International Journal of GEOMATE, Aug., 2016, Vol. 11, Issue 24, pp. 2370-2377
Geotec., Const. Mat. & Env., ISSN: 2186-2982(Print), 2186-2990(Online), Japan

A NOVEL PRODUCTION PROCESS MODELING FOR ANALYTICS

Rich Lee[1,3] and Ing-Yi Chen[2]
[1,2]National Taipei University of Technology, Taiwan
[3]IBM, Taiwan

ABSTRACT: Nowadays the manufacturing is facing the critical challenges from various aspects including the trend of moving towards the new era of Industrial 4.0 [1]—an analytical and predictive driven production thinking, the Smart Factory. To effectively embed the necessary processes for analytics, a new way of modeling the process flows is essential to realize the goal of the predictive lean production. To reach these objectives, this paper presents a novel process modeling approach for analytics which is vital to the practitioners and the industries. The analysis of the smart factory theme includes the statistics, the data mining, and the operation research approaches [2] based on the various management improvements or the prediction objectives. The proposed process modeling for analytics extends the XML (e**X**tensible **M**arkup **L**anguage), which is also commonly used in software engineering [3]. The purpose of using this is to streamline the latter integration with the analytical processes among the software systems and will play a key part of the factory knowledge management for continuous optimization.

Keywords: Smart Factory, Production Modeling, Business Analytics, Knowledge Management, Process Modeling

1. INTRODUCTION

Nowadays, the business environment is volatile and harsh, making-decision intuitively cannot answer this complexity with confidence; many organizations are evolving their operations and decision-making processes to be more analytical and predictive driven. In manufacturing, these enterprises commence their Industry 4.0 initiatives and experience their journeys towards a smarter factory. Using the analytical approach to enhance the quality and the precision of operational activities is not a new thing to the enterprises, for instances, Engineering Data Analysis (EDA), Manufacturing Execution System (MES) and Management Accounting have been a part of daily operations for decades in modern factories. These discontinuous analytical processes have limited synergistic influence on the enterprise efficiency improvement. On the other hand, these processes are a part of intellectual capital of an enterprise, which is unique and not easily to mimic from the competitors [4]. The essence of smart factory is not just looking for the factory automation—deploying the robotic equipment to replace the labors, nor limited in pursuing the efficiency of processes. Rather the smart factory is an attitude of an enterprise to take the analytical perspective as the tool in exploring the potential causes of and the feasible approaches in resolving the problems.

Such an attitude requires a systematic scheme to reposit and adopt these analytical processes in a synergetic way. The Knowledge Management (KM) is aimed to capture, classify, store, transform, analyze, implicate, disseminate, and adopt the information synergistically. During this knowledge generation process, the taxonomy of the information plays a significant role in extracting and adopting the information from the knowledge repository effectively. Intensifying the positive externality [5] from these analytical processes requires more capabilities from the general knowledge management, including the execution orders and sequences among these processes. These process execution orders and sequences are parts of operation activities that are embedded in the enterprise business process management. Therefore, the smart factory demands these analytical processes to be governed by both knowledge and the Business Process Management (BPM) at the same time [6].

Pursuing the vision of Smart Factory, not just looking for the production automation by applying the smart sensors, but also focusing on the culture change and the transformation, this paper addresses a feasible starting point by presenting a novel way to incorporate the knowledge and the business process management for intensifying the outcome from the synergy of analytical processes, and eventually to evolving the factory towards a smarter organization.

2. SMART FACTORY THEME

The lean production—to illuminate all possible wastes including the tangible and the intangible ones which refer to the labor, the resources, and the time—has governed the factory management for years. The concept of the Smart Factory extents the lean production management into a more proactive way by applying the analytics and the prediction to improve the quality of decision-making throughout the production stages. One major reason that causes the unpredictable volatility is the variance of the coming customer orders. This paper conducted the literature review by looking up the Google Scholar using the keywords of "Smart factory" OR "Industrie 4.0"—which is the original idea of smart factory from—respectively contained in their titles from the year of 2014—after the Industry 4.0 was brought up with clear pictures—to the present. There were 17 articles titled with the keyword of "Smart factory", 12 in English, 4 in German, and 1 in Russian language; while there were 81 articles titled with the keyword of "Industrie 4.0" which means "Industry 4.0" in English, 9 in English and11 in German language of the first 20 articles appeared in the search. Two word-cloud diagrams were generated against the term frequencies appearing in different sizes accordingly, one was derived from the titles illustrated in **Fig. 1**; the other was derived from the abstracts, total 6,216 terms were processed, the most significant ones of the abstracts were: "production" (318 times), "systems" (277 times), "processes" (259 times), "technology" (212 times), "information" (187 times), "integration" (150 times), "models" (124 times), "networks" (119), "technical" (114 times), "revolution" (109 times), "approach" (105 times), "structures" (101 times), "engineering" (97 times), "organization" (94 times), and "change" (91 times) .

Fig. 1 The Word-Cloud Diagram Derived from the Article Titles

Fig. 2 The Word-Cloud Diagram Derived from the Abstracts

From the word-cloud diagram illustrated in **Fig. 2**, it gives an idea of what smart factory is; it is about innovation, technology, solution, algorithm, computing, and systems; it implies the potential opportunities and the challenges as well; and it focuses on sustainable, environment, and management. Therefore, this paper examines the current lean production processes where the smart factory theme can facilitate the production in pursuing better responsive with higher quality manner. The smart factory theme in predictive perspective, illustrated in **Fig. 3**, contains three major kinds of analyses commonly applied in the manufacturing: (1) the statistics, (2) the data mining, and (3) the operation research approaches. In the lean production processes, the proposed minimal analyses are: (1) Purchase Order, (2) Production Scheduling, (3) Inventory Management, (4) Quality Assurance and Control, (5) Production Management, (6) Logistics Management, and (7) Management Accounting; shown in **Table 1**.

Table 1 The Proposed Minimal Analyses for the Lean Production

Category	Analytic Model	
	Statistical or/and Data Mining	Operation Research
Purchase Order	Purchase Order Analysis and Prediction	Order Contribution and Sequencing Analysis
Production Scheduling	Production Scheduling Variance Analysis	Production Resources Allocation Optimization
Inventory Management	Aging Analysis and Prediction	Safety Stock Estimation and Cost Prediction
Quality Assurance and Control	Quality Risk Measurement and Analysis	Inspection Measurement and Analysis
Production Management	Production Process Variances Analysis	Outsourcing Contribution Analysis and Optimization
Logistics Management	Logistics Variances Analysis	Logistics Cost Optimization
Management Accounting	Operation Risk Measurement and Analysis	Investment Return Analysis and Optimization

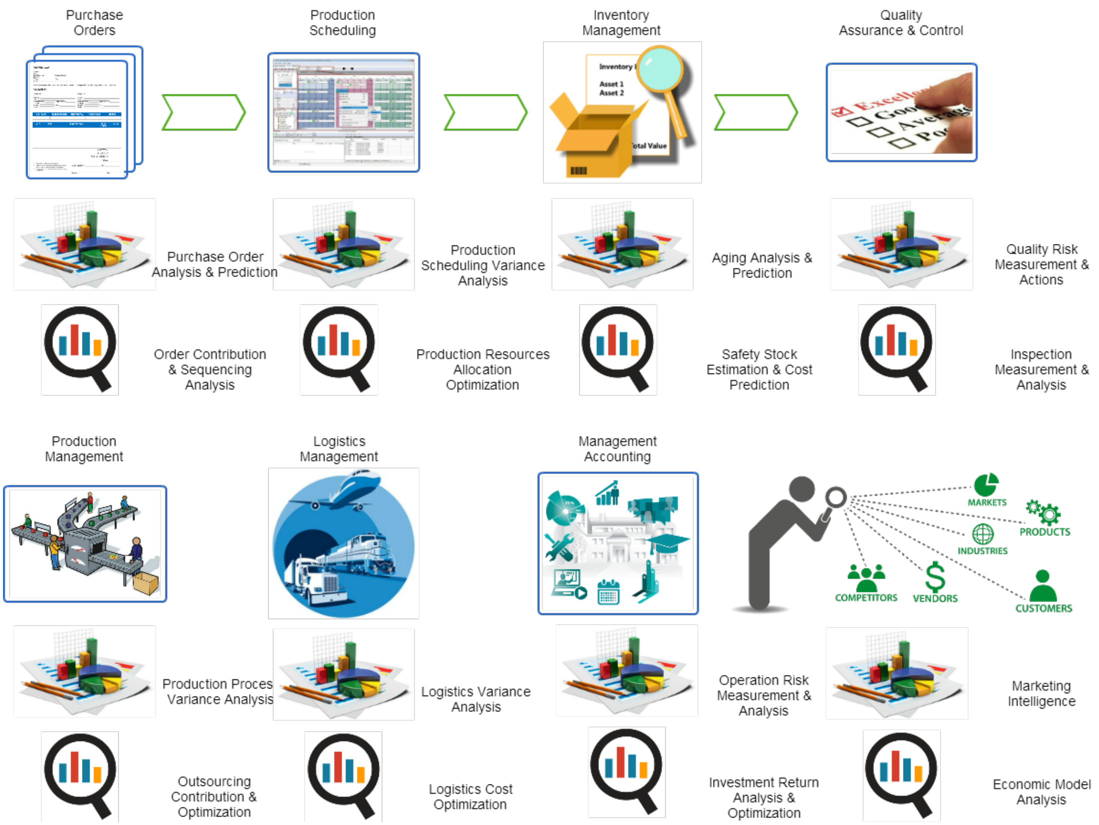

Fig. 3 The Smart Factory Theme

3. MODELING ANALYTICAL PROCESS

In the holistic view of an analytical process, it involves the participants and the components including: (1) the actor—who initiates the process; (2) the process—which consumes the input information and generates the results; (3) the actant—who takes the actions accordingly; (4) the dispatch—which usually triggers another series of processes sequentially or simultaneously. The **Fig. 3** illustrates the basic pattern of an analytic process; the dispatch can be another analytical process, a computational script task, or a manual task to take managerial actions. In many occasions, the actor is actually time-driven; the dispatch can send messages to an electronic Kanban device serving as the dashboard role to provide the significant information to the factory staffs, to trigger a persistent service task, or to reposit information into the knowledge management system through a receive task.

Each analytical process has a unique identifier so do the participants and the components. This paper proposes 5 types of participants and the components, shown in **Table 2**, including: (1) actor/actant, (2) analytical process, (3) manual task, (4) script tasks, and (5) mail task. Among the information column, each array that contains nothing means no following task or a list of consecutive tasks. The script task is the actual activity applying analytic methods such as descriptive statistics, multi-variable regression, or k-mean classification. **Fig. 4** illustrates the basic pattern of a generic analytical process; while **Fig. 5** shows a specific pattern of a time-driven analytical process.

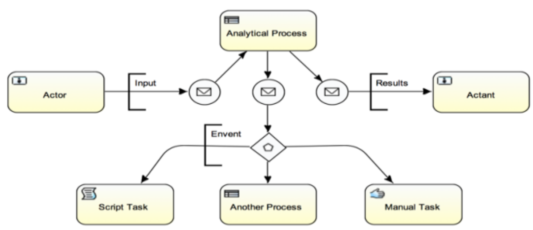

Fig. 4 Basic Pattern of an Analytical Process

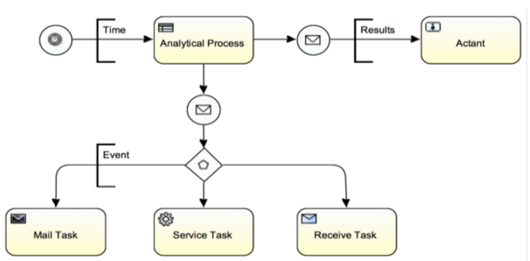

Fig. 5 A Pattern of a Time-driven Analytical Process

Table 2 Analytical Process Participants and Components

Participants/Components	Information (at least inclusive)
Actor/Actant	• Unique Identifier • Role Description • Name of Role • Message Sent/Received
Analytical Process	• Unique Identifier • Purpose of Analysis • Result Implication • Script Identifier (Script Array) • Dispatch (Task Array)
Manual Task	• Unique Identifier • Purpose of Task • Actor (Array) • Message Sent/Received • Dispatch (Task Array)
Script Task	• Unique Identifier • Purpose of Script • Data Source • Script Language • Major Methods of Analysis • Result Data
Receive Task	• Unique Identifier • Purpose of Task • Message Received • Taxonomy
Service Task	• Unique Identifier • Purpose of Task • Message Received • Trigger Time • Script Identifier (Script Array)
Mail Task	• Unique Identifier • Purpose of Task • Message Received • Device Identifier (Device Array)

The participants of the business processes, a combination of series of tasks often use a process modeling tool—BPM systems—to describe how these tasks collaborate together to accomplish the business objectives; in many occasions, the process flows are implicitly embedded within the IT systems and no modeling required; such systems like the ERP, MES, and EDA are the examples of them. The conventional BPM are development-driven focusing on the automation of the predefined process flows. The positive externality of synergistic effect can be also expected within a boundary. The KM is kind of Open Innovation Model—stimulating the participants willing to share their creativity and the solutions of the raised questions [7]; for simplicity, the proposed analytical process is a BPM element in the KM. Both BPM and KM can be facilitated by the BPMN—a form of XML. Two aforementioned analytical process patterns described in XML form, the first part in grey color is the common header of the XML; the second part addresses the detail of analytical process description.

There are XML tags for the details: (1) *targetNamespace*—used for the stages of a lean production; (2) process—used for describing the whole analytical process; (3) *userTask*—used for identifying the participants; (4) *analyticalProcess*—used as the main body of analysis; (5) *eventBasedGateway*—used as the dispatch; (6) *manualTask*—used for manual operation; (7) *scriptTask*—used for a analytical program such as Python, R, or designed in other computing language; (8) *messageEventDefinition*—used for describing the message content as the input or the result; (9) *timerEventDefinition*—used as a time trigger to kick the analytical process; and (10) *sequenceFlow*—used as the link between connected tasks.

4. ANALYTICAL PROCESS KNOWLEDGE MANAGEMENT

The ultimate purpose of the analytical processes is to improve the business agility—toward a smart factory—through the synergy of the Open Innovation Model. To accomplish this mission, setting the Knowledge Goal in phases is essential. Some factories commence their smart factory journeys without a clear goal, usually over-invested the automation equipment and realigned their business strategy less. In fact, the smart factory is not just pursuing the factory automation but transforming their enterprises toward a learning organization—the employees applying a system thinking to resolve the business obstacles [8].

The knowledge initiator (as a participant) addresses a need of a piece of knowledge based on the business situation and reality; using an analytical modeler to form and develop the knowledge generating scheme, an analytical process, and then reposit this knowledge—the qualitative or/and quantitative work products—into the analytical KM. Another source of knowledge development is through predefined big data processes, collecting raw data, transforming the data into information, and giving the business implication to derive the quantitative knowledge.

Effectively disseminating the knowledge—a common feature of any KM system—to other participants including the external partners will speed up the decision-making cycle and enhance the quality of the decisions. The knowledge consumer (as a participant) using the information retrieval features of the KM to extract and reuse the required knowledge to resolve their business issues retains the knowledge with scenarios and the associated data; during this process, the consumer assesses the usefulness, the applicable situations, and the request-for-improvement about the knowledge and feedbacks to the initiator. This whole iterative process refines the quality and the usefulness of the knowledge; through reusing the retained knowledge, consequently, a learning organization is seamlessly formed. The **Fig. 6** illustrates how analytic knowledge management process, setting the goal, identifying, developing, disseminating, utilizing, retaining, and assessing the knowledge, can benefit the business agility—such as improving the quality of delivery, illuminating the wastes by taking advantage of the outcomes from the analytics—through the synergy among the participants.

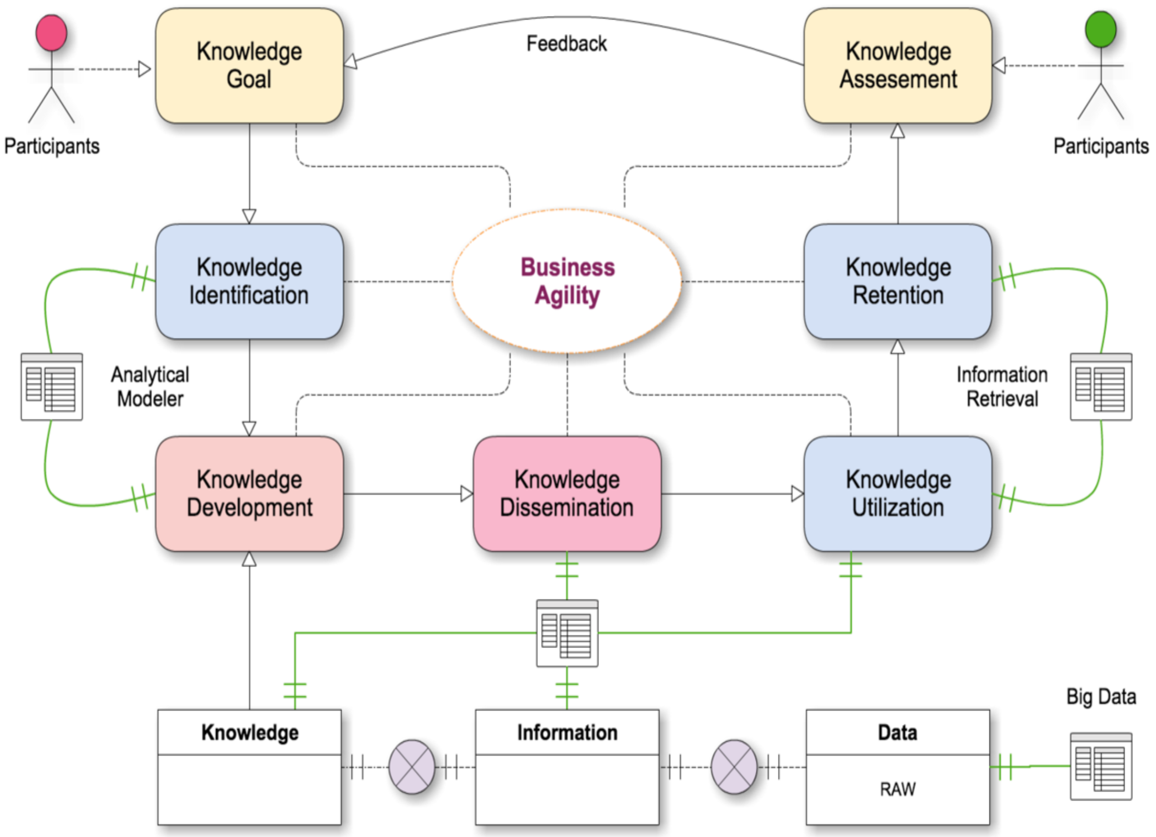

Fig. 6 The Analytical Process Knowledge Management

5. THE EMPRICAL CASE

The research subject was selected elaborately. Many types of manufacturing such as semiconductor, oil refining, etc., in nature, they rely on the automation equipment during the production; to some extent, these factories are already moving towards the vision of Smart Factory for quite a long time. In order to tell the significant changes of factory transformation, this paper chose a listed textile company XYZ in Taiwan as the research subject for the following reasons: (1) vision—setting a clear picture and the associated roadmap about their smart factor initiative with strong commitments; (2) technology—producing the functional fibers and the special outfits; (3) automation—not all processes can be automated and still depend on skillful workers to perform; (4) quality—planning to deploy new equipment or sensors into the defect-prone processes; (5) efficiency—just launched their new ERP (Enterprise Resource Planning) system to disclose more information to the operations and the executives as well; and (6) capability—recruiting the external subject-matter experts to expand their knowledge boundaries and continuously conducting the internal trainings to improve their skills.

The XYZ company followed the analytic tasks shown on the Smart Factory theme illustrated in **Fig. 2**, they formed a steering committee not just to ensure the direction of the initiative, but also to propose the requirements of the analytical processes shown in **Table 1** as well. To realize the goals of smart factory, applying an efficient information system is essential; the system must satisfy the needs of the analytical processes knowledge management illustrated in **Fig. 6**, it contains several key components: (1) portal—easily let the privileged participants to access, contribute, and reuse the information; (2) dashboard—presenting the fruitful information to different roles of participants according to their purposes; (3) repository—holding and organizing the datasets including the structural data and the documents; (4) engine—processing the analytic scripts and dispatching the results to the repository; (5) search—providing handy ways to look up the information by using the classification (the taxonomy in KM) of the datasets, the keywords referred to the datasets, and the general text within the datasets.

Each dataset has an associated metadata depicting the characteristics about the information; the major fields of the metadata are: (1) classifications—based on the knowledge taxonomy, the dataset belongs to; (2) keywords—anchored by the dataset's owner who thinks these terms are the most representable to the dataset; (3) references—the top few significant terms besides the keywords occurred in the dataset populated by an information retrieval engine shall be used in determining the relevance among the datasets; and (4) version—including when the dataset was created, modified, and referred by whom (the participants).

To manage these metadata well and to meet the aforementioned requirements of the KM, the paper proposed the conceptual analytical information framework illustrated in **Fig. 7** to the XYZ company. There is a Distributed File System (DSF) works as the dataset repository to hold the contributed artifacts from the participants and the analytic engine including the offshored ones. The Data Storage system, the database, is where the structural data—collected during the business activities, the metadata of the datasets—stores. The portal service is marked with a dashed circle and the statistical charts and reports in the center, it serves the on-demand requests from the participants through metadata search and then extracting the desired artifacts from the DFS.

When a participant who wishes to contribute his/her findings, he/she becomes the analyst role who uses a number of modeling tools to explore the tacit knowledge or to validate the business behavior is as expected or not. Once the analytic model is affirmative that contains the insights to guide and support the further managerial activities, the analyst presents the model and the potential contributions to other related participants.

After the participants agree to embed this model into their daily activities, the analyst deploys the model into the analytic engine where the model script (in Python, R, or other analytic modeling language) will be executed chronically. The analytic engine populates the results in the forms of files (such as reports, graphics, spreadsheets, etc.) and/or the derived datasets stored in the Data Storage.

The collaborated participants can also be the analysts looking up the results and to form another analytic models for their own purposes. Eventually, all these models and the results are the cornerstones of KM which is the essential part in pursuing the Smart Factory vision. The visibility of information is crucial in manufacturing when making the decisions. However, a pitfall of information-overloading—too much information indirected to the daily activities may hesitate the participants in digesting them. Therefore, it is imperative that the steering committee to classify the models and the results into categories: (1) activity-based—such information will directly enhance the manufacturing; (2) causality-based—which gives a various of perspectives about why

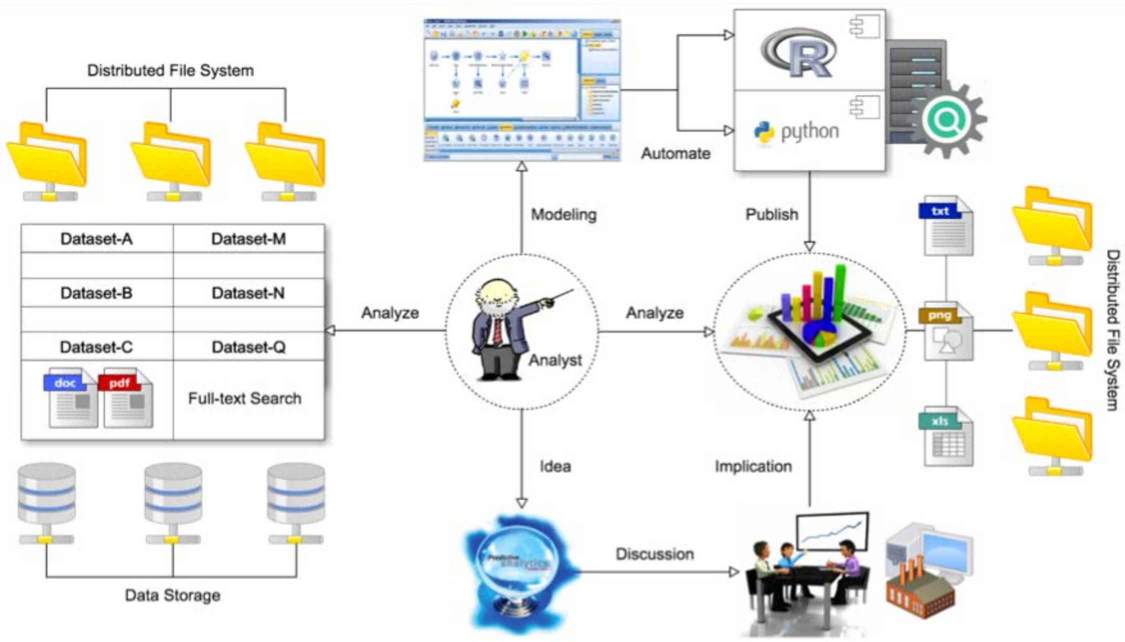

Fig. 7 The Conceptual Analytical Information Framework

the problem occurred or the possibility of a potential failure may happen; (3) summary-based—a brief information that discloses an overview about the activities or implies the following remedial actions; (4) optimization-based—requiring further actions to gain the optimization, such as the effective routes for logistics or the suggested safe-stock against the certain materials; and (5) strategy-based—such as the market movement against the competitors, the socio-economic report against the targeted new market, etc.

6. DISCUSSION

During the implementation of building the proposed analytic KM and applying the information framework, there were several worth-mentioning perspectives regarding to the success factors: (1) technology-selection—to choose the appropriate technologies to align with the business objectives is not easy because of the information asymmetry between the best practice of the industry and the perceptions of the participants, for choosing the database as an example, whether to use NoSQL or if it is affirmative decision then which brand is more fit to the goal is a lengthy proof-of-concept process; (2) boundary-spanning—the participants lack of the ability to acquire the information or the experience from the outside of the firm [9]; (3) investment—setting priority among the objectives usually is a dilemma attributed to the limited resources (such as budget, depends on how knowledge will be classified, it is a continuous improvement work and it is vague and debatable to the participants especially in the early phase of the implementation.

As far as the design of the analytic engine, because it runs the submitted analytic scripts in the batch mode at different timeslots, and each script requires various processing time, therefore, applying the asynchronous model—it usually comes with the inbound request box and the outbound result box at the same time for each participant—is a common practice to deal with the uncertain executing time. Some of the scripts are similar accessing the similar datasets and applying the similar analytic models. These requests will consume the system resources inefficiently, therefore, how to look up the KM, to find these similar scripts, and to consolidate them as one script is inevitable house-keep task as the analytic KM requests grows. On the other hand, some models can be processed in parallel, but some don't, the analytic engine should meet the needs for both scenarios, after all, getting the responsive results is the objective of Smart Factory not to unify the information processing models.

7. CONCLUSION

The Smart Factory is the next level of lean production; not just deals with the present wastes, but also foresees the potential coming wastes and take actions proactively. To extract the previous experience against a similar identified problem and solving it effectively and promptly is what the major contribution of the analytic KM is. The analytic KM accumulates the information, transform them into knowledge, and gives the business insights to the firm; and this becomes an effective differentiating mean against the rivals. This is the same reason why Business Analytics [9] is a necessary capability for every successful firm.

The analytic KM itself is a part of the firm-wide information system, its successful adoption will determine the overall outcome of the Smart Factory initiative. The well-adoption depends on the reliable and creditable functionalities that shall satisfy the participants' needs to respond the challenges from daily activities. Since it involves the participants across the firm and shall improve their skillsets and thus will also expand the firm's capability.

On the other hand, to make the participant to contribute the analytic models efficiently and disseminate them easily, it requires a handy modeling tool to elaborate the analytic models and a KM system to reposit the artifacts. This paper identifies there is a strong need to formalize the analytic process by using a modeling notation system from both the recent literatures and the empirical case. For practical concerns, to avoid the reinvestment on the already-existing IT systems, this paper proposes to apply the KM and BPM that may have been already deployed in many factories for non-analytic purposes. Finally, this paper emphasizes that transforming a factory into a learning organization—inspiring the staffs to possess the system thinking capability and accumulating the intellectual capital through successful knowledge sharing [12]—is equally important as the factory automation. Never the less, to model the analytic processes to form a knowledge repository is the uncontroversial starting point of the journey towards the vision of the Smart Factory.

8. REFERENCES

[1] M. Ackermann, Reporting and Big Data. Big Data as One Megatrend of Industry 4.0 and the Impacts on Controlling, Munich: GRIN Verlag, 2015.

[2] A. Goryachev, S. Kozhevnikov, E. Kolbova, O. Kuznetsov, E. Simonova, P. Skobelev, Y. Shepilov and A. Tsarev, "“Smart Factory”: Intelligent System for Workshop Resource Allocation, Scheduling, Optimization and Controlling in Real Time," *Advanced Materials Research*, vol. 6, no. 30, pp. 508-513., 12 2012.

[3] T. Stahl and M. Völter, Model-Driven Software Development-Technology, Engineering, Management, Chichester: John Wiley & Sons Ltd, 2006.

[4] K. Wright, Drivers for Corporate Competitiveness. Intellectual Capital and Related Intangible Assets and Intellectual Property, Munich: GRIN Verlag, 2014.

[5] J. Torrent-Sellens, "Knowledge Products and Network Externalities: Implications for the Business Strategy," *Journal of the Knowledge Economy*, vol. 6, no. 1, pp. 138-156, 2015.

[6] C. Stary, "Non-disruptive Knowledge and Business Processing in Knowledge Life Cycles–Aligning Value Network Analysis to Process Management," *Journal of Knowledge Management*, vol. 18, no. 4, pp. 651-686, 2014.

[7] H. Chesbrough, "Open Innovation: A New Paradigm for Understanding Industrial Innovation," in *Dynamics of Industry and Innovation: Organizations, Networks and Systems*, Copenhagen, Denmark, 2015.

[8] P. M. Senge and G. Roth, The Dance of Change: The Challenges to Sustaining Momentum in a Learning Organization, Crown Business, 1999.

[9] S. Harvey, R. S. Peterson and N. Anand, "The Process of Team Boundary Spanning in Multi-Organizational Contexts," *Small Group Research*, 2014.

[10] R. K. Yeo and M. J. Marquardt, "Think before You Act: Organizing Structures of Action in Technology-induced Change," *Journal of Organizational Change Management*, vol. 28, no. 4, pp. 511-528, 2015.

[11] S. H. M. S. LaValle, E. Lesser, R. Shockley and N. Kruschwitz, "Analytics: The New path to Value," *MIT Sloan Management Review*, vol. 52, no. 1, pp. 1-25, 2010.

[12] J. Loermans, "Synergizing the Learning Organization and Knowledge Management," *Journal of Knowledge Management*, vol. 6, no. 3, pp. 285-294, 2002.

International Journal of GEOMATE, Aug., 2016, Vol. 11, Issue 24, pp. 2370-2377.
MS No. 5127j received on July 23, 2015 and reviewed under GEOMATE publication policies.

Corresponding Author: Peter Nichols