Hence, we consider this performance issue a challenging open problem that can be handled using MDA. [PAIM et al. 2002] addressed the enhancement of Data Warehouse design by extending the Non-Functional Requirement (NFR) Framework proposed by [CHUNG et al. 2000]. Catalogues of major DW NFR types and related operational methods has been defined. [PAIM et al. 2002] highlighted the importance of set of quality factors such as integrity, accessibility, performance, and other domain-specific Non-Functional Requirements (NFRs) that governs the success of the DW project. Based on [PAIM et al. 2002], we identified the needed performance objects that can be conceptually modeled at early stages of system development to enhance the DW performance.

3. **Profile Concepts**

This section presents the new concepts that will be involved in the proposed performance UML profile. Figure 1 gives a big picture about these concepts which will be described in detail in this section.

3.1 Fact

In data warehousing, information is structured into facts and dimensions using MultiDimensional Model [ALBERTO et al. 2001][KIMBALL 2002]. A fact can be seen as a point in a MultiDimensional space to which some measurable business facts such as "quantity sold", "amount sold" are assigned [JENS et al. 2003]. Most of business

processes have significant measures that contained in a fact such as "unit cost", "unit price". So we can define a fact as an item of interest for an organization that has a set of attributes called measures or fact attributes. This set of measures is linked to a set of dimensions that surrounding the fact [SERGIO et al. 2006]. As presented in Figure 1, we have represented this concept using "OmFact" stereotype. In the case study as presented in Figure 2, we have conceptually defined a fact for a sales process at a computer store. We named the fact "SALES" and it contains "amount_sold" as fact attribute.



Figure 1: PIM-level Performance Metamodel for DW.

3.2 Dimension

Dimensions provide the context in which facts are to be analyzed. Every fact has set of surrounding dimensions (product, customer, time, etc.) represents the area of interest that is going to be analyzed [MARK 2003]. Unlike Fact concept, dimensions are characterized by descriptive attributes (customer name, product description), which are usually called dimension attributes [INMON 2005]. As presented in Figure 1, we have represented this concept using "OmDimension" stereotype. The case study as presented in Figure 2 contains five dimensions surrounding the SALES fact. These dimensions are TIME, CUSTOMERS, PRODUCTS, CHANNELS, and PROMOTIONS.

3.3 DW Index

DW index is a concept that represents an indexing approach suitable for Data warehousing applications that link large facts with its surrounding small dimensions [MICHAL et al. 2009]. In this case, low cardinality attributes (small number of distinct values) such as Gender (male, female) or State (MD, NY, etc.) are included in the query of interest. For such applications, DW indexing provides a reduced response time for such types of queries [PATRICK et al. 1997]. DW index is a concept that will be mapped

into Bitmap Index which has a significant space and performance advantage over other structures for such data. Bitmap Index uses bitmaps to answer queries by executing bitwise logical operations (XOR, NOT, OR, AND) on these bitmap [GUADALUPE et al. 2009][NAVNEET et al. 2009]. As depicted in Figure 1, we have represented this concept using "OmDWindex" stereotype. In the case study as presented in Figure 3, while creating the PIM input model, we have used this stereotype to model the following indices: SALES_CHANNEL_BIX, SALES_CUST_BIX, SALES_PROD_BIX, SALES_PROMO_BIX, SALES_TIME_BIX, CUSTOMERS_GENDER_BIX and CUSTOMERS_MARITAL_BIX.



Figure 2: Modeled Star Schema.

3.4 Normal Index

Normal Index is a concept that will be used to help us to conceptually model indices that will be mapped to a normal B-tree index in relational database. Even though this type of concept is not heavily used in DW environments [GOETZ 2006], it is needed to create a normal B-tree index for some attributes used mainly by dimensions. This concept is suitable to be used to index attributes that have high cardinality (large number of distinct values) such as "product number" and "customer number" [IBRAHIM et al. 2006]. In the proposed metamodel, as depicted in Figure 1, we have represented this concept using "OmNormalindex" stereotype. In the case study as presented by Figure 3, while creating the PIM input model, we have used this stereotype to model one index "CUST_LAST_NAME_IDX" to index "LAST_NAME" attribute of "CUSTOMERS" class.

3.5 Function-Based Index

A Function-Based Index is a concept that is used to create an index that solves the problem of retrieving case-sensitive information using case-insensitive predicates. In Data warehousing environments, most of end users perform ad hock queries to retrieve data using case-insensitive predicates. For example we may need to retrieve all sales transactions that occurred in specific city such as "Amman" using where initcap (city) =

'Amman'. Because "City" information may be entered in different format such as "AMMAN" or "amman" and we need records related to Amman regardless of its case, we have to have a Function-Based Index based on this formula Initcap (city) to effectively retrieve the needed records. Indexing "City" attribute using traditional Normal Index will not solve the problem and will cause a full table scan and more I/O operations. So for such situation, using Function-Based Indexes will be our super silver bullet for optimizing our Data Warehouse to do a minimum amount of I/O to get the needed information [RICHARD 1999]. In the proposed metamodel, as depicted in Figure 1, we have represented this concept using "OmFunctionalIndex" stereotype. In the case study as presented by Figure 3, we have created UPPER_CUST_CITY_IDX as an instance of "OmFunctionalIndex" Class in the PIM input model; this instance has been mapped to relational Function-Based Index in the proposed PSM RDBMS model.



Figure 3. Modeled Indices.

3.6 Semi Persistent

Semi Persistent is a concept that will be mapped to a relational Materialized View [LEONARDO et al. 2009]. This concept is heavily used in Data warehousing environment as well as in Online Transaction Processing Systems (OLTP) to cache expensive queries in persistent state. This concept is one of the most important performance tuning tools that gives the facility to pre-join complex data source and pre-compute summaries for super-fast response time by reducing repetitive I/O [GORET et al. 1999]. Unnecessary long-full-table scan can be avoided while doing aggregations and summarization by accessing the needed information from already existing Materialized View that contains the expected result [MING et al. 2007]. In the proposed metamodel, as depicted in Figure 1, we represented this concept using "OmSemiPersistent" stereotype. As presented in Figure 4, while validating the proposed profile, we have created CAL_MONTH_SALES_MV as instances of "OmSemiPersistent" Class in the PIM input model; this concept has been mapped to relational Materialized Views in the proposed PSM RDBMS model.

3.7 Partition

Partitioning is the process of dividing a logical data source into distinct parts for the sake of increasing the performance and availability by locating each partition on different file system (Hard drive), different databases or servers [GEORGE et al. 2008]. This concept is deeply used in Data Warehouse environments to spread very large data source

(Fact table) into set of partitions to reduce the amount of data read so that overall response time is reduced by accessing only the needed partitions and skipping the others [VINCENT et al. 2003]. Partitioning is usually done for persistent objects such as database tables. There are two major forms of partitioning [SANJAY et al. 2004]:



Figure 4: Modeled Materialized View

- Horizontal Partitioning this form of partitioning divides available data records into distinct group of physical datasets that can be accessed individually or collectively. All attributes defined to a data source are found in each set of partitions so no actual attributes are missing. Most of partitioning operations in data warehousing use this form of partitions.
- Vertical Partitioning this partitioning approach is used to reduce the width of a target data source by dividing the data source vertically so that only certain attributes are included in a one partition and the remainder attributes are included in another partition, with each partition including all rows. An example of vertical partitioning might be a data source that contains a number of very wide text attribute that aren't used often being broken into two partitions that has the most referenced attributes in one partition and the seldom-referenced text data in another.

Horizontal partitioning can be done in three main modes [SANJAY et al. 2004]:

- Range this partitioning mode allows us to specify various ranges for which data is assigned. For example, we may create a partitioned data source that is divided by four partitions that contain data for the 1970's, 1980's, 1990's, and everything beyond and including the year 2000.
- Hash this partitioning mode allows us to separate data based on a computed hash key that is defined on one or more data source attributes, with the end goal being an equal distribution of values among partitions.
- List this partitioning mode allows us to partition data based on a pre-defined list of values. For example, we may create a partitioned data source that contains three partitions based on the main cities in the regions. Irbid, Jerash, and Ajloun for North_Region. Amman, Zarka and Salt for Mid_region. Karak, Ma'an and Aqaba for South_region.

To conceptually model partitions in the PIM model, as depicted in Figure 1, we have created a new class with a stereotype name "OmPartition" to create partitions for OmFact classes. Each class may have two or more partitions. As presented in **Figure 5**, while

validating the proposed profile, we have created 20 partitions for the "SALES" fact class using range partition mode on "TIME_ID" attribute.



Figure 5: Modeled Data partitions

4. Expression Attribute

Expression attribute is a concept used to model complex attribute such as the sum of two attribute or create function-based attribute such as uppercase (customer_name). This concept is not a major Data Warehouse performance technique; but it is a mandatory model element used to handle complex expression data types at conceptual level. This concept will be used by semi-persistent concept (Materialized View) to formulate a complex attribute, if needed. Moreover, it is used also by Function-Based Index concept to determine the associated function for the index key.

To conceptually model "Expression Attribute" in the PIM model, the metamodel has a new class with a stereotype name "OmExpressionAttribute" to create an expression attribute for OmFunctionIndex classes or OmSemiPersistent classes. While validating the proposed UML profile, as presented in Figure 4, we have created an expression attribute named "dollars" to represent the sum of the amount sold "sum (amount_sold)"; this attribute is one of CAL_MONTH_SALES_MV semi-persistent class attributes.

5. UML Performance Profile

In this section we show the main stereotypes needed to represent the concepts described previously. Table 1 lists the stereotypes that we have defined, the related concept for each stereotype, as well as the base UML metaclass from which stereotypes are derived and brief description of the stereotypes.

NOTATION	RELATED	BASE	DESCRIPTION		
	CONCEPT	UML			
		META			
		CLASS			
< <omfact>></omfact>	Fact	Class	Represents the main Fact		
			table		
< <omdimensin>></omdimensin>	Dimension	Class	Represents the surrounding		
			Dimension tables		
< <omsemipersistet>></omsemipersistet>	Semi	Class	Represents Materialized		
	Persistent		View		
< <omnormalindex>></omnormalindex>	Normal	Class	Represents a Normal Btree		
	Index		index		
< <omfunctionaliindex>></omfunctionaliindex>	Function-	Class	Represents a Function-		
	Based Index		Based Index		
< <omdwindex>></omdwindex>	DW index	Class	Represents a Bitmap Index		
< <ompartition>></ompartition>	Partition	Class	Represents database		
			partition for table		
< <omexpressionattribute>></omexpressionattribute>	Expression	Class	Represent expression		
	Attribute		column for Materialized		
			View or Function for		
			Function-Based Index		

Table 1. Steleotypes for the UNIL renormalice round.	Table 1. Stereotypes	for the	UML	Performance Profile.
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6. **Proposed RDBMS Platform Specific Metamodel (PSM)**

This section presents the proposed Platform Specific Metamodel which is an updated version of the RDBMS PSM metamodel created by Eclipse Tutorials. Because most of data warehousing systems are running under relational databases, we choose our Platform Specific Metamodel to be an RDBMS one.

The first purpose of this metamodel is to enable us to store all needed information about the database objects (schema, tables, Materialized Views, indices, partitions) that we will generated from PIM model using the transformation process. Moreover, this metamodel will be used as an input to the code generation process. This code generation process will create a database script file (xxxxx.sql) that will be used to create all Data Warehouse objects including the performance-related objects such as Table Partitions, Bitmap Indices and Materialized Views. Figure 6 shows a UML class diagram for all needed classes that compose the proposed RDBMS metamodel.

7. Validation and Analysis

This section demonstrates how we build the case study to validate the UML performance profile. Next a detail analysis for the validation results is presented. This work validates and analyzes the performance profile by:

- (i) Creating a DW system that does not contain any object of the performance profile.
- (ii) Creating a DW system using the proposed performance profile.
- (iii) Comparing the number of I/O operations between the two systems.



Figure 6. Proposed RDBMS PSM Metamodel.

The case study starts with developing of a PIM UML model (see Figure 2, Figure 3, Figure 4 and Figure 5) that describes at conceptual level a quality-aware Data Warehouse system. This conceptual PIM model is a subtype of the proposed PIM metamodel (see Figure 1). From the conceptual PIM model we built a physical PSM model using QVT model transformation. From the physical PSM model, we generate the SQL code to create the DW system using Acceleo Model to Text (M2T) language.

To ease the process of creating and populating such DW with relevant information, we use the Data Warehouse example provided by Oracle to create a similar Data Warehouse system [ORACLE 2009]. Oracle DW schema is a very practical DW example because it include all performance elements that are needed to have a highly efficient Data Warehouse system. Table 2 presents these database objects that are modeled conceptually based on the proposed PIM performance metamodel and the corresponding relational database objects that will be mapped to using QVT transformation program.

7.1 Selecting Modeling and Database Tools

To implement the case study, we need a modeling tool for building new metamodels or updating existing metamodels and support Model-to-Model (M2M) transformation using Query-View-Transformation (QVT) language as well as support Model-to-Text (M2T) transformation based on MDA standard.

Eclipse is a well-known tool that supports most of MDA standards that are needed in this work. Moreover Eclipse allows us to depict models in different formats, using tree or diagram format. In addition, Eclipse has an M2T language which is based on MDA standard named "Acceleo". This language used to transform the proposed PSM model to SQL code. Furthermore, Eclipse supports the OMG QVT standard for M2M

transformations. So based on these advantages of Eclipse, we used Eclipse as our modeling tool. We used Eclipse to:

- 1. Build the proposed PIM performance metamodel.
- 2. Build the proposed PSM performance RDBMS metamodel.
- 3. Build the PIM input model example for the case study.
- 4. Develop the M2M QVT transformation program.
- 5. Develop the M2T transformation program to generate the SQL code.

To build the DW systems, we used TOAD utility from QUEST SOFTWARE [QUEST 2009] which can be connected to Oracle database and provide all performance tuning metrics for any executed query.

Model element name	Concept	Stereotype	Mapped	
			Relational DB	
			object	
SALES	Fact	< <omfact>></omfact>	Table	
CUSTOMER	Dimension	< <omdimension>></omdimension>	Table	
PROMOTION	Dimension	< <omdimension>></omdimension>	Table	
TIME	Dimension	< <omdimension>></omdimension>	Table	
PRODUCT	Dimension	< <omdimension>></omdimension>	Table	
CHANNELS	Dimension	< <omdimension>></omdimension>	Table	
CAL_MONTH_SALES_M	semipersistent	< <omsemipersistent>></omsemipersistent>	Materialized	
V			View	
SALES_CHANNEL_BIX	DW Index	< <omdwindex>></omdwindex>	Bitmap Index	
UPPER_CUST_CITY_IDX	Function-	< <omfunction< td=""><td>Function-</td></omfunction<>	Function-	
	Based Index	Index>>	Based Index	
CUST_LAST_NAME_IDX	Normal Index	< <omnormalindex>></omnormalindex>	B-tree index	
SALES_1995	Partition	< <ompartition>></ompartition>	Partition	
SALES_1996	Partition	< <ompartition>></ompartition>	Partition	
SALES_H1_1997	Partition	< <ompartition>></ompartition>	Partition	
SALES_H2_1997	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q1_1998	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q2_1998	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q3_1998	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q4_1998	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q1_1999	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q2_1999	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q3_1999	Partition	< <ompartition>></ompartition>	Partition	
SALES_Q4_1999	Partition	< <ompartition>></ompartition>	Partition	
		•		
		•	•	
SALES_Q4_2004	Partition	< <ompartition>> Partition</ompartition>		

Table 2. DW PIM model elements.

7.2 Measuring I/O Operations

Because DW system represents a very large database and normally deals with multimillions of records, doing more I/O operation will degrade the system performance. I/O operation can be read logically from memory or physically from hard disk. So we compare the number of I/O operations for a specific query between the two systems. The validation process covers the following performance elements: Materialized View, Table Partitioning, Bitmap Index, Function-Based Index and Normal Index.

7.3 Validating the Usage of Table Partitioning

To validate the usage of Table Partitioning, we use the following query that retrieves the sum of amount sold for every month.

```
SELECT t.calendar_month_desc,sum(s.amount_sold) AS
dollars
FROM sales s, times t
WHERE s.time_id = t.time_id
CDOUD DV t calendar month_desc
```



Figure 7. Performance affect for Table Partitiong.

Figure 7 shows that without using Table Partitioning the DW system used 8981(sum of logical reads and physical reads) read operations to retrieve the requested information while our MDA approach gets the same result using 2997 read operations; this means our MDA approach outperforms traditional approach by 66%. Figure 8 below shows the performance metrics after executing the mentioned query without using Table Partitioning; as we can see the consistent gets (logical reads) is 4496 and the physical reads is 4485. The reason for this large number of I/O operations is the use of "FULL TABLE SCAN" as mentioned by the SQL execution plan depicted by Figure 9 below.

. %	🖻 🖀 📄 🗌) 💊 🐁 😭	🚼 💭 🖓 🛛 ABC abc Abc 🛛 🗊	= •		
SELECT tcalendar_month_desc sum(s.amount_sold) AS dollars FROM sales s times t WHERE s.time_id = ttime_id GROUP BY tcalendar_month_desc						
Dat	ta Explain Plan	Auto Trace	DBMS Output (disabled) Code Statist	tics		
	Description		Value	L		
ſ	ecursive calls		0			
	db block gets		0			
	consistent gets		4496			
F	physical reads 4485					
redo size 0			0			
t	oytes sent via SQL*	Net to client	3527			
t	bytes received via SQL*Net from clien 1095					
	SQL*Net roundtrips to/from client		5			
1	sorts (memory)		2			
1	sorts (disk)		0			

Figure 8. I/O operations without partitioning.

Data Explain Plan Auto Trace DBMS Output (disabled) Code Statistics Script Output							
Operation	Object Name	Rows	Bytes	Cost	ļþ		
SELECT STATEMENT Optimizer Mode=ALL_ROWS	;	60		981.950720882274	T		
🖻 SORT GROUP BY		60	1 K	981.950720882274			
📄 - HASH JOIN		904 K	25 M	906.701267365405			
- TABLE ACCESS FULL	AABFS_DW.TIMES	1 K	28 K	13.05990047358			
TABLE ACCESS FULL	AABFS_DW.SALES	904 K	11 M	884.787311999637			

Figure 9: Execution Plan without using partitioning.

Figure 10 below shows the performance metrics after executing the mentioned query using Table Partitioning; as we can see the consistent gets (logical reads) is 1773 and the physical reads is 1224. The reason for this reasonable number of I/O operations is the use of partitions as mentioned by the SQL execution plan as depicted in Figure 11 below.

i X 🖦 🛍 🚞 🗅 🔌 🐜 🗞	🖍 🖓 ABC abc Abc 🗱 🗱					
SELECT tcalendar_month , sum(s.amount_sold) A FROM sales s , times t WHERE s.time_id = t.time GROUP BY tcalendar_mo	_desc S dollars e_id nth_desc					
Data Explain Plan Auto Trace DB	MS Output (disabled) Code Statistics					
Description	Value					
recursive calls	0					
db block gets	0					
consistent gets 1773						
physical reads	1224					
redo size	0					
bytes sent via SQL*Net to client	3522					
bytes received via SQL*Net from clien 1095						
SQL*Net roundtrips to/from client 5						
sorts (memory)	2					
aarta (diak)	0					

Figure 10. I/O operations with Table Partitioning.

X 🖻 🛍 🗎 🗋 隆 🖌 🔏 🗠 🗠 1	ABC abc Abc 🗐	= 💷 🥚							
SELECT t.calendar_month_desc									
, sum(s.amount_sold) AS dollars									
FROM sales s									
, times t									
WHERE s.time_id = t.time_id									
GROUP BY t.calendar_month_desc									
							••••• 🔻		
D. L. Euclain Blan, J. J. T. D. D. LO. G. J. J. C.			-						
Data Explain Fildri Auto Trace DBMS Uutput (dis	abled) Code Stat	tistics Script	Output						
Operation	abled) Code Stat	tistics Script Rows B	Output ytes	Cost	Object Node	In/Out	PStart	PStop	
Data C×prain Frain Auto Trace DBMS Dutput (dis Operation ☐ SELECT STATEMENT Optimizer Mode=ALL_ROWS	abled) Code Stat Object Name	tistics Script Rows B 60	Output lytes	Cost 452.732328876677	Object Node	In/Out	PStart	PStop	
Data Explain Field Auto Trace DBMS Output (dis Operation ■ SELECT STATEMENT Optimizer Mode=ALL_ROWS SORT GROUP BY	abled) Code Stat Object Name	tistics Script Rows B 60 60	Output lytes 1 K	Cost 452.732328876677 452.732328876677	Object Node	In/Out	PStart	PStop	
Data Explain Field Auto Trace DBMS Dutput (dis Operation SELECT STATEMENT Optimizer Mode=ALL_ROWS SORT GROUP BY B-HASH JOIN	abled) Code Stat Object Name	tistics Script Rows B 60 60 918 K	Output lytes 1 K 25 M	Cost 452.732328876677 452.732328876677 376.208020115945	Object Node	In/Out	PStart	PStop	
Data Explain Film Auto Trace DBMS Butput (dis Operation SELECT STATEMENT Optimizer Mode=ALL_ROWS SORT GROUP BY HASH JOIN TABLE ACCESS FULL	abled) Code Stat Object Name	tistics Script Rows B 60 60 918 K 1 K	Output lytes 1 K 25 M 28 K	Cost 452.732328876677 452.732328876677 376.208020115945 13.0605563195257	Object Node	In/Out	PStart	PStop	
Data Explain Field Auto Trace DBMS Dutput (dis Operation SELECT STATEMENT Optimizer Mode=ALL_ROWS SORT GROUP BY HASH JOIN TABLE ACCESS FULL PARTITION RANGE ALL	abled) Code Stat Object Name S SH.TIMES	tistics Script 60 60 918 K 1 K 918 K	Output lytes 1 K 25 M 28 K 11 M	Cost 452.732328876677 452.732328876677 376.208020115945 13.0605563195257 354.160194110533	Object Node	In/Out	PStart	PStop	28

Figure 11. Execution Plan with Table Partitioning.

Due to the scope constraints of this paper, Table 3 and Figure 12 present a performance comparison between our MDA approach and non-MDA approaches for all proposed DW performance objects. The outcomes from the validation process gave clear evidences that the proposed development framework for DW will outperform any development method that does not handle performance requirement at early stages of system development.

Performance	Other	Our	Our
Object	approaches	approach	approach
	Read	Read	effectiveness
	Operations	Operations	
Partition	8981	2997	66%
Materialized	9138	678	92%
View			
Bitmap Index	3387	344	89%
Normal	11837	3387	71%
Index			
Function-	12005	3696	<u>69</u> %
Based			

Table 3. Performance Analysis



Figure 12. Performance Comparisons using Number of Read Operations.

8. Conclusions

This paper has targeted the development of quality-aware DW framework that is based on MDA standard by addressing the DW performance requirements at early stages of system development. After surveying the related literature, the main focus of MDA and DW framework is not as much on the performance needs as on database issues; and so this work presented an extension of the Unified Modeling Language using UML2 profile. This profile is defined by set of new stereotypes to enable DW team to elegantly represent the DW performance requirements with MD properties at the conceptual level. The proposed approach is MDA compliant and uses Query-View-Transformation and Model-to-Text languages for automatic generation of Platform Specific Model and code in target platform. Finally, this work has been validated and showed the benefit of the proposed profile by developing a case study for sales DW system using Eclipse modeling tool. The outcomes from the validation process gave clear evidences that the proposed development framework for DW will outperform any development method that does not handle performance requirement at early stages of system development.

Regarding future work, promising challenges wait in many areas touched by this paper. Our work focus only on performance part of Non-functional requirements while other types such as user friendliness and multidimensionality have promising challenges. Even though our work handle commonly used performance elements such as partitioning and indexing, it neither handle the parallelism while executing a specific query nor it deals with optimizing disk usage. Moreover, our work focused on developing Relational PSM and its related transformation rules; hence there is a space for handling other PSM such as object and object-relational databases.

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