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Toward a Diagnostic and Prognostic Method for Knowledge-Driven Decision Making in Smart Manufacturing Technologies

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Abstract

Making high-quality manufacturing decisions in real-time is difficult. Smart manufacturing requires sufficient knowledge be available to the decision maker to ensure the manufacturing system runs efficiently and effectively. This paper will present background information for managing and controlling decision making and technological innovation. We present a process definition for decision making that implements closed-loop diagnostic and prognostic control. Lastly, we discuss our emerging concept relative to smart manufacturing.

Keywords: decision making, smart manufacturing, technological innovation

1. Introduction

Smart manufacturing cannot be successful without proper management and technological innovation. The Oxford English Dictionary [1] defines *technology* as “the application of such knowledge for practical purposes.” *Innovation [2]* is defined as “the alteration of what is established by the introduction of new elements or forms.” And, *management [3]* is defined as “organization, supervision, or direction.”

Using these definitions, we may define technological innovation as the *process for creating a new application of practical knowledge.* Thus, the management of technological innovation is the *organization, supervision, or direction of the process for creating a new application of practical knowledge.*

While, several “smart” technologies have existed in manufacturing since the 1980s, the integration of those technologies along with the convergence of information technology (IT) and operational technology (OT) has kicked off a period of an increased rate of innovation in manufacturing. In general, Tidd and Bessant [4] presented “key lessons learned about managing innovation.” Tidd and Bessant [4] recommended that organizations be visible in promoting innovation across the whole business, build a project-based organization with a good portfolio management structure, utilize a stage-gate system, and institutionalize the use of tools. We must remember innovation requires the creation of something new. Therefore, creativity, development processes, and change management must be accounted for in decision making within the overall technological-innovation process.

Collaborative Product Development (CPD) [5], Concurrent Engineering [6], Designed for Manufacturing (DFM) [7], Design for Six Sigma (DFSS) [8], and Integrated Product and Process Development (IPPD) [9] are popular business strategies for managing new-development activities. Decision making is a common function in all of these strategies. Companies may combine these popular strategies with stage-gate processes to form their complete operating models. Further, industry desires to couple these methods with model-based systems engineering (MBSE), the “vee” diagram, and the larger-scoped model-based enterprise concept to enable effective decision making during development and manufacturing processes [10].

However, organizations often apply these methods without ever re-asking if the development and manufacturing activities are still the right pursuits -- that is, should the organization's overall goals change during and throughout the activities? This question and the desire to ensure the optimality, stability, effectiveness, and efficiency of technological-innovation process motivated this paper.

In this paper, we present our emerging and beginning work toward a diagnostic and prognostic method for knowledge-driven decision making in smart manufacturing technologies. We will show that decision-making, technological innovation, and the management/control of both are not mutually exclusive. First, we provide background knowledge discussing decision making, technological innovation and the management of both, while also comparing various types of control theories (e.g., controls engineering, management control, human factors). Then, we will present a process definition for decision making and discuss the relationship between technological innovation, its management, and smart manufacturing. We will use this information to describe the beginings of a concept for implementing closed-loop diagnostic control in technological-innovation and decision-making processes. Next, we will analyze and discuss our emerging concepts in relation to the “Digital Thread” in the manufacturing domain. Lastly, we will conclude with the utility of the concepts in supporting efficient and effective decision making.

2. Background

While developing our concept for controlling the manufacturing decision-making process, we had to collect cross-discipline understanding of technological innovation because the various roles (e.g., marketing, engineering, management, finance) that might affect manufacturing decisions. We focused our research on three areas of understanding. The first focus area was in defining the technological-innovation process. The next focus area was in managing decisions for creativity, development projects, and changes in organizations. The final focus area was on control theories in the context of engineering, manufacturing, and management interactions.

2.1. Defining the Technological-Innovation Process

Knight [11] proposed technological innovation means an organization has adopted a new concept beyond the generation stage of the concept. Porter [12] suggested technological innovation is a “new way of doing things that is commercialized.” Freeman and Soete [13] said, “an innovation in the economic sense is accomplished only with the first commercial transaction involving new product, process system, or device...” Tidd and Bessant [4] agreed innovation is the process of growing inventions into practical use. A diagram of the technological-innovation process based on Hollen [14] is shown in Fig. 1. The literature [14, 15], both recent and past, show technological innovation as a three-step process of discovery, development, and deployment.

The first phase in the technological-innovation process is discovery. We may consider this phase synonymous with invention. New knowledge is created during the discovery phase. The output from the discovery phase is typically a conceptual design from a Research and Development (R&D) activity.

The second technological-innovation phase is development. This phase is a transition activity. In product development, the conceptual-design task is transitioning towards detailed-design activities. Management of technological innovation is important during the development phase because successful commercialization depends on the maturity level of the technology. The output of the development phase is a complete definition for the technology.

The third phase is deployment. This phase is where a process is being deployed to production operations, or products are available for delivery to the marketplace. Development is complete or near completion when the deployment phase begins. The output of the last phase is a new and complete technology.

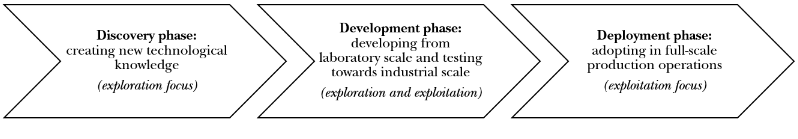

Fig. 1. Three-phase process definition for technological innovation (based on [14])

Management must remain a critical focus during the deployment phase because many scholars consider the commercialization of technology the least managed activity in the technological-innovation process [16]. The methods used to commercialize and market technology significantly influence the success or failure of products [17]. Products with newly-commercialized technology fail at a rate of 40% to 50% [16]. The demonstrated importance of management and decision-making is the motivation behind this paper.

2.2. Managing Decisions for Creativity, Development, and Change

"Creativity is the production of novel and useful ideas in any domain" [18]. Amabile [18] proposed a model of creativity that requires abilities in three major components, which are expertise, creative thinking, and intrinsic task motivation. The combined skills in each category enable creativity. The field of psychology teaches that anyone is capable of creativity, but the level of creativity is enhanced or limited by interactions with the social environment.

Lewin's Equation [19], $B = f(P, E)$, proposed behavior (B) is a function of interactions between people (P) and their environment (E). Following this idea, we argue innovation is a function of a person's creative ability and his/her interaction with the social environment. Further, Hoegl and Parboteeah [20] suggested that the quality of team collaboration influences the utilization of the teams' technical skills and directs those skills toward the critical-performance dimensions.

Considering, Hoegl and Parboteeah [20], we propose extending Lewin's Equation [19] to organizations by arguing that innovation is a function of the organization's overall creative ability and its social interactions within the environment. That is $I = f(\sum P_i, E \in O)$, where I represents innovation, i represents individuals in the organization, and O represents the organization. Therefore, managing and encouraging creativity at the personal level should support a positive environment for innovation at the organizational level.

Amabile [18] argued that individuals with basic capacities can develop moderately creative solutions to some problems some of the time. However, challenging problems of high importance require subject matter experts with extensive knowledge in the field of work. A baseline level of expertise in the engineering domain is needed to ensure the ideas produced by the creative process are "novel and useful" [18].

Amabile's [18] and Hoegl's and Parboteeah's [20] conclusions support Cooper's [21] recommendations for including all critical roles in a product-development process from the start of the process. Cooper further suggests there are two ways to succeed in innovation -- (1) doing projects right and (2) doing the right projects. Doing projects right requires a process to follow commonly accepted management guides. These guides should include using teams effectively, doing up-front research before starting development, analyzing the voice of the customer, and ensuring a stable product definition prior to deployment or launch. Doing the right projects requires the "right" expertise to know what the right portfolio of projects looks like. This relates to Amabile's [18] conclusion that a basic level of expertise is needed to determine if something is "novel and useful."

Cooper also developed a stage-gate process model that breaks the product-innovation process into five stages, each requiring the passage of a gate before proceeding to the next stage. The gates provide quality control to the process by incorporating go/no-go decisions at strategic points in the process. While Cooper's model provides a good foundation for managing product-development activities, it may fall susceptible to disruptive changes that could occur during the activities -- specifically changes due to the technological-innovation process. This opens up Cooper's model to the risk of pursuing decisions that are no longer the right decisions.

Manufacturing organizations operate in an environment of constant change. Organizations must be prepared to manage the changes through effective decision-making. Managing changes effectively is an important part of ensuring sustainable success within an organization. Organizational strategies, structures, skills, and cultures must evolve over time to reflect changes in markets and technology [22].

Specifically related to technology, change happens in cycles [22]. These cycles are best explained with an illustration presented in Fig. 2. Technology cycles begin with high rates of innovation until a dominant technology emerges. As technology matures, the rates of innovation slow. As competition continues in the market, eventually new technology needs to be developed to sustain success. This forces a rapid increase in the rate of innovation – leading to substitute technologies via the technological-innovation process.

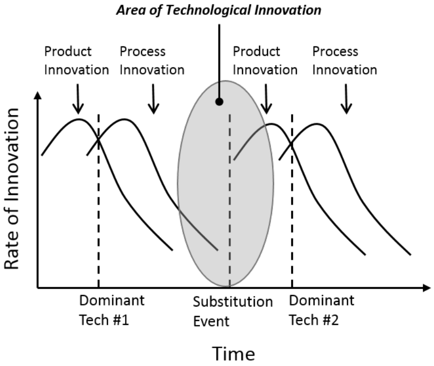

Fig. 2. Technology cycles and technological-innovation (based on [22])

In the manufacturing domain, data are being used in new ways that are beginning to enable near-real-time decision making. Data-driven decision making is at the core of Industrie 4.0, Industrial Internet of Things (IIoT), and Smart Manufacturing strategies. Significant innovations in data-driven techniques were achieved in the 1980s, but other technological innovations were dominant at that time. As the 2000s approached, the rate of manufacturing-related technical innovation decreased, causing manufacturing to look for new avenues to grow and increase productivity. Manufacturing is again in a time of increased innovation and the we believe the shaded area of technological innovation shown in Fig. 2 is imminent. New technologies and new integrations of technologies are revolutionizing the way manufacturing is conducted.

2.3. Control Theory Related to Manufacturing Decisions

Control means measuring a quantity or condition in a system and applying a determined quantity or condition to the system to correct or limit the deviation of the measured value from a desired value [23]. Using the word “system” in control problems refers typically to a representation of the actual thing that someone is trying to control.

In engineering, mathematical modeling is a common way of representing a system for controls analysis [23]. Modern control theory has become popular for analyzing complex systems, which often have multiple inputs and outputs as parts of the overall system [23]. A popular method for analyzing these types of complex systems is state-space analysis [24].

In our work, without pretension of being exhaustive, we were less interested in the formulation of representative models. Our interest was in developing a foundational structure to describe the behavior of the system completely at any point in time. That is important for being able to accurately assess the decision-making process. This is why we were interested in control theory – specifically state-space analysis.

While modern control theories provide great values to the engineering domain, they tend to lack complete diagnostics to facilitate controlling the decision-making process. We must also review control in the contexts of management and human-factors. Management-control systems include human-resource tools. Organizations might employ management-control techniques in budgets, rules, operating procedures, and performance-appraisal systems to help gain control over employee behaviors [25].

Performance-appraisal systems may include goal setting, which is important to achieving organizational objectives [26]. Organizations implement goal setting with employees because studies show goal setting supports positive motivation and contributes to improved employee performance [27]. Goal setting has also been shown to create competition amongst employees and teams, which increases motivation throughout an organization [28] and improves decision-making processes [27].

Since the 1960’s, organizations have used Drucker's [29] work, “Management by Objectives,” to control behaviors. Drucker's work has five steps: (1) define organizational objectives, (2) set worker objectives, (3) monitor progress, (4) evaluate performance, and (5) reward results. In the first step, management describes the organization's vision and objectives to the employees. In the second step, each employee meets with management to set specific goals for the employee. The third and fourth steps relate to monitoring and measuring the progress of each employee's goals and providing an evaluation at the end of the performance period. In the last step, the organization rewards each employee based on his/her results.

In Drucker's theory, goal setting is an integral part in all levels of an organization. Ceresia [27] suggested robust management control is supported by both taking into account Drucker's guidance and ensuring positive employee motivation. However, Drucker's theory and Ceresia's recommendations also lack guidance in continuously assessing organization objectives and goals.

Simon [30] published directly on the topic of using control systems to drive strategic renewal. He defines management control systems as “formal, information-based routines and procedures managers use to maintain or alter patterns in organizational activities.” Simon also outlines a business strategy with four variables that require assessment. He called these variables “levers of control,” which he defined as belief systems, boundary systems, diagnostic-control systems, and interactive-control systems.

We are most interested in the diagnostic-control-systems lever, which provides controls in an optimal spot of the organization because input controls and process standardization do not provide diagnostic management. Input controls maximize creativity but increase risks to cost controls, while organizational goals and standardization minimize creativity and innovation. Diagnostic control systems monitor organizational outcomes, which get compared against important performance dimensions of a strategy. Simon called these “critical performance variables.”

In manufacturing industries, critical performance variables are called key performance indicators (KPIs). Simon suggested using KPIs to track the probability of meeting goals or the largest potential for gain over time. These categories of KPIs are considered effectiveness criterion and efficiency criterion, respectively.

The standard ANSI/ISA 95 [31] provides guidance to integrating control systems into enterprise hierarchies. The standard describes a pyramid hierarchy starting with an enterprise level at the top, then moving down to an operations-management level, then a sensing and control level, and finally a devices level. The standard, itself, focuses on the operations-management level.

In Fig. 3 we combine the work of Ogata [23], Drucker [29], Simons [30], and ANSI/ISA 95 [31] to form a model for strategy diagnosis in a manufacturing-enterprise-control-system integration. This model demonstrates how organizational strategies, structures, skills, and cultures could evolve according to Tushman [22]. The model depicted in Fig. 3 provides a good foundation for controlling the strategies of organizations implementing smart manufacturing, but, like Cooper's [21] model and Drucker's [29] theory, our model for strategy diagnosis may be susceptible to the various types of change -- resulting in organizations pursuing strategies that are no longer ideal.

Argyris' [32] developed the concept of double-looping learning. We can represent the concept as a control system. Examples of single-loop-learning and double-loop-learning as control systems are shown in Fig. 4. In the double-loop example, there are two “sensors.” The first sensor measures the system output in context to the local goal. The second sensor measures the system output in context to the overall goal.

In double-loop learning, the system inputs are modified based on the system output compared to the local goal, but the local goal may also be modified in light of the system output not trending toward the overall goal. The system could also be controlled by modifying the overall goal instead of the local goal.

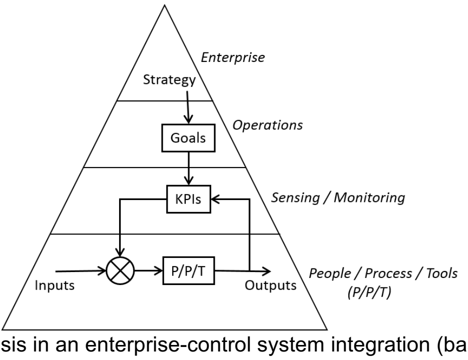

Fig. 3. Strategy diagnosis in an enterprise-control system integration (based on [23, 30, 31])

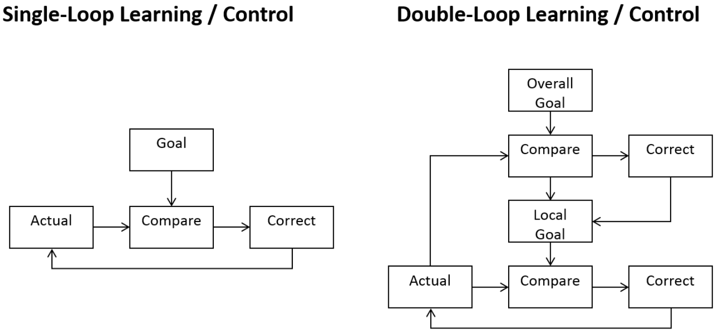

Fig. 4. The single-loop learning process compared to the double-loop-learning process (based on [33])

3. Process Definition for Knowledge-Driven Decision Making in Smart Manufacturing Technology

Informed by literature cited in Section 2, we developed a concept for controlling decision making through the technological-innovation process to close the gaps we identified in previous works, specifically continuous assessment of goals and why an organization pursues the technological innovations that they do.

Double-loop learning is a control technique for managing change [32-34]. Double-loop learning may be used by an organization to decide when to increase the rate the of innovation. Double-loop learning is a way for organizations to break the single-loop learning pattern of, “this is the way we have always done it.” Strategically-driven organizations typically define governance goals to influence actions that lead to results and consequences. The goals define why organizations do what they do. The actions are what the organizations do. The results and consequences are what organizations obtain.

In single-loop learning, organizations only modify what they do (actions) based on what the organizations obtain (results). This is a process of repeated attempts at the same problem with no variation of method and without ever questioning the goal. With double-loop learning, organizations modify what they do (actions) and reevaluate why they do what they do (goals) basing both on what the organizations obtain (results). This is a process of modifying goals in light of experience or possibly rejecting goals all together after multiple failed attempted [34].

Double-loop learning is important to the technological-innovation process because of the 40% to 50% failure rate of new-commercialized technology as estimated by Chiesa [16]. While single-loop learning may assist organizations in developing the smart manufacturing technology, double-loop learning would ensure the technology is the right technology the organization should be pursuing.

Double-loop learning, knowledge bases, and popular management-control techniques are integrated into the decision-making process to form our knowledge-driven decisions concept shown in Fig. 5. Our concept represents the decision-making process based on generated knowledge and experience. In the decision-making process, our knowledge represents a group of “answers” to previous, and even future, questions. Our decision represents our recognition of a question. We use our knowledge to make decisions. Unfortunately, that is often where the process stops. Due to our interactions and pressures with the work environment, a secondary question of, “how good was the decision?” is not often addressed.

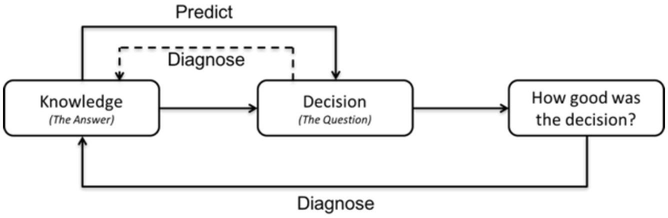

Fig. 5. The knowledge-decision cycle for knowledge-driven decision making

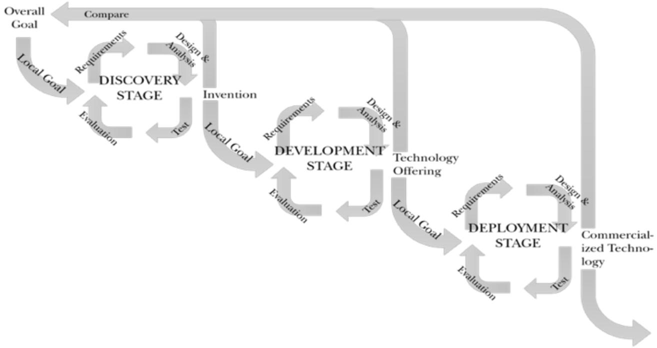

Fig. 6. Phase-gate process definition for the management of technological innovation with integrated double-loop control

For smart manufacturing to be successful, we must analyze each decision outcome against the expected results. This analysis enables the decision maker to diagnose if the knowledge used to make the decision was sufficient or if new knowledge is required to improve the decision in the future. This is a feed-back control loop. But just knowledge supports making decisions, we can also use the knowledge to predict the type of decisions we can make in the future. That prediction (i.e., prognosis) activity is a feed-forward control loop that enables secondary diagnosis of the knowledge to determine if new knowledge is needed.

For example, double-loop learning may be integrated with a stage-gate process as shown in Fig. 6 by setting an overall goal at the start of the process, defining local goals for each stage of a design or manufacturing process, and then comparing the output of each stage with the overall goal. Requirements are managed within each stage to ensure design, analysis, test, and evaluation meet the local goals.

in developing our concept, we assume the activities of the discovery, development, and deployment stages are out of scope. We represent each stage as a system, enabling us to integrate each stage using system-of-systems methods. Stage-internal processes and methods are irrelevant; we focus on the inputs and outputs of each stage and the interactions required between each stage.

We also recognize that feedbacks could come from many different disciplines (e.g., marketing, finance, supply chain). We assume those feedbacks are made directly to the stage that has a need to know. Therefore, those feedbacks are out of scope for this work.

The first step in employing our concept is to determine the overall goal(s) of the decision cycle – in this case, deploying a new technology. Goal development should follow commonly-used processes. We are not proposing a change to existing goal setting practices; our concept is concerned with making goal assessments a continuous process throughout the decision-making process.

Next, the overall goal(s) are broken down to appropriate localized goals for each stage of the technological-innovation process. This process is similar to developing a work breakdown structure in project management. Local goals should be determined for each stage based on the expected outcome of each stage. In addition, the outputs of each stage become a part of the inputs for the next stage.

When a stage is near completion, an evaluation of the stage's requirements and localized goals is conducted. The results of the evaluation would determine if the technology is ready to move to the next stage. If the technology passes the stage evaluation, that stage is complete. But the technology doesn't move to the next stage yet. The technology needs to be assessed against the overall goal(s). For example, in the discovery stage potential questions that should be asked are:

- Does the technology align with the overall goals of the organization or vice-versa?
- Would the technology provide continuous value or provide a competitive advantage?
- Are there any other overall goals to which the technology could align?

We adapted Cooper's [21] purpose for gates to our concept. The purpose of each gate is to provide an assessment of the quality of the technology while ensuring the right technologies and overall goals are pursued. Gates are meant to deal with three quality issues in the technological-innovation process [21]: (1) quality of execution in the process, (2) business rationale for the technology and overall goals, (3) and quality of the action plan for controlling the process.

4. Discussion

Our example for technology deployment using our decision-making concept could be applied to the concept of the "Digital Thread" and model-based enterprise (MBE). The digital thread is concerned with how data flows between engineering, manufacturing, business processes, and across supply chains. A MBE approach uses these models, rather than documents, as the data source for all engineering activities throughout the product lifecycle. The core MBE tenets are models are used to drive all aspects of the product lifecycle and data is created once and reused by all downstream data consumers.

Hedberg et al. [35] proposed a conceptual lifecycle information framework and technology (LIFT) for digitally integrating all phases of the product lifecycle. digital thread is key to a successful deployment of the framework and requires an accurate definition of the product (system). The product definition includes the shape, context, and behavior of the system. For example, the shape defines geometry and associated parameter configuration requirements. The context provides information for the various viewpoints across the product lifecycle; such that information is available for each function / role in the lifecycle at the time when the information is needed. Lastly, the behavior describes how the system is required to interact in a given context (e.g., how the system should interact with a cutting tool in manufacturing or how the system should interact with the product end-user).

The LIFT concept is described in three layers: (1) linked-product-lifecycle data, (2) data certification and traceability layer, and (3) data-driven applications. Data is linked together across the entire product lifecycle using agent-based methods. A certification and traceability layer would ensure trust in the linked data by adding meta-data denoting who had done what to the data and when it was done. Lastly, data-driven applications leverage data for knowledge-bases, decision support, requirements management, and control.

Combining our decision-making concept with the LIFT concept supports a new paradigm that treats the product lifecycle as a cyber-physical-social system. In this context, computer-aided technologies (CAx), machines, products, and people are combined, analyzed, and measured for performance outputs and decision outcomes. Decisions are made under uncertainty throughout the entire lifecycle. How do we reduce the uncertainty and variation? Further, how do we define and understand stakeholder needs, convert those needs into system requirements, and ensure the system attributes comply with the requirements? Answering those questions relates to the feed-back and feed-forward loops in our decision-making concept. Machine learning techniques may be applied to the linked data layer of the LIFT concept. This enables knowledge to be built by diagnosing decisions in the lifecycle. That knowledge is then used to predict the types of decisions that could be made, so before any decision is made, it is possible to determine whether sufficient knowledge exists.

We invested heavily in double-loop feedback during the development of our decision-making concept. Single-loop control has many uses, but our literature review identified several gaps with single-loop control in decision-making activitis. The primary gap is the overall goal in development and manufacturing projects is not being reassessed. We believe the integration of double-loop control in our concept results in better decisions through reducing the risk of bullwhip or oscillatory effects.

While bullwhip effects traditionally apply to distribution channels, the decision-making process can experience oscillatory swings when not controlled properly. Our concept ensures the inputs, outputs, and requirements of decision are carefully assessed at the appropriate point in time against the overall goals of the organization. This ensures a stable and steady flow through the technological-innovation process. Without our concept, deploying smart-manufacturing technologies could potentially experience performance swings above and below optimal states as technology is aligned to the goals of the various process stages in a manufacturing enterprise, the eventual development of new processes, and the overall goals of the organization.

5. Conclusion

The successful maturing of a new concept through commercialization requires nurturing and oversight, which only proper management controls would provide, in our case, with the use of double-loop learning. The process of technological innovation and its management must coexist and complement each other through the decision-making process. Cooper [21] outlined eight key factors of success in product development from which we extracted the following technology development insight:

- Quality of executing the technological-innovation process is key to an eventual product's success.
- Quality of executing (e.g., market research, technical assessments, business analysis) the discovery stage of the technological-innovation process is pivotal to the success of an eventual product.
- Quality of executing marketing activities, including building the voice of the customer, potentially increases the success rate of technology by over 100%.

Our concept for controlling the decision-making process supports Cooper's [21] eight key factors of success. Furthermore, the key factors could be the foundation for assessment criteria throughout the concept. This would enable the application of quality-assurance-like methods to decision making.

We've begun to show that proper management and technological innovation are critical for successful deployment of smart manufacturing. We've also proposed literature-supported process definitions for technological innovation and a concept for controlling it. We believe organizations would benefit from understanding the relationship of the proposed concept and activities of each phase in technological-innovation process. Additional research is needed in quantifying measures throughout the technological-innovation process.

We recognize that evaluation-based decision outcomes are subjective. Additional research in evaluation criteria and methods for implementing stage-gates into our concept is needed to make outcomes objective. For example, we are interested in how decision trees, heuristics, Markov chain, and Bayesian networks could assist in evaluating the outcome of decisions and how knowledge building could be automated.

Also, additional research is needed to develop measures related to output-input relationships in decision making. The goal of these measures would be to provide the user of our concept with an efficient way to determine the effectiveness and performance efficiency of each decision against an overall goal. This would help the user determine if an overall goal needs to be revised in light of the work determined by the local goals or vice-versa.

In closing, we believe our concept supports effective and efficient management of the technological-innovation process. Our concept for data-driven decision making could enable a harmony between the technological-innovation process and its management that would support

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