Design of a Knowledge Flow Network for the Personnel of an Organization under Various Scenarios and its Solution using Lagrangian Relaxation

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1. INTRODUCTION

Knowledge has been overgrown in the past decades, such progress in gained knowledge for the last decade is known by many to be larger than that accumulated throughout history up to the previous decade. It has earned knowledge the status of an essential competitive advantage, and every firm bears responsibility for gaining and applying knowledge [1, 2].

Knowledge can be transferred between organizations (inter-organizational) or within an organization (intra-organizational) [3]. Clearly, effective intra-organizational knowledge transfer is critical for a sustainable competitive advantage [4, 5]. The main topic of the present research is intra-organizational knowledge transfer, because knowledge transfer between the personnel of an organization can be led to considerable time and budget saving.

This research primarily focuses on answering the question of how to use the existing knowledge in an organization to guide the knowledge flow between the personnel to maximize the knowledge level and to minimize the duration time of knowledge transfer. To realize this goal, considering budget constraints and the parameters affecting the model, one must determine the knowledge, the field, and the personnel involved in knowledge transfer so that the overall level of knowledge in the organization can be maximized in the shortest possible time.

To this end, first, the existing literature on the subject is reviewed, and the research gap is highlighted. Then, the problem is stated, and the associated mathematical model is introduced. In the subsequent section, the solution method is explained, after which the different solution methods are compared, and the sensitivity analysis is performed. Finally, the results are discussed, and suggestions are made for future research.

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The remaining structure of the paper is as follows: the literature review of the related papers is presented in section 2. Problem description, assumptions, and mathematical model are given in section 3. Using solving methods consist of the LP-metric, and the Lagrangian relaxation methods are in section 4. Section 5 introduces examples and sensitivity analysis for the determination of important parameters. Finally, computational results and discussions for small, medium, and large-sized problems with 25 different samples and two methods are presented in the last section.

2. LITERATURE REVIEW

The literature review of this paper is organized in knowledge flow networks, factors affecting knowledge transfer, and mathematical modeling. First, research on knowledge flow networks is mentioned. Rózewski et al. [6] have stated that an open atmosphere encouraging knowledge transfer and an appropriate field of cooperation are required for successful knowledge discovery. Collaborative learning in an organizational social network is based on knowledge resource distribution via creating a knowledge flow network. In this network, the nodes represent the persons in an organization and contain information about their social and cognitive abilities. In addition, the persons are described by their skill sets, their knowledge level in these skills, and their collaborative learning behavior, which can be recognized by analyzing the knowledge flow. They assume knowledge level increasing is the result of collaborative learning. In other words, cooperative learning can be analyzed as a process involving the flow of knowledge in the network. Chandra et al. [7] aimed to understand the knowledge sharing in projects based on knowledge flow patterns. An interpretive structural model for the knowledge network in knowledge-based organizations (specifically, an automotive research and development center) was discussed by Rezaeian et al. [8]. They identified and ranked the factors affecting the formation of knowledge networks and their relationships in knowledge-based organizations. Environmental factors, knowledge content, cultural factors, IT and network systems, communication mechanisms, organizational structures, and management processes were the factors influential in knowledge network formation in their research.

The second topic investigated in the literature review is the factors affecting knowledge transfer within an organization. In another research, Lin [9] concluded that organizational commitment is directly related to implicit knowledge transfer. Duan et al. [10] explored, confirmed, and mapped the significant factors affecting transnational knowledge transfer (TKT). Ten factors had been selected by more than 50 percent of specialists as the significant factors influencing TKT projects. These were cultural relations and awareness, language, motivation, knowledge gap, appropriate selection of teacher and learner, scope and focus, transfer channel, trust, and constraint removal. Knowledge transfer and learning capacity in multinational corporations (MNCs) addressed by Lee and Wu [11]. The knowledge absorption capacity of the learner is the most critical factor in internal knowledge transfer in MNCs. This research defines absorption capacity as the personnel’s capability and motivation. The impact of trust on selecting the knowledge transfer mechanism was investigated by Sreckovic and Windsperger [12]. Alexopoulos and Buckley [13] stated that, despite the fundamental role of trust in facilitating intra-organizational knowledge flows, the existing limited empirical research shows what kind of trust is related to the adequate knowledge transfer between persons and when these types of trust gain significance. Hence, they examined the effects of personal and professional trust on knowledge transfer. They found that professional trust and personal trust are both positively and considerably related to knowledge transfer. Moreover, they demonstrated that professional trust has a remarkably more substantial positive effect than personal trust on knowledge transfer. Swart et al. [14] investigated the reasons of knowledge sharing with the colleagues. The impact of commitment, personal and professional trust on the transfer and application of knowledge was studied by Ouakouak and Ouedraogo [15]. The relationship between trust, knowledge transfer and organizational commitment in small and medium companies was investigated by Curado. and Vieira [16]. The results indicated that trust has a remarkable positive effect on knowledge transfer and organizational commitment. Knowledge transfer is somehow the intermediary between trust and organizational commitment. García-Almeida and Bolívar-Cruz [17] identified the main factors contributing to the success of knowledge transfer in service-based companies during the creation or sale of new units. Regional transfer of experience, compatibility between the cultural background of the knowledge and that of the learners, the absorption capacity of the learners, motivation of the teachers and learners, and incompatibility during the transfer process are key factors influencing several aspects of success in knowledge transfer in service-based companies. By investigating the effect of commitment on the common intentions of knowledge collaborators in virtual societies in China, Lou et al. [18] attempted to fill the research gap in this area. Their results indicated that emotional and normative commitment could considerably influence the knowledge transfer goals of users.

The third part of the literature review concerns the mathematical modeling of knowledge flow networks. A mixed-integer programming (MIP) model for the
systematic analysis and proper understanding of knowledge flow networks between the personnel in an organization was formulated by Dong et al. [19]. They demonstrated how centralized organizations could facilitate knowledge transfer using knowledge transfer networks and reduce the number of relationships required in a multi-knowledge environment for effective knowledge management. Dezfoulian et al. [2] formulated knowledge transfer between the members of an industrial cluster using a new MIP model. They maximized knowledge transfer between the companies considering the budget and time constraints. Dezfoulian and Samouei [20] formulated knowledge transfer between the members of a chain level using a novel MIP model and implemented it for the producer level of a dairy supply chain. Moreover, they identified the parameters influencing the knowledge flow network.

A comparison between the few mathematical models (of the knowledge flow network) in terms of the objective function indicates that only Dong et al. [19] presented single-objective, where Dezfoulian et al. [1] and Dezfoulian and Samouei [20] discussed multi-objective. Most papers in this area have considered increasing the level of knowledge. The second objective of Dezfoulian et al. [1] was maximizing knowledge transfer between companies in the cluster with the most substantial level of relationship. Also, the second objective of Dezfoulian and Samouei [20] has been to reduce the knowledge transfer cost. The focus of Dezfoulian et al. [1] and Dezfoulian and Samouei [20] was on inter-organizational knowledge transfer, while that by Dong et al. [19] was on intra-organizational knowledge transfer. Dong et al. [19] solved their model using a heuristic method, while the other two papers have used exact methods.

A review of previous studies showed that the maximization of the knowledge level of personnel in an organization and considering budget and time and the associated formulation in the form of a mathematical model as a powerful analysis tool has been rarely addressed. Furthermore, given the importance of knowledge as an essential resource in organizations and the scarcity of resources (especially budget and time), any action to enhance the level of knowledge is a significant step toward improving the competitive status of the organization. For this reason, the present research focuses on mathematical modeling to improve the level of organizational knowledge using intra-organizational knowledge transfer. For this purpose, professional and personal trust, organizational commitment (which has not been considered in previous research), teaching and learning capabilities, which affect the knowledge transfer process, were considered. For a more realistic model, the stochastic nature of the knowledge transfer duration has been considered. However, previous works have considered all the variables and parameters to be deterministic. The problem has been formulated as a stochastic MIP model and solved using the CPLEX solver and the Lagrangian relaxation algorithm.

3. PROBLEM DESCRIPTION AND MODELING

Knowledge is a critical resource in every organization. It has motivated numerous advanced organizations to manage knowledge and use it to their best advantage. In general, the personnel in an organization do not share equal awareness of different types of knowledge. Each personnel member may be an expert in a particular knowledge and a beginner or an intermediate in the others. The personnel can cooperate in knowledge transfer to improve the overall knowledge level. For the best results, it is necessary to maximize the knowledge in the shortest possible time considering the budget limitation. To this end, the knowledge level of each member must be determined at the outset of the knowledge transfer plan. Beginner, intermediate, and expert levels are defined for each knowledge type. Persons with higher levels of knowledge can teach their knowledge to persons with lower levels. Knowledge transfer is affected by various factors. This model considers professional and personal trust, teaching and learning capability, and organizational commitment for knowledge sharing. The duration of knowledge transfer is impacted by the teaching and learning abilities and the organizational commitment. Therefore, to get closer to the real-world situation, the necessary time of knowledge sharing is considered stochastic. Different areas of knowledge have different levels of significance for other persons. Therefore, different knowledge must be prioritized for each person according to their needs and jobs. Hence, this paper presents a stochastic MIP model for knowledge sharing between the personnel of an organization according to professional and personal trust, teaching and learning abilities, organizational commitment, and type and significance of each knowledge. The objectives of this model are to maximize the knowledge level and minimize the duration of knowledge transfer. The proposed model is considered based on three scenarios, namely optimistic, likely, and pessimistic. Then, the problem is solved for each scenario. Finally, the average of the results is reported based on the opinion of the decision-maker and the probability of each scenario. Clearly, the knowledge transfer time in the pessimistic case is longer than the likely and the optimistic cases.

3.1. Assumptions

The assumptions are as follows:

- The knowledge possesses beginner, intermediate, or expert levels, denominated 1, 2, and 3, respectively.
- The knowledge level of a person who teaches another person is higher than the learner knowledge level.
The teacher cannot learn knowledge from another person during the teaching period.
At the end of the teaching period, the learner’s level is upgraded by 1.
The significance of different knowledge types is equal for other persons during the planning horizon.
Knowledge transfer does not occur during regular work hours.
The knowledge transfer duration depends on the type of knowledge and the teaching capability, learning capability, and organizational commitment.
Knowledge transfer that is impossible to complete during the planning horizon is excluded.
The knowledge transfer cost depends on the type of knowledge and the teaching and learning persons.
The cost of knowledge transfer between the organization’s personnel must not exceed the allocated budget.
The persons are unable to teach and learn several types of knowledge simultaneously.
Teaching and learning happen one-on-one and not in groups.
The pessimistic, likely, and optimistic cases (for the given knowledge transfer duration) have the same probability of occurrence.

The indexes, parameters, and decision variables and their definitions in this model are as follows:

**Indexes**
- \( k \): Teacher
- \( l \): Learner
- \( s \): Knowledge type
- \( t \): Period

**Parameters**
- \( K \): Total number of persons
- \( T \): Planning horizon duration
- \( S \): Total number of knowledge types
- \( \gamma_{ks} \): Significance of knowledge type \( s \) for person \( k \)
- \( \alpha_{kl} \): Professional level of trust between person \( k \) and person \( l \)
- \( \beta_{kl} \): A personal level of trust between person \( k \) and person \( l \)
- \( \bar{t}_{ls} \): Duration of teaching (learning) knowledge type \( s \)
- \( \theta_{kl} \): Teaching capability of person \( k \) to person \( l \)
- \( \lambda_{l} \): Learning capability of person \( l \)
- \( (\pi_{l})_{\pi_{k}} \): Organizational commitment of the teacher (learner)
- \( \zeta_{kl} \): Cost of transferring knowledge type \( s \) from person \( k \) to person \( l \)
- \( M \): A sufficiently large number
- \( C \): The total budget allocated to knowledge teaching in the organization
- \( A \): The threshold for professional trust
- \( B \): The threshold for personal trust

**Decision variables**
- \( x_{klts}^{l} \): \( 1 \) if transferring knowledge type \( s \) from person \( k \) to person \( l \) begins in period \( t \); \( 0 \), otherwise.
- \( e_{kl}^{l} \): \( 1 \) if person \( l \) is learning knowledge type \( s \) during period \( t \); \( 0 \), otherwise.

\[ p_{kl}^{t} \begin{cases} & 1 \text{ if person } k \text{ is teaching knowledge type } s \text{ during period } t; \ 0, \text{ otherwise.} \end{cases} \]

\[ w_{kl}^{t} \begin{cases} & \text{Level of person } k \text{ in knowledge type } s \text{ at the beginning of period } t \end{cases} \]

### 3.2. Mathematical Programming Model

The model presented in this paper is a development of the models by Dezfoolian et al. [1], Dong et al. [19], Dezfoolian and Samouei [20]. The problem is modeled as a bi-objective, linear, stochastic MIP model according to Equations (1)-(17).

\[
\text{Max} \sum_{k=1}^{K} \sum_{s=1}^{S} \gamma_{ks} x_{kl}^{t} w_{kl}^{t} \quad (1)
\]

\[
\text{Min} \sum_{k=1}^{K} \sum_{s=1}^{S} \gamma_{ks} x_{kl}^{t} \sum_{l=1}^{L} (\bar{t}_{ls} \times (1.5 - \theta_{kl} \times \pi_{k})) \times (1.5 - \lambda_{l} \times \pi_{l}) \times X_{kl}^{t} \quad (2)
\]

\[s.t.:\]
\[
\sum_{s=1}^{S} x_{kl}^{t} \leq 1 \quad \forall l \in \{1, 2, ..., K\} \forall t \in \{1, 2, ..., T\} \quad (3)
\]

\[
\sum_{l=1}^{L} \sum_{s=1}^{S} X_{kl}^{t} \bar{t}_{ls} = M \quad \forall k \in \{1, 2, ..., K\} \forall s \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (4)
\]

\[
\sum_{s=1}^{S} x_{kl}^{t} \leq 1 \quad \forall k \in \{1, 2, ..., K\} \forall t \in \{1, 2, ..., T\} \quad (5)
\]

\[
\sum_{l=1}^{L} \sum_{s=1}^{S} X_{kl}^{t} \bar{t}_{ls} = M \quad \forall k \in \{1, 2, ..., K\} \forall s \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (6)
\]

\[
x_{kl}^{t} \leq w_{kl}^{t} - w_{kl}^{t-1} + M \times (1 - \chi_{kl}^{t}) \quad \forall k \in \{1, 2, ..., K\} \forall l \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (7)
\]

\[
x_{kl}^{t} \leq \alpha_{kl} - A + M \times (1 - \chi_{kl}^{t}) \quad \forall k \in \{1, 2, ..., K\} \forall l \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (8)
\]

\[
x_{kl}^{t} \leq \beta_{kl} - B + M \times (1 - \chi_{kl}^{t}) \quad \forall k \in \{1, 2, ..., K\} \forall l \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (9)
\]

\[
\sum_{p=r-t_{rs}+1}^{r_{rs}} \chi_{kp}^{p} \leq 0 \quad \forall k \in \{1, 2, ..., K\} \forall l \in \{1, 2, ..., S\} \quad (10)
\]

\[
w_{kl}^{t+1} = w_{kl}^{t} - d \quad \forall l \in \{1, 2, ..., K\} \forall s \in \{1, 2, ..., S\} \forall t \leq \bar{t}_{ls} \quad (11)
\]

\[
w_{kl}^{t} = w_{kl}^{t-1} + \sum_{k=1}^{K} X_{kl}^{t-\bar{t}_{ls}} \quad \forall l \in \{1, 2, ..., K\} \forall s \in \{1, 2, ..., S\} \forall t > \bar{t}_{ls} \quad (12)
\]

\[
\sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{s=1}^{S} \sum_{t=1}^{T} x_{klts}^{l} \times X_{kl}^{t} \leq C \quad (13)
\]

\[
w_{kl}^{t} \leq 3 \quad \forall k \in \{1, 2, ..., K\} \forall s \in \{1, 2, ..., S\} \forall t \in \{1, 2, ..., T\} \quad (14)
\]
\[ \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{p=1}^{P} \frac{1}{\alpha_k} x_{p,t}^k \leq \left( 1 - \sum_{k=1}^{K} X_{kl}^k \right) \quad \forall l \in \{1, 2, ..., K\}, s \in \{1, 2, ..., S\}, t \in \{T - T_k + 1\} \]  
(15)

\[ \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{p=1}^{P} \frac{1}{\alpha_k} x_{p,t}^k \leq 1 \quad \forall l \in \{1, 2, ..., K\}, s \in \{1, 2, ..., S\}, t \in \{1, 2, ..., T\} \]  
(16)

\[ \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{p=1}^{P} \frac{1}{\alpha_k} x_{p,t}^k \leq 1 \quad \forall l \in \{1, 2, ..., K\}, s \in \{1, 2, ..., S\}, t \in \{1, 2, ..., T\} \]  
(17)

The model consists of two objective functions. The first objective, shown in Equation (1), is maximizing the knowledge level of the organization’s personnel in the last period of the planning horizon, and the second objective, shown in Equation (2), is minimizing the duration of knowledge transfer between the organization’s personnel. Equations (3) and (4) indicate that person \( l \) can learn knowledge from at most one person during period \( t \). Equations (5) and (6) indicate that person \( k \) can teach at most one person during period \( t \). Equations (7), (8), and (9) show that person \( k \) transfers knowledge type \( s \) to person \( l \) during period \( t \) if the knowledge of person \( k \) is at least one level higher than person \( l \) and if the professional trust level \( (\alpha_k) \) and personal trust level \( (\beta_{kl}) \) are higher than \( A \) and \( B \), respectively. Constraint (10) indicates that the initial knowledge level \( s \) in the planning horizon cannot begin in \( T_k - 1 \), since there is insufficient time to learn that knowledge type. Equation (11) shows that the level of knowledge type \( s \) in person \( l \) is the same as the initial level during the first periods of the planning horizon. Equation (12) indicates that the knowledge type \( s \) in person \( l \) increases by 1 level after training (period \( T_k \)). Constraint (13) shows that the total cost of transferring knowledge from the teachers \( k \) to the learners \( l \) during the planning horizon cannot exceed the allocated budget \( C \). Constraint (14) shows that the knowledge level of all persons in all the knowledge types must not exceed the highest level defined for expertise during the planning horizon. Equation (15) indicates that if \( X_{kl}^k \) equals one at the beginning of period \( t \), person \( l \) cannot learn from another person during the subsequent \( T_k - 1 \) periods. Equation (16) indicates that while person \( l \) is learning knowledge type \( s \) from person \( k \), a learning higher level of this knowledge from other persons is impossible. Constraint (17) shows that no more than one person can simultaneously learn knowledge \( s \) from person \( k \) during period \( t \).

4. SOLUTION METHOD

The Lagrangian relaxation method is used to solve the model of the knowledge flow network between an organization’s personnel. Hence, first, the algorithm is introduced and, then, the results obtained from solving the model in small, medium, and large scales are presented.

4.1. LP-Metric Method

A multi-objective decision-making model consists of a vector of decision variables, objective functions, and constraints to maximize or minimize the objective functions. Since such problems rarely have a unique solution, the decision-maker selects a solution from among a set of efficient solutions.

The LP-Metric method is a multi-criteria decision-making method (MCDM) that can solve multi-objective decision-making models (MODMs). This method minimizes the sum of the powers of the relative deviations of the objectives from their optimal values and combines several objective functions into a single objective. The LP-Metric method drew interest for two reasons:

- It requires less information from the decision-maker.
- It is practically simple to use.

The point \( x^* \) is called an ideal point if it simultaneously optimizes all the objectives in a problem. However, such a solution does not usually exist due to the conflicts between different objectives. Another definition for the ideal point is when the optimal value of each objective function is determined separately. Then, the metric distance in the LP methods is used to measure the proximity of a solution to the ideal solution.

The parameter \( 1 \leq P \leq \infty \) determines the LP family. The value of \( P \) determines the degree of priority on the present deviations, such that the higher this value is, the higher the emphasis will be on the most considerable variations. Moreover, \( P = \infty \) means that the most significant variations will be considered from among the existing variations for the optimization. The values \( P=1, P=2, \) and \( P=\infty \) are usually used in the calculations and it depends on the decision-maker in any case.

Since the value of LP-Metric can be affected by the measurement scale of the objectives (in case these scales are different), the following formula can be used to resolve this issue:

\[ LP = \sum_{i=1}^{K} w_i \left( \frac{f_i(x^*) - f_i(x)}{f_i(x^*) - f_i(x^*)} \right)^{P/2} \]  
(18)

The metric distance obtained from Equation (18) varies between zero and one. The maximum values of the objectives are desired. \( x^* \) denotes the ideal solution in optimizing the \( i^{th} \) objective, \( x^i \) is a solution that minimizes \( f_i \), \( x \) represents a given solution, and \( w_i \) indicates the significance (weight) of the \( i^{th} \) objective. The LP-Metric function must be minimized to minimize deviations from the ideal value. If the objectives are minimization, the LP formula is obtained as Equation (19):
\[
LP = \left\{ \sum_{i=1}^{K} w_i \left[ \frac{f_i(x) - f_i(x')}{f_i(x) - f_i(x')} \right] p_i \right\}^{\frac{1}{p}}
\]  
(19)

All the objective functions (minimization and maximization) are added via the LP-Metric method, and the minimum value of the overall function is calculated. In the LP-Metric technique, the preferences of the decision-maker to various objectives are represented by their related weights.

For this purpose, we used lower bound, and upper bound for each objective function, and calculated Z3 according to the following equation:

\[
Z_3 = w_1 (\frac{UB1-z_1}{UB1-LB1}) + w_2 (\frac{z_2-LB2}{UB2-LB2})
\]  
(20)

UB1 (upper bound 1), LB1 (lower bound 1), UB2 (upper bound 2), and LB2 (lower bound 2) are the bounds of Z1, and Z2, respectively. For UB1, LB1, UB2, and LB2 calculation, we used the following relations:

\[
UB1 = \sum_s \sum_k w_{ks} \gamma_{ks}
\]  
(21)

The first objective function is maximizing the knowledge level of the organization’s personnel in the last period of the planning horizon. Clearly, according to situations, knowledge is transferred from the first to the last period. Since the maximum level of each knowledge (for the experts) is three, we used this value for UB1. Because this objective function value cannot exceed this value.

\[
LB1 = \sum_s \sum_k w_{ks} \gamma_{ks}
\]  
(22)

In lower bound 1 we used the knowledge level of each person at the first period. Clearly, after knowledge sharing, the level of the organization’s personnel in the last period of the planning horizon cannot be less than their initial levels.

\[
LB2=0
\]  
(23)

The second objective function is minimizing the duration of knowledge transfer between the organization’s personnel. We choose LB2=0. If we don’t have any knowledge sharing, we will not consume any time for teaching or learning. Therefore, this value can be 0.

\[
UB2=\sum_{k=1}^{K} \sum_{s=1}^{S} \sum_{r=1}^{R} (T_{rs} \times (1.5 - \min(\theta_k \times \pi_k)) \times (1.5 - \min(\lambda_i \times \pi_i))) (3 - w_{rs})
\]  
(24)

For upper bound 2 calculation, we considered to maximum necessary time for all persons to become experts or have level 3 in all the fields. In the worst case, we assume two persons with the first and the second-lowest organizational commitment to be teacher and learner. Clearly, for these persons minimum teaching and learning capabilities are considered. Therefore, in UB2 we used \(\min(\theta_k \times \pi_k)\) and \(\min(\lambda_i \times \pi_i)\).

4. 2. Lagrangian Relaxation Method

The Lagrangian relaxation method is a common technique for solving some optimization problems. This method was first introduced by Held and Karp to solve the Traveling Salesman Problem (TSP) and is a technique that solves a constrained and hard optimization problem via a more straightforward problem. The main idea behind Lagrangian relaxation is relaxing the complicated constraints, multiplying them by coefficients called Lagrangian multipliers, and adding them to the objective function of the problem. The relaxed problem is expected to be easier to solve than the original problem due to eliminating some of the constraints and the enlargement of the feasible region.

The relaxation of the Lagrangian multipliers as a method to obtain the upper (lower) bounds of the objective functions of mathematical problems attracted interest after the successful solution of the TSP, the scale of which was considerably large compared to the computational power of the time, in 1970. Given the computational burden in large-sized problems, determining the upper and lower bounds is of utmost significance in increasing the method’s efficiency.

The Lagrangian relaxation algorithm begins by considering a \(\lambda\) for each constraint. The \(\lambda\)‘s, called Lagrangian multipliers, act as shadow prices in linear programming (\(\lambda\) represents the variation of the objective function for a unit change in the number to the right of the corresponding constraint). Then, the Lagrangian function, which is a combination of the constraints and the objective function, is formulated as Equation (25):

\[
\theta(x, \lambda) = f(x) + \sum_{i=1}^{m} \lambda_i [b_i - g_i(x)]
\]  
(25)

In this equation, \(\theta(x, \lambda)\) denotes the objective function of the relaxed problem, \(f(x)\) represents the objective function of the original problem, \(b_i\) is the right side of the relaxed constraint, and \(g_i(x)\) denotes the left side of the relaxed constraint. Finally, the derivatives of the Lagrangian function are calculated for each of the variables separately [21].

In this research, Lagrangian relaxation is used to solve the presented model. It is done by adding each relaxed constraint to the objective function of the problem with a Lagrangian multiplier. To find appropriate Lagrangian multipliers a loop is formed, and the problem is solved with different values. The solution obtained from the Lagrangian relaxation algorithm may violate the relaxed constraints. The steps of the Lagrangian relaxation algorithm are presented as follows:

1. Calculate an initial upper bound (UB) and LB\(^*\)= \(-\infty\) and the vector of the initial Lagrangian coefficient (\(\lambda\)).
2. Solve the relaxed problem (D) and compute x\(^*\) and LB.
3. If LB>LB\(^*\), then LB\(^*\)=LB.
4. \( \lambda(t) = \lambda(t - 1) + k(b - Ax) \) while \( k = \theta \frac{UB - LB^*}{\sum_{i=1}^{n}(b_i - a_i x_i)^2} \)

5. If after \( m \) consecutive repetitions there is no improvement in the amount of the best limit then \( \theta = \theta/2. \)

6. Refer to the second step and continue until the algorithm stops.

5. Sensitivity analysis

In this section, Table 1 introduces several small, medium, and large-sized problems. Then, various sensitivity analysis results are presented. After ensuring the model’s validity, the sample problem is solved using the Lagrangian relaxation method at the mentioned scales in pessimistic, likely, and optimistic cases.

Sample problem 1 consists of 5 persons, three types of knowledge, and a 4-period planning horizon. The sensitivity of this problem was analyzed using the LP-Metric objective function, with the result shown in Figure 3-9. Figures 1 and 2 show the Pareto layer of the objective functions and the Pareto layer of the probability of the pessimistic, likely, and optimistic cases.

Figure 1 displays all eleven cases of the Pareto layer for the average objective functions in pessimistic, likely, and optimistic conditions. In the first case, the weight of the first objective function is considered 1, and that of the second objective function is regarded zero. Then, 0.1 is deducted from the weight of the first objective function and added to that of the second objective function case by case until all the eleven cases are formed.

As shown in Figure 1, up to the 5th case, the weight of the first objective function is reduced and the weight of the second objective function is increased. In these conditions, the LP-Metric objective function varies from zero in the first case to 0.275 in the 5th case. From the 5th case up to the 11th case, the weight of the first objective function is reduced and the weight of the second objective function is increased. The LP-Metric objective function varies from 0.275 to zero.

Figure 2 shows the results of the objective function for the optimistic (1), likely (2), pessimistic (3) and average (4) situations for a problem. Average situation is calculated as follows:

\[
pessimistic\text{ situation} + 4 \times \text{likely situation} + \text{optimistic situation}
\]

(26)

![Figure 1. Pareto layer of the LP-Metric objective function](image1)

![Figure 2. Pareto layer of the probability of occurrence of random cases](image2)

### TABLE 1. Sample problem size

| Sample Problems | Size  | Number of Persons | Number of Knowledge | Planning Horizon |
|-----------------|-------|-------------------|---------------------|------------------|
| 1               | 5     | 3                 | 4                   |                  |
| 2               | 10    | 3                 | 4                   |                  |
| 3               | Small | 15                | 4                   | 5                |
| 4               |       | 20                | 4                   | 5                |
| 5               |       | 25                | 5                   | 6                |
| 6               |       | 50                | 5                   | 6                |
| 7               |       | 55                | 6                   | 7                |
| 8               | Medium| 60                | 6                   | 7                |
| 9               |       | 65                | 6                   | 8                |
| 10              |       | 70                | 7                   | 8                |
| 11              |       | 100               | 7                   | 8                |
| 12              |       | 105               | 8                   | 8                |
| 13              |       | 110               | 8                   | 9                |
| 14              |       | 120               | 7                   | 9                |
| 15              |       | 130               | 8                   | 10               |
| 16              |       | 130               | 11                  | 12               |
| 17              |       | 130               | 12                  | 12               |
| 18              | Large | 135               | 13                  | 12               |
| 19              |       | 135               | 14                  | 12               |
| 20              |       | 140               | 15                  | 12               |
| 21              |       | 140               | 16                  | 12               |
| 22              |       | 145               | 17                  | 12               |
| 23              |       | 145               | 18                  | 12               |
| 24              |       | 150               | 19                  | 12               |
| 25              |       | 150               | 20                  | 12               |
It must be noted that the sensitivity analysis in this section, performed in sample problem 1 for likely situation.

Figure 3 shows that an increase in the planning horizon increases the time available for knowledge transfer, leading to a rise in the knowledge level and an increase in the duration of knowledge transfer in the organization.

Figures 4-9 display sensitivity analysis of the teaching and learning capabilities, the organizational commitment, and the professional and personal trust in a range of -100 to 100%.

Figures 4 and 5 show that an increase in the teaching capability and learning capability merely reduces the second objective function, i.e., duration of knowledge transfer, and does not affect the first objective function, i.e., knowledge level of the organization. Also, the teaching capability has more significant effect on the second objective function than does the learning capability, such that a 100% increase in the teaching capability leads to a 12% decrease in the second objective function. In comparison, a 100% increase in the learning capability results in only a 5% decrease in this function. Furthermore, a 100% reduction in the teaching capability increases the second objective function by about 107%, while a reduction in the learning capability increases it by only about 41%.

The impact of changes in the organizational commitment on the objective function is shown in Figure 6. Similar to the last two parameters, organizational commitment only reduces the duration of knowledge transfer (second objective function) and does not affect on the knowledge level in the organization. A 100% increase in this parameter reduces the knowledge transfer duration by 35%, and a 100% decrease in it increases the knowledge transfer duration by 194%. These values indicate that the influence of organizational commitment on knowledge transfer duration is greater than those of teaching and learning capabilities.

Regarding Figures 6, 7, and 8, it must be mentioned that the model constraints associated with professional and personal trust indicate that these parameters are interdependent, and knowledge transfer occurs only when they exceed the specified thresholds.

Figure 7 indicates the sensitivity analysis of professional trust. As can be seen, the knowledge transfer and its duration increase by 4 and 103%, with a 100% increase in this parameter decreases the knowledge transfer duration by 12%.
increase in professional trust. In addition, a reduction in this parameter does not change the objective function since it violates the threshold and Constraint 8.

As observed in Figure 8, in this particular problem, a 100% increase in personal trust has no impact on the two objective functions due to the dependence of this parameter on professional trust. This is evident in Figure 9, which displays the simultaneous change of professional and personal trust.

Simultaneous changes in personal trust and professional trust these parameters are analyzed in Figure 9. It shows a 100% increase in professional and personal trust increases the first and second objective functions by 4 and 194%, respectively.

6. COMPUTATIONAL RESULTS AND DISCUSSION

In this section, the problems are solved at small, medium, and large scales using the CPLEX solver and Lagrangian relaxation and compared. It is worth mentioning that knowledge transfer occurs between persons if the professional and personal trust values are higher than the specified thresholds. The thresholds considered for the professional and personal trust values in all the problems studied in this paper were selected based on the quantitative research presented by Ouakouak and Ouedraogo [16], conducted among 307 employees in Canadian organizations. All the structures in their study have been measured according to the 5-point Likert scale. The following questions were asked of the employees for professional and personal trust. The resulting average professional trust and personal trust threshold values obtained for knowledge transfer were 0.822 and 0.653, respectively (see Table 2).

6.1. Solution of Small-scale Problems

In this section, 5 sample problems are evaluated. The pessimistic, likely, and optimistic cases were generated for each sample problem and solved using the LP-metric method in GAMS software and the Lagrangian relaxation algorithm. The objective function values and computation time for each sample are shown in Tables 3 and 4.

Figures 10-13 are for a better comparison of the solution methods using the values in Tables 3 and 4. These figures show the Lagrangian relaxation method usually produces better results than the CPLEX solver for the first objective function.

TABLE 2. Factors affecting the determination of professional and personal trust [16]

| Parameter          | Question                                                                 |
|--------------------|---------------------------------------------------------------------------|
| Professional Trust | I believe my colleagues trust me to perform my tasks correctly.            |
|                    | I trust my colleagues in their ability to perform their tasks correctly.   |
|                    | I believe that my colleagues perform tasks assigned to them professionally and committedly. |
| Personal Trust     | I believe that the intentions and motivations of my colleagues are sincere. |
|                    | I believe that my colleagues look after my interests.                     |
TABLE 3. Solution of the small-scale problems using GAMS software

| Problem | Indicator | GAMS Software |      |      |      |
|---------|-----------|---------------|------|------|------|
|         |           | Pessimistic   | Likely | Optimistic |
| 1       | Z1        | 18.748        | 18.748 | 19.082 |
|         | Z2        | 1.537         | 1.537  | 2.149  |
|         | Solve Time | 0.311         | 0.335  | 0.344  |
| 2       | Z1        | 34.657        | 35.002 | 35.002 |
|         | Z2        | 8.119         | 6.368  | 6.368  |
|         | Solve Time | 0.639         | 0.558  | 0.697  |
| 3       | Z1        | 52.654        | 53.019 | 55.598 |
|         | Z2        | 9.948         | 9.948  | 17.568 |
|         | Solve Time | 1.213         | 1.236  | 1.342  |
| 4       | Z1        | 87.510        | 87.510 | 88.418 |
|         | Z2        | 8.978         | 8.978  | 12.086 |
|         | Solve Time | 1.798         | 1.909  | 1.900  |
| 5       | Z1        | 142.234       | 143.123| 143.123|
|         | Z2        | 36.046        | 41.339 | 40.016 |
|         | Solve Time | 3.365         | 3.714  | 3.892  |

TABLE 4. Solution of the small-scale problems using the Lagrangian relaxation method

| Problem | Indicator | Lagrangian Relaxation Method |      |      |      |
|---------|-----------|------------------------------|------|------|------|
|         |           | Pessimistic | Likely | Optimistic |
| 1       | Z1        | 21.101       | 21.553 | 23.570 |
|         | Z2        | 5.618        | 7.132  | 9.857  |
|         | Solve Time | 3.096        | 3.223  | 3.387  |
| 2       | Z1        | 38.779       | 40.012 | 40.843 |
|         | Z2        | 14.933       | 14.367 | 17.567 |
|         | Solve Time | 4.864        | 4.459  | 4.850  |
| 3       | Z1        | 58.305       | 63.115 | 67.844 |
|         | Z2        | 21.595       | 36.120 | 33.315 |
|         | Solve Time | 5.786        | 7.910  | 7.922  |
| 4       | Z1        | 97.333       | 101.076| 103.308|
|         | Z2        | 22.278       | 33.476 | 32.650 |
|         | Solve Time | 9.120        | 10.561 | 11.233 |
| 5       | Z1        | 147.855      | 154.252| 156.588|
|         | Z2        | 47.983       | 79.270 | 81.115 |
|         | Solve Time | 15.066       | 17.088 | 17.076 |

6. 2. Solution Of Medium-Scale Problems

In this section, Sample Problems 6-10 are evaluated. The pessimistic, likely, and optimistic cases were generated.
for each sample problem and solved using the CPLEX solver in the GAMS software and the Lagrangian relaxation algorithm. The objective function values and computation time for each sample are shown in Tables 5 and 6.

Figures 14-17 are for a better comparison of the solution methods using the values in Tables 5 and 6. As can be seen in these figures, more knowledge transfer occurs in the Lagrangian relaxation method than in the solution using the CPLEX solver. For the larger problems, the Lagrangian relaxation method reaches the solution faster than the CPLEX solver.

6.3. Solution of Large-scale Problems In this section, five large-scale sample problems are evaluated. The pessimistic, likely, and optimistic cases were
generated for each sample problem and solved using the CPLEX solver and the Lagrangian relaxation algorithm. The objective function values and computation time for each sample are shown in Tables 7 and 8.

**Figure 14.** Average graph of the objective functions of the medium-scale sample problems in the optimistic case

**Figure 15.** Average graph of the objective functions of the medium-scale sample problems in the likely case

**Figure 16.** Average graph of the objective functions of the medium-scale sample problems in the pessimistic case

**Figure 17.** Average graph of the objective functions of the medium-scale sample problems
### TABLE 7. Solution of the large-scale problems using GAMS software

| Problem | Indicator | GAMS Software |
|---------|----------|---------------|
|         |          | Pessimistic   | Likely       | Optimistic  |
| Z1      | 825.429  | 867.715       | 901.553     |
| 11      | 342.826  | 394.597       | 371.124     |
| Solve Time | 1060.848 | 1068.224      | 1067.315    |
| Z1      | 986.869  | 1006.240      | 1030.502    |
| Z2      | 312.949  | 332.498       | 403.207     |
| Solve Time | 1083.767 | 1092.608      | 1095.609    |
| Z1      | 987.680  | 1033.086      | 1067.017    |
| 12      | 453.209  | 551.923       | 563.889     |
| Solve Time | 1109.767 | 1116.027      | 1122.732    |
| Z1      | 963.671  | 983.462       | 1008.336    |
| Z2      | 446.644  | 438.087       | 429.772     |
| Solve Time | 1114.210 | 1123.539      | 1122.166    |
| Z1      | 1207.750 | 1227.054      | 1233.216    |
| Z2      | 382.905  | 416.643       | 425.026     |
| Solve Time | 1161.307 | 1167.212      | 1174.656    |
| Z1      | 1168.396 | 1283.952      | 1475.807    |
| 15      | 416.603  | 457.806       | 526.214     |
| Solve Time | 1493.652 | 1573.324      | 1634.021    |
| Z1      | 1412.303 | 1569.225      | 1705.679    |
| Z2      | 452.956  | 503.284       | 547.048     |
| Solve Time | 1721.320 | 1764.378      | 1813.225    |
| Z1      | 1631.315 | 1733.169      | 2086.081    |
| Z2      | 390.268  | 424.204       | 499.063     |
| Solve Time | 1853.326 | 1893.601      | 1961.254    |
| Z1      | 1952.676 | 2194.018      | 2411.009    |
| Z2      | 486.913  | 547.093       | 601.201     |
| Solve Time | 2002.336 | 2010.325      | 2029.321    |
| Z1      | 2414.407 | 2624.355      | 2948.714    |
| Z2      | 474.915  | 516.212       | 580.014     |
| Solve Time | 2998.356 | 2180.957      | 2259.325    |
| Z1      | 2686.056 | 2951.710      | 3354.216    |
| Z2      | 509.380  | 559.758       | 636.089     |
| Solve Time | 2323.255 | 2490.521      | 2501.378    |
| Z1      | 2756.253 | 3178.452      | 3695.874    |
| Z2      | 486.981  | 559.748       | 650.870     |
| Solve Time | 2651.355 | 2730.301      | 2681.021    |
| Z1      | 2750.099 | 3197.790      | 3997.238    |
| Z2      | 445.547  | 518.078       | 647.598     |
| Solve Time | 2932.631 | 3110.665      | 3054.221    |

### TABLE 8. Solution of the large-scale problems using the Lagrangian relaxation method

| Sample Problems | Indicator | Lagrangian Relaxation Method |
|-----------------|----------|------------------------------|
|                 |          | Pessimistic | Likely | Optimistic |
| 24              | Z1       | 3527.419    | 3876.285 | 4259.654 |
|                 | Z2       | 497.898     | 547.141  | 601.254  |
|                 | Solve Time | 3742.332    | 3893.602 | 3721.225 |
| 25              | Z1       | 3645.842    | 4050.936 | 4501.040 |
|                 | Z2       | 569.065     | 632.294  | 702.549  |
|                 | Solve Time | 4398.021    | 4553.221 | 4630.232 |

Note: The table entries represent the solution times (in seconds) for different problems and indicators using various software and methods.
Table 10. Comparison results for different cases with two objective functions

| Case | Z1 | Z2 | Solve Time |
|------|----|----|------------|
| 22   | 764.431 | 840.034 | 954.584 |
| Z1   | 1433.109 | 1574.845 | 1789.597 |
| 21   | 633.885 | 728.604 | 847.214 |
| Z1   | 2806.825 | 3263.750 | 4079.687 |
| 23   | 515.002 | 598.838 | 748.547 |
| Z1   | 1385.652 | 1611.223 | 2014.029 |
| 24   | 3760.662 | 4132.596 | 4541.314 |
| Z1   | 2843.906 | 3268.857 | 4541.314 |
| 25   | 847.191 | 941.323 | 1045.914 |
| Z1   | 1993.308 | 2214.787 | 2460.874 |

Figures 18-21 were plotted for a better comparison of the solution methods using the values in Tables 7 and 8. They showed that the Lagrangian relaxation method can transfer more knowledge than GAMS. Furthermore, the Lagrangian relaxation method is usually faster than the GAMS computational time.

Figure 18. Average graph of the objective functions of the large-scale sample problems in the optimistic case

Figure 19. Average graph of the objective functions of the large-scale sample problems in the likely case

Figure 20. Average graph of the objective functions of the large-scale sample problems in the pessimistic case
7. CONCLUSION AND SUGGESTIONS

In the present knowledge-based era, knowledge as the most valuable capital in organizations, requires a novel management approach toward issues concerning the organization and the personnel. A change in the nature of activities performed in organizations toward knowledge-based ones has increased the essential of knowledge management. One of the most important knowledge management processes is knowledge transfer, which it can be done by internal or external resources of an organization. Clearly, knowledge upgrade in an organization using external resources requires more time and budget. For this reason, reliance on internal resources is preferred in organizations. Factors such as professional and personal trust and organizational commitment play a key role in such knowledge transfer.

This paper designs a knowledge flow network between the personnel of an organization using stochastic MIP for maximizing the knowledge level and minimizing the knowledge transfer duration time. To solve the knowledge flow network model, several sample problems were designed; then, sensitivity analyses were performed on one of the sample problems. After model’s validity several small, medium, and large-sized problems in pessimistic, likely, and optimistic cases were solved using the CPLEX solver and the Lagrangian relaxation method. Finally, a comparison was drawn between the methods. The results indicate that organizational commitment has the most considerable effect on the knowledge transfer duration, followed by teaching and learning capabilities. Moreover, the effect of an increase in professional trust is considerably more significant on the reduction in the knowledge transfer duration than on the increase in the knowledge level. It indirectly contributes to a decrease in the costs of knowledge transfer. Comparing the two solution methods indicates that the Lagrangian relaxation algorithm produces better results than the CPLEX solver in all cases and reaches the solution faster in larger problems.

Given the increasing importance of knowledge management and knowledge transfer in organizations and the lack of quantitative research on this topic, various approaches can be taken to develop the work in this paper. Examples include using multiple teaching methods in the knowledge transfer process, considering the possibility of group teaching, and assuming stochastic learning. Furthermore, using rough set theory in the field of knowledge management is another direction of developing our future investigations.

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Persian Abstract

انتقال دانش در دو سطح درون سازمانی و بین سازمانی می‌تواند انجام شود با کمک دانش‌گرایی دانش از خارج از سازمان نیاز به بودجه و زمان قابل توجهی دارد. در حالی که با اشتراک و انتقال دانش موجود در سازمان که توسط کارکنان انجام می‌گردد، نیاز به بودجه و زمان قابل توجهی ندارد. این امر نشان‌دهنده اهمیت تأکید بر دانش از خارج از سازمان در سازمان‌های کوچک، متوسط و بزرگ دارد. همچنین نتایج نشان می‌دهد که افزایش آموزش و پرورش کارکنان و پایداری در دانش‌گرایی دانش‌های مورد نظر، نشان از کارایی بالای الگوریتم آزاد است که در این مقاله به آن پرداخته می‌شود.