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Optimization Management of Industrial Organizations Based on Performance Indicators

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Abstract

This paper proposes an intelligent management system (IMS) to help managers in their delicate and tedious task of exploiting the plethora of data (indicators) contained in management dashboards. This system is based on intelligent agents, ontologies and data mining. It is implemented by PASSI (Process for Agent Societies Specification and Implementation) methods for agent design and implementation, the Methodology for Knowledge Modeling and Hot-Winters for data prediction. Intelligent agents not only track indicators but also store the knowledge of managers within the company. Ontologies are used to manage the representation and presentation aspects of knowledge. Data mining makes it possible to: make the most of all available data; model the industrial process of data selection, exploration and modeling; and transform behaviors into predictive indicators. An instance of the IMS named SYGISS, currently in operation within a large brewery organization, allows us to observe very interesting results: the extraction of indicators is done in less than 5 minutes whereas manual extraction used to take 14 days; the generation of dashboards is instantaneous whereas it used to take 12 hours; the interpretation of indicators is instantaneous whereas it used to take a day; forecasts are possible and are done in less than 5 minutes whereas they did not exist with the old management. These important contributions help to optimize the management of this organization.

Keywords

Performance Indicator, Intelligent Agent, Data Mining, Intelligent Management System, Enterprise Management

1. Introduction

Managing a company consists in planning, organizing, directing or controlling with the aim of satisfying its shareholders through the results obtained. Several tools have been put in place to facilitate the manager's work, the most well-known and most used are the Blake and Mouton grid [1], the Deming-PDCA (Plan-DO-Check-Act) wheel [2], the Eisenhower matrix [3], the Lean method [4], the WWWWHW (What, Who, Where, When, How, Why) [5], the job description and the dashboards [6]. In addition to these tools, the following decision-making techniques are used: thinking for yourself, trusting your intuition, doing what others do and analyzing the numbers. Several editors have invested in this sector through: dashboard software, decision support systems, expert systems, data mining and knowledge representation systems. Their contributions allow: a slight reduction in decision time; the instantaneous implementation of corrective actions; the prediction of the state of the company at a given date and the learning of managers.

Table 1 summarizes the weaknesses and advantages of the existing systems to support our managers in the exercise of their function.

When reading **Table 1**, it is clear that our managers are not equipped with the tools that allow them to anticipate the instantaneous management of their business, hence the bitter observation that we experience on a daily basis with the plethora of bankruptcies throughout the world because the existing systems are not flexible. Specific problems, changes of direction and strategy, and the expansion or reduction of company tasks are difficult to manage instantly. The time it takes for the measures to be made available to interpret the good functioning of our organizations remains very long from one system to another, which excludes real-time decision making, any forecasting and a credible anticipation of the future.

Although current systems offer facilities for automatic generation of dashboards (TB) thanks to flexible query tools, the burden on decision-makers is still significant. It is therefore important to look at the ways and means that can be made available to decision-makers to assist them in the construction, extraction, calculation and analysis of indicators, thereby giving them more time to define and reorient their core business strategy. Therefore, the implementation of dashboards questions the consideration of distributed artificial intelligence technologies, through intelligent agents for their autonomous and social character, decision support systems for their decision-making assistance and expert systems for their ability to mimic human behavior [7] [8]. The question that this work tries to answer is the following: can we propose a model of Intelligent Management System, to help optimize the work of managers on the basis of performance indicators? In other words, how can an intelligent management system model contribute to reducing the manager's decision time to a time (Td) much lower than the threshold time (Tds) beyond which the company can no longer be saved?

Our main objective is therefore to couple to the Information System (IS) an Intelligent Management System (IMS) to assist the management, the first one (IS) providing the necessary data for the operation of the second one (IMS). The

Table 1. Summary of advantages and disadvantages of existing management systems.

Existing systems	Dashboard	Decision support systems	expert systems	Data mining	Knowledge management
Data Extraction Time	Long	Very long	Very long	Long	Very long
Calculation time of the indicators	Very long	Very long	Very long	Very long	Very long
Time Generation of dashboards	Long	Very long	Very long	long	Very long
Relevance and hierarchy of indicators	Included in the formulas	Non-existent	Non-existent	Included in the formulas	Non-existent
Data forecasting	Semi-hand-held	Integrated	Integrated	Semi-hand-held	Integrated
Alerte incident	First level alert	Non-existent	Non-existent	Non-existent	Non-existent
indicator Presentations	Well organized	Acceptable	Acceptable	Acceptable	Acceptable
indicator Interpretations	Manual	Integrated	Integrated	Manual	Integrated
Flexibility	Very long to set up	Very long to set up	Very long to set up	Very long to set up	Very long to set up

Long: more than one week; **Very long**: more than one month.

IMS proposed for the coupling is a model of Multi-Agent System [9] [10] able to help the manager to accomplish his management tasks (analysis and interpretation of indicators then decision making).

Our approach to achieving this objective passes by an abstraction of the existing system which allows us to detect the parameters which enter the time of decision, then we rely on the following technologies: Multi-Agent System which allows to introduce in a system, a set of agents able to transform it; ontologies which allow to manage the aspects of representation and presentation of the knowledge[11]; Data mining which serves to model the industrialized process of selection [12], exploration and modeling of data, then to transform the behaviors into predictive indicators. These technologies allow us to add other optimization variables to the existing parameters and thus produce an abstract model of the new system on which we base ourselves for the realization of the concrete model that is the IMS. The implementation of our platform is based on: PASSI [13] for the design and implementation of the MAS on which our platform is based; METHONTOLOGY [14] for knowledge modeling; and Holt-Winters for data prediction [15].

The rest of this article is composed of 3 sections: the methodology, which presents the construction approach of our model and its implementation for a concrete model representing the architecture of the RMS; the experimentation, where we present the validation framework of the model and the obtained results, the discussion where we discuss the obtained results and then we end with a conclusion.

2. Methodology

2.1. Existing Model

From a functional point of view, the current system for constructing management indicators in a company is essentially made up of traditional extraction tools and structured data warehouses. **Figure 1** presents the functional architecture of such a system, consisting of 6 levels. From top to bottom, the first level is essentially dedicated to manager's tools. Level two is concerned with data organization, previously formatted at level 3. Data from the various applications (level 6) are extracted and stored in datamarts on levels 5 and 4 respectively.

The existing KPI construction system consists of six layers. The information and data go from the bottom layer, which is made up of business applications, ERP, CRM and budget planning, to the data warehouse, via the ETL, storage and restitution tools. From the dataware house are produced performance indicators, reports and dashboards, which the manager must analyze and interpret to make decisions. A performance indicator provides a tool for comparing current results with predefined objectives in order to initiate the necessary actions to achieve these objectives [16].

Let *Ma* be the current or existing model, derived from the functional architecture presented in **Figure 1**. The parameters of *Ma* are the following:

- *M*: the manager
- *Pc*: the calculation programs/algorithms
- *Pe*: the extraction programs/algorithms
- *Td*: Decision time
- *Tci*: Indicator calculation time
- *Te*: Extraction/data mining time
- *Pm*: Machine power
- *Ti*: Interpretation time
- *Tds*: Threshold decision time (Decision making time beyond which remediation is no longer possible)

In view of the above parameters, the *Ma* model is as follows:

$$Ma:\begin{cases} Td = f\left(M\right) \\ Td = Te + Tci + Ti \\ Tci = f\left(Pc, Pe, Pm\right) \\ Td > Tds \end{cases} \quad (1)$$

With the existing:

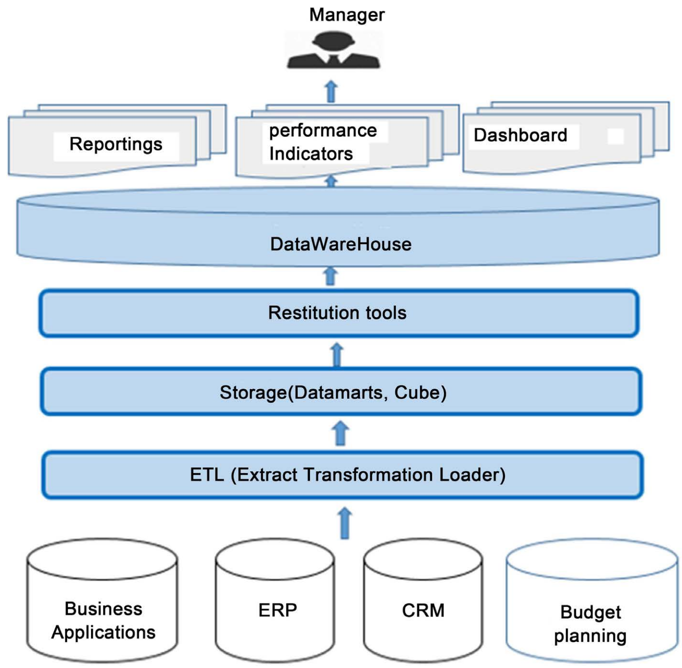

Figure 1. Performance indicator construction system.

- The decision-making time (Td) is a function of the Manager, it is the sum of the times: of extraction (Te), of calculation of indicators (Tci) and of interpretation of indicators (Ti).
- The time of calculation of indicators (Tci) is a function of the calculation programs, the extraction program and the machine power.

The consequence is the obtaining of a decision time Td largely greater than the threshold decision time Tds (time beyond which the remediation is not possible). The cause is the absence or insufficiency in the existing system of the following properties available to the agents: communication, proactivity, cooperation, autonomy, coordination, negotiation, learning and mobility. A management system based on the MAS (Multi-Agent System) would ensure that the company's indicators are made available and interpreted in real time, in order to anticipate the decisions to be taken. The following section presents the model of such a system.

2.2. New System Model: Intelligent Management System (IMS)

The objective is to reduce the decision time Td, *i.e.* the times Te, Tci and Ti presented in the equation model of the existing system. The transformation of the existing system requires the definition of the following new equation variables:

- λ: is our IMS
- M_λ: IMS Model
- A_G: Agent Manager
- A_C: Knowledge Agent
- A_P: Forecast Agent
- A_A: Alert Agent

- A_I: Indicator Agent
- A_{SI} = Agent Sub Indicator
- A_{FDD} = Data Mining Agent
- Te_λ = Extraction time IMS = $f(A_{FDD})$
- Tci_λ = Calculation time IMS = $f(A_I, A_{SI}, Te_\lambda) = f(A_I, A_{SI}, A_{FDD}) = f(A_G, A_G, A_P, A_A)$
- $Ti_\lambda = f(A_P, A_A, A_I, A_c)$
- Td_λ = Decision time = $Te_\lambda + Tci_\lambda + Ti_\lambda = f(A_{SI}, A_{FDD}, A_G, A_G, A_P, A_A, A_I)$
- Tds = Decision time threshold.

This transformation allows to have $Td_\lambda << Tds$ (The decision time with new parameters becomes much less than the threshold decision time). The model M_λ is as follows:

$$M_\lambda : \begin{cases} Td_\lambda = Te_\lambda + Tci_\lambda + Ti_\lambda \\ Td_\lambda \ll Tds \end{cases} \quad (2)$$

Equating the RMS, we can see that:

- The data mining module is a function of the data mining, indicator and sub-indicator agents;
- The knowledge management module is a function of the prediction, alert, indicator and knowledge agents;
- The manager module is essentially composed of the manager agents;
- The user interface module is a function of the alert agent.

These different modules represent the subsystems of the RMS, they allow to optimize the processing and decision making time for the management of the organizations. These subsystems are a combination of specific agents cooperating with each other to make the results and solutions reported by the global system more reliable. **Figure 2** shows the Intelligent Management System (IMS) described below.

- The IMS is made up of five (5) subsystems, consisting of the following agents
- Interface agent: it belongs to the dialogue subsystem. It is the entry point to the system, it ensures the communication between the other agents and the users as well as the configuration of the system. It is a reactive agent with a simple reflex because it only acts under the influence of an external action (user, other agents of the system).
- Notification agent: it belongs to the dialogue subsystem. It is a reactive agent with a simple reflex, responsible for alerting managers by e-mail in the event of a malfunction on the values of the indicators, by generating a detailed report on the state of the indicators.
- Manager agent: this is a deliberative agent, responsible for monitoring the indicators. It combines the data provided by the data mining agent and the knowledge provided by the knowledge agent and returns them to the interface agent. There are as many management agents as there are positions monitored within the company.

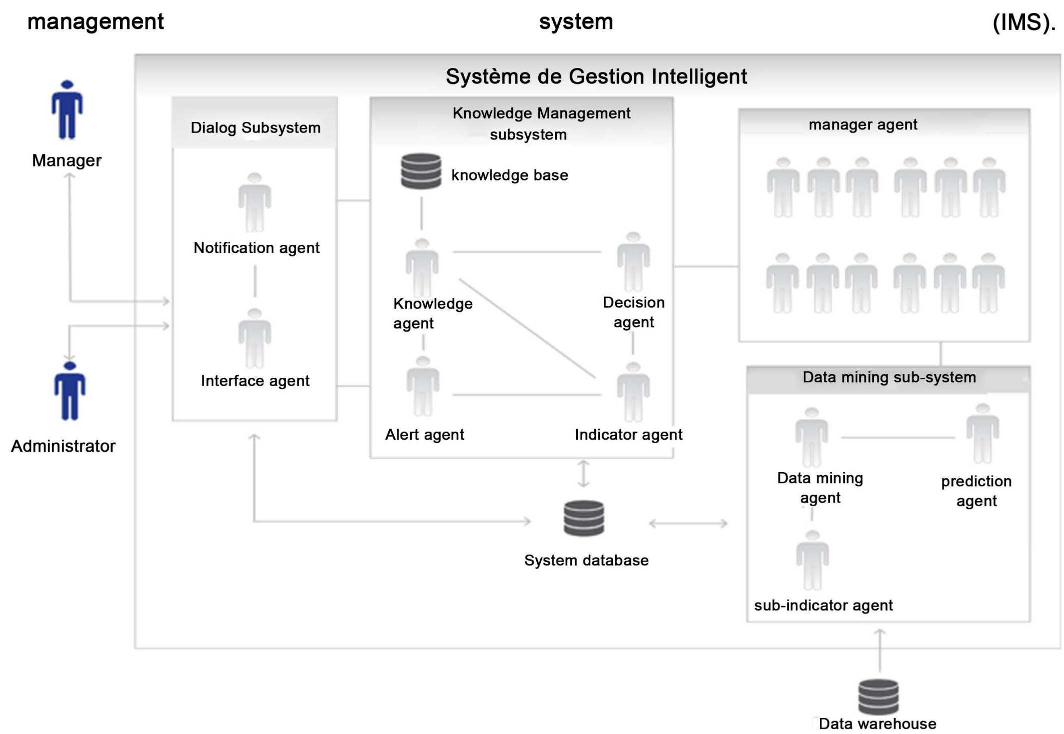

Figure 2. Intelligent management system.

- Data mining agent: it belongs to the data mining subsystem. It is a deliberative agent, responsible only for the analysis of indicators visible to the manager. It highlights the evolution of indicators in relation to specific thresholds. It searches and retrieves data.
- Sub-indicator agent: belongs to the data mining sub-system. It is responsible for making a complete analysis of the sub-indicators of an indicator, clearly showing the evolution of each one. It is a deliberative agent with goals.
- Prediction agent: it belongs to the data mining subsystem. It is responsible for predicting the evolution of the values of an indicator over a given period. It is a reactive agent with simple reflexes.
- Knowledge agent: it belongs to the knowledge management subsystem. It is responsible for monitoring indicators. It combines the data provided by the data mining agent and the knowledge provided by the knowledge agent and returns them to the interface agent. It is a deliberative agent with goals.
- Decision agent: it belongs to the knowledge management subsystem. It interacts with the manager by helping him to make good decisions. It is a reactive agent with simple reflexes because it essentially only acts under the manager's request.
- Indicator agent: it belongs to the knowledge management subsystem. Its role is to load and evaluate the value of the indicator it is monitoring. It is a deliberative agent with goals.
- Alert agent: it belongs to the knowledge management subsystem. It looks for alerts produced by the combination of knowledge, decision and indicator

agents, and still stored in the knowledge base in order to inform other agents (notification agent, ...). It is a reactive agent with simple reflexes. Implementation of the Smart Management System (SMS).

The implementation of the Intelligent Management System (IMS) involved: the design and implementation of the agents, the knowledge modeling and the implementation of the forecasting process.

2.2.1. Design and Implementation

The PASSI (Process for Agent Societies Specification and Implementation) method [7] has allowed us to generate the following models: the domain requirements; the identification of agents; the agent tasks and the agent society. The latter consists of: the ontology description, the agent role description and the communication protocol description. For the implementation of a prototype we relied on two main types of development tools: general tools composed of programming languages (Java, HTML, OWL, SPARQL and R), iText for PDF manipulation, Protégé for ontology editing and Pellet as an ontology reasoner compatible with the OWL 2 language; and tools specific to ADMs like PTK (PASSI Tools Kit) [7]. The parameterization of the IMS implemented for the Information Systems Department (ISD) has allowed us to obtain an instance named SYGISS including, among other interfaces, the interface of **Figure 3** which gives the input view of the Manager. This interface, presented in **Figure 2**, allows the ISD manager to consult: the details of his account (1), the list of indicators he follows (2), the alerts that take place while he is connected (3) as well as the incidents that took place in his absence (4).

2.2.2. Knowledge Modeling

The METHONTOLOGY method is used to model the knowledge. We start with the formation of a glossary of terms of the management domain. The performance indicators (Alert, Decision, SLA—Service Level Agreement, Margin...) are the key words or concepts of the domain. Then, we proceed to an abstraction of these concepts into four (4) high level concepts (KPI (Key performance Indicator) elements, Alert elements, Decision elements and Rules). We finish by creating the relationships between these concepts and refining these relationships. A domain ontology is thus created. The rules are based on predicate logic. Depending on the knowledge domain, with x as the indicator, v as the indicator value, $xSla$ as the indicator threshold value and xM as the indicator margin. The following three types of rules have been described:

Rules for producing the state of an indicator whose objective is set upstream

$$\forall(x)\big(\big(Indicator(x)\wedge value(x,v)\wedge sla(x,xSla)\wedge(v<xSla)\big)\rightarrow state(x,Good)\big)$$

$$\forall(x)\big(\big(Indicator(x)\wedge value(x,v)\wedge sla(x,xSla)\wedge(v>xSla)\big)\rightarrow etat(x,Bad)\big)$$

$$\begin{aligned}&\forall(x)\big(\big(Indicator(x)\wedge value(x,v)\wedge sla(x,xSla)\wedge margin(x,xM)\\&\wedge\big(v\le(xSla+xM)\big)\wedge\big(v\ge(xSla-xM)\big)\big)\rightarrow etatus(x,Average)\big)\end{aligned}$$

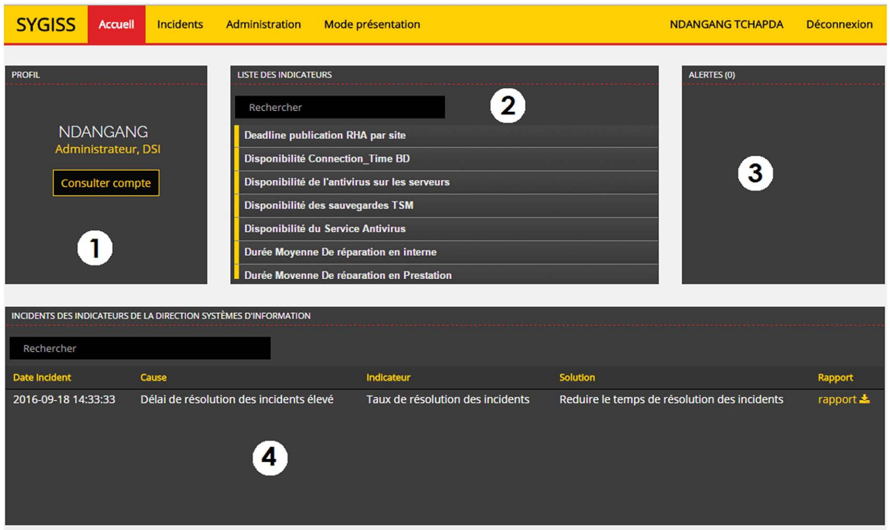

Figure 3. Entry view of the ISD Manager.

Rule for producing the state of an indicator in relation to its previous value

$$\forall(x)\big(\big(Indicator(x)\wedge value(x,v)\wedge sla(x,xSla)\wedge(v<xSla)\big)\rightarrow state(x,bad)\big)$$

$$\forall(x)\big(\big(Indicator(x)\wedge value(x,y)\wedge sla(x,xSla)\wedge(v>xSla)\big)\rightarrow state(x,Bon)\big)$$

$$\begin{aligned}&\forall(x)\big(\big(Indicator(x)\wedge value(x,v)\wedge sla(x,xSla)\wedge margin(x,xM)\\&\wedge\big(v\le(xSla+xM)\big)\wedge\big(v\ge(xSla-xM)\big)\big)\rightarrow state(x,Average)\big)\end{aligned}.$$

Alert generation rule

$$\begin{aligned}&\forall(x)\big(\big(Indicator(x)\wedge state(x,Bad)\big)\\&\rightarrow\big(alerte(Alerte1)\wedge message(Alerte1,"Badindicator")\big)\big)\end{aligned}$$

2.2.3. Forecasting Process

The forecasting process is based on the Holt-Winters method [3]. It is an exponential smoothing method for observation series with both a trend term and a seasonality. Let us consider a time series $(x_t)_{1\le t\le n}$. This method adjusts the series by a line in the vicinity of *t*. This method operates at the local level the simultaneous smoothing of the "level" of the series L_t and the slope b_t of the trend, using the recursive equations [3]:

$$L_t=\alpha x_t+(1-\alpha)(L_{t-1}+b_{t-1})$$
$$b_t=\beta(L_t-L_{t-1})+(1-\beta)b_{t-1}$$

L_t is interpreted as an estimate of the trend at date *t*, et b_t as an estimate of the slope. The forecast at horizon h is thus defined by: $\hat{x}(t,h)=L_t+hb_t$.

3. Expérimentation

The experimental framework is the Information Systems Department (ISD) of the Société Anonyme des Brasseries du Cameroun (SABC). This department is responsible for all the hardware and software components of the information system, as well as the choice and operation of the telecommunications services implemented. We conducted an annual evaluation of this department. The divisions we analyzed are: Operations, Support, Application Maintenance and Helpdesk.

3.1. Management with the Old System

Figure 4 shows the dashboard for the Operations division and the ISD Helpdesk division.

This Figure 4 shows the evolution of the indicator, the target set for it to be within the margin and the values achieved during the week, last week, month, previous quarter and year. In order to monitor these indicators, managers must define a hierarchy between them in order to define which indicator is obtained thanks to the other indicators. At a given period, managers go through their dashboards and examine the evolution of their indicators and their status in order to ensure that they are in the right range. If they are not, they must determine the causes of the dysfunction and once the causes are detected, an appropriate decision must be made to resolve the dysfunction.

Each of these indicators has a specific dashboard, showing all the values taken during the year and the evolution of its sub-indicators. Figure 5 shows the dashboard for each application of the operations division. Here we find the values of each application per week.

Managers are responsible for the analysis, forecasting and decision-making tasks they perform and for the dashboards they generate. They must go through all the applications at a given time to manually extract the indicators. To get the global value of their indicators, they apply formulas (quite complex) on their indicators and sometimes on indicators that do not belong to them. It is not possible: to have a hierarchical view of the indicators with the generated dashboards, to make a feedback of the information, to interpret the values of the indicators, to choose the right indicator, to make a good decision.

3.2. New System

Figure 6 shows the dashboard obtained with SYGISS. It shows the achievements for each indicator as well as its current status and trend compared to its previous value.

In Figure 7, we have the details of the "Database availability" indicator, in addition to information on its status, we also have the evolution curve of this indicator as well as its bar graph. This curve also shows the forecast of the indicator during the year.

Figure 8 shows us the alert report sent by SYGISS and received by email. We can see here:

- The indicator concerned;
- The managers who received the email;
- The title of the alert;
- The problem encountered, the cause and the proposed solutions.

Indice Satisfaction Client Niveau DSI													
Indicateurs	Cible 2017	Janvier	Février	Mars	Avril	Mai	Juin	Juillet	Août	Septembre	Octobre	Novembre	Décembre
Taux moyen de résolution mensuel des incidents	95%	96,7%	95,2%	94,4%	93,6%	95,4%	94,7%	95,4%	95,0%	94,8%	94,4%	97,5%	95,9%
Taux moyen des incident respectant les delais (SLA)	80%	73,2%	74,8%	77,7%	77,8%	77,5%	75,0%	69,2%	72,3%	75,2%	72,1%	76,4%	74,0%
Taux moyen de pannes matériel bureautiques traitées en interne	60%	66,7%	50,0%	76,9%	68,2%	62,5%	81,3%	75,0%	66,7%	91,7%	56,3%	71,4%	100,0%
Taux annuel de satisfaction client	64%												70,1%
Taux moyen mensuel de réalisation de la maintenance préventiv	90%			######	98,1%	96,2%	95,9%	74,4%	99,4%	99,6%	99,6%	99,4%	
Taux moyen mensuel de protection antivirus des postes de trava	98%	99,9%	99,9%	99,9%	99,9%	######	######	100,0%	100,0%	99,9%	99,6%	99,6%	98,5%
Satisfaction Client DSI	**80%**	**84,1%**	**80,0%**	**89,8%**	**87,5%**	**86,3%**	**89,4%**	**82,8%**	**86,7%**	**92,2%**	**84,4%**	**88,9%**	**87,7%**

(a)

	QUALITE DES PROCESSUS												
		REALISE											
	CIBLE	janv-17	févr-17	mars-17	avr-17	mai-17	juin-17	juil-17	août-17	sept-17	oct-17	nov-17	déc-17
Disponibilité des services	99,77%	99,88%	98,94%	98,98%	99,43%	99,85%	99,85%	99,96%	99,91%	99,91%	99,88%	99,91%	99,72%
Système	**99,83%**	99,96%	99,95%	100,00%	99,99%	99,93%	99,88%	99,91%	99,78%	99,84%	99,97%	99,94%	99,54%
Applications métiers	**99,83%**	99,99%	100,00%	100,00%	100,00%	99,95%	99,92%	100,00%	99,98%	100,00%	100,00%	99,96%	100,00%
sécurité	**99,90%**	100,00%	100,00%	100,00%	100,00%	99,96%	99,91%	100,00%	99,98%	100,00%	100,00%	99,97%	100,00%
Bases de données	**99,73%**	99,99%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	99,96%	100,00%	99,99%	100,00%	99,74%
Réseau	**99,65%**	99,47%	94,74%	94,90%	97,17%	99,42%	99,53%	99,90%	99,85%	99,70%	99,46%	99,68%	99,29%

(b)

Figure 4. Evolution of the indicator.

Indicateur	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
Disponibilité du service MOS	100,00%	100,00%	100,00%	100,00%	100%	100%	100,00%	100%	100%	100%	100%	100%	100%
Disponibilité du service BI	100,00%	100,00%	100,00%	100,00%	100%	100%	100,00%	100%	100%	100%	100%	100%	100%
Disponibilité M3 jour sauvegarde journaliere	100,00%	100,00%	100,00%	100,00%	100%	98,04%	100,00%	100%	100%	100%	100%	100%	95,04%
Disponibilité M3 jour sauvegarde système	100,00%	100,00%	100,00%	100,00%	100%	100%	96,66%	100%	100%	100%	100%	100%	100%
Disponibilité des sous systèmes M3	100,00%	100,00%	100,00%	100,00%	100%	98,04%	100,00%	100%	100%	100%	100%	100%	100%
Disponibilité de la replication	100,00%	100,00%	100,00%	100,00%	100%	98,04%	100,00%	100%	100%	100%	100%	100%	100%
Disponibilité du service Antivirus	99,40%	100,00%	100,00%	100,00%	100%	100%	100,00%	100%	100%	100%	100%	100%	99%
Disponibilité de l'antivirus sur les serveurs	96,72%	99,44%	100,00%	100,00%	97,53%	97,56%	99,40%	99,40%	98,09%	98,65%	99,33%	100%	100%
Disponibilité des sauvegardes TSM	100,00%	100,00%	100,00%	100,00%	100%	100%	100%	100%	100%	100%	100%	99,05%	100%
Disponibilité des sauvegardes Systèmes i	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100%	100%	100%	100%	100%	100%
Disponibilité réseau SABC	99,54%	99,67%	99,59%	99,48%	99,49%	98,16%	99,22%	99,54%	99,35%	98,92%	99,54%	99,54%	98,66%
Disponibilité internet	100,00%	100%	100,00%	100,00%	100%	100%	100,00%	98,52%	100,00%	100%	100%	100%	100%
Disponibilité Interface M3	100,00%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Disponibilité Connection_Time BD	99,97%	100%	99,99%	99,65%	99,99%	99,86%	99,98%	99,97%	100%	100,00%	99,98%	99,97%	100,00%
Taux ASP SABC4001	70,42%	68,00%	68,39%	70,19%	69,00%	69,28%	69,19%	70,00%	69,89%	69,55%	69,55%	70,97%	72,00%
Taux ASP SABC4002	63,97%	64,54%	65,91%	65,54%	65,00%	66,26%	66,25%	67,00%	66,97%	67,51%	67,94%	68,43%	66,00%
Taux ASP SABC4003	82,99%	83,17%	83,29%	83,44%	83,00%	83,47%	83,44%	84,00%	84,00%	83,97%	78,35%	85,35%	85,00%
Etat Prioritaire Com	100,00%	100,00%	85,71%	100,00%	100,00%	100,00%	100,00%	100%	100%	100%	100%	100%	100%

Figure 5. Detailed operational department dashboard.

Process dashboards						
Indicators	State	Real S	Objective	Gap	Real S-1	Tendance
Database Availability		99.74%	99.9%	-0.16%	100%	
Service Availability		99.72%	99.85%	-0.13%	99.91%	
Network Availability		99.29%	99.65%	-0.36%	99.68%	
System Availability		99.54%	99.85%	-0.31%	99.94%	
Collaborative Applications Availability		100%	99.95%	+0.05%	99.97%	

Figure 6. New dashboard.

Figure 7. Dashboard of an indicator.

Les Brasseries du Cameroun	RAPPORT INCIDENT	SYCISS
SABC et Filiales	Disponibilité des états financiers	3/10/2016

Affectation	DSI,
Manager	Blasie NDANGANG TCHAPDA,
Responsable	Pilotes d'Exploitation
Alerte	Etats financiers en baisse
Cause	Inconnue
Solution	Consulter responsable

DETAILS INDICATEUR

Indicateur	Obj.	Real	Ecart	S-1	Tendance
Disponibilité des états financiers	99%	97%	-2.0%	95%	Haut

COURBE D'EVOL UTION DE L'INDICATEUR

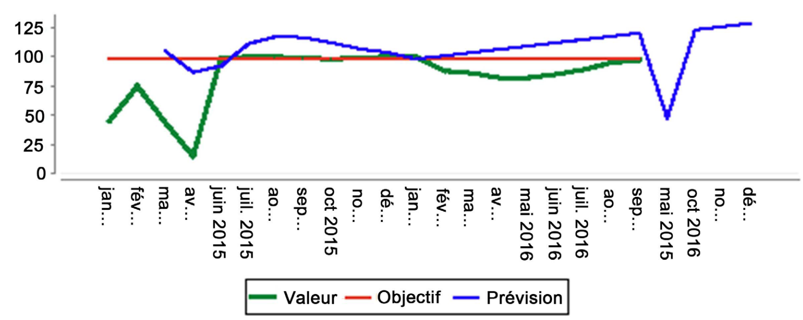

Figure 8. Alert report.

4. Discussions

Table 2 compares management before and after the RMS.

In summary, the SYGISS IMS reduces the time managers spend analyzing indicators and finding solutions. The use of SYGISS gives managers:

Table 2. Comparison of management before and after the RMS.

	BEFORE (BY THE MANAGER)	AFTER (BY THE SMS)
INDICATOR EXTRACTION	Manual, over two weeks, medium difficulty	Automatic, less than 5 minutes, no difficulty
DATA COMPUTATION	Manual, more than 2 days, easy	Automatic, instantaneous, no difficulty
DASHBOARD GENERATION	Manual, 12 hours/week, low difficulty	Automatic, instantaneous, no difficulty
INDICATORS HIERARCHY	Manual, 6 hours, High difficulty	Automatic, instantaneous, no difficulty
NON-REPORTING OF DATA	Non-existent	Automatic, instantaneous, easy to use
DATA FORECASTING	Non-existent	Automatic, 5 minutes/indicator/week, no difficulty
INCIDENT ALERT	Non-existent	Automatic, instantaneous, no difficulty
INDICATORS INTERPRETATION	Manual, 1 day/week, high difficulty	Automatic, instantaneous, no difficulty
SELECTION THE RIGHT INDICATOR	Very difficult because of the lack of measurement of the weight of the indicators	Automatic, instantaneous, no difficulty
Expertise	Non-existent because no knowledge base	Existent

Table 3. Details of management improvement before and after the RMS.

	Dashboard		**Decision support systems**		**Expert systems**		**Data mining**		**Knowledge management**	
	Before	After	Before	After	Before	After	Before	After	Before	After
Data extraction time	Long		Very long		Very long		Long		Very long	
Indicator calculation time	Very long		Very long		Very long		Very long		Very long	
Dashboard generation time	Long		Very long		Very long		Long		Very long	
Relevance and hierarchy of indicators			Non-existent		Non-existent				Non-existent	
Data forecasting	Semi-manual		Integrated		Integrated		Semi-manual		Integrated	
Incident alert	First level alert		Non-existent		Non-existent		Non-existent		Non-existent	

Continued

indicators Presentation	Well organized	Acceptable	Acceptable	Acceptable	Acceptable
Indicators interpretation	Manual	Integrated	Integrated		Integrated
Flexibility	Very long to set up	Very long to set up	Very long to set up	Very long to set up	Very long to set up

- Spontaneity because they already have the final values of the indicators;
- Reactivity because they receive real-time alerts on the indicators and can therefore take decisions directly;
- Anticipation because they have a forecast of the future values of the indicators.

Table 3 presents a detail of the improvements observed following the implementation of the new system compared to the existing system presented in the introduction. We note a very strong improvement of the management following the integration of the intelligent agents.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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