

Using MCDM and FaaS in Automating the Eligibility of Business Rules in the Decision-Making Process

Riadh Ghlala

SMART LAB (LR11ES03), ISG Tunis,
University of Tunis, Tunisia
riadh.ghlala@isetr.rnu.tn

Zahra Kodia

SMART LAB (LR11ES03), ISG Tunis,
University of Tunis, Tunisia
zahra.kodia@isg.rnu.tn

Lamjed Ben Said

SMART LAB (LR11ES03), ISG Tunis,
University of Tunis, Tunisia
lamjed.bensaid@isg.rnu.tn

Abstract: *Serverless Computing, also named Function as a Service (FaaS) in the Azure cloud provider, is a new feature of cloud computing. This is another brick, after managed and fully managed services, allowing to provide on-demand services instead of provisioned resources and it is used to strengthen the company's ability in order to master its IT system and consequently to make its business processes more profitable. Knowing that decision making is one of the important tasks in business processes, the improvement of this task was the concern of both the industry and the academy communities. Those efforts have led to several models, mainly the two Object Management Group (OMG) models: Business Process Model and Notation (BPMN) and Decision Model and Notation (DMN) in order to support this need. The DMN covers the decision-making task in business processes mainly the eligibility of business rules. This eligibility can be automated in order to help designers in the mastering of this important task by the running of an algorithm or a method such as the Multiple Criteria Decision Making (MCDM). This feature can be designed and implemented and deployed in various architectures to integrate it in existing Business Process Management Systems (BPMS). It could then improve supporting several business areas such as the Business Intelligence (BI) process. In this paper, our main contribution is the enrichment of the DMN model by the automation of the business rules eligibility through Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) using FaaS to further streamline the decision-making task in business processes. Results show to strengthen business-IT alignment and reduce the gap between the real world and associated IT solutions.*

Keywords: *Serverless computing, FaaS, BPMN, DMN, decision-making, business-rule, MCDM, TOPSIS.*

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1. Introduction

The last decade has been marked by the rise of various technologies that have contributed to the evolution of IT systems and consequently to a deeper support for managers in their business sectors. Cloud computing is one of those technologies that has promoted the scalability and high availability of these systems [10]. It provides a delegation of computer activity at different levels:

1. Software as a Service (SaaS) which allows to delegate the management of hosting, referencing and exploitation of solutions IT
2. Platform as a Service (PaaS) which allows to delegate the purchase, installation and configuration of development solutions and management of their upgrade.
3. Infrastructure as a Service (IaaS) that allows to delegate the management of servers with different

resources such as processors, memory and storage. Different scenarios allow the company to benefit from the cloud computing technology. Indeed, they can implement their private cloud or subscribe to a public cloud via one of the providers like AWS¹, IBM², Microsoft Azure³, Google⁴ and others. These companies can even adopt a hybrid computing architecture that combines both on-premises and cloud-based applications to manage their information systems.

The cloud computing continues to improve. In fact, the serverless computing feature has opened a new horizon for developers, designers, and users in order to better manage their IT solutions [6]. In Microsoft Azure, Function as a Service (FaaS) is a new approach to develop and deploy in the cloud. It provides, in addition to the benefits gained from cloud computing such as scalability, reliability and high availability other benefits namely:

¹AWS available at <https://aws.amazon.com/>

²IBM available at <https://cloud.ibm.com>

³Azure available at <https://azure.microsoft.com>

⁴Google available at <https://console.cloud.google.com/>

- Low cost by applying the principle of “Pay As You Go” to pay only for what we use [16] instead of other cloud services (SaaS, PaaS and IaaS) that require provisioned resources and therefore will be billed whether in use or in standby status.
- Low latency by keeping the function warm up [2, 12].
- Low administrative tasks by using full-abstracted servers [11].

The evolution of business logic support in the cloud has gone from monolithic applications, centralizing all needs and realizing everything with a single technology, to microservices by exploding the block of applications into independent services, written in different languages and managed by different teams. Figure 1 shows the kinds of business logic in cloud computing. FaaS has added another brick in the applications modularity through the use of stateless functions.

Business processes are the primary concern of managers who are always trying to master, streamline and optimize these processes. To meet this fact, the development of IT solutions that is aligned with their business needs requires a good formulation of these needs by using reliable and ergonomic formalisms [15]. Nowadays, the Object Management Group (OMG)’s Business Process Model and Notation (BPMN)⁵ and Decision Model and Notation (DMN)⁶ models are considered as standards in the high layer of the enterprise architecture to minimize the gap between the expectations of managers and the developed IT solutions and thus guarantee the Business-IT alignment.

We note that decision making task in the business process is very important given the complexity of the choices to be made and their impact on the outcome of the processes. The specificity of this task has attracted researchers to orient their research towards a better support. Work in this area, focused on business rules, followed various tracks such as the modeling and serialization of these business rules as well as dissociation of the decision task from the process itself. Outputs from this research led to the outsourcing of this task using the DMN, a model dedicated solely to decision making. In this paper, we aim to further enrich

the decision-making task in business process by improving the DMN model from a simple graphical model that only represents the business rules without supporting preference of the user to a system that enables eligibility automation of these business rules in the DMN decision table.

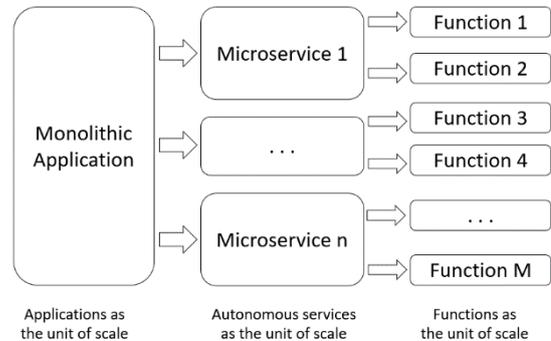


Figure 1. Kinds of business logic in cloud computing.

This automation is based on the invocation of an appropriate function to the decision-making task that is already designed, developed and deployed in the cloud. Thereby, the user no longer has to develop his own DMN decision table relating to a decision-making task, but rather to parameterize the call of the associated function. The deterministic aspect of the function ensures a uniformity of the company’s decision-making strategy in a given area of activity regardless of the representation of the decision table and the Business Process Management Systems (BPMS) used.

The contribution of cloud computing in automating the eligibility of business rules in a decision-making task is valuable. Indeed, FaaS provides a good performance, availability and cost-efficiency in addition to the business need translated by the determinism of the decision.

The sequencing of the integration of FaaS into a decision-making task in a business process is described with the flowchart shown in Figure 2. This solution transforms a heavy operation of implementation and execution into a simple invocation.

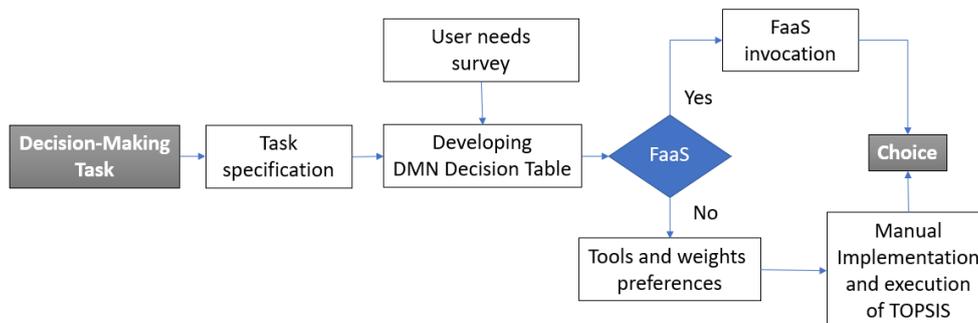


Figure 2. Flowchart of using FaaS in a decision-making task in a business process.

⁵BPMN available at <https://www.omg.org/bpmn/>

⁶DMN available at <https://www.omg.org/dmn/>

The remainder of the paper is structured as follows. First, section 2 describes the related works in this area. Then, section 3 describes business process, decision making in business process and the importance of automation of business rules eligibility in the DMN decision table. This description is guided by the OMG BPMN and DMN models. Next, section 4 describes the contribution of migrating this feature from on-prem to cloud using serverless computing. This migration is discussed to handle data visualization software selection task in a Business Intelligence (BI) process, applying TOPSIS as Multiple Criteria Decision Making (MCDM) method and using the Microsoft Azure FaaS as a cloud provider. Finally, section 5 summarizes the main achievements and concludes by highlighting future works.

2. Background and Related Works

Working with on-premises business rules using Business Rules Management Systems (BRMS) has become a ubiquitous activity in recent years to meet the demands of building complex and high-performance large-scale systems. This scaling up confronts us with a new challenge of delegating this task to a cloud service to benefit from availability and scalability with good cost control by adopting new development paradigms such as serverless computing.

The literature review shows that research work on serverless computing can be classified into three main tracks. First, several works are interested in the fundamentals of serverless computing. Indeed, they focus on the presentation of the different solutions proposed by the principal providers like Amazon Lambda, International Business Machines (IBM) Cloud Functions, Microsoft Azure Functions, and Google Cloud Functions. This track proposes comparative studies between these solutions [9] and the presentation of competing open-source solutions [14]. Second, several research works are interested in the architectural aspect of serverless computing. In this track, researchers are interested in the development, the deployment, the invocation as well as the chaining and the concurrence of these functions. A natural continuation of this aspect is the concentration on the performance aspect [12]. Third, the application domains and the economic impact of serverless computing on business information systems are topics of interest for many researchers. They aim to argue that FaaS are profitable for the company [1] and to substantiate that serverless computing can cover several business activities like multimedia processing, databases access, IoT sensor, stream processing, Chat bots, Batch jobs scheduled tasks, HTTP REST APIs and web apps, Mobile back ends, Business logic and continuous integration pipeline.

Business processes ensure the modeling, orchestration and monitoring of all business activities.

They allow to model graphically these activities offering an interface between the managers and the IT team. According to OMG, business processes are modeled through two standards: BPMN and DMN. BPMN is used to represent the various tasks in the business process and their relationships. It was the subject of several research works focused mainly on the modeling [13] and serialization [7] of business rules as well as their dissociation of the business process itself [4]. Given the importance of the decision-making task in business processes, the OMG has invested in a recent model, the DMN for a simpler and more reliable support of this decision-making task. Research in this area is evolving to improve aspects of decision making such as consistency and distribution [13].

The coupling of cloud computing as architecture of development and deployment of IT solutions and the business process as specification tools ensuring business-IT alignment is very relevant. In fact, up to now, academicians and industrialists are both developing a new cloud service in SaaS mode named the BPaaS [18] to give a better elasticity to business processes [17].

In this paper, we take advantage of new cloud computing services to better manage our business processes. Indeed, our approach does not address the case of a full migration of the business process in the cloud since several companies opt to keep their activities on premise considering several factors such as cost, security and availability. They only want to take advantage of plugins added to their IT solutions to better master complex tasks like decision-making. Our contribution consists especially on the use of serverless computing and especially FaaS to support the automation of business rules eligibility in the DMN decision table.

3. Automation of Business Rule Eligibility in DMN Decision Table

In this section, we present our contribution to enrich the DMN with a new feature that automates the eligibility of business rules in the DMN decision table. This new feature, allowing DMN to be enhanced by user preferences for the criteria, is added at the decision table level and modeled using an MCDM method. This choice is explained by the analogy between the eligibility in the DMN decision table and the concerns of the MCDM methods, as explained in a previous work [8].

3.1. Data Visualization Software Selection as Decision Task in BI Process

Mastering decision making in business processes is a concern in many areas of business. In our research work, we are dealing with this need in a BI process. Indeed, a

BI process can be related to one of the three possible projects that are:

1. Corporate BI project
2. BI project in a big data context
3. Self-service BI projects also designated by Data visualization project.

This last type of BI process is composed of several tasks like data sources, data modeling, data visualization, sharing reports and dashboard. The choice of the visualization tool is also an important task in the process since it contains a decision to optimize this choice

according to different preference criteria such as ease of use, features and functionality, advanced features, integration, performance and customer support. The decision can be more complex if we apply weights to each of these criteria. To solve this problem and guarantee a rational choice, the MCDM methods can be a solution that allows us to avoid subjective choices.

Figure 3 shows an excerpt from a BI process in which an interaction between BPMN and DMN to cover the decision-making task of choosing the data visualization software.

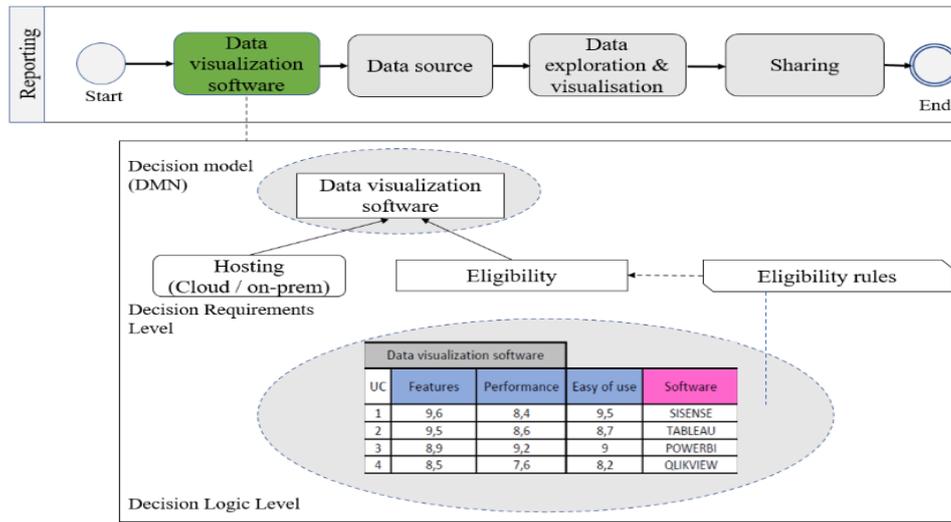


Figure 3. BPMN/DMN modelling of Data visualization software selection in a BI process.

3.2. DMN Decision Table

The decision-making task in business processes is based on business rules. The contribution of DMN in the management of this task is highly valued. Indeed, it provided the designers mechanisms to formulate and graphically represent their business rules. This flexibility of formulating business rules with the Friendly Enough Expression Language (FEEL) has strengthened the support of the decision-making task [5]. It should be noted that this support is only static, based on the visual aspect of the graphic representation, whereas the automation of the business rules eligibility is a much-needed feature. Figure 4 shows the DMN decision table for the data visualization software

selection. The decision is based on user preference criteria and a list of proposals containing tools like SiSense, Microsoft Power BI Pro, IBM Watson Analytics, Tableau Software Desktop, Microstrategy, Dundas BI, QlikSense, Zoho Reports, Yellowfin and Jreport. Knowing that the DMN decision table contains different hit indicators such as Unique (U), First (F), Any (A) and Priority (P) determining statically the business rule election; our contribution can lead to new hit indicator that is Delegate (D) which consists in delegating this mission to be done automatically using a FaaS that covers an exhaustive list of tools instead of a subjective sample.

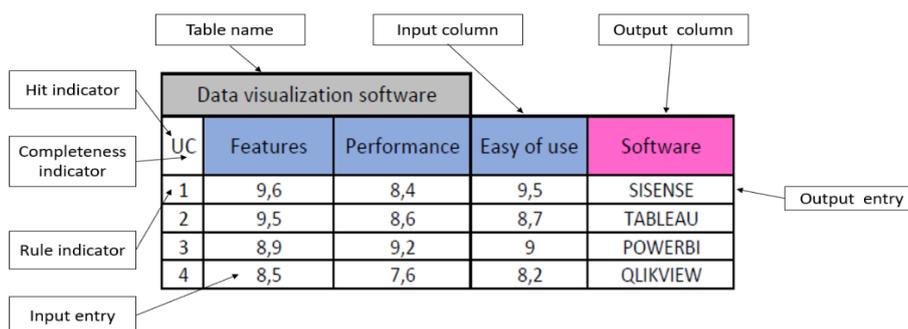


Figure 4. DMN decision table for Data visualization software selection in a BI process.

The need to automate decision-making stems from the complexity of this task, which may be due to several reasons. Indeed, in this kind of situation, we may be confronted with a combinatorial problem offering a large number of possibilities, we may also be influenced by local or personal factors that divert us from the overall strategy of the company in such a decision. With our proposal, the entire decision task is performed by the associated FaaS, which can handle all the possibilities related to the tools, preference criteria and assigned values offered by domain experts. In this case, user is just called to invoke the function with the option to adjust the weightings of the performance criteria.

3.3. MCDM Automates Business Rule Eligibility in DMN Decision Table

This section is devoted to present the MCDM method that is adopted to automate the eligibility of business rules in the DMN decision table. In the literature, we find a multitude of methods mainly Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) and TOPSIS.

A study of these different methods led us to choose the TOPSIS method. This choice is explained by the suitability of this method to our need to take several criteria into consideration in order to satisfy the user's preferences [19]. It should be noted that TOPSIS and the DMN decision table are similar in many aspects such as:

- Analogy between DMN decision table and TOPSIS data matrix.
- Support of criteria (to be maximized) encouraging choice and criteria (to be minimized) discouraging choice.
- Ability to assign weights to the criteria.

We can also defend the choice of the TOPSIS method by the availability and the clarity of its algorithm [3]. This algorithm describes the different steps to follow for the application of this method, from the identification of the different alternatives to the selection of the one to be chosen.

In our case, we are faced with a choice of data visualization tool based on a set of criteria, each of which has a weight reflecting its importance in the decision. The automation of such a task is done by developing a set of business rules which have as trigger clauses the different combinations of criteria and as action the choice to be adopted. Instead of applying this legacy approach, we propose to transform the DMN decision table into a TOPSIS data matrix and then to apply the different steps of this method to determine the optimal choice by considering the different criteria and their weighting.

In this line of research, the emphasis is on the reliability of choices established by the FaaS component which will be invoked to replace the classic scenario of manually implementing and executing the TOPSIS method based on personal data. Another future research track can focus on the performance of this solution by studying the behavior of this component with a large number of factors and weights.

4. Migrating Business Rule Eligibility in DMN Decision Table from on-Prem to the Cloud

4.1. Motivation of the Migration

The migration of eligibility in the DMN decision table is motivated essentially by the following reasons:

- The spread of cloud computing and its various services that cover all business activities. This trend is not only a technical phenomenon but a real opportunity for the company to master cost, technicality, performance and availability of this crucial decision-making activity in its business processes.
- The complexity of decision-making in business processes because of the diversity of choices which leads to studying only a limited set of choices and not treating all the possibilities. The processed sample is generally chosen in a subjective way from the user by limiting himself to the task context rather than aligning with the overall business strategy.

4.2. Migration Process

The business process can contain various decision-making tasks, each of which requires eligibility for associated choices. If we opt for the task migration on the cloud, a FaaS must be developed to cover the list of choices interested by the user. Our experimental study focuses on a cloud service related to the decision task for the choice of a data visualization tool in a BI Business Process.

Once the FaaS is developed, the invocation depends on two aspects: FaaS deployment style and FaaS setting. Indeed, the FaaS deployment is to opt for a service always fired or the application of the principle "Pay As You Go" to make the cost even more profitable. The FaaS setting determines how to identify choice, weight, criteria and associated values. At this level, we specify that these parameters come from the proposals of the domain experts based on existing benchmarks in the net⁷. The user has only to invoke the service in order to receive the choice according to these benchmarks. He also has the possibility to choose from a restricted list

⁷PAT RESEARCH available at <https://www.predictiveanalyticstoday.com/top-data-visualization-software/>

and not the entire list (just the list of tools, while all other parameters are still determined by the experts to ensure

the principle of objectivity and standardization)

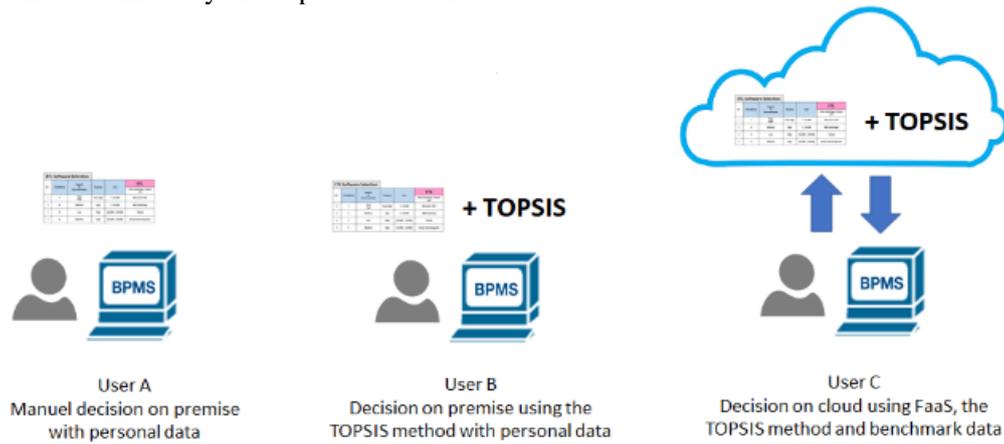


Figure 5. Different decision-making approaches in a business process.

4.3. Numerical Experiments

4.3.1. Approaches Description

The experimental study consists on comparing the different results of choice of a data visualization tool. The choice made is based on a set of weighted criteria and can be done manually or with the TOPSIS method. This decision-making can be based on personal data (criteria, weights and associated values) established on premises or in cloud based on a benchmark data. Figure 5 shows the different approaches adopted in this experimental study.

4.3.2. Simulation Experiments

The experiments carried out consist in showing, on three scenarios, the difference between the results relating to a manual decision-making based on personal data compared to a decision-making using the same data but automatically using the TOPSIS method. These two scenarios are then compared to the results provided by experts in the field by adopting their benchmark relating to the data visualization tools that are the subject of this decision-making task.

Table 1. Manual decision-making task in premises using personal data.

| Data visualization tools | Manual user ranking based on personal data | | | | | | | | | |
|---------------------------|--|----|----|----|----|----|----|----|----|-----|
| | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 |
| Analytics Canvas | - | 10 | 10 | - | - | - | 12 | - | - | - |
| AnswerRocket | 9 | - | - | - | 7 | - | 11 | - | - | - |
| AnyChart | 11 | - | - | 11 | 6 | - | - | - | - | - |
| BizViz Platform | 7 | - | - | 12 | - | - | - | 5 | - | 7 |
| Bright Gauge | - | 11 | - | 7 | - | 11 | - | - | - | - |
| DataLion | - | 12 | - | 4 | - | - | - | - | 6 | - |
| Dundas BI | - | 13 | 8 | 9 | 4 | 7 | 9 | 9 | 11 | - |
| GoodData | 5 | - | - | - | 9 | - | 6 | - | - | 12 |
| IBM Watson Analytics | 1 | 3 | 4 | 1 | - | 2 | - | 1 | 5 | 1 |
| Jreport | 13 | 4 | - | 10 | 10 | 10 | 10 | - | 7 | 3 |
| Microsoft Power BI | 2 | 1 | 2 | 2 | 1 | 3 | 4 | - | 2 | 5 |
| Microstrategy | 3 | - | 7 | 6 | 2 | - | 2 | 2 | 8 | 2 |
| Oracle Business Analytics | - | - | 1 | - | 3 | 4 | 3 | 8 | 4 | - |
| Phocas BI Software | - | 2 | - | - | - | - | - | - | - | 8 |
| QlikSense | - | 5 | 6 | 3 | - | - | - | 3 | - | 4 |
| Salesforce Wave Analytics | 8 | - | - | - | - | 1 | 5 | - | - | - |
| SAP BusinessObject BI | 10 | - | - | - | - | - | - | - | 10 | - |
| SiSense | 12 | 6 | 5 | 8 | - | 9 | 8 | 6 | 12 | 10 |
| Tableau Software Desktop | 4 | 8 | 3 | 5 | - | 5 | 1 | 4 | 1 | 6 |
| Vizdum | - | - | - | - | - | - | - | 10 | - | - |
| Windword Studios | - | - | 9 | - | - | 6 | - | - | 9 | - |
| Wizdee | - | 9 | - | - | - | - | 7 | - | 3 | - |
| Yellowfin | - | 7 | - | - | 5 | - | - | 7 | - | 9 |
| Zoho Reports | 6 | - | - | - | 8 | - | - | - | - | - |
| Zoomdata | - | - | - | - | - | 8 | - | - | - | 11 |

- Experiment 1, referenced by “User A” in Figure 5, consists of asking a set of users (who participated in training sessions related to the design and the deployment of BI process) to choose from a list of data visualization tools based on personal data (the list of tools, the weighted criteria adopted and the

associated values) and without using a mechanism automation as the TOPSIS method. The target users of the survey are heterogeneous. In fact, they belong to different companies, they have different levels of education and they do not have the same seniority in BI projects. This choice aims to faithfully simulate

the industrial fabric formed by the big companies and also a lot of startups in the field of BI. Table 1 shows a sample of the 10 user responses from the list of users surveyed. This number represents the top ten users who proposed the maximum of data visualization tools in the survey. Values shown in this Table represent the ranking of each user of a set of visualization tools according to their own knowledge. A missing value in the table means that the corresponding tool does not appear in the list of tools of the associated user.

- Experiment 2, referenced by “User B” in Figure 5, reproduces the same decision-making task using the average of data provided by the users as a part of the survey carried out. These data are considered as input to the algorithm implementing the TOPSIS method. The algorithm is implemented in premises with the C# language.
- Experiment 3, referenced by “User C” in Figure 5, performs the same decision-making task but is based on data from a benchmark established by experts in the field. Only the data visualization tools that appeared in the survey are taken from the benchmark to make the comparison knowing that it contains almost a hundred tools. These data include the preference criteria that are: Ease of use, Features, Integration, Performance and Customer support with the associated values for each tool. These data are subsequently considered as input to the algorithm implementing the TOPSIS method. The algorithm is implemented in the Microsoft Azure cloud with the FaaS feature of the Compute services. Experimental results from the third approach provided a ranking of all the tools that appeared in the survey.

The discussion will then be based on the comparison of the ranking of the three scenarios.

4.3.3. Analysis and Discussion of Experimental Results

According to the results of Experiment I presented in Table 1, the choice of data visualization tools does not follow any deterministic logic. Indeed, we notice different rankings for the same tool even with the same associated inputs which reflects the subjective aspect of decision making. This aspect also characterizes the choice of the list of tools chosen by the users according to their own limited knowledge in the field or their own preferences which are also, in most cases, influenced by their socio-economic factors.

The results of experiment 2 and 3 are summarized in Figure 6. Indeed, we ensure by the application of the TOPSIS method an automation of the decision-making. This automation, even if it is based on personal data, it comes close to a uniform classification of data visualization tools, whatever the preferences of the users. The gap that still remains between the two classifications is due, in addition to the dependence on

personal data provided by users and not by experts in the field, to the unfamiliarity of these users with the whole landscape of data visualization tools. This figure shows a positive correlation between the number of occurrences of the visualization tool in the survey and its ranking. The more the tool is mentioned in the survey (case of tools 1, 2, 3, 4, 5, 6, 7, and 9), the more its classification provided by experience 2 converges towards the classification provided by experience 3 which proves the importance of mastering the entire landscape of the area in order to obtain the most realistic classification. In this figure, we also notice some exceptions (case of tools 8, 15 and 21) in which the two rankings given by the experiment 2 and 3 are close even with a low number of the tool’s occurrence in the survey which reflects responses provided by skilled users. This exception should not influence us because the industrial fabric is not made up only of high-level users in the field of BI processes and the decision-making support remains a highly desired feature.

In summary, three main facts can be deduced reflecting the three scenarios encountered in this experimental study, namely:

1. *Widespread tools*, indicated by the green color, represent the most common tools in the community. Their automatic ranking using the TOPSIS method is generally correct and reliable both on-premises using personal data and, in the cloud, using benchmark data.
2. *Tools ranked by Experts*, indicated by the blue color, are tools having rankings provided by experts in the field. Although they are not widespread rankings, they are always reliable based on personal data or by referring to benchmarks
3. *Emerging tools* indicated by the orange color, are existing tools that do not have much feedback. Hence, the need to automate their ranking with the TOPSIS method by referring to benchmarks is very rational. We notice a negative correlation which indicates a divergence between the two rankings since the number of occurrences of the data visualization tool is low in the survey.

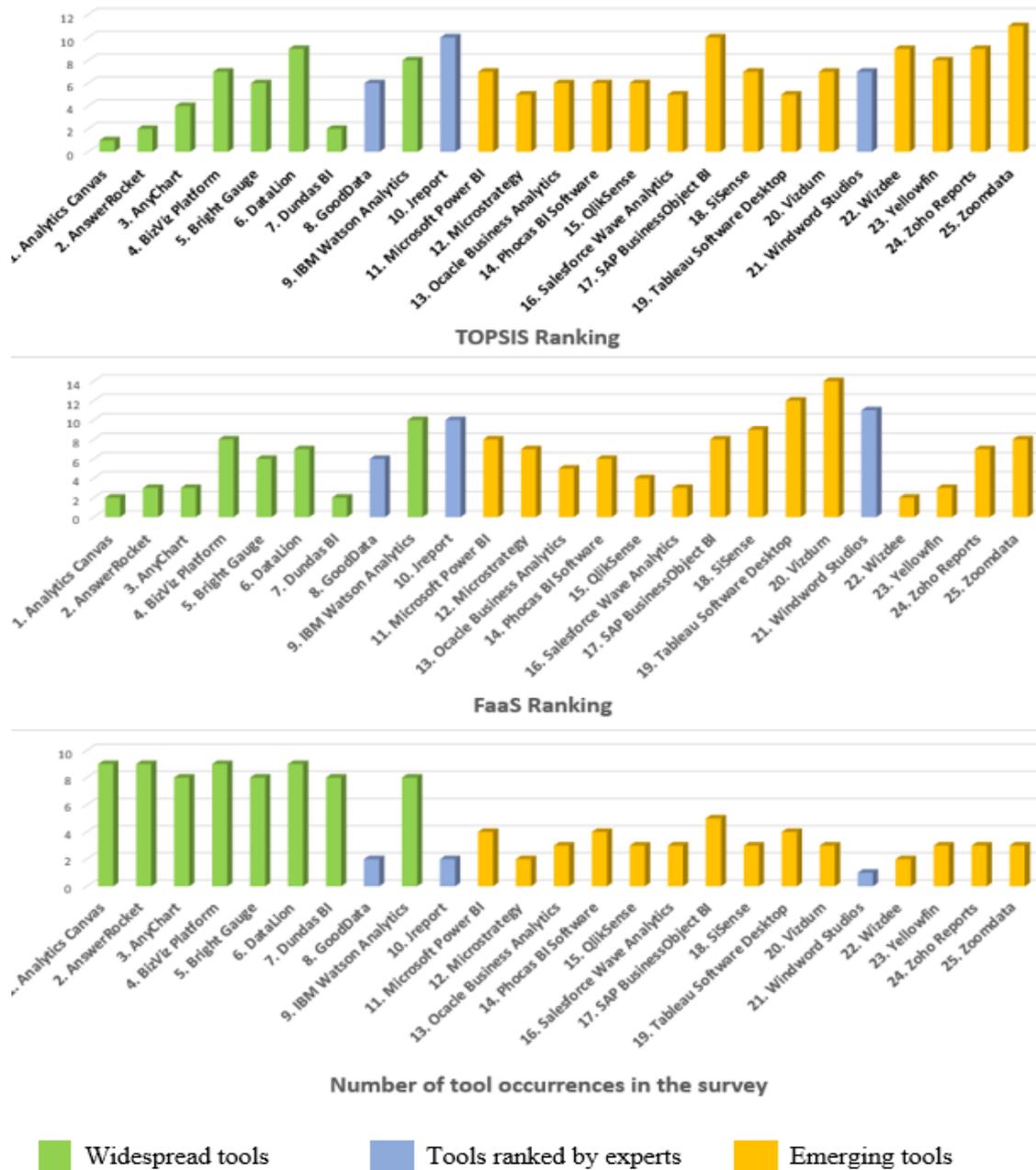


Figure 6. Comparison of ranking approaches for data visualization tools.

5. Conclusions and Future Works

Decision making in business processes continues to improve in order to strengthen business-IT alignment and reduce the gap between the real world and associated IT solutions. Among these improvements, mastery of the decision-making task by automation of business rules' eligibility which is a much-needed feature to automate the election of the business rules to be applied rather than the manual management of the decision table. This feature can be a scope of Serverless Computing, specially FaaS, to support this business activity with maximum efficiency.

Throughout this paper, we first introduced Serverless Computing and especially FaaS as a new mode of development in cloud computing as well as the two OMG BPMN and DMN models, which both serve to master business processes and decision making in these

processes. Then, we presented the automation of business rules eligibility as an important feature to improve decision making in business processes. This automation is provided by TOPSIS as a MCDM method to support the preference criteria of the users. Finally, we described the migration architecture of this functionality from on-prem to the cloud using Serverless Computing, specially FaaS.

To extend research in this area, a broad range of topics needs to be addressed. We highlight future work for some topics around the automation of the eligibility of business rules. These works can be:

- The generalization of this automation with different types of values used in the decision table such as strings, intervals and not only the numerical values required by the TOPSIS method. This extension requires a work of digitization of the associated

values of the choices which can be perfectly ensured by the mechanism of the fuzzy logic.

- Coupling this feature with other important features in order to support decision-making both at the task level by mastering the eligibility of criteria and at the process level by ensuring consistency and harmonization. A track promoting this eventual functionality is the RETE algorithm that can be integrated into the decision-making task in order to ensure, following an inference, the required consistency of the adopted business rule.
- Bring dynamism to FaaS in order to update data leading to the decision. Multi-agent systems can be a good choice for modeling agents ensuring the refreshing of data managed by FaaS from benchmarks through APIs.

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Riadh Ghlala he is an associate university teacher in computer science in the network of Higher Institutes of Technological Studies (ISET) since September 1998 and he is currently a professor technologist (since September 2019) at the Higher

Institute of Technological Studies of Radès (Tunisia). Since 2015, he has been conducting research on improving Decision-Making in Business Processes applied to Business Intelligence (BI) projects. He is also a member of the scientific council of the Strategies for Modeling and Artificial Intelligence (SMART) research laboratory at ISG Tunis. In addition to his academic activities, he is also a certified trainer and consultant in Oracle, Microsoft and Amazon Web Service technologies.



Zahra Kodia she received the B.Sc. degree in Business Computing from the Institut Supérieur de Gestion, University of Tunis (ISG-Tunis), Tunisia, in 2006. the M.Sc. and Ph.D. degrees in Computer Science from Ecole Nationale des Sciences de

l'Informatique (ENSI), University of Mannouba, in 2008 and 2014, respectively. She is a member of the scientific council of the SMART Lab (Strategies for Modelling and ARTificial inTElligence Laboratory). She is an associate professor in computer science in since September 2015 in ISG Tunis, University of Tunis. Since 2009, she has been conducting research on improving Decision-Making in complex systems such as Stock markets, Business Processes, Recommender systems.



Lamjed Ben Said full professor in Computer Science Head of the SMART Lab He received the B.Sc. degree in Business Computing from the Institut Supérieur de Gestion, University of Tunis (ISG-Tunis), Tunisia, in 1998, the M.Sc. and Ph.D.

degrees in Computer Science from the University of Paris VI, Paris, France, in 1999 and 2003, respectively, and the Habilitation degree from the University of Tunis in 2011. He was a Research Fellow with France Telecom, Research and Development Department, Paris, for three years. From 2014 to 2020 he was the Dean of the ISG-Tunis where he is currently a Full Professor in Computer Science, University of Tunis, Tunis, Tunisia, and the Head of the SMART Lab (Strategies for Modelling and ARTificial inTElligence Laboratory). He published over 200 research papers in refereed international journals, conference proceedings, and book series. His current research interests include multi-agent simulation, multicriteria decision making, evolutionary computation, supply chain management, and behavioral economics. Dr. Ben Said is a Reviewer for several artificial intelligence journals and conferences and he is / was member / responsible of several national and international projects.