International Journal of Engineering

Journal Homepage: www.ije.ir

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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PAPER INFO

Paper history:
Received 5 November 2021
Received in revised form 3 February 2022
Accepted 13 February 2022

Keywords:
Nowledge Flow Network
Knowledge Transfer
Stochastic Programming
Lagrangian Relaxation

ABSTRACT

Knowledge transfer can occur on two levels: intra-organizational and inter-organizational. Acquiring knowledge from outside an organization usually requires significant budget and considerable time. However, through awareness and reliance on knowledge already acquired by the personnel, and creating a knowledge flow network, knowledge level of the organization can be increased in the shortest possible time. The present paper addresses the design of a knowledge flow network between the personnel of an organization according to the professional and personal trust levels, teaching and learning capabilities, knowledge level of the personnel, organizational commitment level, type and importance of each knowledge, and the stochastic nature of the knowledge transfer duration. This problem was formulated as a stochastic multi-objective mixed-integer programming. The objectives of the proposed model were maximizing the knowledge level and minimizing the knowledge transfer time. The model was solved using the Lagrangian relaxation algorithm and the CPLEX solver. Results indicate the high efficiency of the Lagrangian relaxation algorithm specially in computational time of large-sized problems. Moreover, the results show that the organizational commitment parameter has more significant influence on the knowledge transfer duration, followed by teaching and learning capabilities.

doi*: 10.5829/ije.2022.35.06c.07*

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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Please cite this article as: A. Makarchi, H. R. Dezfoulian, P. Samouei, Design of a Knowledge Flow Network for the Personnel of an Organization under Various Scenarios and its Solution using Lagrangian Relaxation, ***International Journal of Engineering, Transactions C: Aspects***, Vol. 35, No. 06, (2022) 1154-1169

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	Periods

Parameters

K	Total number of persons
T	Planning horizon duration
S	Total number of knowledge types
γ_{ks}	Significance of knowledge type s for person k
α_{kl}	Professional level of trust between person k and person l
β_{kl}	A personal level of trust between person k and person l
$\widetilde{tt_s}$	Duration of teaching (learning) knowledge type s
θ_k	Teaching capability of person k
λ_l	Learning capability of person l
$(\pi_l)\ \pi_k$	Organizational commitment of the teacher (learner)
ζ_{kls}	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_{kls}^t	1, if transferring knowledge type s from person k to person l begins in period t; 0, otherwise.
E_{ls}^t	1, if person l is learning knowledge type s during period t; 0, otherwise.
F_{ks}^t	1 if person k is teaching knowledge type s during period t; 0, otherwise.
W_{ks}^t	Level of person k in knowledge type s at the beginning of period t

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

$$Max \sum_{k=1}^{K} \sum_{s=1}^{S} \gamma_{ks} \times W_{ks}^{T} \tag{1}$$

$$Min \sum_{k=1}^{K} \sum_{\substack{l=1 \\ k\neq l}}^{K} \sum_{s=1}^{S} \sum_{t=1}^{T} \left(\widetilde{tt_s} \times (1.5-\theta_k \times \pi_k) \times (1.5-\lambda_l \times \pi_l) \right) \times X_{kls}^t \tag{2}$$

$s.t.$:

$$\sum_{s=1}^{S} E_{ls}^t \leq 1 \quad ,\forall l \in \{1,2,\dots,K\}, \forall t \in \{1,2,\dots,T\} \tag{3}$$

$$\left(\frac{\sum_{\substack{k=1 \\ k\neq l}}^{K} \sum_{p=t-\widetilde{tt_s}+1}^{t} X_{kls}^p}{M} \right) \leq E_{ls}^t \quad ,\forall l \in \{1,2,\dots,K\}, \forall s \in \{1,2,\dots,S\}, \forall t \in \{1,2,\dots,T\} \tag{4}$$

$$\sum_{s=1}^{S} F_{ks}^t \leq 1 \quad ,\forall k \in \{1,2,\dots,K\}, \forall t \in \{1,2,\dots,T\} \tag{5}$$

$$\left(\frac{\sum_{\substack{l=1 \\ l\neq k}}^{K} \sum_{p=t-\widetilde{tt_s}+1}^{t} X_{kls}^p}{M} \right) \leq F_{ks}^t \quad ,\forall k \in \{1,2,\dots,K\}, \forall s \in \{1,2,\dots,S\}, \forall t \in \{1,2,\dots,T\} \tag{6}$$

$$X_{kls}^t \leq W_{ks}^t - W_{ls}^t + M \times (1 - X_{kls}^t) \quad ,\forall k, l \in \{1,\dots,K\}, k \neq l, \forall s \in \{1,\dots,S\}, t < (T - \widetilde{tt_s} + 1) \tag{7}$$

$$X_{kls}^t \leq \alpha_{kl} - A + M \times (1 - X_{kls}^t) \quad ,\forall k, l \in \{1,\dots,K\}, k \neq l, \forall s \in \{1,\dots,S\}, t < (T - \widetilde{tt_s} + 1) \tag{8}$$

$$X_{kls}^t \leq \beta_{kl} - B + M \times (1 - X_{kls}^t) \quad ,\forall k, l \in \{1,\dots,K\}, k \neq l, \forall s \in \{1,\dots,S\}, t < (T - \widetilde{tt_s} + 1) \tag{9}$$

$$\sum_{p=T-\widetilde{tt_s}+1}^{T} X_{kls}^p \leq 0 \quad ,\forall k, l \in \{1,\dots,K\}, k \neq l, \forall s \in \{1,\dots,S\} \tag{10}$$

$$W_{ls}^{t+1} = W_{ls}^t \quad ,l \in \{1,2,\dots,K\}, s \in \{1,2,\dots,S\}, t < \widetilde{tt_s} \tag{11}$$

$$W_{ls}^t = W_{ls}^{t-1} + \sum_{\substack{k=1 \\ k\neq l}}^{K} X_{kls}^{t-\widetilde{tt_s}} \quad ,l \in \{1,2,\dots,K\}, s \in \{1,2,\dots,S\}, t > \widetilde{tt_s} \tag{12}$$

$$\sum_{k=1}^{K} \sum_{\substack{l=1 \\ k\neq l}}^{K} \sum_{s=1}^{S} \sum_{t=1}^{T} \zeta_{kls} \times X_{kls}^t \leq C \tag{13}$$

$$W_{ks}^t \leq 3 \quad ,\forall k \in \{1,2,\dots,K\}, s \in \{1,2,\dots,S\}, \forall t \in \{1,2,\dots,T\} \tag{14}$$

$$\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{p=t+1}^{t+\widetilde{tt}_s-1}X_{kls}^{p}\leq\left(1-\sum_{\substack{k=1\\k\neq l}}^{K}X_{kls}^{t}\right)\ ،\forall l\in\{1،2،\dots،K\}،s\in\{1،2،\dots،S\}،t\leq(T-\widetilde{tt}_s+1) \quad (15)$$

$$\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{p=t}^{t+\widetilde{tt}_s}X_{kls}^{p}\leq 1 \quad ،\forall l\in\{1،2،\dots،K\}،\forall s\in\{1،2،\dots،S\}،\forall t\in\{1،2،\dots،T\} \quad (16)$$

$$\sum_{\substack{l=1\\k\neq l}}^{K}\sum_{p=t}^{t+\widetilde{tt}_s}X_{kls}^{p}\leq 1 \quad ،\forall k\in\{1،2،\dots،K\}،\forall s\in\{1،2،\dots،S\}،\forall t\in\{1،2،\dots،T\} \quad (17)$$

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 (α_{kl}) and personal trust level (β_{kl}) are higher than A and B, respectively. Constraint (10) indicates that the last period of teaching knowledge type s in the planning horizon cannot begin in $\widetilde{tt}_s - 1$, 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 $\widetilde{tt}_s$ initial periods of the planning horizon. Equation (12) indicates that the knowledge type s in person l increases by 1 level after training (period tt_s). 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_{kls}^{t} equals one at the beginning of period t, person l cannot learn from another person during the subsequent $\widetilde{tt}_s - 1$ periods. Equation (16) indicates that while person l is learning knowledge type s from person k, learning a 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:

$$LP=\left\{\sum_{i=1}^{k}w_i\left[\frac{f_i(x^{*i})-f_i(x)}{f_i(x^{*i})-f_i(\tilde{x}^{i})}\right]^{p}\right\}^{\frac{1}{p}} \quad (18)$$

The metric distance obtained from Equation (18) varies between zero and one. The maximum values of the objectives are desired. x^{*i} denotes the ideal solution in optimizing the i^th objective, $\tilde{x}^{i}$ 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):

$$LP = \left\{\sum_{i=1}^{k} w_i \left[\frac{f_i(x)-f_i(\tilde{x}^i)}{f_i(x^{*i})-f_i(\tilde{x}^i)}\right]^p\right\}^{\frac{1}{p}} \quad (19)$$

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:

$$Z3 = w1\left(\frac{UB1-z1}{UB1-LB1}\right) + w2\left(\frac{z2-LB2}{UB2-LB2}\right) \quad (20)$$

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:

$$\mathrm{UB1} = \sum_s \sum_k 3\gamma_{ks} \quad (21)$$

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.

$$\mathrm{LB1} = \sum_s \sum_k w_{ks}^1 \gamma_{ks} \quad (22)$$

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.

$$\mathrm{LB2}=0 \quad (23)$$

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.

$$\mathrm{UB2}=\sum_{\substack{l=1 \\ k\neq l}}^{K} \sum_{s=1}^{S} \sum_{k=1}^{K} \left(\widetilde{tt_s} \times (1.5 - min1(\theta_k \times \pi_k)) \times (1.5 - min2(\lambda_l \times \pi_l))\right)(3 - w_{ks}^1) \quad (24)$$

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 $min1(\theta_k \times \pi_k)$ and $min2(\lambda_l \times \pi_l)$.

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 Krap 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 λ for each constraint. The λ's, called Lagrangian multipliers, act as shadow prices in linear programming (λ 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):

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

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*= -∞ and the vector of the initial Lagrangian coefficient (λ).
2. Solve the released problem (D) and compute x* and LB.
3. If LB>LB*, then LB*=LB.

4. $\lambda^{(t)} = \lambda^{(t-1)} + k(b-Ax)$ while $k = \theta \frac{UB-LB^*}{\sum_{i=1}^{n}(b_i - a_i x^*)^2}$

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 Figures3-9. 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.

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

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:

$$\frac{\text{pessimistic situation}+4*\text{likelysituation}+\text{optimistic situation}}{6} \tag{26}$$

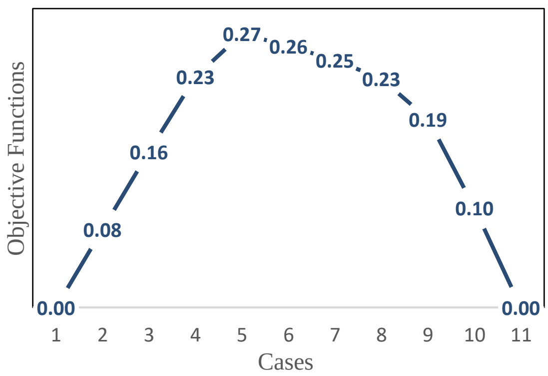


Figure 1. Pareto layer of the LP-Metric objective function

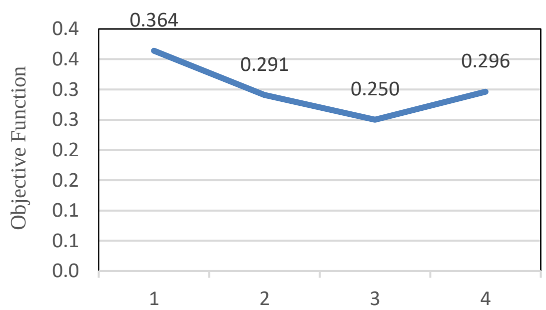


Figure 2. Pareto layer of the probability of occurrence of random cases

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 inter-dependent, 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%

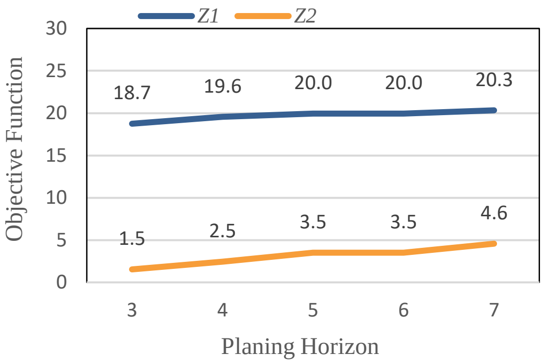


Figure 3. Effect of a change in the planning horizon on the objective functions

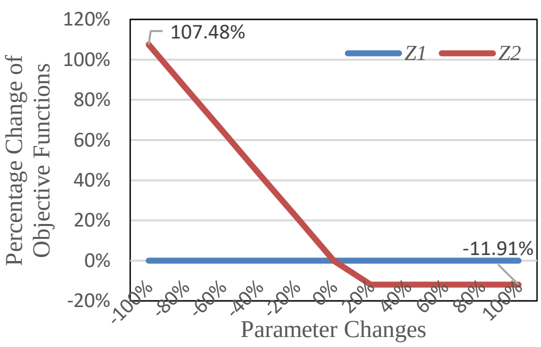


Figure 4. Effect of a change in the teaching capability on the objective functions

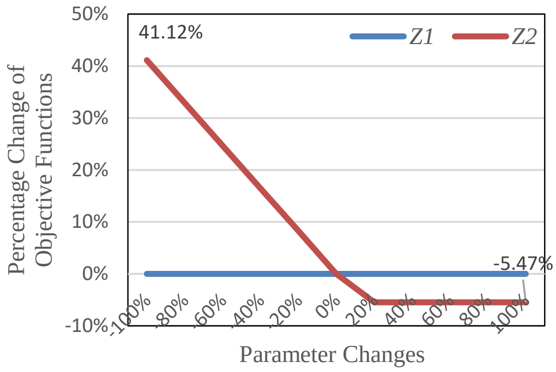


Figure 5. Effect of a change in the learning capability on the objective functions

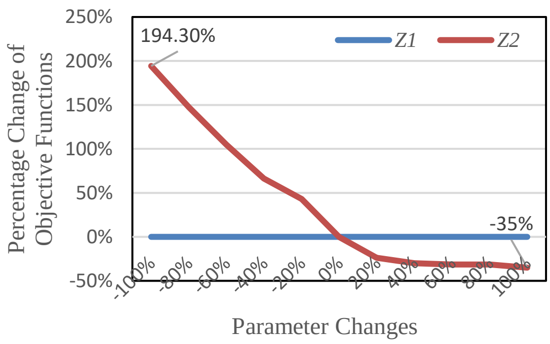


Figure 6. Effect of a change in organizational commitment on the objective functions

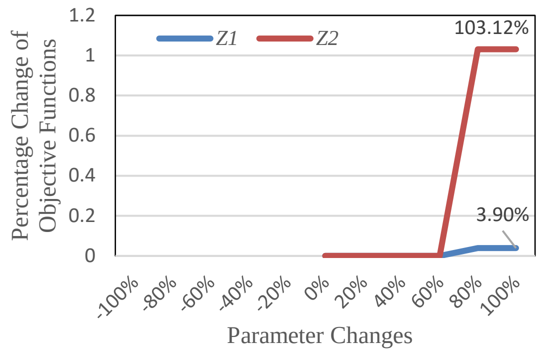


Figure 7. Effect of a change in professional trust on the objective functions

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.

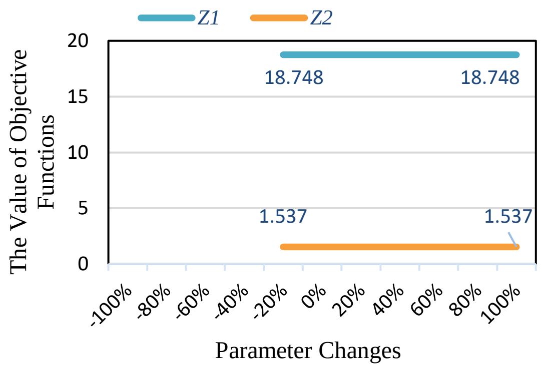


Figure 8. Effect of a change in personal trust on the objective functions

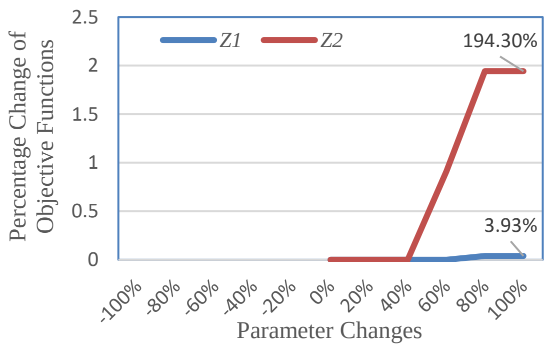


Figure 9. Effect of simultaneous changes in professional and personal trust on the objective functions

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	My colleagues are honest.
	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

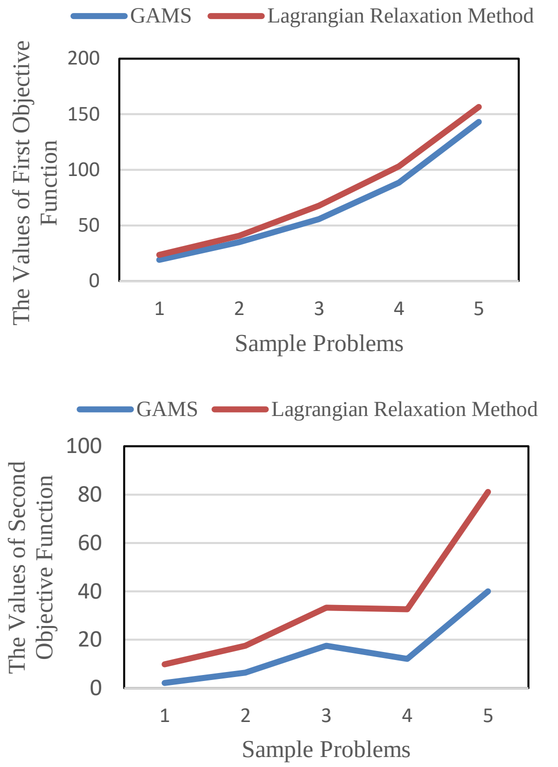


Figure 10. Average graph of the objective functions of the small-scale sample problems in the optimistic case

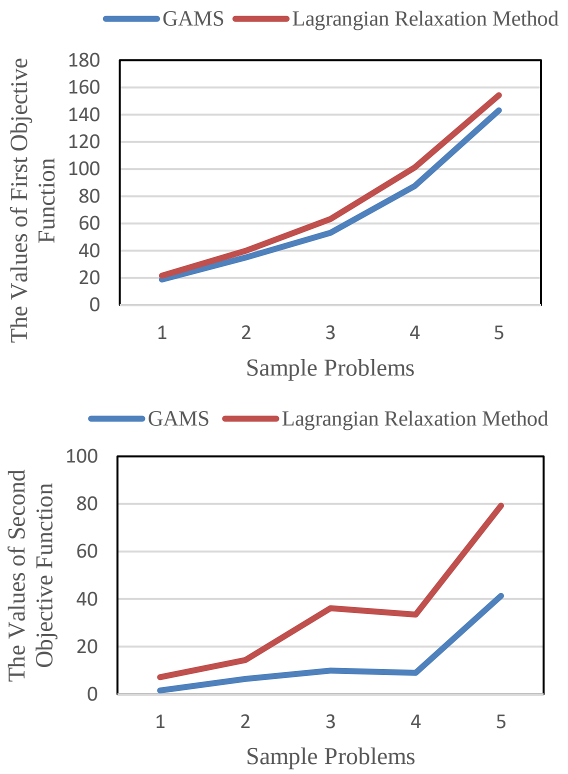
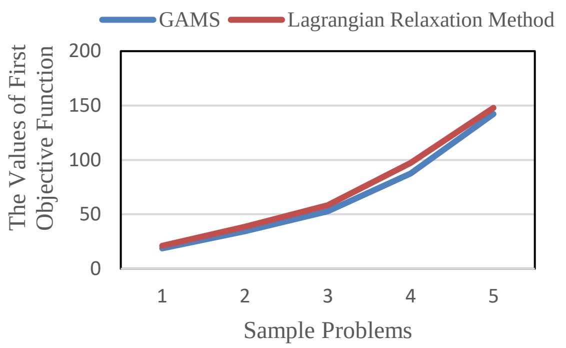


Figure 11. Average graph of the objective functions of the small-scale sample problems in the likely case



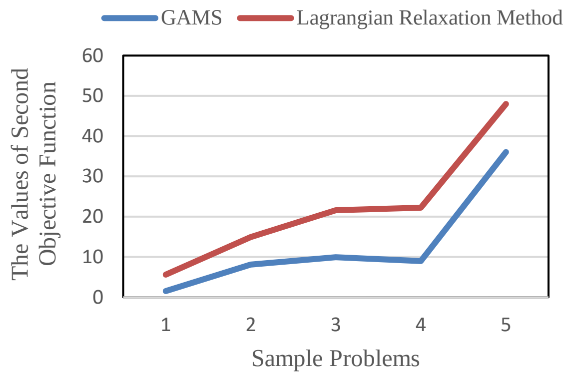


Figure 12. Average graph of the objective functions of the small-scale sample problems in the pessimistic case

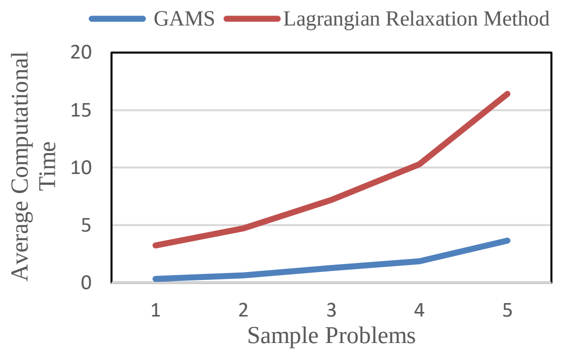


Figure 13. Average graph of the objective functions of the small-scale sample problems

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.

TABLE 5. Solution of the medium-scale problems using GAMS software

Problem	Indicator	GAMS Software		
		Pessimistic	Likely	Optimistic
	Z1	275.881	282.607	291.186
6	Z2	98.708	114.969	107.113
	Solve Time	8.448	9.969	14.502
	Z1	364.446	382.337	401.684
7	Z2	134.560	142.362	166.802
	Solve Time	16.821	82.720	41.422
	Z1	433.738	449.019	475.594
8	Z2	157.475	184.731	194.095
	Solve Time	17.951	43.481	1018.640
	Z1	424.076	435.798	451.921
9	Z2	219.634	240.629	232.977
	Solve Time	40.534	68.920	1022.911
	Z1	550.981	569.321	592.896
10	Z2	280.773	259.136	305.025
	Solve Time	48.365	1028.467	1032.434

TABLE 6. Solution of the medium-scale problems using the Lagrangian relaxation method

Problem	Indicator	Lagrangian Relaxation Method		
		Pessimistic	Likely	Optimistic
	Z1	287.648	302.342	308.466
6	Z2	136.683	165.540	136.014
	Solve Time	39.641	42.345	43.945
	Z1	381.857	400.260	420.441
7	Z2	161.919	166.660	163.821
	Solve Time	75.320	84.547	98.482
	Z1	452.527	472.922	498.502
8	Z2	177.705	171.519	161.457
	Solve Time	88.704	110.981	110.111
	Z1	438.723	449.753	474.080
9	Z2	233.201	240.780	248.319
	Solve Time	148.017	139.822	164.320
	Z1	551.391	595.708	615.980
10	Z2	229.225	311.712	310.039
	Solve Time	170.700	175.286	190.954

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.

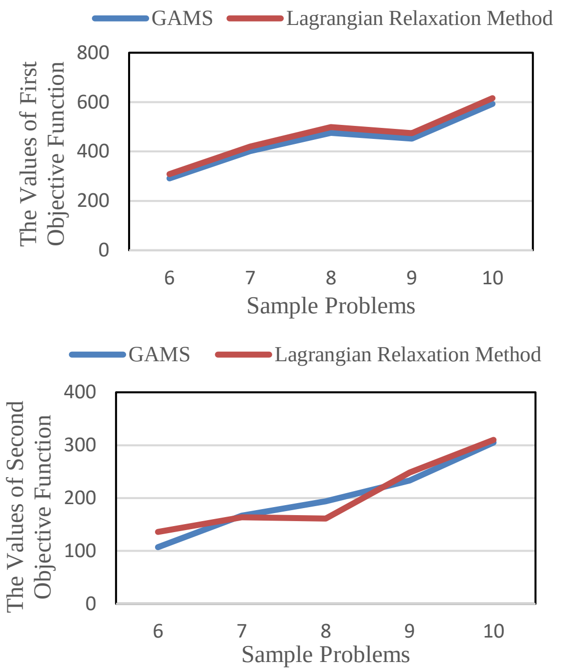


Figure 14. Average graph of the objective functions of the medium-scale sample problems in the optimistic case

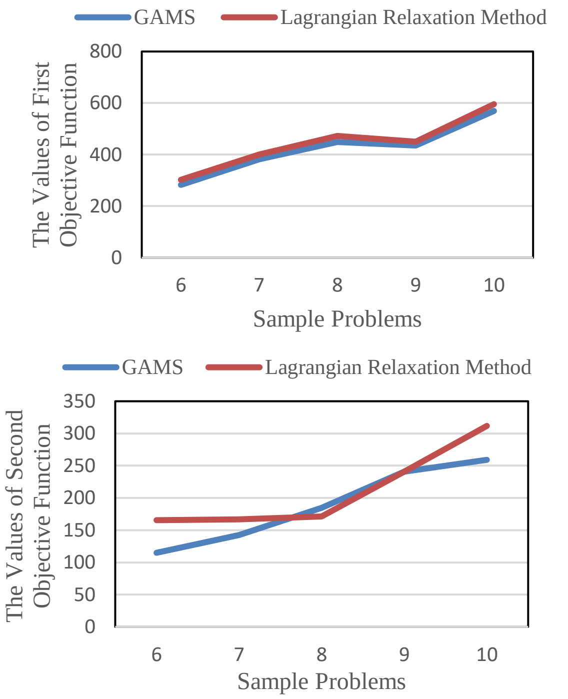


Figure 15. Average graph of the objective functions of the medium-scale sample problems in the likely case

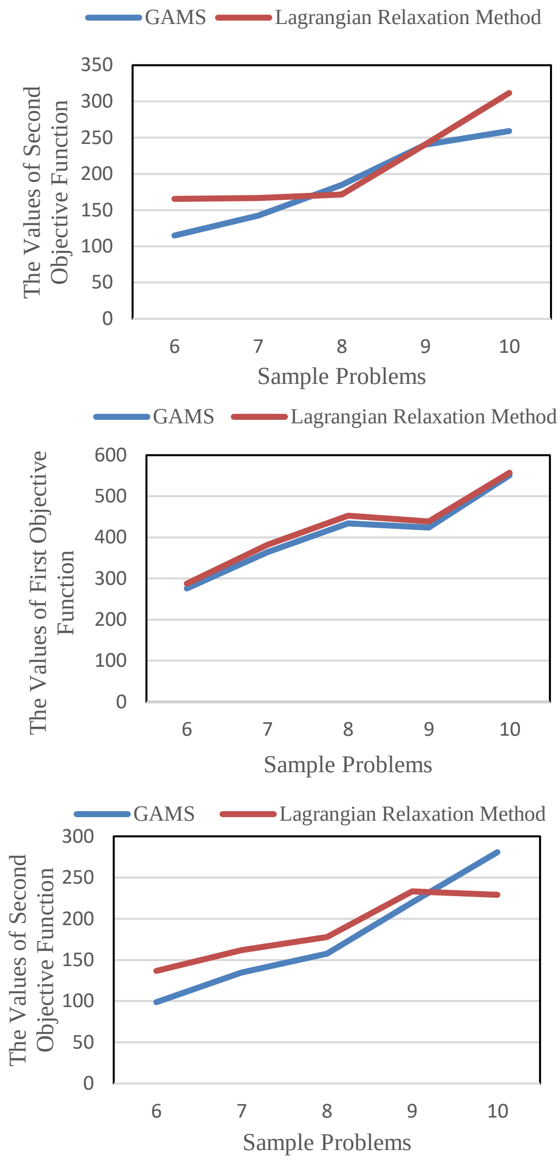


Figure 16. Average graph of the objective functions of the medium-scale sample problems in the pessimistic case

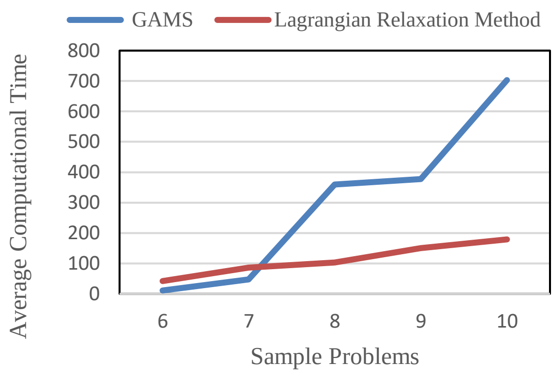


Figure 17. Average graph of the objective functions of the medium-scale sample problems

TABLE 7. Solution of the large-scale problems using GAMS software

Problem	Indicator	GAMS Software		
		Pessimistic	Likely	Optimistic
11	Z1	825.429	867.715	901.553
	Z2	342.826	394.597	371.124
	Solve Time	1060.848	1068.224	1067.315
12	Z1	986.869	1006.240	1030.502
	Z2	312.949	332.498	403.207
	Solve Time	1083.767	1092.608	1095.609
13	Z1	987.680	1033.086	1067.017
	Z2	453.209	551.923	563.889
	Solve Time	1109.767	1116.027	1122.732
14	Z1	963.671	983.462	1008.336
	Z2	446.644	438.087	429.772
	Solve Time	1114.210	1123.539	1122.166
15	Z1	1207.750	1227.054	1233.216
	Z2	382.905	416.643	425.026
	Solve Time	1161.307	1167.212	1174.656
16	Z1	1168.396	1283.952	1475.807
	Z2	416.603	457.806	526.214
	Solve Time	1493.652	1573.324	1634.021
17	Z1	1412.303	1569.225	1705.679
	Z2	452.956	503.284	547.048
	Solve Time	1721.320	1764.378	1813.225
18	Z1	1631.315	1773.169	2086.081
	Z2	390.268	424.204	499.063
	Solve Time	1853.326	1893.601	1961.254
19	Z1	1952.676	2194.018	2411.009
	Z2	486.913	547.093	601.201
	Solve Time	2002.336	2010.325	2029.321
20	Z1	2414.407	2624.355	2948.714
	Z2	474.915	516.212	580.014
	Solve Time	2098.356	2180.957	2259.325
21	Z1	2686.056	2951.710	3354.216
	Z2	509.380	559.758	636.089
	Solve Time	2323.255	2490.521	2501.378
22	Z1	2756.253	3178.452	3695.874
	Z2	486.981	559.748	650.870
	Solve Time	2651.355	2730.301	2681.021
23	Z1	2750.099	3197.790	3997.238
	Z2	445.547	518.078	647.598
	Solve Time	2932.631	3110.665	3054.221
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

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

Sample Problems	Indicator	Lagrangian Relaxation Method		
		Pessimistic	Likely	Optimistic
11	Z1	980.408	1009.717	1005.554
	Z2	1013.379	917.578	635.009
	Solve Time	409.579	448.384	441.293
12	Z1	1123.060	1179.430	1208.948
	Z2	948.131	1067.769	913.085
	Solve Time	618.205	655.781	696.747
13	Z1	1184.371	1214.392	1215.821
	Z2	1102.582	1341.834	1035.959
	Solve Time	843.691	903.050	956.417
14	Z1	1086.948	1128.485	1167.396
	Z2	1027.694	1200.839	1037.956
	Solve Time	886.937	967.430	1005.905
15	Z1	1291.978	1465.508	1492.896
	Z2	989.330	1166.494	1006.252
	Solve Time	892.354	973.231	1016.325
16	Z1	1193.562	1311.607	1507.594
	Z2	671.088	737.459	847.654
	Solve Time	1034.393	1136.696	1306.547
17	Z1	1552.706	1725.229	1875.249
	Z2	793.620	881.800	958.478
	Solve Time	1088.844	1209.827	1315.029
18	Z1	1681.032	1827.209	2149.658
	Z2	781.732	849.709	999.658
	Solve Time	1099.247	1194.834	1405.687
19	Z1	2106.723	2367.104	2601.213
	Z2	686.515	771.365	847.654
	Solve Time	1299.314	1459.903	1604.289
20	Z1	2558.147	2780.595	3124.264
	Z2	797.641	867.001	974.158
	Solve Time	1366.588	1485.422	1669.014
21	Z1	2840.915	3121.885	3547.597

	Z2	764.431	840.034	954.584
	Solve Time	1433.109	1574.845	1789.597
	Z1	2843.906	3268.857	3800.997
22	Z2	633.885	728.604	847.214
	Solve Time	1413.265	1624.443	1888.887
	Z1	2806.825	3263.750	4079.687
23	Z2	515.002	598.838	748.547
	Solve Time	1385.652	1611.223	2014.029
	Z1	3760.662	4132.596	4541.314
24	Z2	784.338	861.910	947.154
	Solve Time	1861.567	2045.678	2247.998
	Z1	3889.328	4321.475	4801.639
25	Z2	847.191	941.323	1045.914
	Solve Time	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 transfers more knowledge than GAMS. Furthermore, the Lagrangian relaxation method is usually faster than the GAMS computational time.

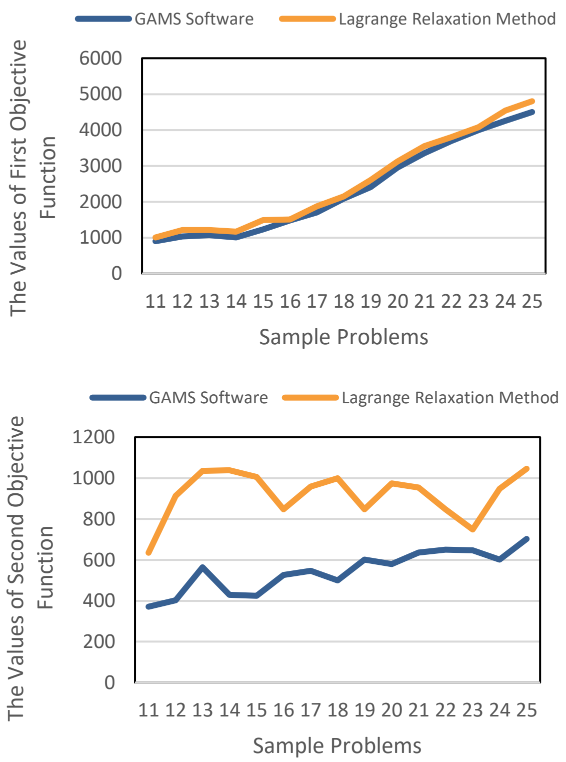


Figure 18. Average graph of the objective functions of the large-scale sample problems in the optimistic case

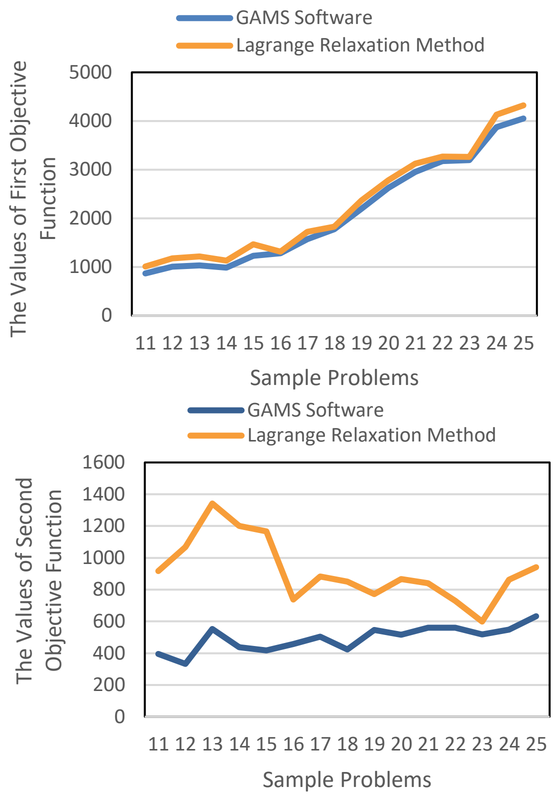


Figure 19. Average graph of the objective functions of the large-scale sample problems in the likely case

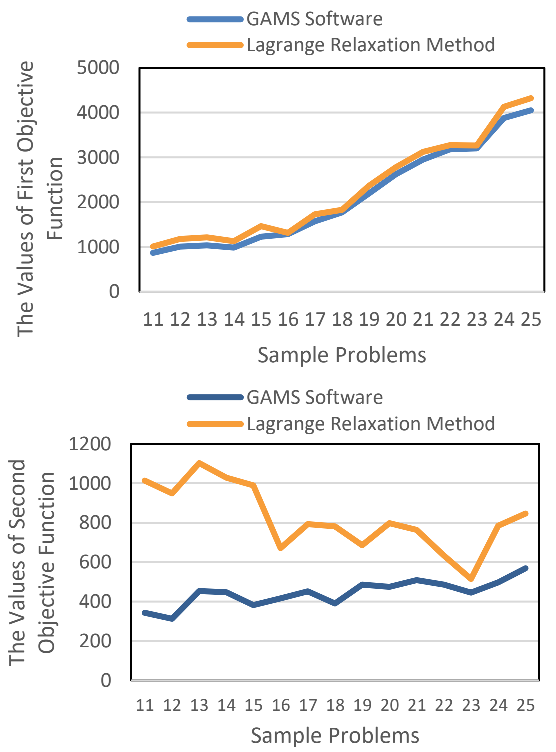


Figure 20. Average graph of the objective functions of the large-scale sample problems in the pessimistic case

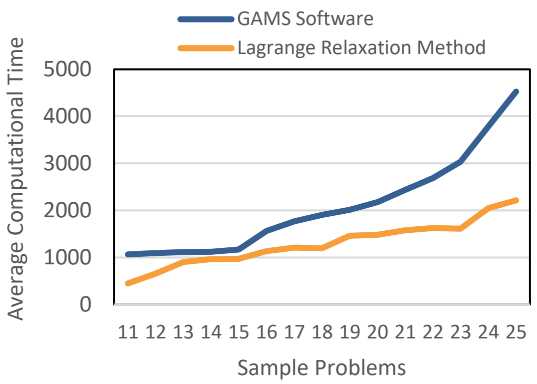


Figure 21. Average graph of the objective functions of the large-scale sample problems

The Lagrangian relaxation method transfers more knowledge than CPLEX solver in all the optimistic, likely, and pessimistic situations. Consequently, the knowledge transfer duration is longer in the Lagrangian relaxation method. Concerning computation time, the larger the sample problems become, the shorter the solution time using Lagrangian relaxation becomes compared to the CPLEX solver.

In addition, Montazer [22] developed a new approach for knowledge based systems reduction using rough sets theory

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 investigans.

8. REFERENCES

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Persian Abstract

چکیده

انتقال دانش در دو سطح درون سازمانی و بین سازمانی می‌تواند انجام شود. یادگیری دانش از خارج از سازمان نیاز به بودجه و زمان قابل توجهی دارد، در حالی که با اشراف و اتکاء به دانش موجود در سازمان که نزد کارکنان است می‌توان با ایجاد یک شبکه جریان دانش بین کارکنان اقدام به ارتقاء سطح دانش آن‌ها با صرف کم‌ترین زمان نمود. طراحی یک مدل شبکه جریان دانش بین کارکنان سازمان با توجه به سطح اعتماد حرفه‌ای و شخصی، توان آموزش و یادگیری، سطح دانش کارکنان، میزان تعهد سازمانی، نوع و اهمیت هر دانش و همچنین غیرقطعی بودن مدت انتقال دانش مسأله‌ای است که در این مقاله به آن پرداخته می‌شود. این مسأله در قالب یک مدل ریاضی برنامه‌ریزی عدد صحیح مختلط غیرقطعی با توابع هدف حداکثر کردن سطح دانش و حداقل کردن مدت انتقال دانش موزون فرموله شد. مدل به کمک حل‌کننده CPLEX و الگوریتم آزادسازی لاگرانژ حل گردید. نتایج به‌دست آمده از حل مدل در همه اندازه‌های مورد نظر، نشان از کارایی بالای الگوریتم آزادسازی لاگرانژ در یافتن کران بالا برای مسأله اصلی در هر سه اندازه کوچک، متوسط و بزرگ دارد. همچنین نتایج نشان می‌دهد که پارامتر تعهد سازمانی تأثیر بیشتری نسبت به توان آموزش و یادگیری در مدت زمان انتقال دانش دارد.