A Quality-based ETL Design Evaluation Framework

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Abstract: The Extraction, Transformation and Loading (ETL) process is a crucial component of a data warehousing architecture. ETL processes are usually complex and time-consuming. Particularly important (although overlooked) in ETL development is the design phase, since it impacts on the subsequent ones, i.e., implementation and execution. Addressing ETL quality at the design phase allows taking actions that can have a positive and low-cost impact on process efficiency. Using the well-known Briand et al. framework (a theoretical validation framework for system artifacts), we formally specify a set of internal metrics that we conjecture to be correlated with process efficiency. We also provide empirical validation of this correlation, as well as an analysis of the metrics that have stronger impact on efficiency. Although there exist proposals in the literature addressing design quality in ETL, as far as we are aware of, this is the first proposal aimed at using metrics over ETL models to predict the performance associated to these models.

1 INTRODUCTION

A data warehouse (DW) is a data repository that consolidates data coming from multiple and heterogeneous sources, in order to be exploited for decision-making. This consolidation is performed through a collection of processes denoted Extraction, Transformation and Loading (ETL). ETL development is usually composed of four phases, shown in Fig. 1 (Inmon, 2002). It has been widely argued that the ETL process is complex and time-consuming, at a the point that roughly 80% of a DW project is due to this phase (Inmon, 2002; A. Simitsis and Sellis,).

ETL processes are typically implemented as SQL or Java programs orchestrated to answer organization requirements. Thus, ETL optimization cannot be reduced to SQL query optimization as usual in databases: it should also take into account the process structure. Structural optimization must manage two main aspects: tasks combination and order. The latter has been studied in (A. Simitsis and Sellis, 2005) as a state space problem where, by changing the order of the process tasks, an algorithm finds the process alternative providing the best execution. However, the combination aspect has not been covered in the literature. This factor is also relevant, since to tackle the same integration problem, several process alternatives are possible, having different number of tasks and work combinations (e.g., a process containing few tasks, each one performing heavy work, can be equivalent to a process that contains many less loaded tasks). Comprehensive approaches aimed at finding the best process structure are still lacking.

A line of research oriented towards enhancing the ETL process proposes conceptual modeling languages to define ETL workflows (Z. El Akkaoui and Zimányi, 2012; Trujillo and Luján-Mora, 2003; P. Vassiliadis and Skiadopoulos,), sometimes presented together with ETL design guidelines (U. Dayal and Wilkinson, 2009). We comment on these proposals in Section 2. Most of them propose metrics that can lead to improve characteristics like usability and maintenance. However, to the best of our knowledge, no work has studied and validated ETL model design criteria with respect to the crucial issue of ETL process *efficiency*.

To provide a solution to this problem, in this paper we present tools that, based on the ETL design characteristics, can help to predict the efficiency of the process. We do this by means of a set of structural (also denoted *internal*) metrics, defined based on the Briand et al. (L. Briand and Basili, 1996) theoretical framework in order to guarantee the mathematical validity of the approach. The nice property of these metrics is that they can be *computed at design time*, and that, as we will show, they are *correlated with ETL ef-*

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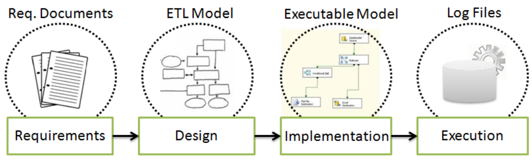


Figure 1: Development steps & improvement criteria.

ficiency, specifically with the process throughput (an *external* metric). Therefore, proving the correlation stated above is an important achievement in ETL design, since, given a collection of alternative ETL models, it would allow predicting the one that is likely to deliver the best performance without actually needing to code a single line, dramatically dropping the costs of the DW project.

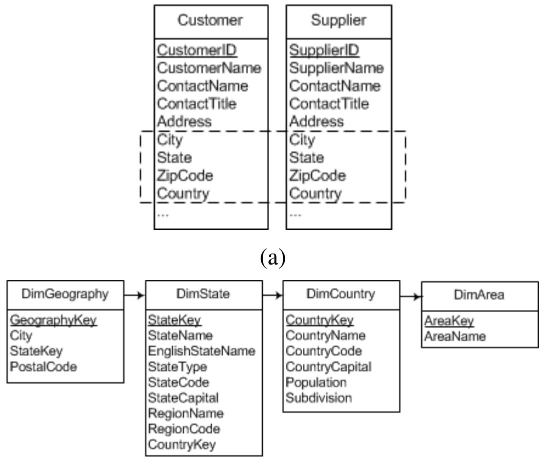
The paper is organized as follows. Section 2 discusses related work. Section 3 presents our running example, while in Section 4 we introduce the formal data model for the ETL process graph. Section 5 studied the internal and external measures used to evaluate the design quality of the ETL model. Section 6 reports the experimental validation and its results, concluding in Section 7.

2 RELATED WORK

A quality model (e.g., (B. Boehm and Merritt, 1978)) defines a set of quality goals together with a set of practices for achieving and evaluating them. The ISO/IEC 9126 standard[1] provides a standard quality model for software products. Built on software quality approaches, ETL process quality evaluation methods have been proposed. These proposals mainly address ETL usability or maintainability evaluations. Quality evaluations for ETL design proposed in (L. Muñoz and Trujillo, 2010; P. Vassiliadis and Skiadopoulos,) derive measures based on the Briand et al. (L. Briand and Basili, 1996) evaluation framework. While Vassiliadis et al. (P. Vassiliadis and Skiadopoulos,) limit to propose supposedly useful measures for ETL models, Muñoz et al. (L. Muñoz and Trujillo, 2010) validate the measures empirically by studying their effect over two ISO quality dimensions, namely usability and maintenance. Further (Z. El Akkaoui and Trujillo, 2013; G. Papastefanatos and Vassiliou, 2009) cover maintainability and support data source evolution.

Enhancing ETL efficiency at the *implementation* step has been studied in some few works. Simitsis et al. (A. Simitsis and Dayal, 2013) proposes an opti-

[1]http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=22749



(a)

(b)

Figure 2: (a) Tables from source database; (b) Location hierarchy.

mizer that converts the logical flow to an executable form that is optimized for the underlying infrastructure according to user-specified objectives. Another optimization approach (A. Simitsis and Dayal, 2012) intends to avoid bad execution plans by partitioning the original data model into submodels that we run on each engine. Another contribution (T. Majchrzak and Kuchen, 2011), by defining a set of performance measures, a comparison is made between Talend (a code generation-based tool) and Pentaho (an engine-based tool). Results showed that Talend is more efficient in terms of execution time and CPU usage, while Pentaho is less memory-consuming. Further, (Ali and Wrembel, 2017; G. Kougka and Simitsis, 2018) survey almost aforementioned data flow optimization techniques. But (G. Kougka and Simitsis, 2018) expands the study to various other data-centric flow topics besides ETL processes, including database engines, MapReduce systems, and business processes. In the present work we go further than existing proposals, quantitatively assessing the relationship between a set of *design* quality metrics evaluated over the *structure* of the ETL process model, and external metrics obtained at *execution* time.

3 RUNNING EXAMPLE

To model a DW we use the well-known star-schema (Kimball and Ross, 2002), where DW tables are of two kinds: dimension and fact tables. Dimensions actually represent aggregation hierarchies along which fact data are summarized. ETL processes take data from the sources into the star-schema tables. To illustrate our evaluation framework, we use a portion of an ETL process that loads a collection of dimension tables containing customer and location data. Fig. 2b shows dimension tables DimArea, DimCountry, DimState, and DimGeography. The first three ones are populated using an XML file denoted Territories.xml. DimGeography is populated using geographical data with attributes City, State, ZipCode, and Country, present in the Customer and Supplier tables of the Northwind database[2] (Fig. 2a). Before populating the Location hierarchy, the geography data needs some cleansing and transformation operations to fit the data warehouse requirements, namely: (a) *Data completion*, which requires dealing with null values. For example, the attribute State may be null in the Customer and Supplier source tables. The ETL process fixes this by using an external source file Cities.txt, which contains three fields: city, state, and country. (b) *Data consolidation*. For example, in the source databases, attribute State contains either a state name (e.g., California) or a state code (e.g., CA). In the latter case, the state code is either left empty or converted into the state name using the State table with attributes StateId, StateName, and Code (the ISO standard code), which contains the link between the state name and its code. (c) *Consistency,* in particular with respect to referential integrity constraints. During the loading of the data into the data warehouse, referential integrity between all the hierarchy tables must be ensured.

To model complex processes, several conceptual modeling tools (mentioned in Sections 1 and 2) have been proposed in the literature. In this paper we use an ETL model based on BPMN4ETL (El Akkaoui and Zimányi, 2012), which models ETL processes as workflows, extending the BPMN notation. Fig. 3 shows the loading process for the DimGeography dimension of our running example, modeled in BPMN4ETL. More in detail, an ETL model in BPMN4ETL is perceived as composed of a *control process* containing several *data processes.* A control process (top process of Fig. 3) manages the coarse-grained groups of tasks and/or sub-processes, while a data process (bottom processes of Fig. 3) operates at finer granularity, detailing how input data are transformed and output data are produced. For example, populating each fact (dimension, view, temporary, etc.) table in the data warehouse constitutes a data process, whereas sequencing the load of different dimension levels constitutes a control process.

[2]http://www.microsoft.com/en-us/download/details.aspx?id=23654

4 DATA AND QUALIY MODELS

4.1 ETL Data Process Graph

We now present the ETL model we use in this paper. Due to space limitations we restrict ourselves to study the data process perspective, which constitutes the portion of the ETL process where transformations occur, and we do not deal with the control process.

There is T, a set of node types. T = {“data input”, “data output”, “filter”, “field lookup”, “field derivation”, “field generation”, “join”, “union”, “aggregation”, “sort”, “pivot”, “script”}. There is also a set A containing a list of possible actions performed by a node. A = {“field manipulation”, “field generation”, “join”, “lookup”, “branching”, “extraction”, “load”}, where “field manipulation” action covers field computation, deletion, addition, sorting, pivoting, and splitting. In addition, a node has a traversing stream. The input stream of a node has schema:

$((field_1,\ \ field_1.datatype),...,(field_i,\ \ field_i.datatype))$

Definition 1 (Data Process Graph (DPG))**.** *A data process graph is a directed graph G(N,E) where* $N = n_1, n_2, ..., n_p$ *is the set of nodes representing the data tasks, and* $E = e_1, e_2, ..., e_q$ *is the set of edges between nodes. An edge* $e = (a,b) \in E$ *means that b receives data from node a for further processing. In addition, the following holds:*

- *There is a function with signature* $N \mapsto T$*, that maps a node n to its type.*
- *Each node has an associated set of actions, which is a subset of A. There is a relation* actions $\in N \times A$*, reflecting this association.*
- *A relation* schema $\in N \times S$ *defines the input fields of a node.*
- *A node belongs to a flow category. It is either a* branching *node: “filter”, a* join *node: “join”, a* union *node, a* lookup *node: “fieldlookup” or a* unitary *node, for the other nodes.*
- *A node belongs to a script category. It is either a* script *node “script”, or a* non-script *node. In addition, “datainput” and “fieldlookup” nodes can also be considered script nodes when they include a data extraction script. Otherwise, they are considered* non-script *nodes.*
- *A node belongs to a stream category according to the applied treatment on its traversing data. It is either a* row-by-row *node (“field derivation”, “field generation”), a* row-set *node (“sort”, “pivot”, “aggregation”), or an* input-output *node (“data input”, “data output”). Row-by-row nodes are asynchronous (each row is pro-*

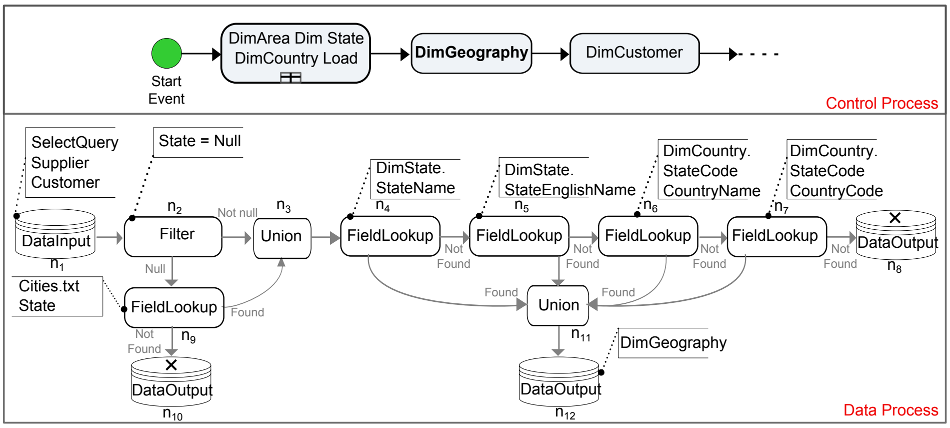


Figure 3: DimGeography load data processes.

cessed when it arrives), while row-set nodes are synchronous (processing starts only when the whole row-set arrives).

- *Data annotations can be associated to nodes and edges as free text.*

Definition 2 (Valid Data Process Graph)**.** *A Data Process graph G is valid if the following constraints hold:*

- *G has at least two nodes: a "data input" node and a "data output" node.*
- *Each node in G respects the allowed in- and out-degrees, predefined according to its type.*
- *Each node in G has at least one predecessor except for the "data input" nodes.*
- *Each node performs a number of actions. Script nodes have no predefined number of actions, while non-script nodes have one action.*

The ETL process in Fig. 3 depicts a graph with 12 nodes. According to the definitions below, the node n_1= DataInput, is a unitary, non-script, and row-by-row node, such that type(n_1) = "data input", and actions(n_1) ="extraction".

4.2 Measure Families

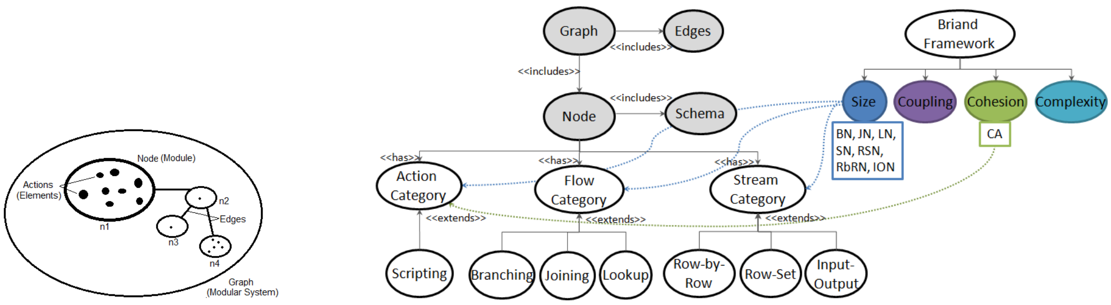
Quality concepts like complexity, coupling, cohesion or size are very often subject to interpretation. Thus, Briand et al. (L. Briand and Basili, 1996) proposed a framework facilitating the definition of quality measures based on mathematical properties. This guides the designer in creating mutli-aspect and non-redundant measures. The authors proposed a set of mathematical properties general enough to be applicable to a wide set of artifacts, not only programming code. We next show how the proposal can be applied to the ETL process context.

The framework defined by Briand et al. identifies the following families of measures, which also can be called quality dimensions (each family allows creating a collection of associated measures that 'operationalize' the concept): (a) *Size*: reflects the number of elements in a system; (b) *Coupling*: measures the strength of the connections between system elements; (c) *Cohesion*: characterizes the interaction between elements in sub-systems or modules. It assesses the tightness with which related program features are grouped together in sub-systems or modules. A highly cohesive system has few interactions between its elements; (d) *Complexity*: in general it is used for assessing complex system behavior. It informs about the effort needed to maintain, change and understand a system. Complexity is a *system* property that depends on the relationships between elements, rather than a property of an isolated element.

Fig. 4a depicts the *modular system* decomposition borrowed from (L. Briand and Basili, 1996), and its correspondence with the DPG of Definition 1. The modular system includes *modules* that contain *elements*. A *system* is a tuple $< N,E >$ where N is the set of elements of the system, and E is the set of edges between the elements. A module *m* is a subset of the elements of the system. In general, modules can overlap. When the modules partition the nodes in a system, then this system is called *modular*. The DPG corresponds to a modular system where nodes correspond to modules and actions to elements.

By definition, size and complexity measures are computed over the whole *modular system*, while the other measures are computed over *modules* composing this modular system. Following (L. Briand and Basili, 1996), the measures belonging to a family must verify a set of properties, e.g.:

- Non-negativity: the measure must not be inversely related to the studied aspect. (Applies to



(a) (b)

Figure 4: (a) The structure of a system in (L. Briand and Basili, 1996); (b) Its mapping to the DPG.

Size, Coupling and Complexity).

- Null value: the measure must be null when a system does not contain any element. (Applies to the measures in the four families).
- Additivity: when several modules do not have elements in common, the size of the system is the size of its modules. (Applies to Size).
- Non-negativity and normalization: the measure is independent of the size of the system or module, and belongs to a certain interval. (Applies to Cohesion).
- Monotonicity: states that adding internal relationships in modules does not decrease a measure's value (however, adding an edge between modules decreases the measure). (Applies to Coupling and Cohesion).

From Definition 1 we can devise the node classification hierarchy of Fig. 4b. At the bottom of this classification, we identify seven node categories. Actually, the rationale behind these seven size measure categories is that we conjecture that these categories impact on efficiency (we validate this in Section 6). Moreover, Fig. 4b shows the relationship between the graph definition and the measure families in (L. Briand and Basili, 1996). For example, the *Action* category is related to the *Cohesion* family. The other node categories are linked to the *Size* family.

In our approach, we consider a DPG as a modular system, where a node is a module, an edge is the inter-module relationship, and actions are the module elements. Hence, *size measures* are defined over the whole graph, and *cohesion measures* are defined over its modules. The *cohesion measure* is aimed at reflecting the intra-module interactions between elements within modules (actions). No coupling and complexity measures are defined because coupling is an inter-module relationship, and there is no inter-module interaction among their elements (actions). *Complexity* is linked to the inter-module relationships, and because of the DPG structure, the size measures also inform about the complexity.

5 ETL DESIGN QUALITY MEASURES

Efficiency is an ISO 9126 quality dimension that evaluates the capability of a model to provide appropriate performance relative to the amount of resources used, under stated conditions. In this section we first present efficiency (*external*) measures from the ISO 9126 (Becker, 2008), typically used to compute the ETL process performance. Then, based on the measure families studied in Section 4, we propose a set of structural (*internal*) measures, particularly describing the graph node combination, to be applied at the design level. These internal measures are likely to impact the ETL process efficiency.

5.1 External Measures

The ISO 9126 quality dimensions include *functionality*, *reliability usability*, *efficiency*, *maintainability*, and *portability*. The set of measures proposed by the ISO standard to evaluate ETL execution efficiency are depicted in Table 1. For example, *Execution Time* (ET) is the server time required to complete the execution of an ETL process. A more significant measure to evaluate ETL efficiency is *Throughput* (Th), which takes into account the size of the data processed by the ETL system. The throughput is computed as the number of rows per unit of time processed. Additional performance measures address resource usage. For example, the *Disk I/O* computes the number of disk readwrite actions performed during the ETL execution. Note that the evaluation of the external measures require a complete implementation and execution of the ETL process.

Table 1: External measures.

Measure	Name	Description
ET	Execution Time	Time the server takes to complete the execution
NL	Network Latency	Time the network takes to transfer data from data sourcetarget to the data staging
Th	Throughput	Size of data served by the ETL model per unit of time
DIO	Disk IO	Number of disk readwrite
Me	Memory	Memory amount usage

5.2 Internal Measures

We next propose a collection of internal measures, formalize them, and show that they satisfy the properties defined in (L. Briand and Basili, 1996). We base the definition of the internal measures in the formal definition of a DPG (Definition 1). To represent the framework in (L. Briand and Basili, 1996), we call G = (N, E) a graph, and m = (N_1, E_1) a module in G, such that a set of nodes N_1 is linked with edges E_1 such that $N_1 \subseteq N$, and $E_1 \subseteq E$. A module can include only one node.

Size Family. It appears straightforward to assume that the larger the graph size, the lesser the efficiency we can expect from an ETL process, and that each additional node will increase the execution time and/or resource usage. Importantly, the data processing of a decomposed ETL graph are delayed by the data transfer time between nodes. In addition, a decomposed graph has a latency time due to different transformations (instead of a single combined transformation) applied over each row. As mentioned in Definition 1, a node belongs to a stream category according to the way it is processed (row-by-row, row-set or input-output). A higher latency is hence expected for decomposed row-set nodes. For this reason, we define a size measure for each node category since we expect that each has a specific influence on the efficiency. We next define the measures in the *Size* family.

Definition 3 (Branching Nodes)**.** *Given a graph G. The* Branching Nodes *measure of G, BN(G), is the number of branching nodes in G. It is computed as the cardinality of the nodes in the "branching" category:*

$$BN(G) = card(\{n \in N \mid type(m) \in \text{“}filter\text{”}\}\})$$

Definition 4 (Joining Nodes)**.** *Given a graph G, the* Joining Node *measure of G, JN(G), is the number of node in the "joining" category:*

$$JN = card(\{n \in N \mid type(m) \in \{\text{“}join\text{”}, \text{“}union\text{”}\}\})$$

Definition 5 (Lookup Nodes)**.** *Given a graph G, the* Lookup Nodes *measure of G, LN(G), is the number of nodes in G belonging to the "lookup" category and which perform only one action (it does not include scripts).*

$$LN(G) = card(\{n \in N \mid type(m) \in \{\text{“}fieldlookup\text{”}\} \wedge card(actions(n)) = 1\})$$

Definition 6 (Script Nodes)**.** *Given a graph G, the* Script Nodes *measure of G, SN(G), is the number of script nodes in the module m, and it is computed as the cardinality of the nodes having a number of actions greater than 2.*

$$SN(G) = card(\{n \in N \mid card(actions(n)) \geq 2\})$$

Example 1. *For G= DimGeography in Fig. 3, we have:*
$BN(G) = card(\{n_2\})$ = *1.*
$JN(G) = card(\{n_3, n_{11}\})$ = *2.*
$LN(G) = card(\{n_4, n_5, n_6, n_7, n_9\})$ = *5.*
$SN(G) = card(\{n_1, n_6, n_7\})$ = *3.*

Finally, we define three measures on the *stream* category. The more resource-consuming stream type is the row-set type because it implies a blocking strategy that delays the execution, in particular when dealing with large data volumes. The row-by-row type is less time-consuming. The input-output type is in charge of importing and exporting data from and to databases.

Definition 7 (RS, RbR, and IO Nodes)**.** *Given a graph G, the* Row-Set (RS) Nodes *measure*

$$RSN(G) = card(\{n \in N \mid type(n) \in \{\text{“}sort\text{”}, \text{“}pivot\text{”}, \text{“}aggregation\text{”}\}\})$$

The Row-by-Row (RbR) Nodes *measure of G, RbRN(G), is the number of row-by-row nodes in G.*

$$RbRN(G) = card(\{n \in N \mid type(n) \in \{\text{“}fieldderivation\text{”}, \text{“}fieldgeneration\text{”}\}\})$$

The Input-Output (IO) Nodes *measure of G, ION(G), is the number of data input and data output nodes in G.*

$$ION(G) = card(\{n \in N \mid type(n) \in \{\text{“}datainput\text{”}, \text{“}dataoutput\text{”}\} \text{ and } card(actions(n)) = 1\})$$

Example 2. *For G = DimGeography graph of Fig. 3, we have: RSN(G) = 0 (G does not contain any row-set node), RbRN(G) = 0 (G does not contain any row-by-row node), and ION(G) =* $card(\{n_1, n_8, n_{10}, n_{12}\})$ = *4.*

The mathematical properties that must characterize any *size* measure are verified by the proposed ones as shown next (proofs omitted).

1. *Non-negativity*. Meaning that for any graph G, BN(G) ≥ 0, JN(G) ≥ 0, LN(G) ≥ 0, SN(G) ≥ 0, RSN(G) ≥ 0 RbRN(G) ≥ 0, and ION(G) ≥ 0;
2. *Null value*, implying that if G = $\varnothing \implies$ BN(G) = 0, JN(G) =0, LN(G) = 0, SN(G) = 0, RSN(G) = 0 RbRN(G) = 0, and ION(G) = 0;
3. *Module additivity*, having $m_1 =< N_{m1}, E_{m1} >$ and $m_2 =< N_{m2}, E_{m2} >$ it holds that ($m_1 \subseteq G$ and $m_2 \subseteq G$ and $N = N_{m1} \cup N_{m2}$ and $N_{m1} \cap N_{m2} = \varnothing$) $\implies$ $BN(G) = BN(m_1) + BN(m_2)$, $JN(G) = JN(m_1) + JN(m_2)$, ...

   It is worth mentioning that in our graph system, a module is a unitary node sub-system, therefore N_{m1} contains only one node.

Size measures inform about the high-level organization of the work in the graph. We need a complementary characteristic in order to quantify the distribution of the work through the graph nodes. We define it next.

Cohesion Family. Cohesion is related to the amount of work processed by the graph nodes. Depending on the scripting category, some nodes may perform more actions than other ones. In particular, script, field lookup, and data input nodes can perform a large, unpredictable, amount of actions. The *Cohesion Action* measure, defined next, is aimed at reflecting the amount of work carried out by such nodes. We expected that nodes with a low cohesion (i.e., performing more actions) consume more time and resources than nodes with a high cohesion. Note that this measure is defined for each system module or node.

Definition 8 (Cohesion Action)**.** *Given a module m = $< N, E >$ from a graph G, the Cohesion Action measure of m, CA(m), is defined as:*

$$CA(m) = \frac{LCAN(m)}{CAC(G)}$$

where $CAC = \sum_{n \in N} card(actions(n))$ *and*

$$LCAN = \sum_{n \in N} card(actions(n)) \; s.t. \; actions(n) \geq 2$$

CA(m) is the proportion of low cohesion nodes in the graph G. It determines the participation of each node in performing the work. CAC(m) is the number of all actions performed by the nodes in G. It estimates the work produced by the whole graph. LCAN(m) is the cardinality of the actions of low cohesion nodes.

Example 3 (Cohesion Action)**.** *For our example graph, n_1, n_6, n_7 are low cohesion nodes. Node n_1 is a "data input" node using a script which applies both, extraction and join actions (annotated e, j as specified by the set of actions A in Definition 1). Also, n_6 and n_7 are "field lookup" nodes containing a join script in their lookup condition (annotated lk, j).*

$CAC(G) = card(\{e, j\}) + 4 \times card(\{lk\}) + 2 \times card(\{lk, j\}) + 3 \times card(\{l\}) + 2 \times card(\{j\})$= 15;
$LCAN(\{n_1\}) = card(\{j, e\})$ = 2; $LCAN(\{n_6\}) = card(\{b, j\})$ = 2;
$LCAN(\{n_7\}) = card(\{c, j\})$ = 2;
$CA(\{n_1\}) = CA(\{n_6\}) = CA(\{n_7\})$ = 2/15 =0.13.

The mathematical properties that must be accomplished by any cohesion measure are verified by CA, that are not been demonstrated due to space limitation.

6 EXPERIMENTAL VALIDATION

In this section, we describe a set of experiments aimed at providing a preliminary empirical validation of the relationship between the proposed internal measures, and the external measure Throughput (Th). We chose Th as the external measure since it can be computed using the execution elapsed time extracted from the system's log file, allowing obtaining meaningful results. Our hypotheses are:

- H1: The number of join, lookup, script, row-set, and input-output nodes are correlated with Th;
- H2: The number of row-by-row nodes has low impact on the Th;
- H3: Adding branching nodes does not decrease Th;
- H4: The best script node form is the data input node using a script. This is better than using a specific script node.
- H5: For optimization purposes, replacing join nodes with a data input script node increases Th. On the contrary, replacing lookup nodes with data input script nodes is not beneficial for throughput.

The validation of these hypothesis will guide the ETL designer in answering fundamental questions such as: *which construct should I use to optimally add a specific ETL transformation? What are the design criteria that are increasing or decreasing the throughput? Given two graphs, can we anticipate on which one will have the best throughput?*

6.1 Experimental Setting

We ran our experiments using Microsoft's SQL Server Integration Services (SSIS)[3], over a computer equipped with an Intel Dual-Core processor at 2.10GHz and 4 Gigabytes of RAM running Windows 7 OS.

The internal measures to be evaluated may influence on each other. At this point we are interested in finding out the relation between a single variable (measure) and Th. Thus, we performed a set of controlled experiments, in order to detect the individual impact over Th of each internal design factor. We created 54 graphs in the following way: we defined an initial ETL model using BPMN4ETL, and translated the graph to a data flow SSIS component. To analyze each measure we modified the initial graph by modifying the combination of nodes (ETL tasks). For example, to study the influence of the number of branching nodes (measure BN), we started with a combination of the graph having BN = 1, and then we increase BN by adding neutral branching nodes to obtain seven graphs with BN = 1, 3, 5, 8, 10, 15, and 20. We performed the same with join nodes, lookup nodes, script nodes, row-by-row nodes, row-set nodes, input-ouput nodes. To assess cohesion action we created 7 graphs with different number of actions in data input and script nodes. All these yielded 54 graphs to perform, basically, the same job. We measured Th for each graph execution. In addition, and to take into account the data size, we ran each graph for different data sizes: the initial data source size is 56Kb, including 290 rows. We multiplied it by 100, 500, and 1000, producing, respectively, a data input varying from 65Kb to 65Mb. In the figures of this section, Th is expressed in KBytes by millisecond (Kb/ms).

6.2 Discussion of Results

We now analyze the results from our experiments with respect to the hypotheses H1 through H5. First, we studied the correlation between each measure and Th, for different data source sizes (1x, 100x,..). The results are depicted in Table 2, where measures are indicated as BN, JN, etc. Table 2 shows that all the measures are strongly correlated to the throughput, except for BN, JN and CA-S. For BN, this implies that an additional branching node has a low impact on the throughput. For the JN and CA-S measures, the very weak throughput results reflect the low performance of join nodes in the SSIS tool. Thus, further experiments are required over different tools. All other measures are negatively correlated to the throughput, confirming that adding nodes decreases Th. Therefore, as a first result, these strong correlations validate our measures and confirm their influence over the efficiency goal represented in this study by the throughput external measure. For the CA measure we performed two kinds of experiments: (a) adding node actions to the data input (DI) script, yielding the CA measure (denoted CA-DI) computed on a DI script node; (b) adding the specific script (S) node action, yielding the CA measure (denoted CA-S) computed on an specific script node. The correlations for the (CA-DI) measure were good, although no correlations could be computed for (CA-S) because of the very low throughput.

The second analysis, shown in Fig. 5a captures (for the largest dataset) the throughput variation for each measure. In the X axis we represent the number of nodes of each type, and on the Y axis, the throughput. Fig. 5a shows that adding all kinds of nodes (except from branching nodes) strongly decreases Th. Adding branching nodes does not reduce throughput, confirming results shown in Table 2. However, adding BNs could be beneficial for other external measures (e.g., related with parallel execution). These results were the same for all dataset sizes. Thus, the results above confirm hypotheses H1 through H3.

We now analyze hypotheses H4 and H5. Fig. 5b shows (also for the largest dataset) that script nodes (CA-DI) can be used (whenever possible) instead of join ones since the latter deliver worse throughput. Analogously, we can join several input nodes in a single script node to increase Th. Fig. 5b also shows that lookup nodes are better than script ones. This can be explained by the optimization capabilities provided by the ETL server in managing such type of nodes. In summary, our results suggest that ETL thoughput can be enhanced if at the design stage we choose more efficient kinds of nodes. Note, however, that this is not always possible (e.g., it is not reasonable to group several row-set nodes in the same script). Again, results were the same for all dataset sizes. Therefore, hypotheses H4 and H5 are confirmed by our experiments.

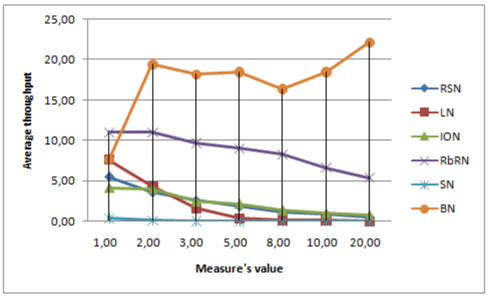
7 CONCLUSION

We have formally presented, and empirically validated, a collection of measures that, computed over alternative ETL process graphs (i.e., representing different combinations of tasks), allow predicting how they will perform with respect to each other before writing even a single line of programming code. As

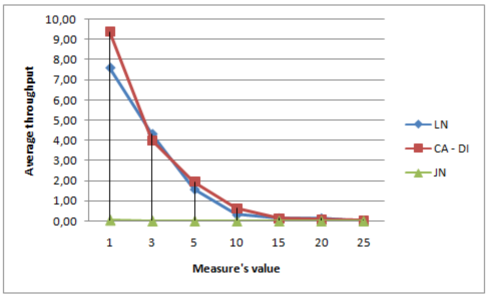
[3]http://msdn.microsoft.com/en-us/library/ms141026.aspx/

Table 2: Correlations.

Size	BN	JN	LI	SN	RSN	RbRN	ION	CA - DI	CA-S
65Kb	-0.82	-	-0.90	-0.93	-0.81	-0.94	-0.88	-0.97	-
6.5Mb	-0.69	-	-0.88	-0.74	-0.72	-0.93	-0.81	-0.97	-
32.5Mb	0.13	-	-0.82	-0.62	-0.81	-0.97	-0.93	-0.96	-
65Mb	0.64	-0.51	-0.80	-0.69	-0.78	-0.99	-0.93	-1.00	-



(a)



(b)

Figure 5: (a) Throughput vs. # of nodes; (b) Lookup nodes vs. join nodes vs. script nodes.

a consequence, our results allow us to draw a set of guidelines to design efficient ETL workflows. As future work, we will work in the assessment of the complete impact over performance of the measures proposed in this paper, since at this stage we focused on the individual (partial) impact of each one of such measures.

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