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Hierarchical intelligence platform designed for wastewater management systems: information technology integration

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ABSTRACT

An interdisciplinary approach for designing a hierarchical intelligence platform correlated with wastewater management system diagnosis is designed. The information system allocates significant funds for IT projects for the implementation of hierarchical intelligence platforms. The methodology supports reducing the risks of a project for implementing such a platform. The methodology ensures the achievement of the organization's hierarchical intelligence platform without wasting time and money. Since the goal of a hierarchical intelligence platform is to provide decision support at all levels, it is very important that that organization knows their processes well and that they have unified definitions. A knowledge base is thus essential for an organization that wants to implement a hierarchical intelligence platform that meets their needs. Most often an IT hierarchical intelligence platform project is approached as strictly an IT project when, in fact, such a platform is structured and works best in an organization that has very good standardized and documented internal hierarchical and IT processes. The methodology will include tools and methods for analyzing wastewater management system knowledge, identifying the processes involved and provide a unified definition of the concepts used by the organization within its operations. A hierarchical intelligence platform also requires educated users. The methodology will formalize the training and analytical skills of the platform users, providing reliable solutions related to the types of employees. The next stage of the design methodology defines the stages required for designing the platform, correlated with economic considerations. This step is necessary to produce a hierarchical intelligence platform that best fits the organization's characteristics.

Keywords: Hierarchical intelligence tools; Platform design; Wastewater management system

1. Introduction

Hierarchical intelligence tools are varied, and without a deep knowledge of the intended destination, the structure of a hierarchical intelligence platform and the methodologies for their design, any project for developing a hierarchical intelligence platform may easily fail [1–3]. Any wastewater management system that wants to use a hierarchical intelligence tool to achieve feasible solutions to improve or develop their hierarchical model must have a clear picture of what the tool is destined to be used for [3]. When we talk about hierarchical intelligence tools, we must take into consideration the category to which they belong and their capabilities, and how and what the structure will enfold [4,5]. Thus, it is necessary to study the platform's architecture and where in this structure the hierarchical intelligence tool can be used. We discuss the architecture, design methodologies, the means for constructing the hierarchical intelligence

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platform such as the data warehouse, data modeling, online analytical processing (OLAP), and other common elements and concepts related to hierarchical intelligence [6].

2. Research methodology

A systematic investigation was conducted through documentation, observation, experiments, and simulations. Documentation was the first step. We studied the definitions of hierarchical intelligence, hierarchical intelligence tools, methodologies for data warehouse design, the concept of data mining models, and the principles of data modeling [7–9].

Scientific observation was used to study the hierarchical intelligence platforms already implemented in the real world to understand the components and the typology of hierarchical intelligence tools and their use in a wide range of applications such as for data analysis, self-service reports, making dashboards dynamic, and especially for the interactive analysis of data for shaping and transforming data from operational systems of wastewater management [10–13].

The scientific experiments involved the testing of some of the most commonly used hierarchical intelligence tools. A practical model for achieving a methodology to design a hierarchical intelligence platform was defined. The initial objective was to obtain knowledge of hierarchical intelligence tools, using both the hierarchical intelligence tools provided by the big players in the commercial market and open-source hierarchical intelligence tools. In this study we cataloged them into tools for loading and transforming data, data modeling tools and reports for presentations and universal self-services, hierarchical intelligence tools for designing dynamic dashboards and interactive visualization tools. Each of these categories are very complex and dynamic.

Given the diversity of hierarchical intelligence tools, the next step was to identify the hierarchical intelligence platform's architecture and the locations of the different types of hierarchical intelligence tools within this architecture. A hierarchical intelligence platform should have a structure that allows the integration of data from operational systems, a data warehouse, OLAP technology modeled data, the hierarchical intelligence tools needed to achieve these elements and the means data visualization. This structure is presented in Fig. 1.

To show how the data from operational systems bring value to the hierarchy through the use of hierarchical intelligence tools, it was necessary to study the data transformation processes and to determine how to use this data virtually.

After loading the data, modeling to meet specific hierarchical needs must occur. In this context, the next step was to analyze the hierarchical needs to build the data model and perform modeling. A modular approach is taken to build the data model, based on the categorization of hierarchical units. For hierarchical modeling analysis and conceptual data model, we used the IT tools of Visio, BPM modeling, and Oracle Data modeler. These instruments are not included in the hierarchical intelligence tools, but without a hierarchical analysis and a data modeling procedure adapted to the hierarchical approach, a hierarchical intelligence platform could be useless.

Hierarchical intelligence tools represent an important part of those that are used for data mining. In this context,

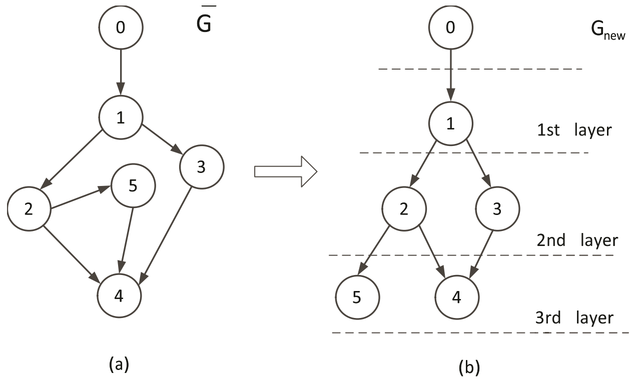

Fig. 1. Hierarchical intelligence architecture.

we study the concept of data mining and how this is done, how to construct data mining models for large data warehouses. Data mining research remains a topic of great interest on its own.

2.1. Hierarchical intelligence tools

The artificial intelligence tools used for management information and wastewater treatment systems are quite powerful [14–18]. They can be used for the identification, extraction and analysis of data available to the company to provide decision support.

The need to inform the people is constant, but what defines the current period is the huge volume of data available and the need to obtain answers quickly. Because of congestion in growth markets and competitive economic environments, the ability to collect data and to transform it into information useful for decision making is what makes the difference.

Several specialized software tools generically called business intelligence (BI) tools have been developed to answer these types of questions.

Hierarchical intelligence systems are tools for collecting, processing and analyzing data, which a company can use to assess results. Depending on the nature of these results, they may be updated either periodically or in real-time. The latest hierarchical intelligence systems are essential for increasing efficiency in decision-making processes and improving relationships with customers, suppliers and employees.

Hierarchical intelligence applications include decision support systems, query and reporting tools, OLAP and forecasting and data mining systems. Ultimately, the final results of hierarchical intelligence implementations are for the in-depth analysis, refining and concentrating a large amount of hierarchical information in concrete performance indicators and, ultimately, organizational knowledge. Implementation efforts involve multiple aspects of the organizational management strategy and organizational processes, from application management to information infrastructure changes. Hierarchical intelligence projects do not aim to teach managers how to make the right decisions; instead, they help them to make decisions based on facts and figures rather than assumptions.

Depending on how the tools of hierarchical intelligence are used, we have identified the following areas: tools for extracting, loading and mapping, labeling data into data warehouses (e.g., computerized) modeling tools for data repositories (type structures OLAP). Such modeling is approached by reaching an intuitive structure called for by the end-user to issue reports only on data structures corresponding to the characteristics of the hierarchical structure.

2.2. Hierarchical intelligence platforms

Hierarchical intelligence platforms are platforms within which are integrated hierarchical intelligence tools. Making hierarchical intelligence tools function within an organization is essential for laying a foundation. This foundation is structured from data taken from the operational systems of the wastewater management system. Such tools provide hierarchical solutions for wastewater management systems based on historical data.

Operational systems are those systems that record the transactions made by the company. They can be billing systems, customer systems, achievement system sales, payment systems, accounting systems and/or online inventory management systems, as well as others. These systems do not store historical data but simply keep information about transactions at the time. For example, customer information and their status (active, closed), the invoice value of the product purchased and product information are all available at one time and can be made available to the operational system. Analysis of this kind can be performed if we have information from the operational systems stored in so-called data warehouses. For this type of analysis, we need to build a data warehouse as part of the hierarchical intelligence platform. Hierarchical intelligence tools can be used for data extraction and loading in the Tier 1 stage. The tools can be used to construct the data warehouse, a data mart site and OLAP-type organization for data analysis or we can use hierarchical intelligence tools for visualization, self-service reporting, and for making dynamic dashboards.

A modern BI platform should provide a complete infrastructure, solutions and technologies that support the following areas: information integration, data management, data warehousing, BI tools.

2.3. Hierarchical intelligence platform architecture

As described in the previous chapter, we can say that a hierarchical intelligence platform comprises four levels described in Fig. 1: the operational systems from which the data are level extraction, transformation and loading data into the data warehouse modeling. The last level is the hierarchical intelligence tools used for decision making.

We think about the accompanying fluffy guidelines R^j: If x_1 is F_1^j and x_2 is F_2^j … and x_n is Fe_n^j, then y^j is P^j.

where $x = (x_1,x_2,x_n)^T \in \mathbb{R}^n$ and $y \in \mathbb{R}$ denotes the information and yield of the fluffy rationale frameworks separately, F_i^j and $P^j(i = 1,2,n; j = 1,2,N)$ belong fuzzy sets in $\mathbb{R}$. The fuzzy rationale frameworks can be portrayed as:

$$I_{x_j}y(x) = \frac{\sum_{j=1}^{N} h_j \prod_{i=1}^{n} \mu_{F_i^j}(x_i)}{\sum_{j=1}^{N}\left(\prod_{i=1}^{n} \mu_{F_i^j}(x_i)\right)} \tag{1}$$

where $\mu_{F_i^j}\left(x_i\right)$ represents fuzzy function, h_j in which satisfy $\mu_{P^j}\left(h_j\right) = 1$.

Eq. (1) can be re-represented as:

$$y(x) = \phi^T(x)w \tag{2}$$

in which $w \triangleq [h_1,\ldots,h_N]^T$, $\phi(x) \triangleq [\phi_1(x),\ldots, \phi_N(x)]^T$ belong that:

$$\phi_j(x) = \frac{\prod_{i=1}^{n} \mu_{F_i^j}(x_i)}{\sum_{j=1}^{N}\left(\prod_{i=1}^{n} \mu_{F_i^j}(x_i)\right)} (j = 1,2,\ldots, N) \tag{3}$$

The fuzzy rationale frameworks have the accompanying critical property:

Lemma 1: Given any consistent $f(x)$:$\Omega \to \mathbb{R}$ to such an extent that $\Omega \subseteq \mathbb{R}$ is a conservative set $\epsilon > 0$, and a subjective little steady at that point there exists a fluffy rationale framework to such an extent that $\sup_{x\in\Omega} | f(x) - \phi^T(x)w | \le \epsilon$.

where $\phi(x)$ denotes the fuzzy functions, w is a weighting math matrix.

Remark 1: It ought to be underlined that the above lemma must be received in both of the two conditions: (1) working function $f(x)$ is limited; and (2) the reduced set state of the is $f(x)$ fulfilled, for example with the end goal $x \in \Omega$ that Ω is a smaller set. This is basic in the controller structure, generally, the above lemma may not hold.

Definition 1: Think about a gathering of N adherents. The information system trade among these supporters are depicted by the chart $\bar{\mathcal{G}}$ and $\mathcal{G}_{\text{new}}$ in Segment II–A. The dynamic for every adherent is depicted by the accompanying nonlinear frameworks:

$$\begin{aligned} \dot{x}_{ik} &= g_{ik}^{\sigma_i(t)}(\bar{X}_k)x_{i,k+1} + f_{ik}^{\sigma_i(t)}(\bar{X}_k)\,, \\ \dot{x}_{in} &= g_{in}^{\sigma_i(t)}(\bar{X}_n)u_i + f_{in}^{\sigma_i(t)}(\bar{X}_n)\,, \\ y_i &= x_{i1},\, k = 1, 2,\ldots, n-1 \end{aligned} \tag{4}$$

in which $i = 1,2,N$ indicates the quantity of operators. x_{ik} $(i = 1,N;\ k = 1,\ldots,n)$ signifies the kth state for the ith devotee. $\bar{X}_k = (X_1, X_2,\ldots,X_k)^T \in \mathbb{R}^{\text{Nk}}$ in which $X_k = (x_{1k},x_{2k},\ldots,x_{\text{Nk}}) \in \mathbb{R}^n$ belongs to the kth states gathered from N adherents. y_i is the yield for the ith supporter. $\sigma_i(t)$ is an obscure discretionary exchanging signal and characterized $\sigma_i(t)$:$(0,+\infty) \to P_i = \{1,p_i\}$ thusly that p_i is a limited obscure number. Note that for different devotees, $\sigma_i(t)$ can be diverse which results in a nonconcurrent exchange among adherents $g_{ik}^{p}(\bar{X}_k)$, $f_{ik}^{p}(\bar{X}_k)(k = 1, n; p = 1, p_i)$.

2.4. Hierarchical intelligence platform design methodology

Based on the elements studied, a methodology for the construction of a hierarchical intelligence platform needs to include the following stages:

- Establish the hierarchical areas
- Analysis of hierarchical processes which will be modeled in the platform

- Identification of information needed
- Identification of the operational systems that provide useful information
- Identification of the tools needed to develop a BI platform
  - Identification of the tools for data extraction, data transformation and data loading
  - Modeling tools
  - Tools for achieving OLAP models
  - Data visualization tools and tools for making self-service type reports
  - Tools for constructing interactive dashboards
  - Data mining tools
  - Modeling hierarchical processes to be implemented in the DW platform
  - Analysis and design processes for extracting, transforming and loading data from operational sources
  - Analysis and modeling inputs depending on their hierarchical model. Making conceptual models
  - Modeling OLAP data using the model schema STAR

2.5. Hierarchical intelligence example

Based on the stages described in section VI, this paper contributes to providing a comprehensive example study given as follows:

- Definition of hierarchical area

The hierarchical area is related to the cost expenses of electronic devices, the revenues obtained from device sales, after sales processes and the application of storno invoices, credit notes and different discounts.

- Process is described in Fig. 2.
- Information needed

The necessary information is described in Fig. 3

- The information for operational systems is described in Fig. 3
- The extract, transformation and load (ETL) process is described in Fig. 4

3. Conclusion

This paper presents a proposed methodology for hierarchical intelligence platform design in wastewater management systems. The implementation describes hierarchical intelligence tools from which the entire system is derived. The main contributions include the theoretical foundations, system architecture, and technology paradigms of a design for a wastewater management system. Overall, the proposed approach not only explores the groundbreaking facets of platform architecture known as fuzzy membership frameworks but also introduces cutting-edge intelligence systems in this context. Based on the intelligence models, systematical moderation for the physiological, practical, logical, and engineering levels have been sketched to form a functional theory for use in future studies on machine intelligence and natural design management in wastewater treatment.

The effectiveness of the proposed model is verified and we can obtain high system reliability derived from the information for operational systems. The model could be used in many industrial devices in a variety of areas such as in the pharmaceutical industry, biomedical industry, fertilizer manufacturing, oil refineries, and many more. Further efforts to establish this model will include synthesizing management information systems using big data on water characteristics and combining other proficiencies to address water analysis problems in the wild.

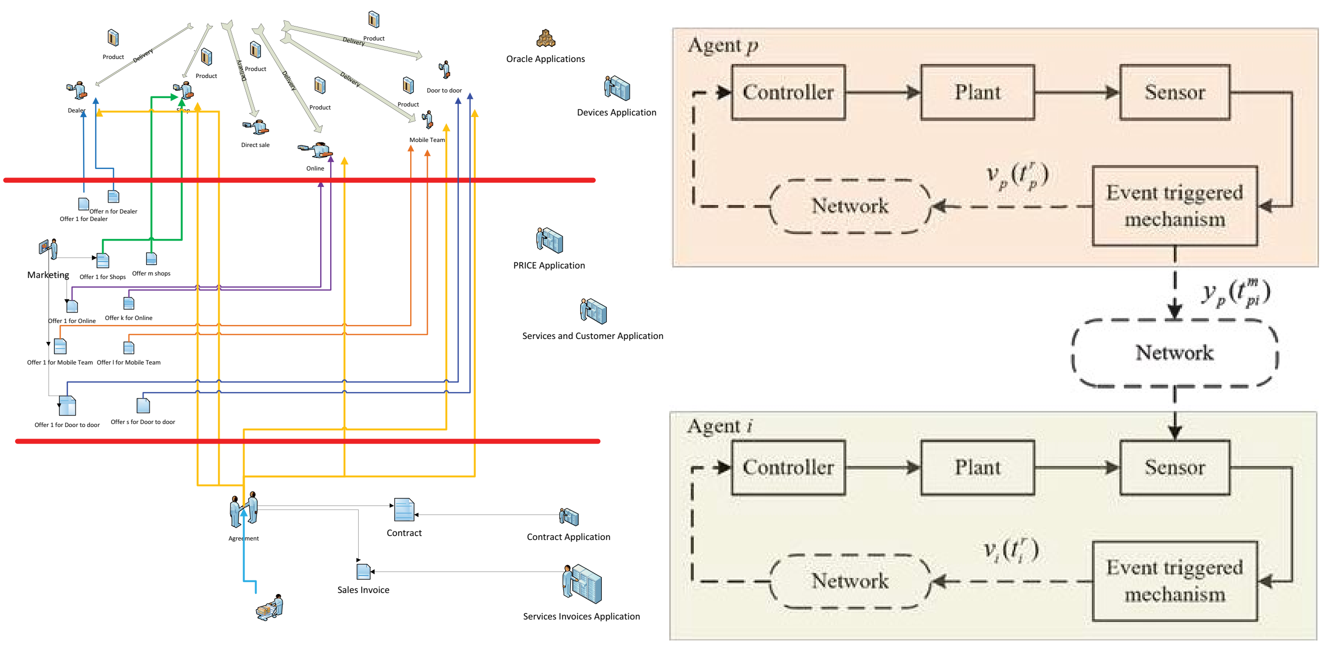

Fig. 2. (a) Process analysis for hierarchical platform area design and (b) system triggered network.

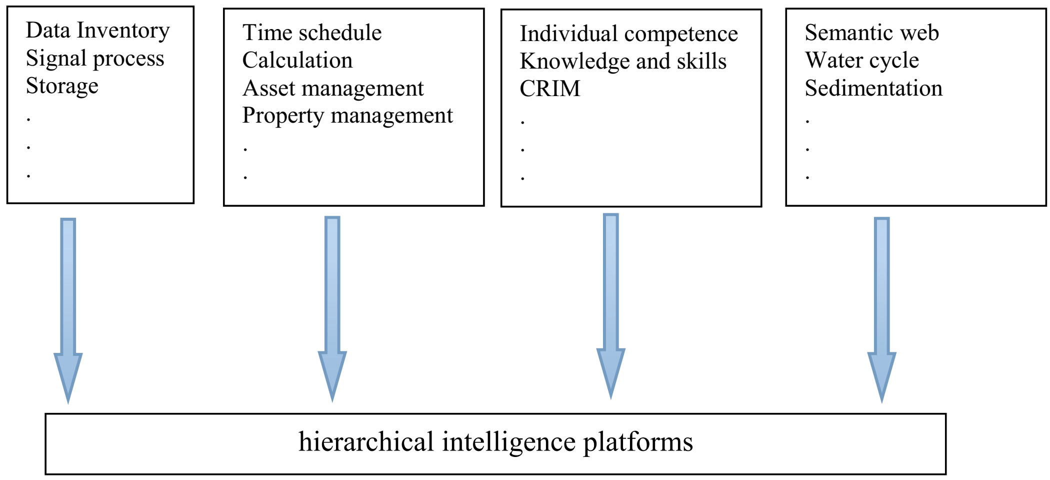

Fig 3. Necessary information.

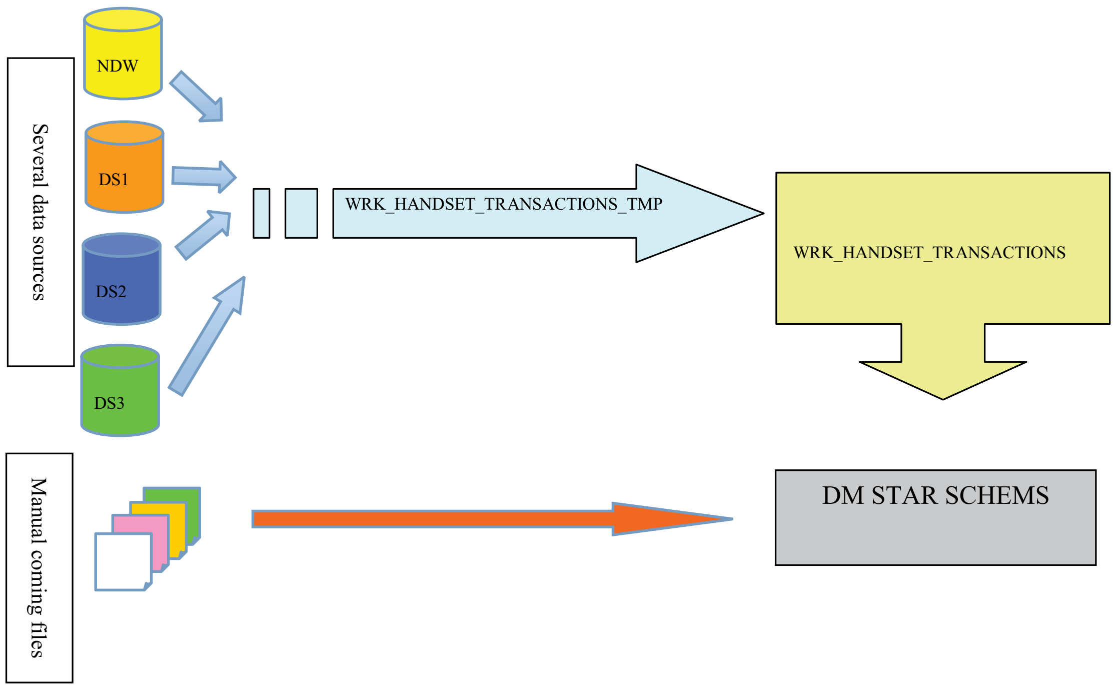

Fig 4. Data transformation.

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