2013 年度博士後期課程（ソフトウェア情報学）論文

主観的知能に基づく意思決定支援システム

Decision Support System based on Subjective Intelligence

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要旨

本研究は、意思決定支援システム（DSS）が推奨する目標や計画を達成可能な行動（代替案）の順位付けに対する有効性のさらなる改善に寄与する研究である。DSS は個人や組織の意思決定に対して、意思決定者の選択可能な代替案を科学的な評価に従って順位付けることによって、助言や支援を与える多基準意思決定（MCDM）の情報システムである。DSS は目標や計画に関連する情報に従って意思決定をモデル化し多様な判断基準を設けることによって代替案の順位づけを可能にしている。従来の DSS は目標や計画の達成に対して静的に設定された判断基準に基づいて、客観的に代替案を評価して順位付けをしている。しかしながら、意思決定者の状況は時間とともに変化するため、客観的な判断基準による静的な代替案の評価結果では意思決定者の異なる状況においては適合しない可能性がある。したがって、システムが評価した代替案の順位付けが意思決定者に対して不一致の場合は、意思決定を支援する効果をシステムから得ることができなくなってしまう。

本研究では、従来の DSS が参照する目標や計画の達成に対して静的な判断基準と意思決定者の状況に基づく判断基準を統合することによって、意思決定者の状況に合わせた代替案の順位評価を可能にするアプローチを提案する。提案 DSS がユーザである意思決定者の状況に合わせた代替案の順位付けを可能にすることによって、最適な意思決定の支援をユーザに与えることが可能になり DSS の評価結果の信頼性が向上する。

本論文では DSS を評価するために、会社内のソフトウェア開発ワークフローの事例モデルに適用した。従来の MCDM 手法による代替案の分析結果と主観的な判断基準を考慮した提案アプローチの分析結果を、同じ事例を用いて比較することによって、提案アプローチが有効であることを示す。

意思決定の支援はシステムが代替案を判断基準に従って順位づけをすることによって与えることが可能だが、代替案の数が増えることによって、意思決定者に対する支援情報の数が多くなる。過剰な情報表示は意思決定者に対して有効な情報を複雑にする。この問題を改善するために、単一の配列を判断基準に基づいて更新することを可能にする発見的問題解決（メタヒューリスティクス）手法の側面からも代替案の評価を行った。したがって、本論文では意思決定を支援する方法として、主観的な知能に基づく代替案の順位付けをするアプローチの他に、主観的な知能に基づくメタヒューリスティクス手法を用いた代替案の選出アプローチにおいても提案手法の有効性を比較評価している。

本研究の提案アプローチは、医療診断の意思決定や地図ナビゲーションの意思決定など様々な社会的 DSS の信頼性を高めるために応用することが可能である。

Abstract

This research contributes further improvement of validity for ranking achievable activities to objective or plan of decision maker as alternatives that are provided by Decision Support System (DSS). DSS is an information system of Multiple Criteria Decision Making (MCDM) that provides advice or support for decision maker of individual or organization by ranking alternatives according to scientific evaluation. Alternatives of DSS can be ranked by modeling decision making and setting multiple criteria according to related information to objective or plan of decision maker. Typical DSS ranks alternatives by objective evaluation based on static criteria for achieving objective or plan. There is a possibility of mismatched advice by DSS that is based on objective criteria due to changing situation of decision maker with time. Therefore, decision maker cannot get valid recommendation within mismatched alternatives to the situation of decision maker by DSS.

In order to improve the mismatched recommendation to situation by DSS, this research proposes an approach for aggregating objective criteria and situation based criteria. Situation of decision maker is changed by changing subjective attributes that are aggregated by individual perception of decision maker. Situation based criteria can be represented by aggregating subjective attributes according to individual perception of decision maker. Therefore, proposed DSS ranks alternatives by utilizing intelligence based on subjective criteria of decision maker.

In this thesis, the proposed approach is applied to case model of decision making in software development of a company to evaluate validity of aggregating objective criteria and subjective criteria. Validity of proposed approach is indicated by comparing analyzed result of conventional MCDM approach and proposed MCDM approach with applying to same case model.

Although decision making can be supported by ranking alternatives based on criteria, too many advices are indicated to decision maker by increasing number of alternatives. Too many information generates decreasing of understanding appropriate information for decision maker. In order to improve this issue, this research evaluates an alternative also from an aspect of Metaheuristics approach that can update a matrix according to criteria. Therefore, proposed approach is applied to criteria for ranking alternatives and criteria for updating.

Application of proposed DSS based on subjective intelligence can improve validity of many social DSS such as decision making of medical diagnosis or route navigation system.

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Chapter 1

Introduction

1.1 Background

Recently, personal computer and mobile phone are widely used by people. Supporting decision making by system is required to utilize efficiently computer by diverse users. For example, searching keywords are recommended for assisting thinking of user in searching data to huge database such as internet by reasoning of system that uses incremental search [1], fuzzy string search [2] and so on. In utilization of mobile phone such as smart phone, related content in museum [3] or appropriate route on map [4][5] is recommended by system according to information of user's position. These systems that are called Recommender System (RS) provide adaptive recommendation to users for supporting decision making by involving information of user's situation (i.e. input character or present location). Although RS can provide related information to decision maker by utilizing such as collaborative filtering methods [6], approach for achieving objective must be considered by decision maker.

The labor for consideration of decision maker can be supported by providing ranked achievable activities to objective of decision maker as alternatives by Decision Support System (DSS). DSS is one of Man-Machine Interactive System to support semi-structured or unstructured problem resolution of decision maker. Expected profits by problem resolution or objective achievement of decision maker have uncertainty. In other words, DSS supports problem resolution of decision maker by ranking alternatives based on criteria that include uncertain profits.

Uncertainty of profits can be classified objective uncertainty and subjective uncertainty. Christof Tannert, et al. defined taxonomy of uncertainties and decisions for objective and subjective [7]. Objective uncertainty is further divided into epistemological uncertainty and ontological uncertainty [8]. Epistemological uncertainty is caused by gaps in knowledge that can be closed by applying a comparative risk assessment of similar situations. Ontological uncertainty is caused by the stochastic features of a situation, which will usually involve complex technical, biological and/or social systems. Therefore, objective criteria that can be weighted risks and benefits based on knowledge as ontological uncertainty can be utilized to alternatives ranking of DSS such as medical diagnostics [9][10], logistic route [11][12], management of energy systems [13] and so on.

Meanwhile, subjective uncertainty is characterized by an inability to apply appropriate moral rules. Subjective uncertainty can be also distinguished to two types which are moral uncertainty and rule uncertainty. The moral uncertainty is caused by a lack of applicable general moral rules such as someone's philosophy or consciousness. In this case, decision makers have to fall back on more general moral rules and use them to deduce guidance for the special situation in question. The rule uncertainty is related to intuition-guided decisions based on individual moral rules. In specific situations, decision maker can make decisions only by relying on own intuition rather than knowledge, or explicit or implicit moral rules. This means that decision maker acts on the basis of fundamental pre-formed moral convictions in addition to experiential and internalized moral models.

Subjective criteria based on uncertainty of complex and diverse moral rules of decision makers are not utilized to typical DSS because risks and benefits for objective of decision making are not measurable. Importance of subjective criteria tends to decreasing by changing situation of decision maker. Situation of decision maker is changed by occurring external negative influence to achieving objective in objective criteria. Therefore, in this case, improving negative influence according to objective criteria is more important approach than considering uncertain profits of subjective criteria in decision making.

However, uncertainty of subjective criteria includes future risks and expected benefits that are not simply measurable by individual moral rule. In changed situation of decision maker, alternatives by conventional DSS without subjective criteria are ranked without considering possible of losing profits that lead to future benefits of decision maker. Therefore, validity for ranking of alternatives by conventional

DSS in changed situation is decreased by insufficient criteria. Situation of decision maker in opportunity of utilizing DSS is changing with time. There are approaches for uncertainty reduction related to decision making by prediction based on expert knowledge provided by experts based on linguistics fuzzy values [72] [73]. It is required consensus among experts. Although the criteria are assumed to be independent, this would make the system unrealistic in some situation. In this thesis we use subjectivity such that to provide relative dependency among criteria.

1.2 Objective of this thesis

The main objective of this thesis is to apply subjective intelligence to DSS for adjusting alternatives ranking of DSS to situation of decision maker. In order to improve issue of ranking alternatives by conventional DSS without subjective criteria, this research proposes DSS according to aggregation of objective criteria and subjective criteria. Figure 1.1 indicates over view of proposed DSS. Subjective criteria are weighted for aggregating to objective criteria in proposed DSS based on subjective attributes of decision maker. Subjective attributes are composition element for individual profile of decision maker that is based on multiple moral rules. Changing of situation can be estimated by comparing difference of subjective attributes in terms of time with normalizing subjective attributes of decision maker. Alternatives for improving negative influence by changing situation under objective criteria can be formulated by estimating degree of negative impact based on estimated difference of subjective attributes. Therefore, subjective attributes must be normalized to reduce uncertainty of subjective criteria by applying moral rules to subjective attributes.

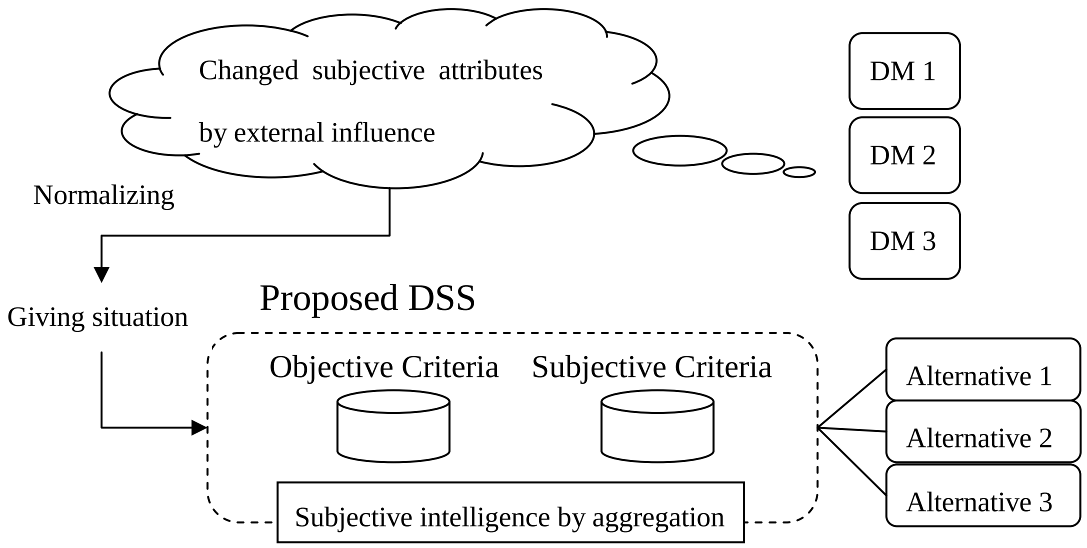

Figure 1.1: Overview of proposed DSS

Although decision making can be supported by ranking alternatives based on criteria, too many advices are indicated to decision maker by increasing number of alternatives. Too many information generates decreasing of understanding appropriate information for decision maker. In order to improve this issue, this research evaluates an alternative also from an aspect of Metaheuristics approach that can update a matrix according to criteria. Therefore, proposed approach is applied to criteria for ranking alternatives and criteria for updating.

1.3 Outline of the thesis

This thesis is structured as follows:

This Chapter introduces main concept of the thesis. Issue of conventional DSS is indicated on objective and subjective uncertainty. Chapter 2 explains related works to our research. DSS needs methodology to rank alternatives for supporting decision making. Therefore, some methodologies of ranking alternatives are explained in Chapter 2. In addition, approach for finding alternative as supporting decision making is discussed by explaining Metaheuristics method. Chapter 3 is representation of proposed approach on existing case model. Chapter 4 discusses evaluation of proposed approach by comparing proposed approach and conventional approach. Final Chapter concludes our approach and indicates future works.

Chapter 2

Related work

2.1 Introduction

This Chapter explains related works to our research. In Section 2.2, history and definition of DSS are explained to assist the reader's understanding for target DSS of this thesis. Decision making in DSS is assisted by indication of ranked alternatives according to multiple criteria. Therefore, some methodologies of ranking alternatives are explained on Multiple Criteria Decision Making (MCDM) in Section 2.3. In addition, approach for finding alternative as supporting decision making is discussed by explaining Metaheuristics methods in Section 2.4.

2.2 What is DSS?

Decision support system (DSS) is a subset of computer-based information systems. According to Keen and Scott Morton, the concept of decision support has evolved from two main areas of research: the theoretical studies of organizational decision making done at the Carnegie Institute of Technology during the late

1950s and early 1960s, and the technical work on interactive computer systems, mainly carried out at the Massachusetts Institute of Technology in the 1960s [14]. It is considered that the concept of DSS became an area of research of its own in the middle of the 1970s, before gaining in intensity during the 1980s [15]. In the middle and late 1980s, Executive Information System (EIS) [16], Group Decision Support System (GDSS) [17], and Organizational Decision Support System (ODSS) [18] evolved from the single user and model oriented DSS. EIS that supports senior executive information and decision making needs provides easy access to internal and external information relevant to organizational goals. GDSS is one of systems for supporting decision making in electronic meetings. ODSS provide mechanisms for ensuring that the decisions being made throughout such organizations are consistent with each other and with the overall organization goals. Through means of an ODSS, information and guidance is automatically passed from higher levels to lower levels for use in decision-making models. Beginning in 1990s, data warehousing and On-Line Analytical Processing (OLAP) [19] began broadening the realm of DSS with growing data transmission speed of computer network. Since 2000s, web-based analytical applications were introduced to DSS with spreading internet among people.

2.2.1 Definition of DSS

Early definition of DSS was a computer based information system used by decision-makers to support their decision-making activities for semi-structured or unstructured problem resolution in the situations where it is not possible or not desirable to have an automated system perform the entire decision process [20]. Little introduced decision-making activities for semi-structured or unstructured problem resolution according to defined decision calculus in 1970 [21]. Under this approach a manager’s implicit model of a situation is formalized into an explicit model which is then used to evaluate alternative decisions. The decision calculus was defined as a set of six criteria that a model should meet [22]. The six criteria meaning as follows:

(1) Simple. Simplicity promotes ease of understanding.

(2) Robust. By this it is meant that a user should find it difficult to make the model give bad answers.

(3) Easy to control. A user should be able to make the model behave the way he wants it to.

(4) Adaptive. The model should be capable of being updated as new information becomes available.

(5) Complete on important issues. Completeness is in conflict with simplicity. Structures must be found that can handle many phenomena without bogging down.

(6) Easy to communicate with. The manager should be able to change Inputs easily and obtain outputs quickly.

Adaptive that is the above fourth criteria can be improved in proposed approach by utilizing subjective criteria based on situation.

2.2.2 Taxonomies of DSS

Taxonomies of DSS are different by researchers. Hättenschwiler differentiates passive, active and cooperative DSS [15]. A passive DSS is a system that aids the process of decision making, but that cannot bring out explicit decision suggestions or solutions. According to this definition, RS is belonged to the passive DSS. An active DSS can bring out such decision suggestions or solutions. A cooperative DSS allows the decision maker (or its advisor) to modify, complete, or refine the decision suggestions provided by the system, before sending them back to the system for validation. The system again improves, completes, and refines the suggestions of the decision maker and sends them back to the criteria for validation. The whole process then starts again, until a consolidated solution is aggregated. Although proposed DSS is belonged to the active DSS, a solution as alternative for decision making is improved by cooperation (aggregation) of objective criteria and subjective criteria as situation of decision maker.

At the conceptual level, Power differentiates Communication-Driven DSS, Data-Driven DSS, Document-Driven DSS, Knowledge-Driven DSS, and Model-Driven DSS [23]. Communication-Driven DSS supports more than one person working on a shared task. Data-Driven DSS or Data-oriented DSS emphasize access to and manipulation of a time-series of internal company data and, sometimes, external data. Document-Driven DSS manage, retrieve and manipulate unstructured information in a variety of electronic formats. Knowledge-Driven DSS provide specialized problem-solving expertise stored as facts, rules, procedures, or in similar structures. Finally, Model-Driven DSS emphasizes access to and manipulation of a statistical, financial, optimization, or simulation model. Proposed DSS is belonged to the Knowledge-Driven DSS because proposed DSS ranks alternatives by applying rule model of decision maker as knowledge. Although there is an approach of Expert System (ES) [24] for supporting decision making based on knowledge, objective of proposed DSS and ES is different [25].

2.2.3 Difference of DSS and ES

ES is a system that employs human knowledge captured in a computer to solve problems that ordinarily require human expertise [26]. Pigford and Braur define that ES is a computer program that emulates the behavior of human experts who are solving real-world problems associated with a particular domain of knowledge [27]. DSS focuses on supporting decision makers in semi-structured or unstructured problems. Meanwhile, ES concentrates on replacing human decision makers in structured and narrow problem domains. Therefore, ES is to replace and mimic expert decision makers in making repetitive decisions in a narrow domain. This difference has resulted in two completely different design philosophies.

2.2.4 Structure of DSS

Structure of DSS is identified different components by researchers. Sprague and Carlson identify three fundamental components of DSS [28]:

(a) the database management system (DBMS)

(b) the model-base management system (MBMS)

(c) the dialog generation and management system (DGMS).

According to Power, academics and practitioners have discussed building DSS in terms of four major components [23]:

(a) the user interface

(b) the database

(c) the model and analytical tools

(d) the DSS architecture and network.

Hättenschwiler identifies five components of DSS [15]:

(a) users with different roles or functions in the decision making process (decision maker, advisors, domain experts, system experts, data collectors)

(b) a specific and definable decision context (model)

(c) a target system describing the majority of the preferences

(d) a knowledge base made of external data sources, knowledge databases, working databases, data warehouses and meta-databases, mathematical models and methods, procedures, inference and search engines, administrative programs, and reporting systems,

(e) a working environment for the preparation, analysis and documentation of decision alternatives.

These components of each researcher have a commonality for database, model and user interface. Proposed approach is a novel improvement by applying subjectivity to database as situation in changed situation model.

2.3 MCDM

Opportunity of Multiple Criteria Decision Making (MCDM) is often occurred as one of event in life of people. Decision making is a process of selecting appropriate approach for achieving objective and plan or for solving problem by individual or organization. Wang Yingxu, et al. defines that decisions are not guided just by expectations of the benefits that will ensue but also by expectations about costs [29]. Daniel M Wolpert and Michael S Landy said the subject (e.g. human, primate, rat or pigeon) in typical decision-making tasks is given two or more options from which to choose [30]. Appropriate approach of decision making is different according to criteria for achievement of objective. Many decisions are based on beliefs concerning the likelihood of uncertain events such as the outcome of an election, the guilt of a defendant, or the future value of the dollar.

Decision maker decides appropriate action under uncertain events according to judgmental heuristics as criteria [31]. Judgmental heuristics consists of several types of experimental biases for judgment of decision maker. Experimental biases as criteria for decision making are acquired through individual perception of decision maker. Therefore, ranking of alternatives is depending on experience of decision maker. In other words, inexperienced decision maker may not be able to choose appropriate alternative to objective. Even if decision maker has many experiences, ranking of alternatives according to unrelated criteria to objective by the decision maker is insufficient.

DSS can rank alternatives according to multiple criteria for achieving objective without depending on individual experience of decision maker. In order to rank alternatives by DSS, evaluation model of decision making must be applied to DSS. Recently, various approaches for evaluation model of decision making are studied to find appropriate solution for achieving objective. Following sections explain some methodologies for ranking alternatives in MCDM.

2.3.1 AHP method

Analytic Hierarchy Process (AHP) is a popular decision-making method proposed by Saaty [32]. The applications of AHP have produced extensive results in many problems involving planning, resource allocation, priority setting, and selection among alternatives [33]. Generally, AHP consists of three main principles, including hierarchy framework, priority analysis and consistency verification. Formulating the decision problem in the form of a hierarchy framework is the first step of AHP with the top level representing overall objectives, the middle levels representing criteria, and the lowest level standing for decision alternatives in Figure 2.1. Once a hierarchy framework is constructed, users are requested to set up a pairwise comparison matrix at each hierarchy and to compare each other by using a scale pairwise comparison. Finally, in the synthesis of priority stage, each comparison matrix is then solved by an eigenvector method to determine the criteria importance and alternative performance. Pairwise comparison matrixes (whose column and row are the alternatives) must be formed based on the number of criteria. After determining the alternatives importance in each matrix, the overall importance of each alternative is calculated.

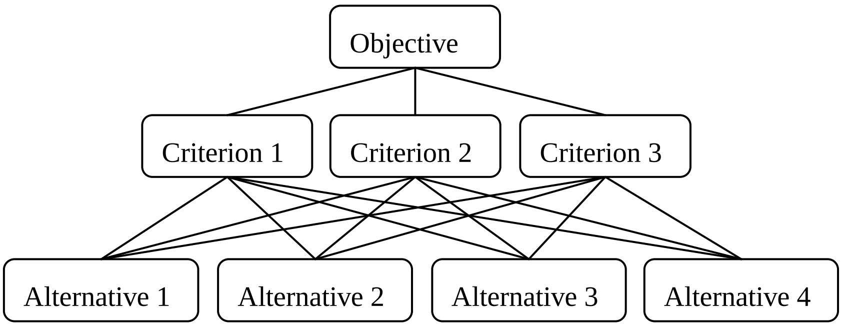

Figure 2.1: Hierarchy framework of AHP

Although AHP can extract subjective moral rule from expert for reducing uncertainty of subjective criteria by weighting criteria based on pairwise comparison, various type of situations must be reasoned to weight criteria by expert.

2.3.2 DEMATEL method

Decision Making Trial and Evaluation Laboratory (DEMATEL) method is used in order to put forward the interrelationship among the main criteria which are determined in the study for outsourcing selection process [34]. DEMATEL is a comprehensive method for building and analyzing a structural model involving causal relationships between complex factors or criteria. The DEMATEL method is based on digraphs, which can separate involved factors into causal and effect groups. The digraphs are based on the concept of contextual relations between criteria, in which the numerals represent the strength of influence. Therefore, the DEMATEL method can convert the relationship between the causes and effects of criteria into an intelligible structural graph.

For applying DEMATEL, there are 5 main steps:

(1) making the direct-influenced matrix

(2) calculating the direct-influenced matrix normalization

(3) achieving the total-relation matrix

(4) Producing a causal diagram

(5) Obtaining the inner dependence matrix and impact relationship map

In step (5), the sum of each column in total-relation n x n matrix is equal to 1 by the normalization method and then the inner dependence matrix can be acquired.

DEMATEL can be applied to MCDM methods as criteria because it is a widespread technique which is able to evaluate and formulate all intertwined causal and effect relationships in each structural model. Wu stated that Knowledge Management (KM) strategy selection is a kind of multiple criteria decision making problem, which requires considering a large number of complex factors as multiple evaluation criteria [35]. A robust multi criteria decision making method should consider the interactions among criteria. Hence, he proposed an effective solution based on a combined Analytical Network Process (ANP) and DEMATEL approach to help organizations evaluating and selecting KM strategies. ANP is an extension of AHP, and it is the general form of analytic hierarchy process [36]. Gülçin and Gizem evaluate green suppliers by combining fuzzy DEMATEL, fuzzy ANP and fuzzy Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [37]. TOPSIS method will be explained by section 2.3.3. DEMATEL technique has combined also with VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method methods [38] [39]. VIKOR method will be discussed in section 2.3.4.

DEMATEL method can set criteria of DSS as objective criteria based on clustering causal relationship of various data. However, objective criteria by DEMATEL method cannot be utilized as subjective criteria in changed situation of proposed DSS.

2.3.3 TOPSIS method

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is was proposed by Hwang and Yoon (1981) to determine the best alternative based on the concepts of the compromise solution [40]. TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS) in Figure 2.2. The PIS is defined as the solution containing the best values of the criteria within the set of alternatives, whereas the NIS contains the worst values within the set of alternatives. Equation 2.1 indicates calculation of geometric distance. Score of criterion ($C1$ or $C2$) are increased by shortening distance of coordinate of alternatives from coordinate of PIS ($TDP1$ or $TDP2$) or elongating distance of coordinate of alternatives from coordinate of NIS ($TDN1$ or $TDN2$).

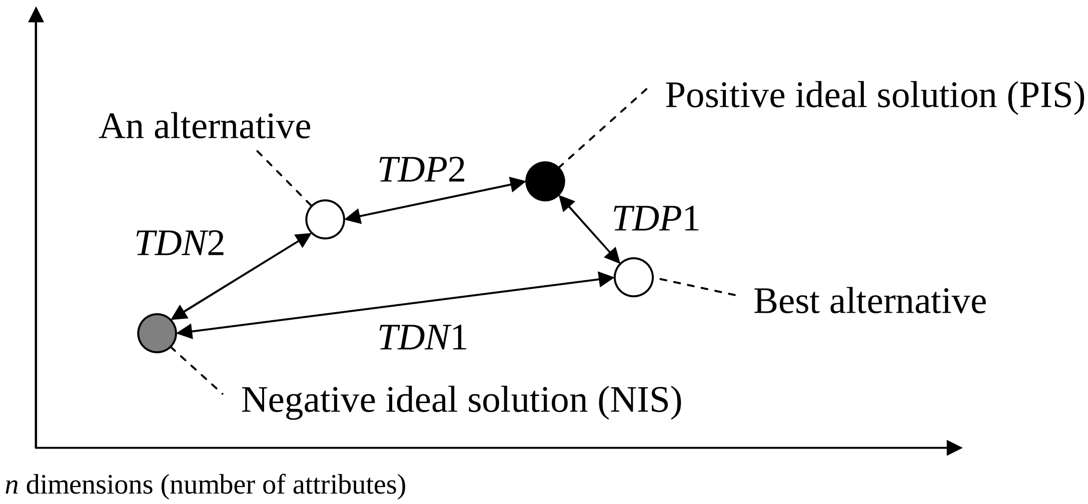

Figure 2.2: Geometric distance of TOPSIS

$$C1 = \frac{TDN1}{TDP1 + TDN1} > C2 = \frac{TDN2}{TDP2 + TDN2} \tag{2.1}$$

Under many real situations crisp data are inadequate to model real life situation since human judgments are vague and cannot be estimated with exact numeric values. Fuzzy TOPSIS [41] can extend crisp data of PIS and NIS in traditional TOPSIS by weighting criteria as objective criteria.

TOPSIS method can be applied to MCDM problem that is defined best value and worst value. There are approaches for setting ideal solution by aggregating individual decision making as group decision [42] [43]. Although consensus for appropriate decision making can be improved by including individual decisions as group decision, these approaches make decision based on objective criteria only. Proposed DSS in changing situation should maximize subjective profit of decision maker as best value for providing appropriate alternative that can satisfy objective profit. Therefore, proposed DSS employs TOPSIS method as decision making model to fit changed situation. This thesis proposes a novel extension of conventional TOSPSIS by aggregating objective criteria and subjective criteria.

2.3.4 VIKOR method

VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is a compromise ranking and selection technique [44]. S.Opricovic had developed the basic ideas of VIKOR in his Ph.D. dissertation in 1979, and an application was published in 1980 [45]. Like TOPSIS, VIKOR is also a MADM technique and implies similar principles of application. However, the two differ slightly in that VIKOR technique uses linear normalization technique. It also uses a compromise (utility) weight for the decision maker to choose his policy which could be optimistic, pessimistic and neutral. In VIKOR, the best solution will have the VIKOR index closest to 0 and the worst alternative will have VIKOR index closest to 1.

The steps involved for ranking alternatives for a decision matrix having alternatives and attributes using VIKOR are as follows:

(1) calculation of normalized decision matrix

(2) determination of ideal and negative ideal solution

(3) calculation of utility measure and regret measure

(4) ranking alternatives

(5) propose as a compromise solution best alternative

VIKOR method ranks alternatives between ideal score of criteria and worst score of criteria. Although VIKOR method also can rank with linear normalization by using PIS and NIS, alternatives that are better than PIS cannot be provided to decision maker. This thesis expects improvement of profit for subjective criteria by adjusting ranking of alternative to changing situation of decision maker. Therefore, proposed DSS employs TOPSIS method than VIKOR method.

2.4 Metaheuristics

A Metaheuristic is a set of concepts that can be used to define heuristic methods that can be applied to a wide set of different problems. In other words, a Metaheuristic can be seen as a general algorithmic framework which can be applied to different optimization problems with relatively few modifications to make them adapted to a specific problem. A Metaheuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions [46]. A new kind of approximate algorithm has emerged which basically tries to combine basic heuristic methods in higher level frameworks aimed at efficiently and effectively exploring a search space. These methods are nowadays commonly called Metaheuristics [47]. Many of the Metaheuristic methods can be interpreted as introducing a bias such that high quality solutions are produced quickly. This bias can be of various forms and can be cast as descent bias (based on the objective function), memory bias (based on previously made decisions) or experience bias (based on prior performance) [48]. These types of bias can be applied to criteria for finding alternative in decision making. Therefore, Metaheuristics approach is employed to evaluate alternatives without dependent for number of alternatives in MCDM by proposed DSS. Some methodologies of Metaheuristics are discussed in following sections.

2.4.1 Genetic algorithm

Genetic algorithms (GA) are a specific type of evolutionary algorithms by mimicking natural selection of gene [49] [50]. Evolutionary algorithms are population-based, adaptive search algorithms designed to attack optimization problems. These are inspired by models of natural evolution of species and use the principle of natural selection which favors individuals that are more adapted to a specific environment for survival and further evolution. The three main operators used in GA are selection, mutation, and recombination.

(1) Selection prefers fitter individuals to be chosen for the next generation and for the application of the mutation and recombination operator.

(2) Mutation is a unary operator that introduces random modifications to an individual.

(3) Recombination combines the genetic material of two individuals, also called parents, by means of a crossover operator to generate new individuals, called offspring.

The three main algorithmic developments within the field of evolutionary algorithms are genetic algorithms, evolution strategies [51] and evolutionary programming [52]. These algorithms have been developed independently and, although these algorithms initially have been proposed in the sixties and seventies, only in the beginning of the nineties the researchers became aware of the common underlying principles of these approaches [50].

In GA, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible [53]. GA updates target matrix by repeating mutation, dump and combine according to fitness function. However, GA cannot be utilized for proposed DSS because profits of objective criteria or subjective criteria are minimized by dumping.

2.4.2 Tabu search

Tabu Search (TS) is among the most cited and used Metaheuristics for combinatorial optimization problems [54]. Combinatorial optimization problems are approach of looking for an object from a finite or possibly countable infinite set [55]. This object is typically an integer number, a subset, a permutation, or a graph structure. The simple TS algorithm applies a best improvement local search as basic ingredient and uses a short term memory to escape from local minima and to avoid cycles [56]. The short term memory is implemented as a tabu list that keeps track of the most recently visited solutions and forbids moves toward them. The neighborhood of the current solution as allowed set is thus restricted to the solutions that do not belong to the tabu list. At iteration of the best solution from the allowed set is chosen as the new current solution. Additionally, this solution is added to the tabu list and one of the solutions that were already in the tabu list is removed (usually in a FIFO order).

Although TS can update target solution as alternative by dumping unfit value according to tabu list, target solution is updated to prevent from endless cycling according to tabu list even if the target solution is wrong. Updating wrong solution generates possible of inappropriate solution as alternative in MCDM. Therefore, TS cannot be used for formulating alternative of proposed DSS.

2.4.3 Harmony search

Harmony Search (HS) is a phenomenon-mimicking algorithm as meta-heuristic algorithm inspired by the improvisation process of musicians [57]. The HS approach finds a vector which optimizes (minimizes or maximizes) a certain objective function from generated random vectors that called Harmony Memory (HM). The HS approach optimizes target vector as worst harmony by comparing with a new harmony. If a new harmony is better than the existing worst harmony, a new harmony is updated as new worst harmony and the current worst harmony is excluded from target vector. The number of vectors of the HM is defined by pre-setting harmony memory size (HMS). The vectors of HM are optimized by comparing and updating the new vector that is generated randomly according to certain conditions. HS can be applied to solve computer science problems or engineering problems [58] [59] [60] [61].

HS can update vector of target matrix without dumping each value of vector by setting objective function that is criteria of objective improvement. Therefore, this thesis selects HS approach to formulate alternative of proposed DSS. However, conventional HS approaches update target vector based on objective criteria. In order to fit solution as alternative to changed situation of decision maker, proposed approach is applied to objective function by aggregating objective criteria and subjective criteria.

2.5 Conclusion

This chapter discussed about DSS, MCDM and Metaheuristics. Proposed approach employs TOPSIS method and Harmony Search method for fitting to changing situation of decision maker according to related works. Next chapter explains about mental model by applying proposed methodologies with normalizing subjective attributes of decision maker.

Chapter 3

Applied case model

3.1 Introduction

In a working environment, opportunity of decision making by worker is occurred to generate higher profit or to eliminate severe loss. Herbert A. Simon defined three decision making processes that are Intelligence Activity, Design Activity and Choice Activity [62]. According to this definition, the worker who is a decision maker for operating assigned tasks must retrieve information to formulate alternatives by analyzing context of related tasks. The worker chooses appropriate decision after evaluating developed alternatives. Context of target tasks selected by the worker consists of objective attributes that are gettable several innate profits by task operation and costs to achieve pre-assigned objective. The worker selects appropriate task according to multi criteria of objective attributes that each task has. Tasks for getting profits are assigned to the workers depending on objective of organization as criteria for appropriate task selection of the worker by superior decision maker who could be manager, project leader or customer. Assigned tasks to the workers are structured to get profits for belonging organization of the workers by steps as workflow through consideration of experts.

The worker has subjective attributes for task operation based on worker's profile such as experience or operational skills. Degree of expected profits by operating task is changed by applying subjective attributes of the worker to objective attributes of task through task assignment. Expected profits for the organization by assigning tasks are increased by improving work efficiency of current work or forthcoming work. Work efficiency of current work is improved by reducing labor cost that is engagement time of the worker to the assigned task while keeping achievement of the task. Completion time of task as engagement time of the worker is shortened by assigning experienced worker. Although the completion time of task by inexperienced worker is longer than experienced worker, applicable experience for forthcoming similar task is accumulated with time by engaging to the task. Therefore, shortening time for improvement of work efficiency in current task and experience to forthcoming work are trade-off.

In this situation of decision making by worker, shortening completion time of task can be classified objective criteria by computing profits according to time. Meanwhile, uncertain profits of subjective expected experience for worker can be categorized to subjective criteria [7] [8]. Work environment of worker and organization is often changed by external influence. In order to support decision making of worker for appropriate task selection, proposed DSS is applied to the working environment for adjusting changing situation of worker by aggregating objective criteria (shortening completion time) and subjective criteria (getting expected experience of worker).

3.2 Changing situation

Importance of objective criteria for the appropriate task selection is changed by occurring external interference to the worker. The external interference to the worker generates new activity to current workflow of the worker. Corragio defines an interruption as an "externally-generated, randomly occurring, discrete event that breaks continuity of cognitive focus on a primary task" [63]. Interruption of operation continuity by the worker on the workflow is occurred by invoking new or updates another task of the worker. In other words, interruption is occurred by partial participation of multiple workflows. Interruption would produce positive or negative effect to the worker and the current workflow.

Interruption is formalized through two parametric views that are time and context. The time parametric view of interruption is related to operating time of the generated task and completion time of interrupted workflow. The degree of positive or negative effect to forward the current workflow can be represented by normalizing time of the interruption. The context parametric view of interruption is related to operation and process to the current workflow. The context of the generated task by interruption is analyzed to formulate alternatives based on influenced elements of interruption. Although interruption by non-task such as taking rest or enjoying hobby has positive effect to efficiency of the current workflow by improving mental or physical tiredness, any interruption generates negative effect to the current workflow in time parametric view point. Starting time of subsequent tasks on the interrupted workflow is delayed by consuming time for the interruption. Each weight of criteria for selecting appropriate task is changed to improve the delay of the current workflow by re-assigning tasks of inexperienced worker to experienced worker.

There are many approaches for improving work efficiency by handling resources of workers such as job scheduling problem or flow shop scheduling [64] [65]. Although conventional scheduling problem approaches can optimizes work efficiency by scheduling, reduction of experience for inexperienced workers due to assigning tasks to experienced worker are not discussed. Task assignment for improvement of too higher efficiency decreases work opportunity of inexperienced worker. The expected profits of pre-assignment for forthcoming work are reduced by the negative effect of interruption and overmuch improvement by re-assigning tasks. In order to minimize the payoff of expected profit for forthcoming work, the appropriate task selection of the worker in interruption must approximate to the expected profit by pre task assignment as an ideal task selection through the superior decision maker.

Leaving time (disengagement) of the current workflow due to interruption generates negative effects to short term memory of the interrupted worker because of forgetting the task of workflow. Memory of the interrupted worker for the interrupted work is reduced with time. Relation of both time and degree of decreasing memory is represented by Ebbinghaus’s Forgetting Curve [66]. Negative effect of the lacked working memory is appeared when past task is resumed from added tasks. By leaving from the interrupted work, usable time for the interrupted workflow is consumed and accuracy of decision making for the interrupted work is decreased [67]. Experienced worker can decide appropriate task according to own judgment heuristics [31]. The accuracy of decision making by experienced worker also is reduced after long time interruption. Therefore, the authenticity of experienced worker’s decision making for selecting appropriate tasks of the current workflow is decreased by interruption. The next section is shown the outline of the proposed approach for supporting decision making of appropriate task selection of worker.

3.3 Proposed approach

Supporting decision making, for the appropriate task selection in interruption, is improvement of affected work efficiency to the current workflow caused by interruption. Effective alternatives for concerned workers of the interrupted workflow can be ranked according to multi criteria for related tasks by applying MCDM methods or updated by applying Metaheuristics according to objective function as criteria. The attributes for weighting criteria in the interruption model are classified into two aspects; objective attributes and subjective attributes that are based on nature of the attributes.

The objective attributes for weighting criteria mean certain profit for objective achievement of organizations. A worker who is employed by organization is oriented to objective of the organization by company strategy. The objective of organization is aggregation of multi criteria attributes for stakeholders in a company. The criteria of task assignment by superior decision maker include work efficiency of workers for benefit of the organization and training for workers that leads to organization benefits in its progress. Meanwhile, the subjective attributes mean dynamic changing work environment that consists of fuzzy elements of workers and tasks. Since completion time of tasks are depending on assigned worker's operational skill to task, the situation of interruption for operating workflow is consisted by using the subjective attributes of workers for related tasks. Therefore, proposed weights of multi criteria should be computed by aggregating the objective attributes for tasks aligned on the subjective attributes of workers.

The interrupted workers in changing work environment must select appropriate task under objective of organization. In addition, the concerned workers to the interrupted workflow must avoid the overmuch improvement to keep the expected subjective profits for organization such as nurture of inexperienced worker. TOPSIS method for ranking alternatives and Harmony Search method formulating alternative are employed to maximize subjective profit of decision maker with satisfying objective profit by proposed DSS according to discussion of Section 2.3.3 and Section 2.4.4. The objective attributes of the organization is aggregation of subjective attributes that is dependable on worker's experience (extracted from works preferences).

Alternatives for appropriate task selection in interruption must improve delay of workflow to achieve by deadline of the workflow. There is an approach to reduce the number of AGVs (automated guided vehicles) in container terminals without effect on completion time of workflow [68]. Cost of AGVs in this approach is reduced by computing appropriate order of the container quay crane and AGVs' operation on the basis of modeling by using the pseudo-analysis. Concerned workers in interruption already have tasks for achieving workflow by deadline. Therefore, appropriate order of tasks for improving delay as alternatives must includes individual difference of concerned workers' skills as subjective attributes.

The consumed time for the current workflow due to interruption can be improved by supporting tasks of inexperienced worker by the experienced worker as formulated alternatives. The improvable subjective completion time of inexperienced worker's task is changed according to degree of supporting worker's experience. Therefore, provided alternatives for appropriate task selection in interruption are formulated by computing subjective completion time of task based on experience of workers. The scores of provided alternatives for positive or negative ideal solution are computed by estimating expected experience of workers in task operation. Each expected experience of alternatives is computed based on proportion of engagement of experienced worker for improving the consumed time by interruption. Operating time of the inexperienced worker is shortened by asking related information for operating task to the experienced worker without gathering information by oneself. Although the subjective completion time of inexperienced worker is shortened by increasing engaging time of the experienced worker for the task of the inexperienced worker, expected experience of workers by pre-assignment is decreased by reducing working opportunity of the inexperienced worker. Therefore, appropriate alternatives for the expected experiences by pre-assignment are ranked according to reduced expected experiences to achieve required engaging time of supporting worker for tasks of the interrupted worker.

The engaging time for supporting each task is changed based on subjective completion time of the experienced workers for each task. The subjective completion time of the supporting worker for improving negative effect by interruption is shortened by giving related information to the task from documentation of the experienced worker to the supporting worker.

Document for knowhow is reflected by experience of document creator. Expertise of the document to the task is extracted according to similarity of the context of the task and the document. The expected experience of alternatives is reduced by shortening the subjective completion time of each task of the interrupted worker with the similar document. Since the distance of the positive ideal solution's score and the score of alternatives in TOPSIS is shortened by reducing the required engaging time of supporting worker for the tasks of the interrupted worker, the ranking of appropriate task selection for shortening negative effect of interruption is changed depending on degree of improvement for the tasks by the similar document.

In order to recommend appropriate task selection within the negative effect to the workflow caused by interruption, proposed approach utilizes TOPSIS method to rank appropriate alternatives and Harmony Search method to update alternative for the interrupted worker by aggregating objective attributes of task and subjective attributes of worker with objective attributes of related documentations. In our approach the workflow is given. Our purpose is to have the execution of the work be kept or optimized based on the interruptions context project by attributes consider as either objective or subjective ones.

3.4 Definition of Target tasks

Workflow is an optimized representation of steps to achieve work objective by expert worker and specified in optimal manner based on business policy and etc. The steps for goal in Lewin theory represent "cognitive structure" as workflow [69]. These steps are ordered as task by eliminating negative cause such as loss of time, duplicative process and so on. The divided task by steps is an action for achieving simple objective task as input of the other task. Task that needs results of the other task as input is ordered after completing the related task. Tasks that have no input or output relations can be reallocated in parallel.

The parallel tasks on workflow can be assigned to multiple workers or multiple project members for operating tasks simultaneously. The task on the workflow is activity that needs to be accomplished within defined period of time or by deadline. Objective of each task is achieved by completing operation of worker before the deadline of each task. The length of usable time for the task operation of worker is up to the deadline of the task from the completion time of prior task. The task that has deadline of short period is ordered earlier than task of long period deadline. Entire deadline of the workflow is defined by aggregating estimated completion time of each task. Even if there is similar task in the workflow, order of these tasks is sequential based on different operating period. The order of tasks in the workflow can be changed by keeping the completion time of each task related deadlines. Therefore, selectable tasks for improving work efficiency by the concerned workers to the interrupted workflow are tasks that have finished the related prior tasks as inputs without including already finished tasks.

In order to reduce uncertainty of objective criteria in changing environment, operating time of workers is utilized to normalize negative impact of interruption based on pre task assignment. Figure 3.1 shows matrix of worker's operating time (*OT*) for pre-assignment (*PreA*) by the superior decision maker. Number of rows in the matrix of pre-assignment means assigned workers to same workflow. Each operating time (*OT*) of task according to deadline of the task and operable time period of the assigned worker is substituted to each columns of assigned worker. The coordinates of non-assigned tasks has value of zero.

$$PreA = \underbrace{\begin{pmatrix} OT_{11} & \cdots & OT_{1h} \\ \vdots & & \vdots \\ OT_{g1} & \cdots & OT_{gh} \end{pmatrix}}_{g \text{ = number of workers to the workflow}} \left.\vphantom{\begin{pmatrix} a \\ b \\ c \end{pmatrix}}\right\} h \text{ = number of tasks to the workflow}$$

Figure 3.1: Matrix for pre-assignment by superior decision maker

3.5 Relation of time and experience

Subjective completion time of task is changed depending on tasks' context and experience of workers. The context of task can be classified as physical work and mental work. The physical work is an activity based on physical condition of worker such body related problems, or muscular tension or physical change in office or working space. The physical part of the work is related to the objective attributes of task based an organization's objectives represented as criteria. Meanwhile, the mental work is an activity of information gathering for the steps of the task operation that lead to efficient physical work. Operating time for the mental work is related to searching and analyzing time based on individual experience of workers as subjective attributes.

Experienced worker can shorten the time for the mental work by utilizing information for the steps of the task operation based on accumulated experience through a past task operation as knowledge. Workers acquire multiple types of experiences for the mental work depending on context of task through the task operation. The context of task is represented as a set of objective attributes by weighting of operating time of task to each type of experience.

However, impact of experience is uncertain profit as subjective criteria. Therefore, moral rule of superior decision maker is applied to criteria for reducing uncertainty of experience. Impact for each type of experience on operating time of task is weighted as fuzzy membership by experienced worker. The membership function of task for each type of experience is shown in following.

$$\sum_{i=1}^{l} \mu w(i) = 1.0 \qquad (3.1)$$

$\mu w(i)$ = weight of each type of experience

l = number of related experiences for task

Each value of accumulating experience with a time is evaluated as objective attributes of task by linguistic value of experienced worker. Amount of individual knowledge for workers as the subjective attributes is accumulated by multiplying defined weights of experience ($\mu w(i)$) and operating time of task. Accumulation of experience is higher for inexperienced worker according to learning curve [70]. In other words, expected experience for experienced worker from task operation is smaller than inexperienced worker. Subjective expected profit by task for each experience ($SPf(i)$) is computed as in the following expression.

$$SPf(i) = \frac{\left(OT_{gh} * \mu w(i)\right)}{\left(OT_{gh} * \mu w(i)\right) + We(i)} \qquad (3.2)$$

i = type of experience

$$We(i) = We(i) + SPf(i) \qquad (3.3)$$

$We(i)$ = accumulated experience of worker

Operating time (OT) for each task is defined by task assignment based on deadline of each task and operable period of workers. The subjective expected profit ($SPf(i)$) for experiences of the task assigned worker is decreased by increasing the past accumulated experiences ($We(i)$) of the worker. Therefore, enhancement of operating task is maximized by assigning tasks of workflow to the inexperienced worker. The time for operating task has essential core time (ct) and improvable time by the experienced worker. The core time (*ct*) means essential engagement of the worker to the task that includes physical execution or waiting such as running time of machine. Experienced worker can shorten the time for engagement of thinking that includes information gathering for task achievement by utilizing their expertise. Therefore, the core time (*ct*) that is impossible to shorten by experience is decided by the experienced worker. The subjective completion time (*SCt*) of task that is changed by amount of experiences of the task assigned worker is computed by crossing the above defined objective attributes of the task to experience. Small expected experience from the task operation means the task assigned worker has related large amount of experience to the task. Impact (*iSPf*) of the time for the engagement of thinking is computed by averaging each subjective expected profit (*SPf(i)*) for the task assigned worker. Following expression represents the subjective completion time (*SCt*) of the task with the worker.

$$iSPf = \left(\sum_{i=1}^{l} SPf(i) \right) \Big/ l \qquad l = \text{number of related experiences for task} \tag{3.4}$$

$$SCt = ct + \left(iSPf * \left(OT_{gh} - ct \right) \right) \qquad ct = \text{core time for task operation} \tag{3.5}$$

The subjective completion time other than the core time is computed by multiplying the impact (*iSPf*) of subjective profits for the task assigned worker to the shortened operating time by experienced worker. The shortened operating time is computed by subtracting the core time from pre-assigned operating time (*OT*) based on deadline of the task. Therefore, the subjective completion time (*SCt*) is maximized by assigning the task to inexperienced worker for the task.

3.6 Setting PIS and NIS by TOPSIS

PIS (Positive ideal solution) for decision making of improving work efficiency by TOPSIS method is extracted from expected profits of workers by pre-assignment in the proposed approach. Decision of superior worker who assigned tasks is reflected to avoid the task selection of overmuch improvement for the current workflow by extracting from pre-assignment as positive ideal solution. Consensus of alternatives for improving effect of interruption is defined by aggregating the weighting of experienced worker and pre task assignment by superior decision maker of the current workflow. Target tasks for improving negative effect of interruption as alternatives on decision making are the confined tasks that have same deadline. The score of positive ideal solution (*PIS*) is computed as objective attributes by aggregating each subjective profit for experience of each worker from the target tasks by pre-assignment. Figure 3.2 shows matrix of the positive ideal solution (*PIS*) and negative ideal solution (*NIS*) in interruption.

$$PIS = \underbrace{\begin{pmatrix} E_{11} & \cdots & E_{1l} \\ \vdots & & \vdots \\ E_{k1} & \cdots & E_{kl} \end{pmatrix}}_{l} \Bigg\} k \qquad NIS = \underbrace{\begin{pmatrix} E'_{11} & \cdots & E'_{1l} \\ \vdots & & \vdots \\ E'_{k1} & \cdots & E'_{kl} \end{pmatrix}}_{l} \Bigg\} k$$

l = number of related experiences for task
k = number of concerned workers for interruption

Figure 3.2: Matrix of positive ideal solution and negative ideal solution

$$E_{kl} = \sum_{i=1}^{n} SPf_1(i) \qquad SPf1(i) \text{ is based on pre-assignment} \tag{3.6}$$

n = number of target tasks assigned to worker

$$E'_{kl} = \sum_{i=1}^{n} SPf_2(i) \qquad SPf2(i) \text{ is based on shortest total completion time} \tag{3.7}$$

The expected profits (E_{kl}) of each experience to the task assigned workers are computed by aggregating same experience type of pre-assigned tasks that have same deadline. The number of concerned workers for interruption is selected according to the deadline of assigned tasks on the same workflow. In order to avoid overmuch improvement for the current workflow by restructuring of task assignment, the expected profits (E'_{kl}) of task assignment that have shortest total subjective completion time of related workers within possible combination of task assignment in the interruption is computed as negative ideal solution (*NIS*). Number of combinations for the possible task assignment is computed according to the number of workers and deadline of selectable tasks. Therefore, the alternatives that have total expected profits for forthcoming task than pre-assignment are included as improvement for the interruption.

3.7 Context of task and documentation

The context of task in proposed approach consists of the terms for classifying each type of experiences and the weighted values of profit to each experience as scalar value. Context of document that is created by experienced worker can be represented based on the used keywords for linguistic classification of the type of experience (μw). Experts conclude the main criteria for workflow, and evaluate attributes in pair wise fashion based on their strategy etc. The context of document in knowledge base can be represented as vector by counting term frequency of each keyword to compute the relative importance weight of criteria. Therefore relevancy of the target tasks and document of experienced workers are computed with using terms as common features by comparing correlation of two vectors that are the context of the task and the context of the document. The correlation of the two vectors are compared to compute multiple terms of the two vectors on monotonic property by using cosine distance [71]. Following equation shows calculation of similarity by cosine distance.

$$Cos(\vec{p},\vec{q}) = \frac{\sum_{i=1}^{j}\left(\mu w(i) * Tm(i)\right)}{\sqrt{\sum_{i=1}^{j}\left(\mu w(i)\right)^2} * \sqrt{\sum_{i=1}^{j}\left(Tm(i)\right)^2}} \qquad \begin{array}{l} \vec{p} = \{\mu w(1), \mu w(2), \cdots, \mu w(j)\} \\ \vec{q} = \{Tm(1), Tm(2), \cdots, Tm(j)\} \\ j = \text{number of common terms} \end{array} \tag{3.8}$$

The vector *p* consists of proportion of weighted profit for the task ($\mu w(j)$) by classifying named experiences. *Tm(j)* of the vector *q* for the documents are normalized to create the vector for analyzing by using term frequency meaning according to terms of the context of task. The similarity of two vectors is higher by approaching score of cosine distance to 1.0.

3.8 Formulating alternatives with TOPSIS

Appropriate alternatives for ideal expected profits by pre-assignment are formulated based on the subjective completion time of selectable tasks and generated task by interruption. Formulated alternatives must be able to negate to the expected consumed time (*ECt*) by interruption. The expected consumed time (*ECt*) is computed by computing the subjective completion time of the generated task by interrupted worker.

$$ECt = ct + \left(iSPf * (OT' - ct)\right) \tag{3.9}$$

Operating time (*OT'*) for the generated task by interruption is an operable period of the interrupted worker by deadline of the task. Each worker who is concerned to the target tasks in interruption has subjective flexible time (*SFt(i)*) for usable another tasks based on deadline of pre-assigned tasks and each subjective completion time. Total flexible time (*TSFt(k)*) of the interrupted worker who has multiple tasks can be used for the expected consumed time (*ECt*) by interruption.

$$SFt(i) = OT_{gh} - SCt(n) \tag{3.10}$$

$$TSFt(k) = \sum_{j=1}^{n} SFt(i) \tag{3.11}$$

n = number of target tasks assigned to worker
k = number of concerned workers for interruption

Achievement of tasks on the current workflow is failed by exceeding the expected consumed time (*ECt*) from total flexible time (*TSFt(k)*) of the interrupted worker. The subjective flexible time (*SFt(n)*) of each worker also can be utilized to support interrupted worker's tasks. The exceeding time (*EECt*) of the interrupted worker is improved by consuming operating time of the other task within the subjective flexible time of the other worker. Therefore, alternatives (*Alt(x)*) for improving the expected consumed time (*ECt*) by interruption are formulated based on the supporting time of another worker for improving the exceeding time of the interrupted worker. The required time (*Rt*) for supporting the interrupted worker is computed based on proportion of exceeding time (*EECt*) for interrupted worker and the impact of subjective profits (*iSPf*) for the experience of supported task by the workers.

$$EECt = ECt - TSFt(k) \qquad (ECt > TSFt(k)) \qquad (3.12)$$

$$EECt : iSPf(s) = Rt : iSPf'(s) \qquad (3.13)$$

$$Rt = EECt * \frac{iSPf'(s)}{iSPf(s)} \qquad (3.14)$$

iSPf'(s) by supporting worker
iSPf(s) by interrupted worker

The subjective expected profits (*SPf(s)*) of supported task for interrupted worker by other worker is computed by subtracting the exceeding time (*EECt*) from the subjective completion time (*SCt(s)*) of the interrupted worker for the supported task as operating time. The subjective expected profits (*SPf(i)*) of the other pre-assigned tasks for the interrupted worker is computed by using the subjective completion time (*SCt(i)*) of the interrupted worker. Total expected profits (E_{al}) for the interrupted worker who is supported by the other worker in alternatives is computed by aggregating expected profits of the pre-assigned tasks within total flexible time (*TSFt(k)*) of the interrupted worker.

$$SPf(s) = \frac{((SCt(s) - EECt) * \mu w(s))}{(SCt(s) * \mu w(s)) + We(s)} \qquad (3.15)$$

s = type of experience for the supported task

$$SPf(i) = \frac{(SCt(i) * \mu w(i))}{(SCt(s) * \mu w(s)) + We(s)} \qquad (We(i) = We(i) + SPf(i)) \qquad (3.16)$$

$$E_{al} = SPf(s) + \sum_{i=1}^{n-1} SPf(i) \qquad (3.17)$$

l = number of related experiences for task
n = number of target tasks assigned to interrupted worker

Meanwhile, the total subjective expected profits (E_{bl}) for the supporting worker as the score of alternatives are computed by aggregating the subjective expected profits (*SPf(s)*) of the supporting task and the subjective expected profits (*SPf(i)*) of pre-assigned tasks to the supporting worker. The negative effect of interruption is improved by utilizing the subjective flexible time (*SFt*) of the supporting worker as alternatives. Therefore, the total subjective flexible time (*TSFt*) of the supporting worker must be longer than the required time (*Rt*) for improving the exceeding time (*EECt*) of the interrupted worker. The subjective expected profit (*SPf(s)*) of the supporting worker for supporting task is acquired by computing the required time (*Rt*) and impact of subjective profits (*iSPf*) for the supported task.

$$SPf(s) = \frac{(Rt * \mu w(s))}{(Rt * \mu w(s)) + We(s)} \tag{3.18}$$

$$SPf(i) = \frac{((Ot_{gh} - SFt) * \mu w(i))}{((Ot_{gh} - SFt) * \mu w(i)) + We(i)} \quad \begin{array}{l} (SFt < Rt) \\ (Rt = Rt - SFt) \\ (We(i) = We(i) + SPf(i)) \end{array} \tag{3.19}$$

$$SPf(i) = \frac{((Ot_{gh} - Rt) * \mu w(i))}{((Ot_{gh} - Rt) * \mu w(i)) + We(i)} \quad \begin{array}{l} (SFt > Rt) \\ (We(i) = We(i) + SPf(i)) \end{array} \tag{3.20}$$

$$E_{bl} = SPf(s) + \sum_{i=1}^{n} SPf(i) \quad \begin{array}{l} l = \text{number of related experiences for task} \\ n = \text{number of target tasks assigned to interrupted worker} \end{array} \tag{3.21}$$

The subjective expected profit (*SPf(i)*) of the supporting worker by pre-assignment is decreased by subtracting applied flexible time (*SFt*) for supporting from operating time (Ot_{gh}) of the pre-assigned task. When the required time (*Rt*) for supporting the interrupted worker is longer than the subjective flexible time (*SFt*) of the task, the required time (*Rt*) is consumed by utilizing the flexible time of the other tasks of the supporting worker. Distance of alternatives and positive ideal solution (*PIS*) on the expected profits (E_{kl}) of each experience to the workers is shortened by shortening the required time (*Rt*) for the interrupted worker. The required time (*Rt*) for the interrupted worker is shorted by increasing an impact of subjective profits (*iSPf'*) of the supporting worker for the supported task. The proposed approach shortens the required time (*Rt*) of the supporting worker for improving the exceeding time (*EECt*) of the interrupted worker by applying similar document to the supporting worker as experiences for task operation according to experiences (*De(n)*) of document creator. Degree of applied experiences of document creator is computed based on a similarity (*Sm(n)*) of tasks and documents. The impact of subjective profits (*iSPf"*) for shortening the required time (*Rt'*) with the similar document as alternatives are computed as follows.

$$SPf(s) = \frac{(Ot_{gh} * \mu w(s))}{(Ot_{gh} * \mu w(s)) + (We(s) + (De(s) * Sm(s)))} \tag{3.22}$$

$$iSPf''(s) = \left(\sum_{i=1}^{l} SPf(s) \right) \Big/ l \quad l = \text{number of related experiences for task} \tag{3.23}$$

$$Rt' = EECt * \frac{iSPf''(s)}{iSPf(s)} \qquad \begin{array}{l} iSPf''(s) \text{ by supporting worker with similar document} \\ iSPf(s) \text{ by interrupted worker} \end{array} \tag{3.24}$$

The alternatives with the similar document shorten only engaged time of thinking such as information gathering. Therefore, the experiences of the document creator are not added to the expected profits of alternatives. Figure 4 shows matrix of alternatives for improving the exceeding time (*EECt*) of the interrupted worker. The scores for concerned workers who do not include the interrupted worker and the supporting worker are substituted same value of the positive ideal solution (*PIS*) to the matrix of alternatives (*Alt(x)*).

$$Alt(x) = \begin{pmatrix} E_{11} & \cdots & E_{1l} \\ E_{a1} & \cdots & E_{al} \\ E_{b1} & \cdots & E_{bl} \\ \vdots & & \vdots \\ E_{k1} & \cdots & E_{kl} \end{pmatrix}$$

Row $E_{a1} \cdots E_{al}$: Expected profits of supporting worker without including applied experience of document creator

Row $E_{b1} \cdots E_{bl}$: Expected profits of interrupted

l = number of related experiences for task
k = number of concerned workers for interruption
x = type of alternatives

Figure 3.3: Matrix of alternatives

The formulated alternatives (*Alt(x)*) are ranked by computing criteria (*C*) of TOPSIS method based on Euclidean distance of the positive ideal solution (*TDP*) and the negative ideal solution (*TNP*). Each distance of the interrupted worker (*DP(*1*)*) (*DN(*1*)*) and the supporting worker (*DP(*2*)*) (*DN(*2*)*) to the positive or the negative ideal solution are computed by computing following expressions.

$$DP(1) = \sqrt{\sum_{i=1}^{l} \left(E_{kl} - E_{al}\right)^2} \qquad DP(2) = \sqrt{\sum_{i=1}^{l} \left(E_{kl} - E_{bl}\right)^2} \tag{3.25}$$

$$DN(1) = \sqrt{\sum_{i=1}^{l} \left(E'_{kl} - E_{al}\right)^2} \qquad DN(2) = \sqrt{\sum_{i=1}^{l} \left(E'_{kl} - E_{bl}\right)^2} \tag{3.26}$$

$$TDP = \sqrt{\sum_{i=1}^{k} \left(DP(k)\right)^2} \qquad TDN = \sqrt{\sum_{i=1}^{k} \left(DN(k)\right)^2} \tag{3.27}$$

$$C = \frac{TDN}{TDP + TDN} \tag{3.28}$$

l = number of related experiences for task
k = number of concerned workers for interruption

3.9 Alternative by Harmony Search

The vectors of *HM* are optimized by comparing and updating the new vector that is generated randomly according to certain conditions. Negative effect of the interruption to the workflow can be represented as harmony vector by applying harmony search approach. The vectors of pre task assignment to the workers can be represented as *HM* by structuring operating time (*OT*) to each task depending on the assigned worker. Figure 3.4 shows the vectors of pre task assignment (*HM*).

$$HM = \underbrace{\begin{pmatrix} OT_{11} & \cdots & OT_{1h} \\ \vdots & & \vdots \\ OT_{g1} & \cdots & OT_{gh} \end{pmatrix}}_{h \text{ = number of workers to the workflow}} \left.\vphantom{\begin{pmatrix} a \\ b \\ c \end{pmatrix}}\right\} g \text{ = number of tasks to the workflow}$$

Figure 3.4: Vectors of task assignment

The *HMS* in interruption is number of selectable tasks (g) based on deadline of each tasks in the workflow. All the harmonies generated in relation to different interruption are gathered as index. This can be called as harmony index. In that case for new occurring interruption the harmony index is updated. Parameters of pre-assignment (*HM*) are changed by updating new vector that is generated as interruption. The harmony of pre task assignment is changed to worst harmony by the negative update of interruption. Achievement of each task can be computed as objective function by comparing subjective completion time of the assigned workers and the operating time to the assigned tasks. The achievement of task g ($Ta(g)$) is computed by following objective function.

$$Ta(g) = \sum_{i=1}^{h} OT(g,i)/SCt(g,i) \qquad h = \text{number of workers to the workflow} \tag{3.29}$$

The subjective completion time (SCt) means estimated completion time of individual worker to each task based on subjective attributes of worker. The superior decision maker assigns the tasks to the workers for completing up to the deadline of each task by estimating individual subjective completion time based on their experience. Figure 3.5 indicates the estimation (E) of subjective completion time according to the above equation (3.5).

$$E = \underbrace{\begin{pmatrix} SCt_{11} & \cdots & SCt_{1h} \\ \vdots & & \vdots \\ SCt_{g1} & \cdots & SCt_{gh} \end{pmatrix}}_{h \text{ = number of workers to the workflow}} \left.\vphantom{\begin{pmatrix} a \\ b \\ c \end{pmatrix}}\right\} g \text{ = number of tasks to the workflow}$$

Figure 3.5: Matrix of subjective completion time by workers

The operating time of task (OT) is usable time for the task based on deadline of the task and workable time of the assigned worker. The workable time is duty hours without break time according to employment conditions of organization. The score of task achievement ($Ta(g)$) is computed by aggregating each score of the concerned workers (h) who are belonging to interrupted workflow. The worker's operating time of non-assigned tasks is zero in pre-assignment. Therefore, the tasks of workflow are achieved by the score of task achievement ($Ta(g)$) over 1.0 in the above equation (3.29). Each worker can generate flexible time for supporting another tasks by subtracting subjective completion time of each task ($SCt(i, h)$) from operating time of assigned tasks ($OT(i, h)$) as following.

$$TSFt(h) = \sum_{i=1}^{g} (OT(i,h) - SCt(i,h)) \tag{3.30}$$

If the flexible time (*TSFt*) of the interrupted worker is exceeded by the subjective completion time of generated new task, score of task achievement to interrupted worker becomes less than 1.0. Therefore, changed vector of pre task assignment by interruption is changed to the worst harmony as target vector of harmony search. The score of task achievement can be improved by utilizing the flexible time of the other workers. In order to improve the worst harmony of the task assignment, a new harmony vector is created based on flexible time of concerned workers who are assigned tasks of interrupted workflow. Although the parameters of a new harmony vector for comparing with the worst harmony is chosen from the *HM* randomly according to pre set rate in conventional *HS*, work efficiency of all tasks of interrupted workflow is optimized without the nurture of inexperienced worker by pre-assignment. In order to avoid this issue, proposed approach generates the comparing harmony vector by handling subjective flexible time of the workers. Even if the subjective completion time of the workers to the tasks is different, the usable time of the worker to the deadline of the assigned tasks is constant. Therefore, the comparing harmony vector is generated by changing randomly the proportion of operating time for each task among the usable time of each worker. The subjective usable time (*SUt*) of each worker is computed by aggregating the flexible time (*TSFt*) of the worker and each operating time of task (*OT*) among the vectors of pre task assignment (*HM*).

$$SUt(h) = TSFt(h) + \sum_{i=1}^{g} OT(i,h) \tag{3.31}$$

The worst harmony vector in interruption model is restructured based on pre task assignment and remaining time of subtracting the expected subjective completion time of interruption from the subjective usable time. In order to generate the new vector for updating the worst harmony, target worker *z* and two target tasks *x*, *y* for changing operating time are chosen randomly to generate new vector from selectable tasks of the interrupted workflow. The selected tasks *x*, *y* must be different task to change the score of vectors. In order to avoid decreasing the score of already achieved tasks, either of two target tasks *x*, *y* must include the task that has score of achieve less than 1.0. When the operating time of the first target task *x* is reassigned randomly, selectable maximum time (*OTm*) for the task *x* is summation of the flexible time of the target worker *z* and each time of target tasks *x*, *y* related to the target worker *z* in the worst harmony vector.

$$OTm = TSFt(z) + OT(x,z) + OT(y,z) \tag{3.32}$$

After selecting new operating time (*OT'*(*x*,*z*)) of the first task *x*, the achievement of task *x* (*Ta*(*x*)) is computed to avoid overmuch improvement in expression (5) whether the score is exceeding 1.0. If the score of achievement (*Ta*(*x*)) is exceeding 1.0, the new operating time (*OT'*(*x*,*z*)) of the task *x* is reduced up to appropriate time that can be scored to 1.0. The appropriate new operating time (*OT'*(*x*,*z*)) is computed by multiplying required score to the target worker *z* for achieving the task *x* by the subjective completion time of the target task *x*. The required score of the target worker *z* is computed by subtracting the aggregated achievement score (*Ta'*(*x*)) of the concerned workers other than worker *z* for task *x* from 1.0.

$$Ta'(x) = \{\sum_{i=1}^{h} OT(x,i)/SCt(x,i)\} - (OT(x,z)/SCt(x,z)) \tag{3.33}$$

$$OT'(x,z) = (1.0 - Ta'(x)) * SCt(x,z) \tag{3.34}$$

The new operating time (*OT'*(*y*,*z*)) for the second task *y* is assigned the remaining time of subtracting the new operating time (*OT'*(*x*,*z*)) of the task *x* from the selectable maximum time (*OTm*). The score of achievement of the task *y* is also computed for checking overmuch improvement. The overmuch time for achieving task *y* is recharged as the flexible time (*TSFt*) of the worker *z*. All parameters of the worst harmony and the generated new vector are compared about each task achievement according to the objective function. If the total score of task achievement by the new vector is better than the score of the worst harmony, the vector of worst harmony is updated. The above comparing with the vector worst harmony and the generated new vector is continued until all task achievement scores are 1.0. The conclusive scores of the updated vector is the optimized task assignment of the workflow in this interruption.

3.10 Conclusion

This chapter explains applied model of decision making in work environment. Proposed DSS provides appropriate task selection to worker in occurring interruption by aggregating shortening completion time of task as objective criteria and experience of worker for forthcoming task as subjective criteria.

In next chapter, proposed methods are applied to existing sample model of work to evaluate validity of recommended alternatives with comparing with conventional approach.

Chapter 4

Evaluation of proposed approach

4.1 Introduction

Interruption of workflow is occurred by overlapping workflows of collaborative work in office work. Concerned workers to the interrupted workflow must improve work efficiency to achieve related tasks. Overmuch improvement must be avoided to keep expected nurture for pre-assigned workers. In order to evaluate proposed approach and conventional approach, proposed algorithm is applied to existing system development work in a company. A system development work is operated with sharing tasks by multiple workers as collaborative work. Workers who have similar role participate to workflow to achieve objective by sharing tasks of the target workflow. The participated workers who have history of developing another system are interrupted by trouble shooting according to user inquiry. The generated activity is operated by interrupted worker till resolving the problem. In order to assist decision making for adaptive task selection in this interruption case, the proposed approach is applied to concerned workers in certain interrupted workflow.

Assumed situation model for adaptive task selection in interruption is an actual system development of three workers in a Japanese company. Target three workers who have different working history are developing a sales analysis tool in intra network of the company based on assignment of project leader. The sales analysis tool is developed by using Microsoft Excel with VBA (Visual Basic for Applications). The ranking of adaptive task selection is changed according to the situation of interruption and the subjective attributes of interrupted worker.

4.2 Normalizing subjective attributes of workers

Firstly, subjective attributes of concerned workers as working experience are computed according to existing working report of two month by using pre-weighted impact of tasks. The focused type of experiences consists of type of computer language, user supporting and specification creation and so on. Table 4.1 shows sample definitions for weighting impact of experience. The subjective attributes of three target workers are calculated according to working report as Table 4.2. Each score as the past accumulated experiences (*We(i)*) of each worker in Table 4.2 is computed by using equation (3.2)(3.3).

Table 4.1: Target type of experiences

Type of experiences	Keywords
*We(*1*)*	Visual Basic
*We(*2*)*	JavaScript
*We(*3*)*	HTML
*We(*4*)*	VBA
*We(*5*)*	Database
*We(*6*)*	MS Excel
*We(*7*)*	User supporting
*We(*8*)*	Find and fix of bug
*We(*9*)*	Specification consideration
*We(*10*)*	System updating
*We(*11*)*	Document creation

Table 4.2: The subjective attributes of each worker in two month

	We(1)	*We*(2)	*We*(3)	*We*(4)	*We*(5)	*We*(6)	*We*(7)	*We*(8)	*We*(9)	*We*(10)	*We*(11)
Worker 1	6.88	9.50	6.75	2.93	7.59	3.60	4.02	4.36	5.91	5.89	4.65
Worker 2	7.38	10.92	6.74	1.00	12.30	1.00	1.00	1.00	7.38	1.00	5.09
Worker 3	1.00	12.13	9.17	2.71	7.18	3.82	1.67	1.00	2.44	1.00	1.00

Worker 1 who has developed first version of the sales analysis tool has experience of web system development. Although Worker 2 has also the experience of the web system development and database development, he is manager who has small experience for VBA development. Worker 3 has experience of supporting development of Worker 1 and he had been trained to develop web application in first month. The positive ideal solution in assumed interruption situation is computed by using each worker's subjective attributes and pre-assignment of tasks. When the interruption is occurred to Worker 1 by adding the task from another workflow as Task 7 due to trouble for another system, operating time for Task 1 and Task 4 of Worker 1 is consumed by generated Task 7. In order to computing appropriate alternatives for improving negative effect of the interruption to Worker 1, the positive ideal solution is computed based on selectable pre-assigned tasks to the concerned workers. Table 4.3 shows relation of workers and the pre-assigned tasks that have same deadline in assumed interrupted situation. The target workers in this company can work eight hour per day.

Table 4.3: Relation of pre-assigned tasks

	Operating time	Core time	Assigned worker
Task 1	8.0	5.0	Worker 1
Task 2	8.0	4.0	Worker 2
Task 3	8.0	5.0	Worker 3
Task 4	8.0	4.0	Worker 1
Task 5	8.0	4.0	Worker 2
Task 6	8.0	5.0	Worker 3
Task 7	8.0	5.0	nothing

Table 4.4 shows scores of weighted tasks by experienced worker. The weights are scored by using fuzzy membership function according to decision of the experienced worker to each task. Task 1 is bug fix activity for improving duplication of inserting data. Task 2 is changing activity of target database for filtering selectable organization function. Task 3 is designing activity for using the system by web browser. Task 4 is improvement activity for showing data quickly on viewer of the system. Task 5 is changing activity of target database for adding data function. Task 6 is design activity for adding data on web browser.

Table 4.4: Weighted target tasks of same deadline in interruption

	We(1)	*We*(2)	*We*(3)	*We*(4)	*We*(5)	*We*(6)	*We*(7)	*We*(8)	*We*(9)	*We*(10)	*We*(11)
Task 1	0.1	0.0	0.0	0.0	0.2	0.0	0.2	0.4	0.0	0.1	0.0
Task 2	0.0	0.0	0.0	0.2	0.5	0.3	0.0	0.0	0.0	0.0	0.0
Task 3	0.0	0.1	0.5	0.0	0.1	0.0	0.0	0.0	0.2	0.0	0.1
Task 4	0.0	0.0	0.0	0.5	0.0	0.3	0.0	0.2	0.0	0.0	0.0
Task 5	0.0	0.0	0.0	0.2	0.5	0.3	0.0	0.0	0.0	0.0	0.0
Task 6	0.0	0.1	0.4	0.0	0.1	0.0	0.0	0.0	0.3	0.0	0.1
Task 7	**0.1**	**0.1**	0.0	0.0	0.0	0.0	**0.4**	**0.4**	0.0	0.0	0.0

The negative effect (*ECt*) of Task7 to Worker 1 is computed based on the above the subjective attributes of Worker 1 and the objective attributes of Task 7.

$$SPf(1) = \frac{(8.0 * 0.1)}{(8.0 * 0.1) + 6.88} = 0.104 \qquad (4.1)$$

$$SPf(2) = 0.078, \quad SPf(7) = 0.443, \quad SPf(8) = 0.423 \qquad (4.2)$$

$$iSPf = (SPf(1) + SPf(2) + SPf(7) + SPf(8))/4 = 0.262 \qquad (4.3)$$

$$ECt = 5.0 + (iSPf * (8.0 - 5.0)) = 5.79 \qquad (4.4)$$

Table 4.5 shows the computed subjective completion time for each worker according to the subjective attributes of workers and the objective attributes of pre-assigned tasks.

Table 4.5: Subjective flexible time of pre-assigned tasks

	Completion time	Flexible time	Assigned worker
Task 1	5.66	2.34	Worker 1
Task 2	6.09	1.91	Worker 2
Task 3	5.78	2.22	Worker 3
Task 4	5.66	2.34	Worker 1
Task 5	6.09	1.91	Worker 2
Task 6	5.82	2.18	Worker 3

Therefore, the exceeding time of interrupted worker (Worker 1) is 1.11 hours. The alternatives for appropriate task selection must improve this exceeding time by supporting of other worker.

$$EECt = 5.79 - (2.34 + 2.34) = 1.11 \tag{4.5}$$

4.3 Supporting decision making by proposed TOPSIS

Figure 4.1 shows the computed matrix of positive ideal solution according to the above pre-assignment of tasks and target worker's subjective attributes.

$$PIS = \begin{pmatrix} 0.10, 0.00, 0.00, 0.58, 0.17, 0.40, 0.28, 0.67, 0.00, 0.12, 0.00 \\ 0.00, 0.00, 0.00, 1.11, 0.49, 1.29, 0.00, 0.00, 0.00, 0.00, 0.00 \\ 0.00, 0.12, 0.56, 0.00, 0.20, 0.00, 0.00, 0.00, 0.85, 0.00, 0.80 \end{pmatrix}$$

Figure 4.1: Matrix of positive ideal solution by pre-assignment

In order to avoid overmuch improvement for the computed exceeding time of Worker 1, each score of the negative ideal solution is computed by using task assignment that is shortest completion time. There are 90 combinations in this situation that three worker operates two tasks from six tasks. The negative ideal solution in Figure 4.2 is computed by using the task assignment of shortest completion time within 90 combinations.

$$NIS = \begin{pmatrix} 0.10, 0.00, 0.00, 0.58, 0.17, 0.40, 0.28, 0.67, 0.00, 0.12, 0.00 \\ 0.00, 0.14, 0.68, 0.00, 0.12, 0.00, 0.00, 0.00, 0.42, 0.00, 0.27 \\ 0.00, 0.00, 0.00, 0.71, 0.70, 0.75, 0.00, 0.00, 0.00, 0.00, 0.00 \end{pmatrix} \begin{matrix} \text{(W1: Task 1, Task 4)} \\ \text{(W2: Task 3, Task 6)} \\ \text{(W3: Task 2, Task 5)} \end{matrix}$$

Figure 4.2: Matrix of negative ideal solution

The selectable alternatives that can improve 1.11 hours of Worker 1 are four types of supporting in following.

$$Rt(T1\_W2) = 1.11 * 0.41 / 0.22 = 2.04 \tag{4.6}$$

$$Rt(T1\_W3) = 1.11 * 0.46 / 0.22 = 2.33 \tag{4.7}$$

$$Rt(T4\_W2) = 1.11 * 0.71 / 0.42 = 1.89 \tag{4.8}$$

$$Rt(T4\_W3) = 1.11 * 0.53 / 0.42 = 1.42 \tag{4.9}$$

Task 1(*T*1) and Task 4(*T*4) of Worker 1 are selectable by Worker 2 (*W*2) and Worker 3 (*W*3). The required time (*Rt*) for each worker is changed by supported tasks. Since Worker 2 and Worker 3 have two tasks, the number of alternatives is changed to eight by changing applied flexible time of tasks.

Table 4.6 shows each score of alternatives for improving required time of Worker 1. These scores are used to compute the distance of the positive ideal solution and negative ideal solution as Table 4.7 shown. The appropriate alternative in this situation is Alt(7) that Task 4 of Worker 1 is supported by utilizing flexible time of Task 3 of Worker 3.

Table 4.6: Scores of alternatives without similar document

	We(1)	*We*(2)	*We*(3)	*We*(4)	*We*(5)	*We*(6)	*We*(7)	*We*(8)	*We*(9)	*We*(10)	*We*(11)
Alt(1) T1 to T2, T5 of W2	0.06	0.00	0.00	0.49	0.11	0.32	0.18	0.49	0.00	0.07	0.00
	0.03	0.00	0.00	1.05	0.47	1.24	0.29	0.45	0.00	0.17	0.00
	0.00	0.12	0.56	0.00	0.20	0.00	0.00	0.00	0.85	0.00	0.80
Alt(2) T1 to T5, T2 of W2	0.06	0.00	0.00	0.49	0.11	0.32	0.18	0.49	0.00	0.07	0.00
	0.03	0.00	0.00	1.04	0.47	1.22	0.29	0.45	0.00	0.17	0.00
	0.00	0.12	0.56	0.00	0.20	0.00	0.00	0.00	0.85	0.00	0.80
Alt(3) T1 to T3 of W3	0.06	0.00	0.00	0.49	0.11	0.32	0.18	0.49	0.00	0.07	0.00
	0.00	0.00	0.00	1.11	0.49	1.29	0.00	0.00	0.00	0.00	0.00
	0.19	0.11	0.49	0.00	0.23	0.00	0.22	0.48	0.78	0.19	0.73
Alt(4) T1 to T6 of W3	0.06	0.00	0.00	0.49	0.11	0.32	0.18	0.49	0.00	0.07	0.00
	0.00	0.00	0.00	1.11	0.49	1.29	0.00	0.00	0.00	0.00	0.00
	0.19	0.11	0.50	0.00	0.23	0.00	0.22	0.48	0.77	0.19	0.73
Alt(5) T4 to T2 of W2	0.08	0.00	0.00	0.44	0.13	0.27	0.22	0.51	0.00	0.09	0.00
	0.00	0.00	0.00	1.39	0.44	1.49	0.00	0.27	0.00	0.00	0.00
	0.00	0.12	0.56	0.00	0.20	0.00	0.00	0.00	0.85	0.00	0.80
Alt(6) T4 to T5 of W2	0.08	0.00	0.00	0.44	0.13	0.27	0.22	0.51	0.00	0.09	0.00
	0.00	0.00	0.00	1.38	0.44	1.48	0.00	0.27	0.00	0.00	0.00
	0.00	0.12	0.56	0.00	0.20	0.00	0.00	0.00	0.85	0.00	0.80
Alt(7) T4 to T3 of W3	0.08	0.00	0.00	0.44	0.13	0.27	0.22	0.51	0.00	0.09	0.00
	0.00	0.00	0.00	1.11	0.49	1.29	0.00	0.00	0.00	0.00	0.00
	0.00	0.11	0.52	0.21	0.18	0.10	0.00	0.22	0.81	0.00	0.76
Alt(8) T4 to T6 of W3	0.08	0.00	0.00	0.44	0.13	0.27	0.22	0.51	0.00	0.09	0.00
	0.00	0.00	0.00	1.11	0.49	1.29	0.00	0.00	0.00	0.00	0.00
	0.00	0.11	0.52	0.21	0.18	0.10	0.00	0.22	0.81	0.00	0.76

Table 4.7: Scores and ranking of alternatives without similar document

	TDP	*TDN*	*C*	Ranking
Alt(1)	0.624	2.625	0.8080	No.5
Alt(2)	0.626	2.613	0.8067	No.6
Alt(3)	0.659	2.623	0.7993	No.7
Alt(4)	0.660	2.619	0.7987	No.8
Alt(5)	0.512	2.854	0.8479	No.4
Alt(6)	0.504	2.846	0.8495	No.3
Alt(7)	0.420	2.512	0.8572	No.1
Alt(8)	0.421	2.519	0.8569	No.2

However, the ranking of alternatives are changing by applying similar documentation to the supporting workers. When the documents that are written by target workers can be utilized as Table 4.8 shown, the similarity for the supported tasks is computed to shorten required time for the supporting workers.

Table 4.8: Proportion of term frequency for documents

	We(1)	*We*(2)	*We*(3)	*We*(4)	*We*(5)	*We*(6)	*We*(7)	*We*(8)	*We*(9)	*We*(10)	*We*(11)
D1 Written by Worker 1	0.0	0.0	0.0	0.0	0.5	0.0	0.1	0.3	0.0	0.1	0.0
D2 Written by Worker 2	0.4	0.0	0.2	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0
D3 Written by Worker 3	0.0	0.5	0.2	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0

Table 4.9 shows similarity of tasks and documents based on Table 4.8.

Table 4.9: Computed similarity of tasks and documents

	Type of Documents	Similarity
Task 1	D1	**0.82**
	D2	0.30
	D3	0.19
Task 2	D1	**0.68**
	D2	0.49
	D3	0.39
Task 3	D1	0.15
	D2	0.40
	D3	**0.52**
Task 4	D1	0.16
	D2	**0.18**
	D3	0.00
Task 5	D1	**0.68**
	D2	0.49
	D3	0.39
Task 6	D1	0.16
	D2	0.36
	D3	**0.49**

The required time for supporting workers is changed by applying most similar document. Since the similarity of D1 to Task 1 in Table 4.9 is high and the experiences of document creator (Worker 1) is high, the required time for Task 1 is reduced longer than Task 4 as following.

$$Rt(T1\_W2) = 1.11 * 0.19 / 0.22 = 0.95 \quad \textbf{(-1.09)} \tag{4.10}$$

$$Rt(T1\_W3) = 1.11 * 0.20 / 0.22 = 1.00 \quad \textbf{(-1.33)} \tag{4.11}$$

$$Rt(T4\_W2) = 1.11 * 0.76 / 0.42 = 1.80 \quad \textbf{(-0.09)} \tag{4.12}$$

$$Rt(T4\_W3) = 1.11 * 0.51 / 0.42 = 1.36 \quad \textbf{(-0.06)} \tag{4.13}$$

Table 4.10 shows changed ranking of alternatives by applying similar document. Despite the score of experience for Worker 3 to Task 1 and Task 4 is higher than Worker 2, the supporting of Worker 2 to Task 1 is best score of alternatives in this situation.

Table 4.10: Scores and ranking of alternatives with similar document

	TDP	*TDN*	*C*	Ranking
Alt(1)	0.415	2.616	0.8632	No.1
Alt(2)	0.416	2.609	0.8626	No.2
Alt(3)	0.417	2.612	0.8624	No.3
Alt(4)	0.417	2.611	0.8622	No.4
Alt(5)	0.501	2.848	0.8504	No.8
Alt(6)	0.494	2.840	0.8519	No.7
Alt(7)	0.411	2.524	0.8599	No.5
Alt(8)	0.412	2.522	0.8596	No.6

Figure 4.3 indicates graph for comparing expected experience of each worker (W1, W2, W3) by proposed approach and conventional approach. NIS is computed by conventional TOPSIS based on objective criteria. Proposed approach (Alt7 and Alt1 D1) minimizes decrease of expected experience as subjective profit by interruption than conventional approach based on result of the graph.

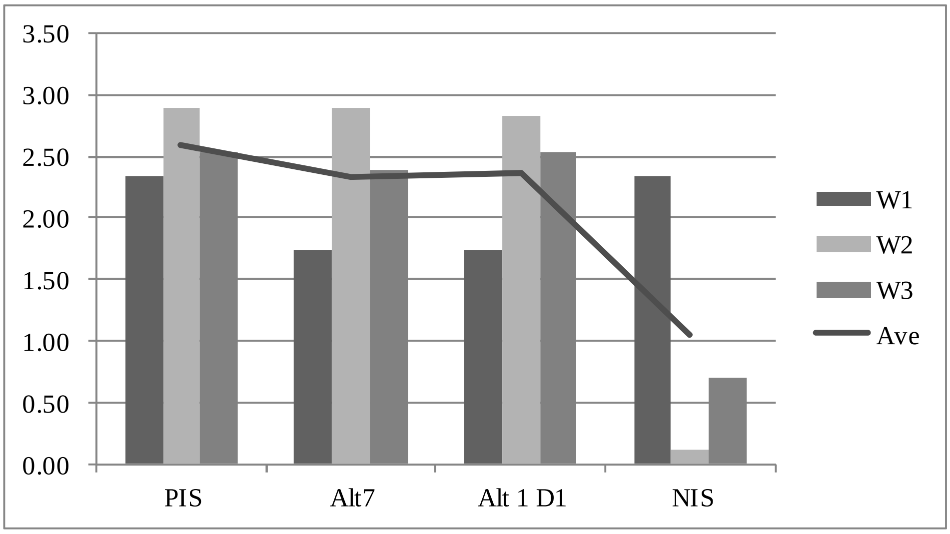

Figure 4.3: Graph of expected experience by alternatives

4.4 Supporting decision making by proposed HS

In order to compare with alternatives of proposed TOPSIS and proposed HS, same case model is used in this section. Table 4.11 shows the computed subjective completion time of the workers per hour to each task according to equation (3.5).

Table 4.11: Estimated subjective completion time to each task

Selectable tasks	Concerned Workers			Pre-assignment
	Worker 1	**Worker 2**	**Worker 3**	
Task 1	**5.66**	6.22	6.39	Worker 1
Task 2	5.46	**6.09**	5.49	Worker 2
Task 3	5.54	5.49	**5.78**	Worker 3
Task 4	**5.66**	6.83	6.13	Worker 1
Task 5	5.46	**6.09**	5.49	Worker 2
Task 6	5.56	5.50	**5.82**	Worker 3
Task 7	5.79	6.27	6.44	Interruption

The above selectable tasks has same deadline. The target workers operate the tasks in two days because the target workers in this company can work eight hour per day. Table 4.12 shows the harmony memory of the pre-assignment. The scores of each task achievement are 1.0. The flexible time of each worker is computed by subtracting subjective completion time of assigned tasks from workable time of two days.

Table 4.12: Harmony memory of pre-assignment

Selectable tasks	Concerned Workers			Score of achievement
	Worker 1	**Worker 2**	**Worker 3**	
Task 1	**5.66**	0.00	0.00	1.00
Task 2	0.00	**6.09**	0.00	1.00
Task 3	0.00	0.00	**5.78**	1.00
Task 4	**5.66**	0.00	0.00	1.00
Task 5	0.00	**6.09**	0.00	1.00
Task 6	0.00	0.00	**5.82**	1.00
Flexible time	4.68	3.82	4.40	-

When an interruption ensemble as Task 7 occurs to Worker 1, the score of achievement is changed by reducing operating time and flexible time of Worker 1. Table 4.13 shows the worst harmony by applying interruption as harmony index.

Table 4.13: Worst harmony by interruption

Selectable tasks	**Concerned Workers**			**Score of achievement**
	Worker 1	**Worker 2**	**Worker 3**	
Task 1	**4.55**	0.00	0.00	**0.80**
Task 2	0.00	6.09	0.00	1.00
Task 3	0.00	0.00	5.78	1.00
Task 4	5.66	0.00	0.00	1.00
Task 5	0.00	6.09	0.00	1.00
Task 6	0.00	0.00	5.82	1.00
Flexible time	**0.00**	3.82	4.40	-

The all flexible time of Worker 1 is consumed by generated Task7. The score of task achievement for Task1 is decreased by exceeding the consumed time of interruption. Table 4.14 shows the updated vector by applying subjective improvement.

Table 4.14: Updated harmony by proposed approach

Selectable tasks	**Concerned Workers**			**Score of achievement**
	Worker 1	**Worker 2**	**Worker 3**	
Task 1	4.55	0.00	**2.33**	**1.00**
Task 2	0.00	6.09	0.00	1.00
Task 3	0.00	0.00	5.78	1.00
Task 4	5.66	0.00	0.00	1.00
Task 5	0.00	6.09	0.00	1.00
Task 6	0.00	0.00	5.82	1.00
Flexible time	0.00	3.82	**2.07**	-

Proposed HS approach recommends supporting of Worker 3 to Task 1 of Worker 1 as appropriate task selection in this situation. This alternative means same alternative with Alt 3 of proposed TOPSIS.

Table 4.15 shows the updated vector by conventional harmony search based on objective improvement.

Table 4.15: Updated harmony by conventional approach

Selectable tasks	Concerned Workers			Score of achievement
	Worker 1	Worker 2	Worker 3	
Task 1	0.92	2.83	3.79	1.21
Task 2	2.66	1.37	2.70	1.20
Task 3	1.23	5.56	0.70	1.35
Task 4	4.38	1.37	1.26	1.18
Task 5	0.83	2.08	3.81	1.19
Task 6	0.20	2.79	3.75	1.19
Flexible time	0.00	0.00	0.00	-

Recommendation for selecting appropriate tasks by the above results of conventional harmony search is to change engagement of all selectable tasks. Each worker must engage to all tasks and overmuch task achievement is invoked by this update.

Figure 4.4 shows graph of expected experience by proposed approach and conventional approach. Each score of expected experience in y-axis is computed based on each result of harmony memory by using equation (3.2). Pre in Figure 4.4 means expected experience by pre-assignment. P-HS and C-HS mean proposed harmony search and conventional harmony search. Subjective profits by subjective criteria are expected by pre-assignment as common objective. Therefore, counted scores of each type of experiences are focused only expected type into pre-assignment.

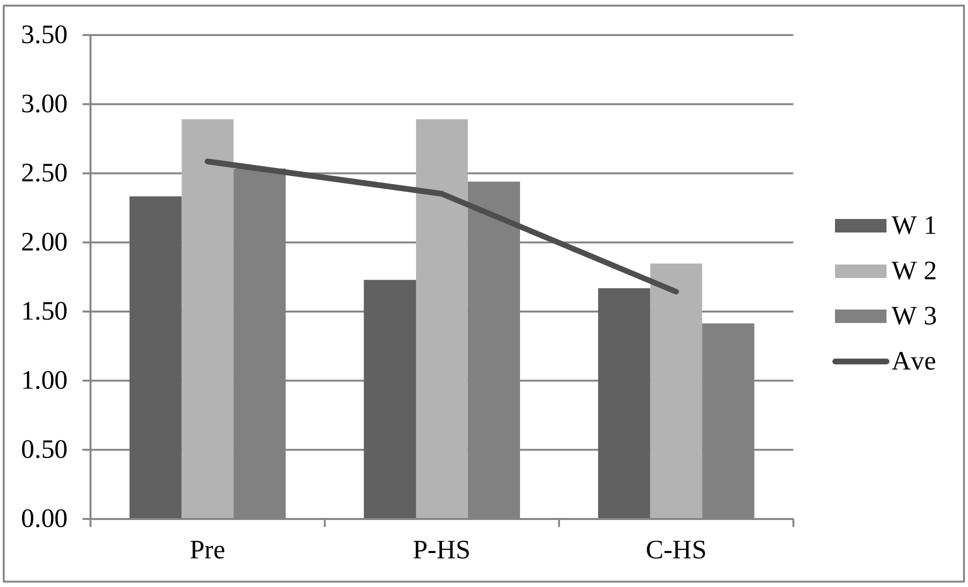

Figure 4.4: Comparing expected experience of workers

The above graph indicates that proposed approach minimizes decrease of subjective profits for worker than objective improvement approach.

4.5 Conclusion

This chapter has indicated validity of alternatives by proposed approach through comparing with conventional approach. Subjective criteria have been able to aggregate to objective criteria by reducing uncertainty for expected experience of worker. In addition, ranking of alternatives in proposed TOPSIS were improved by reducing uncertainty of subjective criteria through applying similar document. Although proposed Harmony Search could not provide best solution, subjective solution without depending on number of alternatives has been able to be recommended in this situation.

The proposed approach has indicated that experienced worker is not always appropriate supporter in the improvement of certain interruption. However, even if there are alternatives to get higher profit for the organization with improving the negative impact of interruption, the proposed approach recommends alternatives to the interrupted worker based on the assignment of the superior decision maker. Therefore, the alternatives for assisting decision making in certain interruption by the proposed approach cannot optimize the objective of the pre-assignment by the estimation of the superior decision maker according to the objective of organization.

Proposed approach normalized context of worker and task in time parametric view point by utilizing only experience. Context of interruption has uncertainty thus there are many types of subjective attributes of worker. Although the risk of interruption is based on the operation time consumed for the workflow in certain time, uncertain context of interruption must be reasoned for more appropriate supporting the decision making of the interrupted worker as future work.

Chapter 5

Conclusions

5.1 Introduction

Proposed approach can select appropriate alternatives in decision making of changing situation by involving subjectivity based on normalized subjective attributes of decision maker. Conventional TOPSIS method and Harmony Search method are extended by applying changed situation. The scores of positive ideal solution and negative ideal solution of TOPSIS method is adjusted to the interrupted workflow by aggregating subjective attributes of the worker and objective attributes of the task. In addition, uncertainty of subjective attributes is reduced by applying similar documentation.

Meanwhile, proposed Harmony Search finds alternative for adjusting changed situation without depending on number of alternatives. Although proposed Harmony Search provides alternative that keeps subjective profit, best solution to the decision making for adaptive task selection cannot be recommended because results of updated vector is rank seventh in alternatives of proposed TOPSIS.

5.2 General conclusions and Future works

This thesis indicates that applying subjective intelligence to DSS is important to enhance validity of ranking alternatives. In addition, subjective attributes of decision maker have many types of uncertain benefits for subjective criteria. I believe DSS becomes more familiar tool for enrich the life of people by further improvement of fitting criteria to situation.

As future work, this study should analyze the subjective attributes of decision maker to provide suitable alternative in which uncertainty of subjective criteria is clarified using big data or knowledge from worker history.

Publications

Journal Paper

[Sugawara 2013a] K. Sugawara and H. Fujita, Intelligent Decision Support for Business Workflow Adaptation due to Subjective Interruption, International Journal of Acta Polytechnica Hungarica, vol. 10 (8) (2013), pp. 5-26, , DOI: 10.12700/APH.10.08.2013.8.1.

Proceedings on Conference or Workshop

[Sugawara 2013a] K. Sugawara and H. Fujita, A Workflow Optimization by Handling Interruption with Meta-heuristic Approach, New Trends in Software Methodologies Tools and Techniques Proceedings of the 12th SoMeT_13 (2013) pp. 243-246

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Acknowledgement

This thesis is done as Doctor Dissertation under supervision of Prof. H. Fujita, in Iwate Prefectural University. I would like to give my thanks to Prof. H. Fujita, Prof. Y. Murayama, Prof. H. Nunokawa, Prof. J. Sasaki, Dr J. Hakura, and Dr. M. Kurematsu for their supportive discussion that could contribute to enhance this work.

In addition, I would like to appreciate the opportunity of PhD given by President M. Sengoku, Dr. R. Maruta and all colleagues in Sangikyo Corporation.

Finally, I would like to thank the support of my wife and my sons for my work.