A TQM case of Centralized Sequential Decision-making Problem

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Abstract

This paper considers that a public department under specialized TQM manpower constraints have to implement multiple total quality management (TQM) policies to promote its service performance (fundamental goal) by adopting a centralized sequential advancement strategy (CSAS). Under CSAS, the decision-makers (DMs) start off by focusing specialized TQM manpower on a single policy, then transfer the specialized TQM manpower to the next policy when the first policy reaches the predetermined implementation time limit (in terms of education and training). Suppose that each TQM policy has a different desirous education and training goal. When the desirous goals for all TQM policies are achieved, we say that the fundamental goal will be satisfied. Within the limitation of total implementation period of time for all policies, assume the desirous goals for all TQM policies cannot be achieved completely. Under this premise, the optimal implementation sequence for all TQM policies must be calculated to maximize the weighted achievement of the desirous goal. We call this optimization problem a TQM case of "centralized sequential decision-making problem (CSDMP)". The achievement of the desirous goal for each TQM policy is usually affected by the experience in prior implemented policies, which makes solving CSDMP quite difficult. As a result, this paper introduces the concepts of sequential effectiveness and path effectiveness. The structural properties are then studied to propose theoretical methods for solving CSDMP. Finally, a numerical example is proposed to demonstrate CSDMP's usability.

Key Words : Total quality management, Resource Centralization, Experience effect, Path effectiveness, Sequential effectiveness

1. Introduction

A public department is expected by citizen, in general, not only operating on high efficiency but also offering the comprehensive and high quality service. Total quality management (TQM) attracts the highly attention of a public department in virtue of the outstanding achievements of the enterprise in recent years.

This paper focuses on the situation where a public department under specialized TQM manpower constraints wish to implement multiple TQM policies by the centralized sequential advancement strategy (CSAS). Under CSAS, decision-makers (DMs) start off by focusing specialized TQM manpower on a single policy, then transfer the human resources to the next policy when the first policy-implementation time reaches the predetermined education and training time limit. Under CSAS, we have to find an implementation sequence by taking advantage of the across-policy effects that leads DMs to achieve the maximal achievement of the fundamental goal within a certainty period of time.

Conventional investigations to solve above problems focused on finding the relative weights by the methods of multiple attribute decision making (MADM) for all policies. The relative investigations to MADM can be found in dyer (1990), Rebai (1993), Badri (1999), Finan and Hurley (1999), Xu (2001) and so on. However, if the DMs have to implement multiple TQM policies to promote a public department's service performance (fundamental goal) and there are extremely interactive effects to intensify the achievement of fundamental goal when all TQM policies achieve their goals. Then, the weighted-based method to determine the priority of implementation may be insufficient and ineffective. Accordingly, in this paper we propose an optimal model based on CSAS to improve the flaw. We call this optimization problem "centralized sequential decision-making problem(CSDMP)".

In summary, this research devotes the second section to describing the TQM case of CSDMP proposed herein. The path effectiveness and sequential effectiveness is defined in the third section, which lays the foundation for Section Four where the properties of the model are discussed. The CSDMP's applicability and feasibility is illustrated with a numerical example in Section Five. Finally, Section Six is focused on comprehensive conclusions and future studies.

2. A TQM case of CSDMP

In this paper we consider a public department plans to implement N TQM policies to promote its service performance. Each TQM policy has its desirous education and training goal. When all policies' goals are achieved, the fundamental goal (promoting the public department's service performance) will be satisfied. With the limited specialized TQM manpower available, the DMs decide to centralize the available specialized manpower in one TQM policy and not transfer the common TQM human resources to another TQM policy until the prior policy reaches the predetermined education and training time limit. Under CSAS, the DMs wish to find the optimal implementation sequence to maximize the achievement of fundamental goal limited to a certainty period of time and experience effect on the policy-implementation sequence. We call this a TQM case of CSDMP.

To construct above TQM case of CSDMP model, related notations are given below. Let P be the non-recurring directed path, $P\in\Omega_N$, where Ω_N is the set of all non-recurring directed paths in between N policies. Also, let P_i be ith policy of path P, $P\in\Omega_N$. In addition, let $R_{P_i|P}$ be the degree of achievement of policy P_i's desirous goal during the predetermined education and training time limit, t_{P_i}, considering the experience effect on path P, $P\in\Omega_N$, with the specialized TQM human resources available, h_0; and let $G(R_{P_1|P},\cdots,R_{P_N|P})$ be the degree of achievement of the fundamental goal. Based on the notations and definitions above, the CSAS to implement TQM policies is illustrated in Figure 1 as follows:

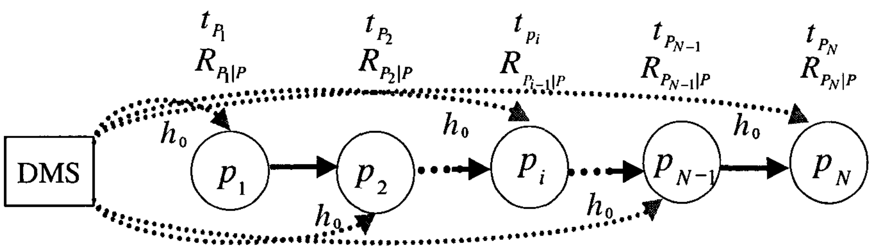

Figure 1. Centralized Sequntial Advancing Strategy

(The dotted line represents the direction of common resource flow, and the solid line represents the implementation sequence)

The TQM case of CSDMP can be initially formulated as follows:

$$\max_{P\in\Omega_N}\{G(R_{P_1|P},\cdots,R_{P_N|P})\} \qquad \textbf{(Model 1)}$$

Let $G(R_{P_1|P},\cdots,R_{P_N|P})=G_1(R_{P_1|P},\cdots,R_{P_N|P})+G_2(R_{P_1|P},\cdots,R_{P_N|P})$, where G_1 denotes the degree of achievement of the fundamental goal contributed by the TQM policies' individual effects and G_2 is the degree of achievement of the fundamental goal contributed by the TQM policies' interactive effects. In addition, assuming π_{P_i} is the relative importance of policy P_i with respect to the fundamental goal, and P^* is the optimal non-recurring directed path such that.

$$P^* = \arg\max_{P\in\Omega_N}\left\{E\left[\sum_{i=1}^{N}\pi_{P_i} R_{P_i|P}\right]\right\} \qquad \textbf{(Model 2)}$$

We can say that P^* is also the optimal solution of Model 1 if G_1 is proportional to G_2 (that is, when G_1 is maximized then G_2 is also maximized). That G_1 is proportional to G_2 is self-evident, hence we view it as an axiom in the TQM case of CSDMP proposed in this paper.

The expected achievement degree $E[R_{P_i|P}]$ for policy P_i during predetermined education and training time limit, t_{P_i}, is hard to estimate directly since it also depends on the prior policies' experience effect. Therefore, we cannot directly use Model 2 to obtain the optimal policy-implementation sequence. The following section is devoted to introducing the concepts of path effectiveness and sequential effectiveness, and based on these definitions converts the original problem form the "maximization of the expected achievement of the fundamental goal" into the "maximization of path effectiveness". As a result, this paper then further converts maximizing path effectiveness problem into the problem of maximizing weighted sum of sequential effectiveness. We do this for the sake of convenience of estimating the model's parameters and obtaining the optimal TQM policy-implementation sequence.

3. Path effectiveness and Sequential effectiveness

3.1 Path Effectiveness

For the TQM case of CSDMP proposed herein, path effectiveness refers to the percentage of increased expected degree of achievement of the fundamental goal due to the influence of experience effect on the TQM policy-implementation sequence. Consider a path P, $P\in\Omega_N$, let $U(P)$ represent path effectiveness and R_{P_i} be the expected achievement of the desirous goal for policy P_i during predetermined education and training time limit when experience effect is not on path P. Since the value of $E\left[\sum_{i=1}^{N}\pi_{P_i} R_{P_i|P}\right]$ is proportional to G_1(the degree of achievement of the fundamental goal contributed by the TQM policies' individual effects) and G_1 is proportional to G_2(the degree of achievement of the fundamental goal contributed by the TQM policies' interactive effects), we can obtain that

$$U(P) = \frac{\{G_1(R_{P_1|P},\cdots,R_{P_N|P}) + G_2(R_{P_1|P},\cdots,R_{P_N|P})\} - \{G_1(R_{P_1},\cdots,R_{P_N}) + G_2(R_{P_1},\cdots,R_{P_N})\}}{G_1(R_{P_1},\cdots,R_{P_N}) + G_2(R_{P_1},\cdots,R_{P_N})}$$
$$= \frac{(1+\gamma)\{G_1(R_{P_1|P},\cdots,R_{P_N|P}) - G_1(R_{P_1},\cdots,R_{P_N})\}}{(1+\gamma)\cdot G_1(R_{P_1},\cdots,R_{P_N})}$$
$$= \frac{E\left[\sum_{i=1}^{N}\pi_{P_i} R_{P_i|P}\right] - E\left[\sum_{i=1}^{N}\pi_{P_i} R_{P_i}\right]}{E\left[\sum_{i=1}^{N}\pi_{P_i} R_{P_i}\right]} \tag{1}$$

Where γ is a constant such that $G_1 = \gamma \cdot G_2$.

3.2 Sequential Effectiveness

For the TQM case of CSDMP, sequential effectiveness refers to the percentage of increased expected achievement of the desirous goal for a specified TQM policy. In other words, consider a path P, $P \in \Omega_N$, let $F_{P_i|P}$ be policy P_i's sequential effectiveness, then

$$F_{P_i|P} = \frac{E[R_{P_i|P}] - E[R_{P_i}]}{E[R_{P_i}]}, \ i = 1,2,\cdots,N;\ P \in \Omega_N. \tag{2}$$

4. Structural properties of CSDMP

4.1 Basic Properties

In order to solve Model 2, after introducing the concepts of path effectiveness and sequential effectiveness in Section 3, this paper will use the following two theorems to convert what if a problem of "maximizing expected achievement" into a problem of "maximizing path effectiveness," and then further to convert "maximizing path effectiveness" into a problem of "maximizing the weighted sum of sequential effectiveness".

Theorem 1 $\underset{P\in\Omega_N}{Max}\{G(R_{P_1|P},\cdots,R_{P_N|P})\}\cong\underset{P\in\Omega_N}{Max}\{U(P)\}$

Proof:

$$\underset{P\in\Omega_N}{Max}\{G(R_{P_1|P},\cdots,R_{P_N|P})\}$$

$$\cong\underset{P\in\Omega_N}{Max}\left\{E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i|P}\right]\right\}$$

$$\cong\underset{P\in\Omega_N}{Max}\left\{E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i|P}\right]-E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i}\right]\right\}$$

$$\cong\underset{P\in\Omega_N}{Max}\left\{\frac{E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i|P}\right]-E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i}\right]}{E\left[\sum_{i=1}^{N}\pi_{P_i}R_{P_i}\right]}\right\}$$

$$=\underset{P\in\Omega_N}{Max}\{U(P)\}$$

□

Remark 1: Theorem 1 shows that the problem of maximization of "the expected achievement of the fundamental goal under time limit" can be converted to the problem of maximization of "path effectiveness". Consider a path $P, P\in\Omega_N$, since path effectiveness, $U(P)$, is the percentage of increased expected achievement of the fundamental goal as a result of the influence of experience effect on path P, the conversion of path effectiveness helps explain the differences in the performance of TQM policies of the various feasible policy-implementation sequences in Ω_N.

Since the quantity of $E[R_{P_i}]$ may vary, let α_{P_i} be $E[R_{P_i}]$'s relative weight with respect to its magnitude, where $\sum_{i=1}^{N}\alpha_{P_i}=1$, then there exists a positive real number μ such that $E[R_{P_i}]$ $=\alpha_{P_i}\mu$.

Theorem 2 Let $w_{P_i}=\dfrac{\pi_{P_i}\alpha_{P_i}}{\sum_j\pi_{P_j}\alpha_{P_j}}$, then $\underset{P\in\Omega_N}{Max}\{U(P)\}=\underset{P\in\Omega_N}{Max}\left\{\sum_{i=1}^{N}w_{P_i}F_{P_i|P}\right\}$

Proof:

$$\underset{P\in\Omega_N}{\text{Max}}\{U(P)\} = \underset{P\in\Omega_N}{\text{Max}}\left\{\frac{E[\sum_{i=1}^{N}\pi_{P_i} R_{P_i|P}] - E[\sum_{i=1}^{N}\pi_{P_i} R_{P_i}]}{E[\sum_{i=1}^{N}\pi_{P_i} R_{P_i}]}\right\}$$

$$= \underset{P\in\Omega_N}{\text{Max}}\left\{\frac{\sum_{i=1}^{N}\pi_{P_i}\left(E[R_{P_i|P}] - \alpha_{P_i}\mu\right)}{\sum_{i=1}^{N}\pi_{P_i}\alpha_{P_i}\mu}\right\}$$

$$= \underset{P\in\Omega_N}{\text{Max}}\left\{\frac{1}{\sum_{i=1}^{N}\pi_{P_i}\alpha_{P_i}} \times \frac{\sum_{i=1}^{N}\pi_{P_i}\left(E[R_{P_i|P}] - \alpha_{P_i}\mu\right)}{\mu}\right\}$$

$$= \underset{P\in\Omega_N}{\text{Max}}\left\{\frac{1}{\sum_{i=1}^{N}\pi_{P_i}\alpha_{P_i}} \times \sum_{i=1}^{N}\pi_{P_i}\alpha_{P_i}\left(\frac{E[R_{P_i|P}] - \alpha_{P_i}\mu}{\alpha_{P_i}\mu}\right)\right\}$$

$$= \underset{P\in\Omega_N}{\text{Max}}\left\{\sum_{i=1}^{N}\left(\frac{\pi_{P_i}\alpha_{P_i}}{\sum_{i=1}^{N}\pi_{P_i}\alpha_{P_i}} \times \frac{E[R_{P_i|P}] - E[R_{P_i}]}{E[R_{P_i}]}\right)\right\}$$

$$= \underset{P\in\Omega_N}{\text{Max}}\left\{\sum_{i=1}^{N} w_{P_i} F_{P_i|P}\right\}$$

Remark 2: Theorem 2 shows that the optimal feasible solution and the value of objective function referring to maximizing path effectiveness are equal to the ones referring to maximizing the sum of all TQM policies' weighted sequential effectiveness. The following discussion of structural properties will prove the model defined in Theorem 2 is a conversion that can be applied to problem solving in real application.

4.2 Further Properties

In order to further study CSDMP's properties, the "completely memoryless property" must be understood. This property is defined as follows:

That experience effect has a completely memoryless property means the experience effect of one TQM policy on subsequent policies' sequential effectiveness is limited to the immediate subsequent policy only because by most people remember new and most recent experience but easy forget preceding experience. In other words, the completely memoryless property implies that DMs will only remember the most recent experiences in which they are learning from the prior policy.

Moreover, we assume that experience effect can be measured by a ratio scale called as "experience intensity". The larger intensity of experience there are when any policy achieves the predetermined education and training time limit, the more significant experience effect the TQM policy has on the subsequent TQM policies. Consider a path P, $P \in \Omega_N$ and a policy P_i, $i = 1,2,\cdots,N$, let e_{P_i} be the DM's experience intensity on TQM policy P_i when policy P_i achieves time limit, t_{P_i}, when experience effect on path P is not took into account; and $e_{P_i|P}$ be the DM's experience intensity on TQM policy P_i when policy P_i achieves the time limit, t_{P_i}, when experience effect on path P is took into account. According to the definitions for $e_{P_i|P}$ and $F_{P_i|P}$, TQM policy P_i's sequential effectiveness $F_{P_i|P}$ depends on $e_{P_{i-1}|P}$ only if experience effect has a completely memoryless property.

In addition, let $\mathrm{E}_{P_i|P}(y)$ be the DM's average experience intensity on TQM policy P_i after the period of time y has passed, and $Z_{P_i}(\mathrm{E}_{P_i|P}(y))$ be the TQM policy P_i's achievement rate of desirous goal (per-unit-experience-intensity) when experience intensity is $\mathrm{E}_{P_i|P}(y)$. Also, let $e^u_{P_i}$ be the minimum experience intensity, the DMs must posses at time t_{P_i}, that enables policy P_i to achieve its desirous goal within the time limit, t_{P_i}. Consider the linear case that $\mathrm{E}_{P_i|P}(y) = \lambda_{P_i|P} \cdot y$ when $y \in [0, t_{P_i}]$, where $\lambda_{P_i|P}$ is a deterministic variable representing the average experience learning rate for DMs at time $y \in [0, t_{P_i}]$. Also, consider the linear case that $Z_{P_i}(x) = \rho_{P_i} \cdot x$, $x \in [0, e^u_{P_i}]$, where ρ_{P_i} is a constant representing the increased achievement of desirous goal (per-unit-experience-intensity on one unit time) that DMs apply experience to achieve policy P_i's desirous goal at experience intensity x, $x \in [0, e^u_{P_i}]$. Based on above, we know that

$$E[R_{P_i|P}] = \int_0^{t_{P_i}} Z_{P_i}(\mathrm{E}_{P_i|P}(y))dy = \int_0^{t_{P_i}} \rho_{P_i} \cdot \lambda_{P_i|P} \cdot y\, dy$$

$$= \rho_{P_i} \cdot \lambda_{P_i|P} \cdot \frac{t_{P_i}^{\;2}}{2} = \frac{\rho_{P_i} t_{P_i}}{2}(\lambda_{P_i|P} t_{P_i}) = \frac{\rho_{P_i} t_{P_i}}{2} \cdot e_{P_i|P} \qquad (3)$$

Since $\frac{\rho_{P_i} t_{P_i}}{2} \cdot e^u_{P_i} = 1$ and $\underset{P\in\Omega_N}{Max} E[R_{P_i|P}] \leq 1$, we define the range of $e_{P_i|P}$ on the interval $[0, e^u_{P_i}]$.

Based on Eq. (3), we known that $E[R_{P_i|P}]$ is the strictly increasing linear function of $e_{P_i|P}$ on the interval $[0, e^u_{P_i}]$. Moreover, we are only interested on the range $[e_{P_i}, e^u_{P_i}]$, hence, we can obtain that

$$E[R_{P_i|P}] = E[R_{P_i}] + (1 - E[R_{P_i}])\left(\frac{e_{P_i|P} - e_{P_i}}{e^u_{P_i} - e_{P_i}}\right),\ i = 1,2,\cdots,N;\ P\in \Omega_N. \tag{4}$$

That is,

$$F_{P_i|P} = \left(\frac{e_{P_i|P} - e_{P_i}}{e^u_{P_i} - e_{P_i}}\right) \cdot \frac{1 - E[R_{P_i}]}{E[R_{P_i}]},\ i = 1,2,\cdots,N;\ P\in \Omega_N. \tag{5}$$

For the sake of convenience, assume that the numbers $1,2,\cdots,N$ represent the number of TQM policies, that is, $S = \{1,2,\cdots,N\}$, where S denotes the set of planned TQM policies. Based above notions, the other relevant symbols are defined as follows:

e_{ij}=DM's experience intensity on policy j when policy j achieves the education and training time limit, t_j, as policy i's implementation experience contributes to policy j by the experience intensity $e_i, \forall\ i, j\in S, i\neq j$.

e^u_{ij}=DM's experience intensity on policy j when project j reaches the education and training time limit, t_j, as policy i's implementation experience contributes to policy j by the experience intensity e^u_i, $\forall\ i, j\in S, i\neq j$.

$e_{ij|P}$=DM's experience intensity on policy j when project j reaches the education and training time limit, t_j, as policy i's implementation experience contributes to policy j by experience intensity $e_{i|P}$, $\forall\ i, j\in S, i\neq j; P\in \Omega_N$.

L_{ij}=The sequential effectiveness that policy i's education and training experience contributes to project by increasing policy j's achievement of desirous goal by experience intensity e_i, $\forall i, j \in S, i \neq j$.

U_{ij}=The sequential effectiveness that policy i's education and training experience contributes to policy j by increasing policy j's achievement of desirous goal by the experience intensity $e_i^u, \forall\ i, j \in S, i \neq j$.

According to above notations and Equation (5), we can obtain the following results.

$$L_{ij} = A_j \frac{e_{ij} - e_j}{e_j^u - e_j},\ \forall\ i, j \in S, i \neq j, \tag{6}$$

$$U_{ij} = A_j \frac{e_{ij}^u - e_j}{e_j^u - e_j},\ \forall\ i, j \in S, i \neq j, \tag{7}$$

where $A_j = \dfrac{1 - E[R_j]}{E[R_j]}$.

In addition, consider the situation that $e_{P_{i-1},P_i|P}$ is the strictly increasing convex or concave function of $e_{P_{i-1}|P}$ on the interval $[e_{P_{i-1}}, e_{P_{i-1}}^u]$. We suppose that there would exist a positive real number, Ψ_{P_{i-1},P_i}, such that

$$e_{P_{i-1},P_i|P} = e_{P_{i-1},P_i} + \left(\frac{e_{P_{i-1}|P} - e_{P_{i-1}}}{e_{P_{i-1}}^u - e_{P_{i-1}}} \right)^{\Psi_{P_{i-1},P_i}} \left(e_{P_{i-1},P_i}^u - e_{P_{i-1},P_i} \right),\ i = 2,3,\cdots,N;\ P \in \Omega_N. \tag{8}$$

Lemma 1 Consider that the experience effect has a completely memoryless property. If on path $P, P \in \Omega_N$, $e_{P_{i-1},P_i|P}$ is the strictly increasing convex or concave function of $e_{P_{i-1}|P}$ on the interval $[e_{P_{i-1}}, e_{P_{i-1}}^u]$, then for every pair (P_{i-1}, P_i) in path P, there exists a positive real number, Ψ_{P_{i-1},P_i}, such that

$$\frac{e_{P_{i-1},P_i|P} - e_{P_{i-1},P_i}}{e_{P_{i-1},P_i}^u - e_{P_{i-1},P_i}} \approx \left(\frac{e_{P_{i-2},P_{i-1}|P} - e_{P_{i-1}}}{e_{P_{i-1}}^u - e_{P_{i-1}}} \right)^{\Psi_{P_{i-1},P_i}} \quad \text{for } i = 2,\cdots,N.$$

Proof: Since the experience effect has a completely memoryless property and $F_{P_{i-1}|P}$ depends on $e_{P_{i-2}|P}$ only, hence the quantity of $e_{P_{i-1}|P}$ approximates the quantity of $e_{P_{i-2},P_{i-1}|P}$. By combining the result in Equation (8), the results of this lemma are obtained.

□

Remark 3:

(i) When $0<\psi_{P_{i-1},P_i}\leq 1$, $e_{P_{i-1},P_i|P}$ is the strictly increasing concave function of $e_{P_{i-1}|P}$ on the interval $[e_{P_{i-1}}, e^u_{P_{i-1}}]$, it means that the experience intensity, $e_{P_{i-1}|P}$, contributes to policy P_i by increasing the DMs' (project leaders') experience learning rate in policy P_i is more significant. In other words, if we let a be the experience learning rate in policy P_i when no prior policy's experience effect on policy P_i is considered, and let b be the experience learning rate in policy P_i when policy P_{i-1}'s experience effect on policy P_i is considered, then the ratio of $\frac{b}{a}$ is very sensitive, i.e., will increase significantly even if $e_{P_{i-1}|P}$ is only slightly increased.

(ii) When $\psi_{P_{i-1},P_i}>1$, $e_{P_{i-1},P_i|P}$ is the strictly increasing "nonlinear" convex function of $e_{P_{i-1}|P}$, it means that the experience intensity, $e_{P_{i-1}|P}$, contributes to policy P_i by increasing the DMs' experience learning rate in policy P_i is not so sensitive, i.e., will not be affected unless the $e_{P_{i-1}|P}$ approaches $e^u_{P_{i-1}}$.

Lemma 2 Consider that the experience effect has a completely memoryless property. If on path $P, P\in\Omega_N$, the expected rewards $E[R_{P_i|P}]$ within the predetermined implementation period of time, t_{P_i}, approximates the strictly increasing linear function of $e_{P_i|P}$ on the interval $[e_{P_i}, e^u_{P_i}]$, sequential effectiveness $F_{P_i|P}$ can be rewritten as

$$F_{P_i|P}=A_{P_i}\frac{e_{P_{i-1},P_i|P}-e_{P_i}}{e^u_{P_i}-e_{P_i}}\ ,\quad i=2,3,\cdots,N\ ;\ P\in\Omega_N.$$

Proof: Since $E[R_{P_i|P}]$ is the strictly increasing linear function of $e_{P_i|P}$ on the interval $[e_{P_i}, e^u_{P_i}]$, then for every pair (P_{i-1}, P_i) in path P, according the Eqs. (4) and (5), we can obtain that

$$F_{P_i|P} = A_{P_i}\left(\frac{e_{P_i|P} - e_{P_i}}{e^u_{P_i} - e_{P_i}}\right), \quad i = 2,3,\cdots,N\ ;\ P\in\Omega_N.$$

Moreover, since the experience effect has a completely memoryless property, the quantity of $e_{P_{i-1}|P}$ approximates the quantity of $e_{P_{i-2},P_{i-1}|P}$, and thus the result of this lemma is obtained. □

Remark 4: The result of Lemma 2 indicates that $F_{P_i|P}$ is the strictly increasing linear function of $e_{P_{i-1},P_i|P}$. It means that the DMs (project leaders) can apply the experience increase to accelerate the achievement of desirous goal well but not very well. Similar to the result of Lemma 1, $F_{P_i|P}$ may be nonlinear convexor concave function; however, this paper only considers the linear case due to the model complexity. The difference between the results in Lemma 1 and Lemma 2 are that a DM has good experiences but no guarantee that he or she can apply them to achieve the fundamental goal very well.

Theorem 3 If we consider that the experience effect has a completely memoryless property, then

$$F_{P_1|P} = 0,$$

$$F_{P_i|P} = L_{P_{i-1},P_i} + \left(\frac{1}{A_{P_{i-1}}} F_{P_{i-1}|P}\right)^{\psi_{P_{i-1},P_i}} \left(U_{P_{i-1},P_i} - L_{P_{i-1},P_i}\right), \quad i = 2,3,\cdots,N\ ;\ P\in\Omega_N.$$

Proof:

(i) Since $e_{P_1|P} = e_{P_1}$, we can directly obtain that $F_{P_1|P} = 0$.

(ii) Since $E[R_{P_i|P}]$ is the strictly increasing linear function of $e_{P_i|P}$ (by Lemma 2) and $e_{P_{i-1},P_i|P}$ is the strictly increasing convex or concave function of $e_{P_{i-1}|P}$ on the interval

$[e_{P_{i-1}}, e^u_{P_{i-1}}]$ (by Lemma 1), we can obtain that

$$L_{P_{i-1},P_i} + \left(\frac{1}{A_{P_{i-1}}} F_{P_{i-1}|P}\right)^{\psi_{P_{i-1},P_i}} \left(U_{P_{i-1},P_i} - L_{P_{i-1},P_i}\right)$$

$$= A_{P_i} \frac{e_{P_{i-1},P_i} - e_{P_i}}{e^u_{P_i} - e_{P_i}} + \left(\frac{A_{P_{i-1}}}{A_{P_{i-1}}} \times \frac{e_{P_{i-2},P_{i-1}|P} - e_{P_{i-1}}}{e^u_{P_{i-1}} - e_{P_{i-1}}}\right)^{\psi_{P_{i-1},P_i}} \times A_{P_i} \frac{e^u_{P_{i-1},P_i} - e_{P_{i-1},P_i}}{e^u_{P_i} - e_{P_i}}$$

$$= A_{P_i} \left(\frac{e_{P_{i-1},P_i} - e_{P_i}}{e^u_{P_i} - e_{P_i}} + \frac{e_{P_{i-1},P_i|P} - e_{P_{i-1},P_i}}{e^u_{P_{i-1},P_i} - e_{P_{i-1},P_i}} \times \frac{e^u_{P_{i-1},P_i} - e_{P_{i-1},P_i}}{e^u_{P_i} - e_{P_i}} \right)$$

$$= A_{P_i} \frac{e_{P_{i-1},P_i|P} - e_{P_i}}{e^u_{P_i} - e_{P_i}} = F_{P_i|P}$$

Hence, the result of this theorem is obtained. □

Remark 5:

(i) According to the recursive formulas in Theorem 3, it is easy to obtain the optimal implementation sequence using "Excel" coding if the number of planned TQM policies is small (for example, 5 or 6 policies).

(ii) According to Eqs. (6) and (7), we can obtain the parameters L^R_{ij} and U^R_{ij} by the method of pairwise comparisons. That is, viewing e_j as a reference point and comparing e_j, e^u_j, e_{ij}, and e^u_{ij} pairwisely, we can find L^R_{ij} and U^R_{ij}, for $i, j \in S$, $i \neq j$.

5. The TQM Applications

Assume a public department in Taiwan intends to implement five TQM policies to improve its service performance. These TQM policies are labeled by number 1 to 5.

This is not an empirical example, so given $\psi_{ij} = 1$, for $i, j \in S$, $i \neq j$, and a set of stochastically simulated parameters are used, to illustrate the procedure of applying Microsoft Excel to obtain the final solution as shown below.

Table 1. Estimated values of U_{P_{i-1},P_i}

(1,2)	(1,3)	(1,4)	(1,5)
9.730	8.049	8.017	9.062
(2,1)	(2,3)	(2,4)	(2,5)
9.517	8.504	8.940	8.784
(3,1)	(3,2)	(3,4)	(3,5)
9.774	9.370	9.533	9.718
(4,1)	(4,2)	(4,3)	(4,5)
9.836	8.569	9.437	8.172
(5,1)	(5,2)	(5,3)	(5,4)
8.917	8.156	9.004	9.539

(*simulated by the uniform distribution ranged on 8~10)

Table 2. Estimated values of L_{P_{i-1},P_i}

(1,2)	(1,3)	(1,4)	(1,5)
5.360	4.424	5.856	4.658
(2,1)	(2,3)	(2,4)	(2,5)
5.273	4.231	4.844	5.042
(3,1)	(3,2)	(3,4)	(3,5)
5.013	4.936	4.8000	4.341
(4,1)	(4,2)	(4,3)	(4,5)
4.276	4.672	4.317	5.334
(5,1)	(5,2)	(5,3)	(5,4)
5.800	4.063	5.350	5.913

(*simulated by the uniform distribution ranged on 4~6)

Table 3. Estimated values of π_{P_i}

π_{P_1}	π_{P_2}	π_{P_3}	π_{P_4}	π_{P_5}
0.913	0.216	0.178	0.189	0.224

Based on the parameters in Table 1, Table 2, and Table 3, apply Microsoft Excel to solve the solution. Finally, we obtained the objective function $\underset{P\in\Omega_N}{Max}\{U(P)\}$=7.5214. The value 7.52 denotes "the percentage of increased expected achievement of the fundamental goal due to the influence of the experience effect on the TQM policy-implementation sequence" is 752%.
The policy-implementation sequence can be graphed as show below.

Figure 2. The Optimal TQM Policy-implementation Sequence

6. Conclusions

This paper considered that a public department under specialized TQM manpower constraints wish to implement multiple TQM policies to promote its service performance (fundamental goal) by adopting centralized sequential advancement strategy (CSAS). Under CSAS, we proposed an optimization model for a TQM case of centralized sequential decision-making problem (CSDMP), and discovers the optimal policy-implementation sequence leading to maximizing the expected achievement of fundamental goal within a limited period of time (the time limit is concerned by DMs). We considered education and training experience as the significant factor that affects the desirous goals for all TQM policy-implementation. Under this premise, we convert the CSDMP of "maximizing the expected achievement of the fundamental goal" into the CSDMP of "maximizing the total of all policies' weighted sequential effectiveness" by introducing the path effectiveness and sequential effectiveness. In addition, due to the difference of correlation among policy-implementation experiences, we considered experience takes the non-linear effect on policy-implementation sequence to affect the expected achievement of the fundamental goal. We also assume that the influences of experience effect on the policy-implementation sequence have a completely memoryless property to construct the recursive formulas to obtain the optimal policy-implementation sequence. By doing so, CSDMP can solve those problems with extremely large interactive effects for achieving the fundamental goal concerned by decision makers, if all projects achieve their goals. In general, CSDMP proposes the strength to complement the weakness in conventional weighted-based methods. This paper only considered the CSDMP model with respect to maximizing expected achievement of the fundamental goal; however, some cases may fit to formulated as the CSDMP model of minimizing the expected completion time. A minimal expected completion time model refers to minimizing the total expected times limit on the condition that each policy-implementation must achieve its goal concerned by DMs. The difference between "maximal expected achievement of the fundamental goal" and "minimal expected completion time model" regarding the model's structural properties and applying conditions should be investigated in the near future.

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