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From Classical to Fuzzy Databases in a Production Enterprise

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Abstract: This article presents the evolution of databases from classical relational databases to distributed databases and data warehouses to fuzzy databases used in a production enterprise. This paper discusses characteristics of this kind of enterprise. The authors precisely define centralized and distributed databases, data warehouses and fuzzy databases. In the modern global world, many companies change their management strategy from the one based on a centralized database to an approach based on distributed database systems. Growing expectations regarding business intelligence encourage companies to deploy data warehouses. New solutions are sought as the demand for engineers' expertise continues to rise. The requested knowledge can be certain or uncertain. Certain knowledge does not any problems and is easy to obtain. However, uncertain knowledge requires new ways of obtaining, including the use of fuzzy logic. It is from where the fuzzy database approach takes its beginning. The above-mentioned strategies of a production enterprise were described herein as a case of special interest.

Keywords: Centralized databases, Distributed database systems, Data warehouses, Fuzzy databases, Production enterprise
Categories: E.1, H.2.8, I.2.4, J.6

1 Introduction

The widespread use of the Internet of Things (IoT) and related technologies (Industry 4.0, Smart Home, iWear, Virtual Reality, Augmented Reality, Ambient Intelligence, Affective Computing) will lead to a rapid growth in the amount of data collected automatically or semi-automatically by the above-mentioned systems. Data collection and analysis have already became a separate industry branch, and they are not only a part of big data and neuromarketing sector, but they can also have a creative impact on the growth of all the other branches (especially the industry), optimizing the ways of providing customers with products dedicated to them as well as the use of limited material, human and energy resources. As the growing automation and e/work/e-learning will only accelerate these processes, we must be prepared for them from both mental and technological perspective.

Data, information, and knowledge are intangible assets of every company and their usability depends on the efficiency in their processing and distributing to users in a form that meets their requirements in the best possible way. They constitute information resources of the company that exist within the company's information systems as databases, data warehouses or more sophisticated information systems, such as knowledge bases. A proper software enables the company to maintain its data resources in information systems and to make them accessible for users. Intangible and legal assets of the company (including economic copyrights and related rights, licences and concessions, rights to inventions, utility models, know-how, or software with its improvements) take on special importance in the information society, as part of the knowledge based economy, and their role will be growing together with the development of the Internet of Things and Industry 4.0 [Gölzer et al. 2015]. The capability of collecting, storing, analysing, and sharing data and transferring it into knowledge is already a source of advantage of new economic leaders, while quickly emerging technologies based on computing intelligence are finding an increasing number of new applications: from reverse engineering to diagnostics of patients and new pharmaceutical treatments. The number of electronic medical data repositories for both commercial use and Open Science is growing [Payrovnaziri et al. 2020]. It seems that this trend will continue and spread across other sectors.

This article presents the evolution of databases from classical relational databases to distributed databases and data warehouses to fuzzy databases in production enterprises. This paper discusses characteristics of this kind of enterprise. The authors have undertaken a review of literature on databases in an enterprise. The above-mentioned strategies of a production enterprise were described herein as a case of special interest.

2 Production enterprise

Today's companies operate in a wide range of organizational structures, although production is a result of a close collaboration between many partners. This collaboration reflects in effective methods of designing, producing, operating and maintaining own products. Nevertheless, the traditional approach let us divide companies into several groups depending on the number of people hired and the number of operating departments. The number of existing departments, functions and competences increases together with the size of a company [Romero and Vernadat 2016]. The degree of computer integration can vary across companies. At one end of the spectrum, there are companies using computer only for office work (correspondence and accounting) and those using CAD/CAM technologies (Computer Aided Design/Computer Aided Manufacturing) or integrated systems of production planning and controlling. At the other end of spectrum, there are companies using integrated systems for the management of the entire enterprise [Conteh and Akhtar 2015].

A modern company has an aim of producing good-quality products in short time and at a low cost. Production enterprises are forced to seek new ways of improving production efficiency and reducing its cost. It can be achieved by deploying effective and innovative implementation concepts of production, such as: LP (Lean Production) [Pettersen 2009], JIT (Just in Time) [Mackelprang and Nair 2010], TQM (Total Quality Management) [Kiran 2016], or VF (Virtual Factory) [Jain et al. 2017]. These methods enable an effective management of means of product, by providing a perfect working system, an optimal usage of employee's competences, and integration of modern tools designed for engineers and managers. Thanks to that the integration of tasks and functions takes place in two areas of the company, i.e. in management and production.

It is possible to identify four basic features of today's production process [Black and Kohser 2017]. They are as follows:

- a large diversity of goods – today's market is consumer-led not manufacturer-led as it used to be;
- a shorter life cycle of a product – the only possible solution to this problem may be to shorten the design and manufacturing phases;
- decreasing production costs – production costs have decreased mostly due to automation;
- short time to market – this rule results from avoiding costs related to storing products and semi-finished products at the final manufacturer's warehouses.

The above-mentioned trends in modern production processes require novel tools supporting processes within the company. With no doubt, advanced computer technology is one of them [Groover 2010; Kovacic and Bogataj 2011; Junior and Filho 2012; Morgan and Gagnon 2013; Li et al. 2014].

3 Literature review

Centralized databases were historically the first databases in enterprises. The database theory was formulated in [Coronel and Morris 2017; Elmasri and Navathe 2017]. A database is a standard tool for structuring management processes in larger organizations. Databases have developed in multiple ways (distributed databases, parallel databases, advanced databases, object databases or data warehouses). Another developments in this area are smart databases, including fuzzy databases, that have been evolving into smart decision support systems integrated with artificial intelligence methods [Rojek 2009; Rojek et al. 2018; Burduk and Biedrzycki 2019; Rojek and Studzinski 2019; Biedrzycki and Burduk 2020; Rojek and Dostatni 2020; Baker et al. 2020].

Databases became indispensable in companies. In typical applications, a database has a centralized architecture. An article [Buonamici et al. 2002] describes a sectoral database made for a furniture company in order to improve the efficiency of management. An effective transfer of information often plays a vital role in modern companies, deciding about proper implementation of all business processes. Nevertheless, companies still use very often separate databases for every business process. Integration of all data used within the company can be achieved with ERP (Enterprise Resource Planning) systems. Implementation of this solution in a company can significantly accelerate many business processes. Data uploaded in one department are fully visible for others. This reduces the risk of downtimes, misinformation or employees' wrong decisions that can be really costly. Processing of all the data is much easier and improves the operation of the whole company [Abd Elmonem et al. 2016; Osnes et al. 2018].

However, there are many applications in which centralized databases do not provide required functionality and efficiency. Big corporations, international companies, sometimes even those working on a global scale, try to find the best possible way to meet the needs of all their customers in order to earn profits. These needs may be radically different not only across continents but also within one country. Because of that they choose systems which ensure that decisions are made at local branches, but at the same time enable the transfer of information as comprehensive as possible from/to the headquarters in order to maximize the synergy effect. A fuzzy database system is a natural choice in such situations [Elmasri and Navathe 2017]. For the reasons set above, making the information accessible to the users from the outside of the organization is a major challenge for information management within a company. The article shows a new approach, the so called "model-assisted global query system", that utilizes an on-line repository of enterprise metadata [Cheung and Hsu 1996]. The concept of multiple database integration was also described in the work of [Mach 2007], in which it was used for solving issues with smart real-time decision support systems. In order to develop a reference architecture and support infrastructure for a virtual enterprise (VE), a component fulfilling all the VE information management requirements was created. The component provides a framework for sharing and co-managing data across companies belonging to the VE, while maintaining the autonomy of individual companies [Afsarmanesh et al. 1998]. Advanced solutions in the field of digitally connected enterprises were also described in the article [Levermore et al. 2010]. It is dedicated to e-commerce, global supply chains and new business concepts in the field of knowledge-based economy. All these aspects require open and scalable information supply chains in independent enterprises. The integration of proprietary and controlled corporate databases in these information supply chains is the key success factor. It is very important for enterprises belonging to retail chains to design and develop an effective, distributed smart system of decision-making management [Peng 2019].

The concept of data warehouse (DW) – a structure enabling decision makers to make optimal decisions on the basis of various sources — was established as an answer to the needs of large corporations requiring a solution for processing data for business purposes [Elmasri and Navathe 2017]. In fact, data warehouses are databases integrating data from all the other database systems within the enterprise. The access to these data may be a problem, as they are often dispersed and heterogeneous. Additionally, data processing in enterprises database systems that supports ongoing operation is usually performed in a transactional mode (OLTP – On-line Transaction Processing), while the decision-supporting process (DSS – Decision Support System) is based on an analytical approach (OLAP – OnLine Analitical Processing). Data warehouses have a potential to deliver Business Intelligence solutions for companies seeking to gain competitive advantage. The development of data warehouses, their implementation, measurements, data quality monitoring and performance monitoring are critical for the implementation and maintenance of a data warehouse [Rahman 2016]. Taking into account the complexity level, business functions and the specific features of the industry, another article presents the Management Information System and divides it into the following components: Enterprises Resources Planning (ERP), Supply Chain Management (SCM), Knowledge and Collaboration Management System (KCMS), Accounting Management Information System (AMIS), Customer Relations Management, Resource Management Information System (HR – MIS), Product Life-cycle Management (PLCM), Enterprise Asset Management Information System (EA – MIS), Project Management Information System (PMIS), and Business Intelligence Systems (BIS) [Zhang 2017]. Next, it identifies the need for the development of one, homogeneous data warehouse to acquire original data with metallurgical production output parameters for every stage of the technological flow. In another approach, authors suggest the structure of an information system that ensures operation and usability of a single data warehouse [Porshnev et al. 2018]. The aim was to see data warehouse processes as a single unified system integrating all the processes, so they would seem to be one. The improvement of interdependencies and switching various threads encountered during the processes would be a subject to effective management [Sharma et al. 2019]. The article examines and shows the process of designing entities with the DSS system of an enterprise on the base of a systemic analysis of the state of a retail chain enterprise with regards to objective enterprise development requirements in the area of the DSS. In the next step, the data warehouse was used to organize and store the supply chain of supermarkets within the supply chain. The aim was to manage data warehouses and to set up their technology in a way that was based on an OLAP analysis of the supply chain performance system and decision-supporting functions of the supply chain management [Zhang 2018]. Enterprises, both small and large, generate vast amounts of knowledge that can be used for strategic purposes to gain key business insights, and therefore, to gain greater competitive advantage [Mabitsela and Pretorius 2016].

Fuzzy logic and fuzzy databases are discussed in many papers [Bose and Kacprzyk 2013; Skrbić and Racković 2013; Apiecionek et al. 2020]. Kacprzyk and Zadrożny present the combination of the Access suit and FQUERY programme as a way to add quires with fuzzy terms into a database [Kacprzyk and Zadrożny 2001]. De Caluwe [2002] presents the rules of using fuzzy databases to describe the reality. A fuzzy database is a result of combining relational databases with the theory of fuzzy logic. Other authors present the models of the information collecting process based on fuzzy logic, genetic algorithms and a combination of fuzzy and rough sets [Kacprzyk et al. 2002, 2007]. The importance of fuzzy logic has been emphasized by various authors. An article b Atanassov et al. [2005] presents directions for development in the field of representing and processing uncertain and vague information with fuzzy sets, intuitive fuzzy sets and classifying methods. Other approaches present new theories regarding analytical modelling based on the Takagi-Sugeno fuzzy expert system [Kluska 2005] and the impact of fuzzy logic on the collaboration of methaheurstics [Cadenas et al. 2008]. The article presents a 3D approach based on fuzzy logic for assessing the compliance of knowledge resources of an enterprise with its Knowledge Management systems (KMS). The authors used the suggested methodology to develop software-based Knowledge Management - Decision Support System (KM-DSS) that was tested in a small and medium-sized enterprise (SME) from the high-tech sector [Centobelli et al. 2018]. The article describes identifying "missing" and "hidden" data during processing well-defined quires to the database. Additionally, it explains the importance of this issue and discusses the problem of organizing, processing and implementing fuzzy queries into database information systems [Fadyeyeva and Gryniuk 2017]. Another article provides a complete marketing system of enterprise-orientated fuzzy queries. This system allows for effective collection of marketing enterprise data, can improve the efficiency of management and brings many more benefits [Li et al. 2017]. In real world applications, there are many authentic situations in which object descriptions may be subject to some uncertainty. The article presents a fuzzy data model, in which fuzzy data were formally mapped into a relational database [Zongmin and Li 2018]. A new method of solving fuzzy problems was presented together with a table of fuzzy rules [Deni Akbar and Mizoguchi 2014]. In the last three decades, there have been various fuzzy database models presented, including relational and objective databases, and they brought large benefits to this discipline. Several major problems related to these models were examined, including quires and data processing, data interdependencies, and normalization [Ma and Yan 2008]. In order to satisfy the demand for modelling complex objects with uncertainty and imprecision, many recent studies have been focused on fuzzy semantic (conceptual) data models. Such studies discuss mostly fuzzy models of ER/EER (Entity Relationship /Enhanced Entity Relationship) and UML (Unified Modeling Language) data. Integrating fuzzy information into database models is an important subject to research, as such information is used in a wide range of applications requiring vast amounts of knowledge and data, such as natural language processing, artificial intelligence, CAD/CAM etc. There have been studies conducted on various approaches to representing and processing fuzzy data in the context of databases. Some techniques, developed on a conceptual level, are called fuzzy conceptual data models and describe the role of fuzzy data within a database, while the others, developed on a logical level, are called fuzzy logic database models and they focus on fuzzy data processing. Originally, the fuzzy data models were subject to intensive studies, mostly with the regard to a popular relational model. However, the classical model of a relational database and its version extended with vagueness do not satisfy the need for modelling complex objects with imprecision and uncertainty. That is why today's efforts focus on extending conceptual data models, so they can support complex objects as well as imprecise and uncertain information [Ma and Yan 2010]. Recently, there have been several approaches to the ER/EER fuzzy model presented. Their authors used fuzzy quantifiers that were thoroughly examined in the context of fuzzy sets and fuzzy database query systems. All these fuzzy extensions give a new meaning and offer greater clarity in conceptual design, while the restrictions can be used in data mining [Galindo and Urrutia 2003]. The integration of modules is another approach that enables defining fuzzy queries for relational databases of classical ERP systems. This article defines database quires described as fuzzy classes and associations. Moreover, an example of a commercial enterprise was used to analyse the thematic area for fuzzy terms. As the system was developed as an extension for existing ERP systems of similar type, it can be easily adopted to solving problems related to fuzzy query processing. With the component integrated with its ERP systems, the enterprise can operate with greater effectiveness and efficiency [Kilic et al. 2016]. Possible applications of ordered fuzzy numbers (OFN, also Kosinski's Fuzzy Numbers) remain undiscovered when it comes to analysing data from business processes of variable dynamics and speed of data accumulation within databases [Prokopowicz et al. 2017].

4 Case study – a production enterprise

4.1 Database of a production enterprise

The case study presented in this article describes a centralized database in a production enterprise (fig. 1). A multifunctional database includes shared data resources accessible for specific users. The same users have also an access to their own resources that are protected from being accessed by other users. This is one of the most common and useful data management structures as it provides the system administrator with control over generally available data that are managed in accordance with the strategic objectives of the enterprise. The integration of computer systems within the enterprise can be achieved by using databases.

Production data within the enterprise are related mostly to three basic groups of objects, such as goods, orders, and means of production. The goods object gathers all the data describing it, including its structure, geometry, material, technological data, technological process and data on its life cycle. The order object is assigned to data related to deadlines and amounts of manufactured goods. The means of production object consists of data describing production capacities of the enterprise (machines, instruments, tools). Databases play a crucial role in an effective application of computer aided systems for designing, planning and managing.
When it comes to industrial applications, there are two basic implementation areas for databases:

- The area of enterprise management, including production, is strictly related to the organizational structure of the enterprise, while logical and physical structures of data are organized under the management functions: finance, marketing and sales, procurement, HR and managerial accounting. In other words, these areas are functionally supported by ERP systems. Data management systems should allow for data processing and accessing to be done on-line.
- The area of technical management is related to the development of a product, design, technology, production planning and other aspects of technical preparation of production. Database management system processes data in the off-line mode. This system of data writing and processing complies with the requirements of CAD/CAP/CAM systems, so it is adjusted to the working methods used by designers and engineers.

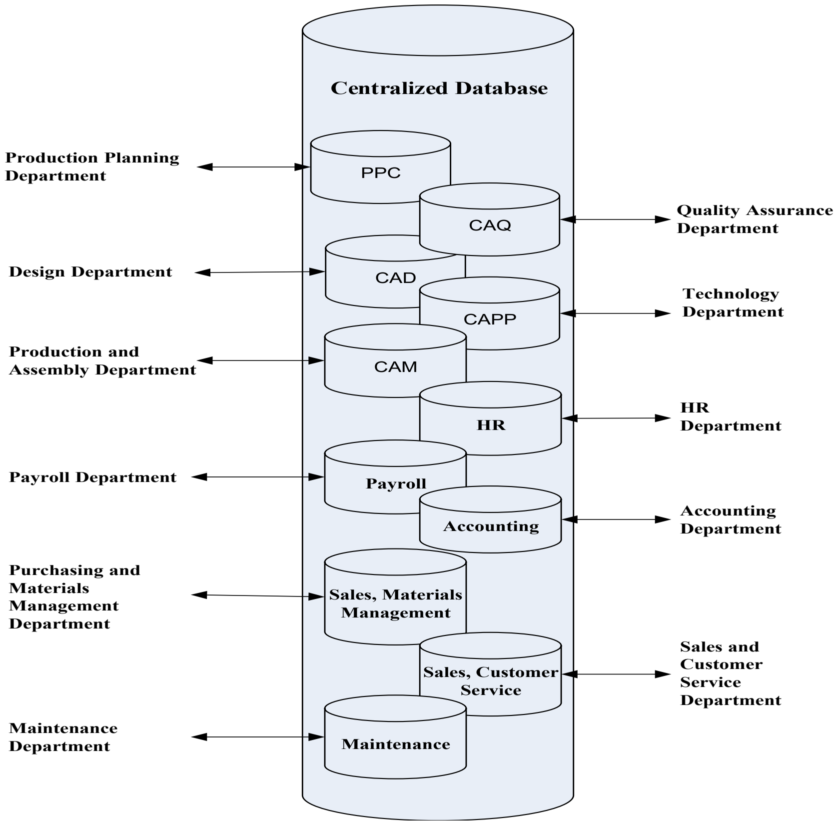

Figure 1: Database of a medium-sized production enterprise
CAP – Computer Aided Planning, CAQ – Computer Aided Quality Control,
CAD – Computer Aided Design, CAPP – Computer Aided Process Planning,
CAM – Computer Aided Manufacturing, HR – Human Resources

This database design enables information flow within the enterprise. Figure 2 shows Data Flow Diagram (DFD) which is a basis for preparing the structure of information flow within an enterprise.

It shows the subsequent phases of the production process together with the data model development phases – from requesting an order for a specific product to other product development phases to planning and controlling the implementation of production orders. The information flow within an enterprise and its organizational structure as well as the structure of means of production are determined by the applied production processes and technologies. The problem-oriented data structure is functionally organized under the Computer Integrated Manufacturing (CIM) system. Relational Database Management System (RDBMS), which is at the same time a database server, fulfils all functions related to data management, protection, access and maintenance.

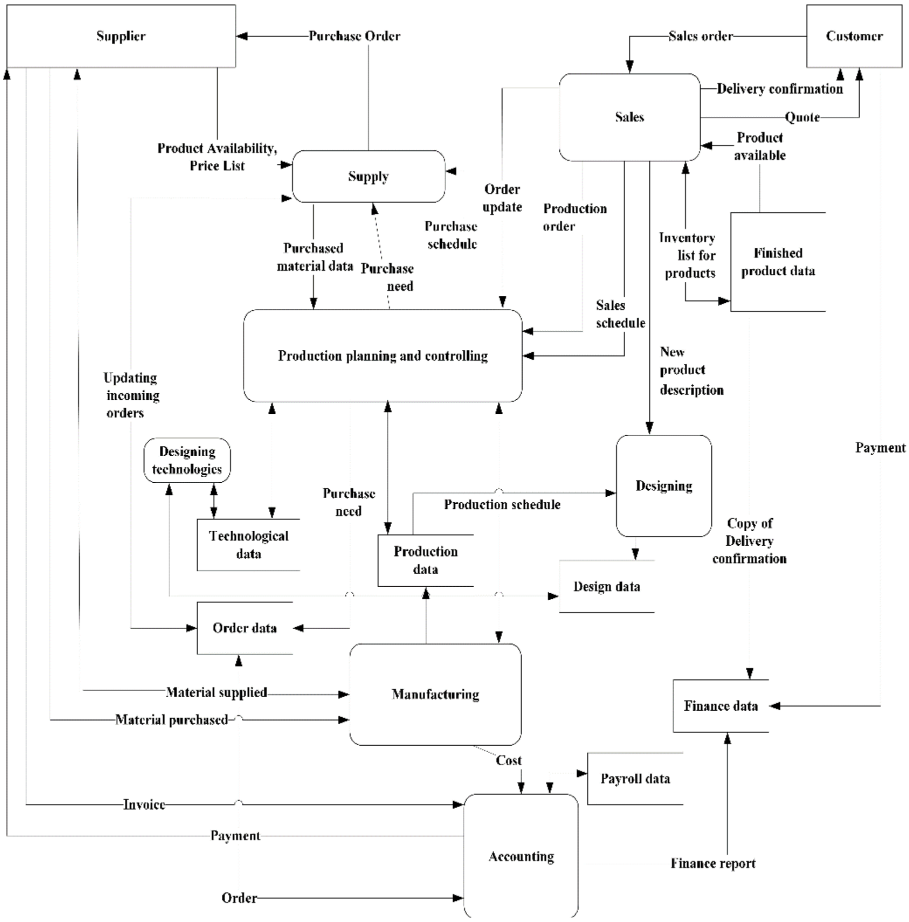

Figure 2: Standard information flow within an enterprise

4.2 Distributed database systems of a production enterprise

The case study presented in this article distinguishes three production enterprises under one management board. All plants produce elements made of plastic. All plants have procurement, production, and sales departments. However, only one of these plants has accounting and finance departments. Data on production planning and material purchases are exchanged on a regular basis. Periodically, the management board collects complete information about production in three plants and optimizes production processes in terms of warehouse and human resources as well as the production itself. This optimization is crucial because products are seasonal. The plants operate in a 2-season system: there is a high season (March-August) and a low season (September-February). When it comes to production, in the high season employees work in a 3-shift system seven days a week, while in the low season they work in a 3-shift system five days a week. In the high season, warehouses must have security stocks of finished goods in necessary amounts. That is why optimization is essential. Figure 3 shows a structure of homogeneous distributed databases that cover three production plants in three different locations. The databases operate under the Oracle system with Windows Server 2012 OS.

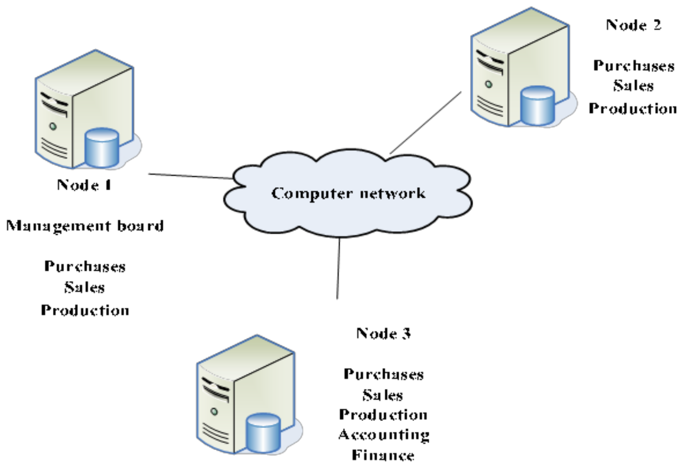

Figure 3: Homogeneous distributed database system of a selected chain of production enterprises

4.3 Data warehouse in a production enterprise

This article proposes to develop a data warehouse on a base of the following stages:
- indication of the enterprise requirements;
- indication of the physical project for a data warehouse;
- analysis, development, and integration of necessary data source;
- development of data warehouse;
- selection and development of access tools for users;
- tests and potential amendments.

The enterprise produces plastic goods in a mixed-mode system upon the customer's request. Therefore, it is required to conduct a data analysis in the environment of decision support systems. This analysis should cover customers and goods that are sold and manufactured. This information is necessary to minimize production costs and to develop a better understanding of market needs in terms of the most popular products of this company. Additionally, this analysis is needed to optimize the product offer by reducing the less profitable production and focusing on products generating the biggest profits. Strategic (rough-cut) planning is based on the data from sales schedules that originate from customers. In the next step, the main plan for the enterprise is created on the base of these schedules. Copies of the main plan may be used to define forecasts and scenarios and to provide simulations in relation to main and rough-cut capacity planning. The main objective of rough-cut capacity planning is to balance the resources, which change in a long-term perspective, with the current demand. Typical resources include: production capacity of machines, storage capacities, production personnel (direct and indirect costs), and transport capacities.

The next step is to move from planning for several weeks ahead to planning for up to four weeks ahead. It should be done with the help of Material Requirements Planning (MRP) and Capacity Requirements Planning (CRP) mechanisms. Production cost estimation is another important element. Specific requirements in the area of production planning may be met by creating three multi-dimensional data cubes that cover materials, material procurement and cost calculation. It requires collecting data from different departments: Sales, Warehouses, Production, Procurement as well as Production Planning. Figure 4 shows a scheme of information sources of a data warehouse together with their destination.

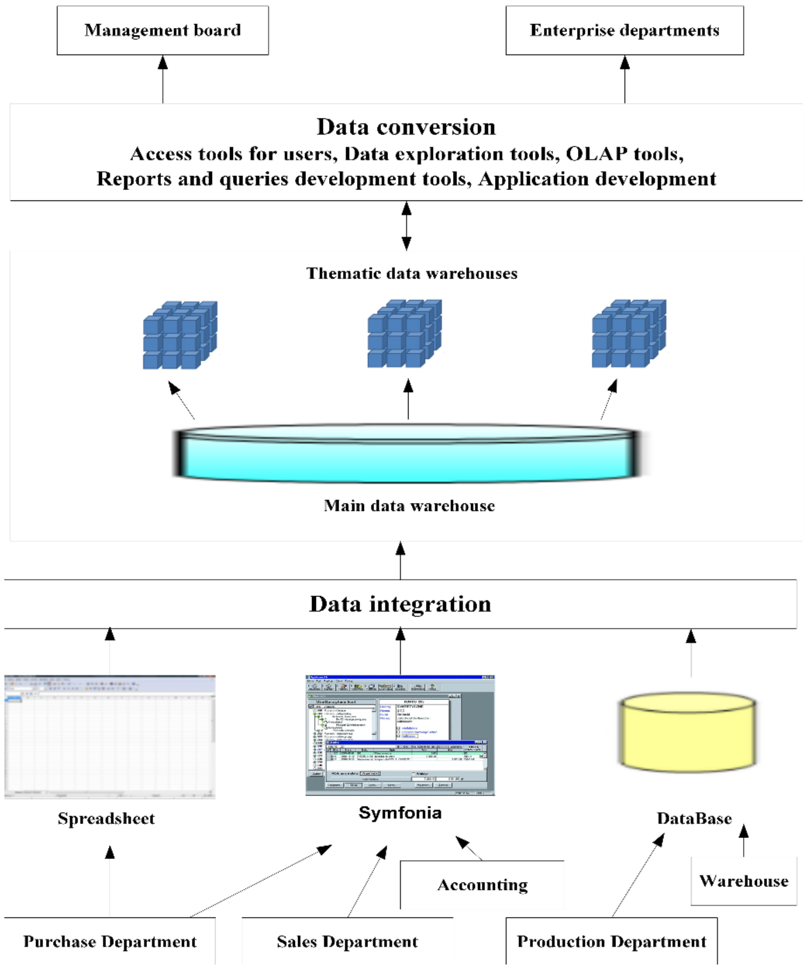

Figure 4: Information sources of a data warehouse together with their destination

4.4 Fuzzy databases in a production enterprise

The efficiency and effectiveness of computer aided decision-making process within an enterprise may depend significantly on the right representation of data or knowledge.

Classical database systems that are commonly used in IT projects in the field of information and decision-making, as well as increasingly popular knowledge bases do not allow for reflecting uncertain or vague character of information resources typical for the decision-making process.

The need for IT solutions able to process proxy data encourages us to consider the use of fuzzy logic in data models based on fuzzy databases.

Information and decision projects play an important role in the wide scope of enterprise operation (planning, designing, manufacturing, monitoring, etc.). They are usually related to solving problems of high complexity that can grow in emergency situations. In such situations, the number of restrictions that set acceptable solutions is significantly growing. The degree of identification of these factors and the degree of randomness of the analysed phenomena define the character of the problem to be solved by an engineer. Due to their limitations, the applied data organization models and models of data processing have usually a direct impact on the final result of the analytical or decision-making process. It applies to both algorithmic problems as well as poorly structured problems. When it comes to the first category, data are usually sourced from databases (data sets are generally organised on the base of a relational structures). Problem of a poorly defined structure are usually supported with knowledge sets (bases), and non-algorithmic reasoning methods (of knowledge management). Nevertheless, also in this case it is necessary to collect and process data with the help of a relational database.

The classical model of a relational database allows for defining objects (e.g. a technological operation, machine tool, tool, machining parameters) and relations between them. Every object is defined by attributes (e.g. a machined surface type, machined material type, the value of the roughness parameter (Ra) for the tool object), and these attributes have specific values from the permitted attribute range.

The unambiguity (sharpness) of attribute values is an important property of a relational data model. The simplifications adopted for relational modelling apply also to data management processes, especially to the process of defining database quires. Parameters of the formulated quires as well as the database search results have a form of unambiguous structures. For an illustrative query: *Show all the possible tools for surface machining* a set of objects (tools) for which the conditions defined in the query are true will be returned as a result of data selection. SQL (Structured Query Language) is a standard query language for the classical model of relational databases. The structure of the query used for indicating surface machining tools will look as follows:

SELECT *tool_symbol, machined_surface_type, Ra* FROM *tools*
WHERE *machined_surface_type= 'surface;*

Linguistic variables play an important role in modelling information and decision processes of a production enterprise. Their application seems to be especially reasonable (and sometimes necessary) in case when it is hard to propose objective rates for values (e.g. the roughness rate of the machined surface determines whether the surface is normal or not, a higher roughness rate generates a warning, and then an intervention is required as long as the defective is not recorded; the rate of vibrations during the process can be used to qualify the cutting edge as good or blunt). It means that in fact a lot of information on process designing and monitoring is partial, vague, and uncertain. Two-valued logic that is used in classical database and knowledge base systems imposes important limits on expressing the approximation of information, and especially its vagueness.

For example, if it is assumed that the roughness rate (Ra [μm]) is one of the parameters for monitoring the machining process, we can assign the descriptive value: *intervention* to the following range: 1,320 < Ra < 2,000. As a result, a classical database system identifies both Ra = 1.460 and Ra = 1.881 as being an *intervention* to the same extent. The limits of classical logic can be largely eliminated by the use of multi-valued logic, including fuzzy logic.

The fundamentals of the fuzzy logic can be summarized as follows:

- An element belongs to a fuzzy set with a certain degree of membership;
- A statement may be partially true or partially false;
- The membership degree is a real number from 0 to 1.

All the quantities that can be found in the fuzzy control describe a selected part of reality, and process of determining taforementioned value is called fuzzy observation. An ordered fuzzy number A is an ordered pair of functions (1),(2):

$$A = (x_{up}, x_{down}) \tag{1}$$

where

$$x_{up}, x_{down} : [0, 1] \rightarrow R \tag{2}$$

are continuous functions.

Images of those two parts are limited by specific intervals, named respectively: UP and DOWN. These parts of the fuzzy number, defined in respective intervals UP and DOWN, are strictly monotonic.

The membership function $\mu_A(x)$ of the fuzzy set (on the R set)is defined in a following way (equations 3-5):

$$\mu_A(x) = 0 \text{ for } x \notin [l_A, p_A], \tag{3}$$

$$\mu_A(x) = x_{UP}^{-1} \text{ for } x \in UP, \tag{4}$$

$$\mu_A(x) = x_{DOWN}^{-1}\, for\ x \in DOWN \tag{5}$$

A membership function of an ordered fuzzy number A is the function $\mu A : R \rightarrow [0, 1]$ defined for x 2 R (equations 6-8):

$$x \notin supp_A \Rightarrow \mu_A(x) = 0, \tag{6}$$

$$x \in (1_A^-, 1_A^+) \Rightarrow \mu_A(x) = 1, \tag{7}$$

$$x \in supp_A \wedge x \notin (1_A^-, 1_A^+) \Rightarrow \mu_A(x) = \max\left(f_A^{-1}(x), g_A^{-1}(x)\right) \tag{8}$$

Explaining it in the traditional way: OFN makes the direction of change its own.

The ability to integrate the fuzziness into data and knowledge processing systems seems to be an important issue. In the case of databases, the imprecision may be reflected in both the applied data model (fuzzy relation model) and the data processing methods (fuzzy queries).

5 The test result of the proposed models

The fuzziness in the relational model can have different levels, especially the fuzziness of attribute values. For example, value 2.00056 of the linguistic variable: roughness assigns the surface quality to the *intervention* value with the membership degree of 0.4, but to the *defective* value with the membership degree = 0.6 (Fig. 5). As a result of formulating an imprecise query, the system returns a set of objects for which the condition is partially met (not to the degree lower than the threshold).

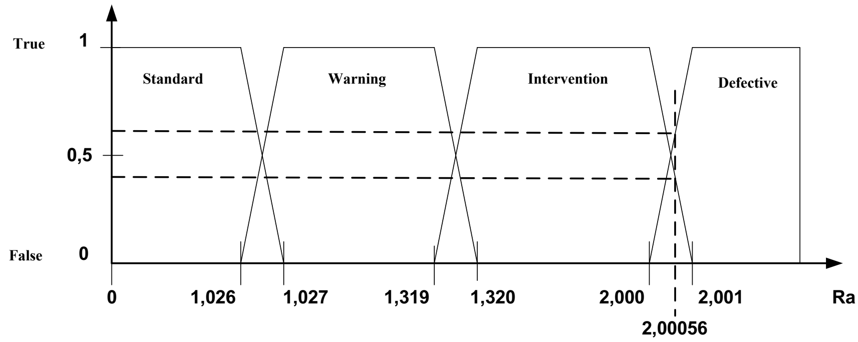

Figure 5: Fuzzy membership of a set

As a result of formulating an imprecise query, the system returns a set of objects for which the condition is partially met (not to the degree lower than the threshold). The selection result will be organised in accordance with the accuracy that is identified as the value of the membership function for the right fuzzy set. FQUERY is one of languages that enable formulation of imprecise database queries. A query in this language can look as follows:

SELECT surface type, roughness FROM <surface_parameters>
WHERE roughness = intervention
[WITH_POSSIBILITY <limit>], in which the limit is within the range of [0, 1].

Imprecise queries can include numerical fuzzy values, non-numerical fuzzy values, fuzzy comparison operators and linguistic quantifiers.

Another example of fuzzy logic application is the process of defining whether the cutting edge is still good or already blunt. The diagnostic was based on the vibration parameters. If the parameter of cutting edge degradation (VBc [mm]) reaches 0.3, the cutting edge is considered blunt. This is the way it works in classical databases that enable only to define sharp limits for selected parameters. As an effect, although the cutting edge degradation is in many cases gradual (not rapid), the analytical engine of the monitoring system does not identify such changes as important. It means that the reaction is possible for a defined state: s_k (set as critical for the parameter). In this situation, the application of a fuzzy database together with membership functions, e.g. functions defined by an expert (or a group of experts), enables an additional analyses and assessment of the changes in the parameter value, risks connected with these changes, as well as making a potential forecast of a safe lifespan or a decision on changing (replacing) the destroyed cutting edge (fig. 6).

At the same time, fuzzy query mechanisms allow for performing the following tasks:

- Find a cutting edge for which the monitored parameters are changing to fast.
- Find a cutting edge for which the values of the monitored parameters are evolving towards the warning limit.

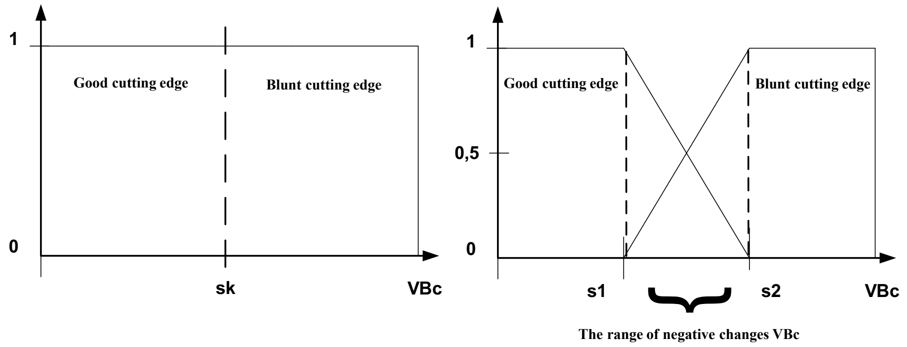

Figure 6: Cutting edge diagnostic, a – classical database, b – fuzzy database

In order to verify the proposed method, two simple database simulations have been built: classical and fuzzy. The testing was prepared and carried out during the preparation and test operation of the databases. For tests we used laboratory environment built on Microsoft Visual Studio Enterprise 2019, SQL Server Data Tools add-on to Visual Studio, which will allow to create a project with tests and connect to MS SQL database, Microsoft SQL Server and tested database. We used a built-in data generator to create realistic test data without exposing real production data. Then we run them from the Database Unit Test Designer. Test results are automatically produced, saved to disk, and summarized in the **Test Results** window.
We were limited by the scope of data shown by the built-in tester, but objectively objectively measurable results ahows, that fuzzy-based approach is more complicated comapred with calssical approach, but allows to achieve quicker results due to smaller oscillations with reference to the set-point inside to be maintained.

6 Discussion and future works

There are few studies/articles on the issue of comparing and rationalising the choice of an approach to the use of collected data (for the purpose of reasoning, gaining an outside view or preparing several versions of strategies for future optimization and change management). In the case of Industry 4.0, in which a technical inspection is performed at every stage of production, and the time of design and prototype works is reduced to the minimum, the problem of wastes generated during the technical inspection or the problem of using renewable energy sources may be solved on an ongoing basis by artificial intelligence monitoring and switching proper resources with the help of historical data from databases. In this context, it can be considered a waste of potential that some companies analyse/share their data only to the extent needed for the purpose of a simple statistical analysis that provides only 15% insights available from the data. Our attitude towards remote working and e-commerce is slowly changing. This can generate a need for even greater responsiveness to customers' needs. In this situation, classical management methods and long supply chains may turn out to be useless. Diversification is the key to success – it is already said that to ensure a fast adaptation to any market situation it is necessary to have a portfolio of at least 11 key customers that are independent from each other. Flexibility can be a deciding factor for maintaining the status quo.

A large variety of enterprise processes translates into diversity of requirements both in the terms of the structure of accessible information resources and the tools for their processing. In many cases, traditional methods based on a two-valued logic, such as classical databases, distributed databases or data warehouse, can be considered as reasonable solutions for data modelling. Nevertheless, the character of certain areas of a production enterprise requires to consider the imprecision of accessible information resources. The application of fuzzy databases for the purpose of representing and processing imprecise data seems to be especially useful in initiatives requiring automated activities that are so important for Industry 4.0. Polish enterprises apply virtually all the possible approaches: centralized databases, distributed databases, or data warehouses. However, fuzzy databases are rather developed in research centres, where thanks to fuzzy logic, especially OFN, is possible to achieve better control on multivariable industrial processes.

Method	Application	Dataset (Conditions)	Result
Classical	Classical databases, distributed databases or data warehouse	Two-valued logic	Data modelling
Fuzzy-based	Research centers	Imprecise information resources	Automated activities

Table 1: Differrences beteween Classical and Duzzy-based databases

Differences between classical and fuzzy-based cann0t be displayed on UML-based diagrams. The difference lies in description of the values and the way of calculation.

In their future studies, the authors will focus on developing fuzzy databases for production enterprises in the context of Industry 4.0 and IoT.

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