The Framework of Stochastic Programming Model with Scenario Generation Approach for Sustainable Knowledge Management under Uncertainty Disruption

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Abstract. Recently, knowledge, as a strategic resource, has become an essential driving forces for business success, in particular in competitive situation. Accordingly, the existence of knowledge management (KM) is to support the business firm to locate, select, organize, distribute, and transfer vital information within the firm. One of the method to increasing effectiveness of knowledge management is to optimize its processes. However, during the process in order to increase the firm performance some disruption may occur. This paper describes a stochastic programming model to optimize the knowledge management processes problem within a firm, considering uncertainty disruption. We adopt scenario generation approach for tackling the stochastic problem.

1. Introduction

In the context of theory, on 1990 Clayton Christensen delivered the theory about disorder. Was originally developed to restrict the disruptive of innovation for companies focused on marketing via the provision of cheaper and easily accessible. Customers, products, and services and after adopting the relevant business model. [1] The disruption theory is a theory that the response to the competition, which shows that if a company innovate in a certain way then they have to compete with other companies. [2] In this highly competitive era against interference. The goal of every organization is to uggul the competition and win new customers. In the 21st century landscape architecture business full of dynamics and uncertainty, due to various factors of globalization, technological developments that increasingly rapid technological diffusion, organisation and compete in a very complex and challenging environment [3]. As a result, the basic organization of competitive.

Disruption must be taken as a change in the structure of the business enterprise. This is not only about the arrival of new competitors or an increase in competitive conditions. This happens in the context of changes in industrial structure. Which in turn must show more players entering the market, significant decreases in the cost of innovation, changes in power relations in an industry or new technologies that change market segmentation. [2]. Disruption can be considered destructive and creative at the same time [1] as a disrupting company that actually transforms the industry into a reverse and changes it deeply and permanently. So, if a company aims to introduce innovations that support old players, it will try to eliminate new competitors, while if they introduce disruptive innovations, older players will be more likely to run away than fight. [2]. Recently, a large number of distractors have significantly changed the
market, such as the Apple iPhone with the fact that Apple products create ecosystem innovations in hardware and software, which makes its competitors struggle and still try to follow them. Besides that, like Google, it has created a market that does not give people the opportunity to become competitors [2]. Thus, it can be concluded that they have become old players. In general, to be a disrupted innovator, companies also need to adopt the right business model and be able to handle new technology [4]. Today, digital transformation can lead to a business model that is not only responsive to customers but customer-centered, able to reflect changes in customer needs, care about value creation for customers and other stakeholders and is willing to engage openly in online collaboration [5], which can cause further disruption of innovation, through crowdsourcing, for example. In essence, business models play an important role in value creation, encouraging disruptive innovation and being able to respond to new disruptive innovations introduced [2]. Today, achieving success in an uncertain environment organizations need the ability to make wise decisions and take action based on relevant knowledge, which must be managed properly [6]. Modern organizations are under intense pressure to increase agility and competitiveness to operate in the global market, and engage in alliances. Knowledge management plays a key role in an organization's ability to drive technological development, understand market context and strategic implications and to gain competitive advantage from it [7]. Although Knowledge Management is increasingly popular with business and scientific circles, generally accepted definitions have not been formulated so far [6]. For the objective of this paper, Knowledge Management is defined as a set of systematic activities that are well organized and flexible to achieve organizational goals in an efficient and effective way. This activity is focused on corporate knowledge sources (individual, collective, organizational, explicit and tacit) and enables the implementation of processes related to knowledge (localization, acquisition, development, sharing, preservation, and use of knowledge) and forms of the environment (human, technical, culture) that is beneficial for KM. In this activity, the right methods and tools are used [6].

Disruptive technology is an uncertain challenge to the sustainability of business organizations. Disruption phenomenon contains uncertain variables, thus the business organizations having difficulties in making decisions to answer the uncertainty of disruption challenges. Usually in practice there would be uncertain parameters, such as disruption, should be considered such that the organization would be able to act intelligently. Therefore, business organizations have to innovate their knowledge management process to achieve the effectiveness of knowledge management. One method proposed to improve the effectiveness of knowledge management is optimizing the processes. The major knowledge management objective is to enable organization to act intelligently [8] in responding to the challenges of uncertainty disruption.

2. Methodology

2.1. Knowledge Management Process

Previous studies on Knowledge Management in the literature builds on multiple discipline, for e.g, management, computer science and information system. In the perspective of information technology, knowledge is completely different from data and information. Data is meaningful facts, size and statistics, while information is processed data that is accurate and timely. This refers to the storage of information and / or models used by people or machines to interpret, predict, and respond quickly to the outside world [12]. Knowledge is information that is contextual, relevant and actionable [13]. To justify the research objective i.e. to proposed the new method in optimization of KM process under uncertainty disruption and to maintain the consistency of literature survey on KM processes.

Knowledge Management activities produce a process of circulation of knowledge; there are five important components played there, namely: knowledge creation, knowledge accumulation, knowledge sharing, utilization and internalization of knowledge [12], meanwhile Eppler and Sukowski [11] have established four core processes in knowledge management, namely assessment of team knowledge, development of team knowledge (creation and acquisition of new knowledge), joint direction and renewal, and systematic reviews or learning sessions. In addition, Lindner and Wald [13] have examined the influence of culture, organization, and structural factors related to the effectiveness of KM by
applying partial least square methods. With regard to the reference above, it is stated that acquisition, transfer and knowledge creation are the three main activities in the knowledge management process. Maria Jakubik [14] constructs and implements a collaborative model of the knowledge management process (CKMP) to take advantage of the latest developments in the theory of knowledge management (KM) creation with collaborative learning approaches (CLA). It should be understood that the development of knowledge resources and the implementation of knowledge management initiatives can directly and indirectly explore knowledge creation, defined by Nonaka and Takeushi [16] as the ability of an organization to create and circulate knowledge in organizations, products, services and systems. While Jader Z and Dai Senoo [15] believe that the creation of knowledge management is a six-dimensional concept that acts as an "accelerator of knowledge creation": absorption capacity. Nonaka et al. [17] studied the creation of KM from an organizational perspective. They study the dynamic process by which companies can create, maintain, and utilize knowledge. According to the references above, it is concluded that knowledge creation as the efficiency of new product development, time to market efficiency and the level of new knowledge applications.

2.2. Optimization Model

The objective of KM process is to enable the organization can act intelligently in fulfil customer demands and sourcing decisions under uncertainty conditions, so as to maximize profit or to minimize operation costs subject to locate, select, organize, distribute, and transfer vital information within the firm. Therefore the problem is inherently an optimization problem. In the term of the parameter of the mathematical modeling, the optimization of knowledge management process can be classified into two class models: deterministic models and stochastic models. In deterministic models the parameters or the data are assumed to be known. These deterministic models would end up solving “mean-value” or “worst-case” problems. The solution to such “worst-case” or “mean-value” problems are often inadequate–large error bounds arise [1]. The deterministic KM process problem models, though widely studied in the literature, very lack and less acceptable. Whenever the parameters are uncertain then the stochastic models used. Typically the uncertainty can be overcome by using “best guesses” of uncertain values.

This paper propose the framework of optimization KM process includes uncertain parameters. Most of the references of optimization problems which contain uncertain parameter come under the heading of stochastic programming [21]. The appropriate structure for our KM process problem is a two-stage stochastic programs with recourse. In such models, generally the objective function value is assigned to minimizing expected costs or to maximizing expected benefits (linear or nonlinear), although the function value can also refer to the expected value of the quadratic deviations of certain specific targets or the variance of the second-stage recourse function. There are two kinds of decision variables involve. Those determined at the first-stage, called here-and-now decision variables, in which the random variables are still unknown; in this paper, they correspond to the production cost and workforce of the first period. Those determined at the second-stage, called recourse decision variables, in which the random variables have been realized. These variables represent reactive decisions made to response to the uncertainty factor.

Stochastic programming are associated with optimal decision-making problems in situations of uncertainty. Uncertainty presented by a probability distribution. Interaction between stochastic and decision making processes modeled so that decision makers have choices which is appropriate based on how uncertainty develops. From perspective in modeling, there are many studies in stochastic program literature relating to exogenous uncertainty problems (Jonsbraten (1998)). That is an optimal decision that cannot influence stochastic processes. Based on these description, the KM process can be represented conceptually by a basic model in such a way to obtain an optimal result. The frame work of the model can be expressed as follows:

\[ \text{Action } x \quad \Rightarrow \quad \text{Observe scenario} \quad \Rightarrow \quad \text{Action } y \]

- \( x \) is the vector of first-stage variables
- \( y \) is the vector of second-stage variables

\textbf{Objective:} \( E \) [total cost performance due to the disruption]
Second stage problem depends on first-stage decision and scenario realized

The conceptual model could represent an optimal formulation of Knowledge Management Process (KMP) that the “action” as a result of the first stage process should be reconsidered due to the uncertainty parameter of “disruption” that occur in the next period of the KMP. Therefore it is necessary to make recourse in order to anticipate the occurrence of disruption. If the pattern of the uncertainty disruption has a discrete probability distribution, the optimal model can be expressed mathematically as follows:

\[ \min cx + \sum_{s=1}^{S} p^{s}Q^{s}(x) \]  
\[ \text{Subject to;} \]
\[ Ax = b \]
\[ x \geq 0 \]

Where,
\[ Q^{s}(x) = \min \{ f^{s}y | D^{s}y \geq h^{s} + T^{s}x \} \]
\[ P^{s} \] is the probability of the disruption occurrence. \( x \) is the vector of variable of the first stage in which there is no disruption. Due to the disruption we will have \( y \) vector of variable as the KM process. \( S \) is the scenario needed to describe parameter for disruption. Vector of variable \( x \) can be regarded as one of the following result from KM process, such as, productivity, profitability, sales growth, or market share. Let for the time being \( x \) is considered as productivity. In the first stage, it is assumed that the model to gain maximum productivity is in the linear program, as described in the Eqs. (1) and (2), without the term \[ \sum_{s=1}^{S} p^{s}Q^{s}(x) \]

To accomplish a process it is necessary to have time period. So during the process uncertain disruption could occur. Due to the problem in the KM process contains random parameter \( \omega \) then the problem has turned out as expressed in Eqs. (1) and (2). This called stochastic programming problem.

It is no doubt that nowadays an organization needs to put sustainable concept in their KM performance so as to handle competitiveness. There are three main factors should be included, viz., economic, environment, and social welfare. Therefore in a way to get the optimal performance in the productivity process involved in the KM process, sustainability must be considered. The component of vector of variable \( x \) and \( y \) involve these three factors of sustainability. Then we can say that the productivity has already made impacts on the profitability, environment risk and social welfare. With the involvement of sustainability in KMP problem, the proposed model is no longer linear as in Eqs. (1) and (2), but it has a non-linear form and can contain variable values that are counted. The problem model proposed in this study can be written in the following form.

\[ \min_{x} f^{1}(x) + Q(x) \]
\[ g^{1}(x) = 0, \]
\[ h^{1}(x) \leq 0, \]
\[ g^{1} : R^{n_{2}} \to R^{n_{1}}, \]
\[ h^{1} : R^{n_{1}} \to R^{n_{0}}, \]
\[ x \in Z_{c}^{n}. \]

Where
\[
Q(x) = E_{\xi} Q(x, \xi(w))
\]
\[
Q(x, \xi(w)) = \min_y f^2(y(w), w)
\]
\[
g^2(x, y(w), w) = 0
\]
\[
h^2(x, y(w), w) \leq 0
\]
\[
g^2 : \mathbb{R}^{n_2+n_s} \times \Omega \rightarrow \mathbb{R}^n
\]
\[
h^2 : \mathbb{R}^{n_2+n_s} \times \Omega \rightarrow \mathbb{R}^n
\]
\[
y \in Y
\]

\(\Omega\) is a probability space equipped with \(\sigma\)-algebra \(F\) and a probability measure \(\xi\) are random variables whose probability sizes exist, and \(f^1, f^2, g^1, g^2, h^1, h^2\) are non-linear functions, which are differentiable but not convex. \(x\) represents the first stage variable, while \(y(w)\) presents the second stage variable.

The set \(Y\) is a combination of two subsets of \(Y_R\) and \(Y_Z\), with \(Y_R \in \mathbb{R}^{n_2}\) and \(Y_Z \in \mathbb{Z}^{n_2}\). So, in the model above, some of the second stage variables (which are indexed by the \(Y_Z\) set) are required to take the count value. The main feature of the two-stage stochastic program model is the "recourse" action. The decision set is divided into two groups. A number of decisions must be made before the parameters of the problem are known: this decision is the first stage decision and this decision is taken in the first stage. Other decisions can be made after the uncertainty is revealed. The recourse decision is a function of the actual realization of uncertain parameters and of the first stage decision. Sequences of events characterize the model as a recourse model. There are a number of things that need to be considered in the multi-stage model, namely, convexity and continuity. This is mainly due to enumeration requirements. If the count variable is only in the first stage, the nature of the recourse function is the same as in the continuous case. In the case of continuous nonlinearity if \(f, h\) convex and \(g\) affine for all \(\xi\), the problem is convex. If the enumeration requirements appear in the second stage, although for the linear case recourse functions are generally not convex. Difficulties in dimensions depend on the number of scenarios. The expectations in Equation (4) include multi-dimensional integration. In order for the problem to be resolved, uncertainty is usually expressed in a discrete distribution that approaches. However, the need for accuracy in modeling results in an increase in dimensions in the optimization program. This adds to the limitations of the stochastic program modeling method and the method of completion is still at an early stage. The assumption of a discrete probability space resulting in an objective function can be written as a finite number and the constraints are replicated for each element in \(\Omega\). Suppose that \(\xi\) has a discrete probability distribution at \(\Omega = 1, ..., S\) with \(P(\xi = \xi_s) = \pi_s\). Then the problem can be written again in the form:

\[
\min f^1(x) + \sum_{s=1}^{S} \pi_s f^2(x, y, \xi_s)
\]
\[
g^1(x) = 0
\]
\[
h^1(x) \leq 0
\]
\[
h^2(x, y_s, \xi_s) = 0 \quad \forall s = 1, ..., S
\]
\[
g^2(x, y_s, \xi_s) = 0 \quad \forall s = 1, ..., S
\]
\[
x \in \mathbb{Z}_n^s, \quad y_s \in Y_s \quad \forall s = 1, ..., S
\]
\[
g^1 : \mathbb{R}^n \rightarrow \mathbb{R}^n
\]
\[
h^1 : \mathbb{R}^n \rightarrow \mathbb{R}^n
\]
\[
g^2 : \mathbb{R}^{n_2+n_s} \rightarrow \mathbb{R}^n
\]
\[
h^2 : \mathbb{R}^{n_2+n_s} \rightarrow \mathbb{R}^n, \quad s = 1, ..., S
\]

Where \(\pi_s\) states the probability that scenario \(s\) occurs. This equivalent deterministic formulation is a problem with large scale nonlinear count programs with variable \(n_1 + n_2S\) and \(m_i + m_i + t_2S + t_3S\) nonlinear constraints. If all random variables have finite uncertainty support that exists in the dual stage model, it
can be presented by the tree scenario. Because algorithms work with discretization, in this section they are linked between scenario (discrete) and filtration trees, which apply to continuous and discrete random variables.

A scenario tree is a rooted tree in which all leaves with a depth of T. Gusset sets at depths are expressed by \( \mathcal{V}_t \), so the set of gussets is \( \mathcal{C}_n \). Each quantity \((n, m)\) has a conditional distribution related to \( q_{mn} \) from the transition to \( n \) with the knowledge that \( n \) is reached. So \( 1_{n \in C_t} \).

Alternatively the scenario tree can be described using filtration where \( \sigma \)-algebra presents information available to decision makers. Assuming \( \mathcal{V}_t \) it has finite support, \( \sigma \)-algebra \( \mathcal{V}_t = \sigma(\mathcal{V}_t) \) which is formed by finite \( \mathcal{G}_t \) and also filtration \( \mathcal{F}_t \). Because \( \mathcal{G}_t \) is finite it is formed by a finite partition \( B_j^t \) of \( \Xi \):

\[
\Xi = \bigcup_{i=1}^{k} B_j^t \text{ dengan } B_j^t \cap B_l^t = \emptyset \text{ untuk } j \neq l.
\]

The same is true for \( \mathcal{F}_{t+1} \):

\[
\Xi = \bigcup_{i=1}^{k+1} B_j^{t+1} \text{ dengan } B_j^{t+1} \cap B_l^{t+1} = \emptyset \text{ untuk } j \neq l.
\]

Filtration properties result in a relationship between 2 partitions \( B_j^t \) and \( B_j^{t+1} \):

\[
\forall i, 1 \leq i \leq k, \exists J_i^{t+1} \subseteq \{1, \ldots, k+1\} \text{ dengan } B_j^t = \bigcup_{k \in J_i^{t+1}} B_k^{t+1}
\]

Note that when a policy \( x = \{x_t(\xi), t = 1, \ldots, T\} \) is taken against filtration \( \mathcal{F}_t \), it means that each \( x_t \) is measured against the corresponding \( \sigma \)-algebra \( \mathcal{V}_t \). This resulted in:

\[
x \text{ is } \mathcal{F}-\text{adaptation} \iff x_t(\xi) = \text{konstan } \forall \xi \in B_j^t, \forall i, t.
\]

The relationship between filtration \( \mathcal{V}_t \) and the scenario tree can be made explicit by identifying the components \( B_j^t \) of the partition with related gussets from the scenario tree.

3. Results and Discussion

The basic design model can be written in form:

\[
\min F(x) + d^T y
\]

Constraint \( f(x) + A_1 y = b_1 \) (\( m_1 \) row)
\( A_2 x + A_3 y = b_2 \) (\( m_2 \) row)
\( \ell \leq (x,y)^T \leq u \)

The algorithm takes place by working on the main iteration sequence, in which constraints are linearized \( X_k \) at some point lines and nonlinearity is combined with objective functions along with Lagrange multiplier estimates. So that the linear constraints sub problem is solved in the main iteration to \( k \). That is

\[
\min_{X_k} L(x, y, \lambda, \rho) = F(x) + d^T y - \lambda^T (f - \hat{f}) + \frac{1}{2} \rho(f - \hat{f})^2 (f - \hat{f})
\]

the constraint
The objective function is a modified Lagrange extension, the penalty parameter $\rho$ accelerates convergence from the initial estimation point which is far from the optimal point. Lagrange multiplier $\lambda_k$ is taken as the optimal value of completion of the previous sub problem. If the main iteration sequence approaches the optimal point (measured by relative changes in estimation $\lambda_k$ and degree to which nonlinear constraints $\mathcal{X}_k$ are filled with penalty parameters $\rho$ reduced to 0. The proposed method uses an active obstacle strategy, which can be presented in the form

$$A\mathcal{X} = \begin{bmatrix} B & S & N \end{bmatrix} \begin{bmatrix} \mathcal{X}_B \\ \mathcal{X}_S \\ \mathcal{X}_N \end{bmatrix} = \begin{bmatrix} b \\ - \\ b_N \end{bmatrix}$$

Where:

$B =$ Base vector set
$S =$ Super base vector set
$N =$ Non-base vector set
$I =$ unit matrix

The non-base variable is within its limits and stays there for the next step. So it can be written

$$B\mathcal{X}_B + S\mathcal{X}_S + N\mathcal{X}_N = b$$

$$\mathcal{X}_N = b_N$$

With is a combination of upper and lower bounds.

The super base variable is free to move in any direction and provides an impetus to minimize objective functions.

The base variable $\mathcal{X}_B$ must follow the following equation:

$$B\mathcal{X}_B + S\mathcal{X}_S = 0$$

So, $\Delta\mathcal{X}$ can be written in changes to the super base variable as:

$$\Delta\mathcal{X} = Z\Delta\mathcal{X}_S$$

with

$$Z = \begin{bmatrix} -B^T S \\ I \\ 0 \end{bmatrix}$$

Here it can be seen that the $Z$ matrix works as a ‘reduction’ matrix and multiplies from the left of the gradient vector to form a reduced gradient $\beta = Z^T g$ with $g = \partial f / \partial \mathcal{X}$. It also multiplies from the left and right of the Hessian matrix from the second partial derivative to produce steps like Newton in the reduced space of the super base variable.

The implementation of the method uses a quasi-Newton approximation of the $R^T R$ to the reduced Hessian matrix, where the triangle-top $R$ matrix. ‘Sparsity’ in the constraints is maintained by storing and updating $LU$ factorization of the Base $B$ matrix.

This factorization gives the meaning that $Z$ or $B-I$ is not explicitly stated. The quasi-Newton $\Delta\mathcal{X}$ step is calculated by the following sequence

a. Complete the $\bar{U}^T L \bar{a} = \bar{g}_a$ for $\bar{a}$ where the gradient vectors $g_a$ partition to be $(g_a, g_s, g_n)$ related to $A$ partition and $\Delta\mathcal{X}$

b. form $h = g_s - S^T \sigma$

c. solve the $R^T R \Delta\mathcal{X}_S = -h$
d. completement the $LU\Delta x = -S\Delta x$

The size of the super base set varies when the search algorithms takes place. If the variable boundary is found, the variable is made into a non-base and moved from the set of super base (or bases). Whereas if the convergence is achieved in a subspace, one or more non-base variables are used as super base if the related 'reduced cost' vector elements $\bar{\mathbf{k}}_N - N^T \mathbf{v}$ are not zero and marked accordingly.

4. Conclusion
In this paper, a two-stage stochastic programming model with scenario generation approach is presented for solving a sustainable Knowledge Management process problem of a firm. The uncertainty disruption turned up from the customer demand and sourcing decision. The model involves to decide the number of knowledge for decision base which is very important to decision maker. The other important thing is to conserve sustainability Knowledge Management process. This paper addressed the scenario tree for solving the stochastic programming problem. For future work, this research will be continue to provide practice guide by implementation the algorithm in small medium enterprises as a case study.

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