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An effective task allocation for customized products

Yongyan Chen*, Wei Dai
Computer Technology Application Key Lab of Yunnan Province, Kunming University of Science and Technology, Jinming Road 727, Kunming, Yunnan Province, (CHINA)
E-mail : dawanmitang@163.com

ABSTRACT

To deal with the problem of task allocation for a large comprehensively customized product, which cannot be assessed very well owing to lack of work unit skills, experience, knowledge, and dependence relationships, we propose a task allocation method based on similar experience and knowledge, and present a task completion time assessment method based on a genetic algorithm. By calculating the similarity between the knowledge required by particular tasks, the new task allocation method will take the task constraints into consideration. The results of simulation experiments on a custom developed wind turbine project show that the proposed method is correct and valid.

KEYWORDS

Task allocation; Similarity; Customized products.

INTRODUCTION

The development of a large comprehensively customized product requires cooperation among the many departments as well as multidisciplinary work. As a potential design pattern, task allocations have their own characteristics, i.e., the components must be standardized and modularized; references and experience regarding a number of customized tasks were previously unable to be found. Two problems still exist for a task allocation method of a comprehensively customized product. The first is that the execution time is generally difficult estimate effectively before task allocation owing to the customized nature of the tasks. The second is that some work must be deeply understood before the assignments are undertaken, such as all of the work unit skills, experience, knowledge, and dependence relationships among the tasks. Such work requires a significant amount of research, which is difficult to achieve. To deal with this issue, we propose a task allocation method for the design of a large comprehensively customized product based on knowledge similarity. In this task allocation process, many issues are taken into consideration, such as the task execution order constraints among tasks, the knowledge requirement of the task, and the knowledge structure of the work unit. Similar knowledge is retrieved using a fuzzy set. The efficiency of the work unit is assessed based on its similar structure with the task knowledge. For a large customized product, a genetic algorithm is better as the optimization algorithm.

RELATED WORK

One of the critical point for customized product tasks allocation is to allocate tasks to work units economically and safely after estimating task completion time. There have been a lot of research works on tasks allocation. However, research on estimating task completion time through similar tasks has been rare. Some previous researches discussed tasks allocation. Liu et al. focused on training workers that varied workers' ability is consisted in assignment issue **[1]**. Ho and Devanur et al. discussed assigning heterogeneous tasks to workers with different, unknown skill sets in crowdsourcing markets **[2-3]**. This paper is inspired by the experience level in crowdsourcing markets. The ability of workers should be fully considered which strongly impacts estimating time of task completion. Nazariana et al. presents mathematical models **[4]** and Eben et al. identified highly similar or even redundant products **[5]**, which is also very useful for customized products. Bao gave a formula of task granularity, coupling degree and equilibrium in the case of lacked for task decomposition of customization collaborative product **[6]**. Jian et al. considered the relationship between skill level of the work unit and requirements of tasks **[7]**. But skill level of the work unit still depended on manager experience **[7]**. Jesus Bobadilla gives us a feasible idea **[8]**.

PRODUCT TASK ALLOCATION MODEL BASED ON KNOWLEDGE SIMILARITY

Product task allocation means the assignment of some tasks to the appropriate work unit. This basic model is used to handle the problem of comprehensively customized task allocation in the product design phase. The basic model is defined as follows:

There are n tasks $T = \{T_1, T_2, T_3 \cdots T_n\}$ which need m work units $P = \{P_1, P_2, P_3 \cdots P_m\}$ to be completed. We tried our best to find an optimal task assignment scheme within the shortest possible finishing time. To allow the estimates of the current task time to be more scientific and rational, a similar previous task should be taken into account. Retrieving similar tasks is very important for estimating the task execution time. This includes two parts, i.e., querying tasks that are similar with the current task from the knowledge database, and estimating the current task time based on the degree of similarity.

Definition 1: Levels of Similarity (LS) is $S(T, C_k) = \sum_{k=1}^{m} \delta_i S(f_i, f_{ik})$, where δ_i is the weighting factor and $\sum_{i=1}^{m} \delta_i = 1$. In addition, $S(f_i, f_{ik})$ presents the LS value between two works f_i and f_{ik}. Assigning $\delta > 0$, we can obtain the LS set under the conditions of $S(T, C_k) > \delta$.

The work unit is the basic design unit used in a complex product collaboration process and is a key to estimating the completion time of the whole task. Owing to the different types of work experience and knowledge structures, when the same task is assigned to different units, it will take these units a different amount of time to finish the task. Fuzzy sets can be used to describe the uncertainty of a task.

It is supposed that the matching degree δ is weighting factor between a task and work unit. Moreover, t_s is the starting time and t_e is ending time. Thus, $\Delta t = t_\delta - t_s = \Delta d_\lambda - (\Delta d_\lambda - \Delta d_\alpha)\frac{\delta - \lambda}{\alpha - \lambda}$, $\Delta d_\lambda = \overline{d_\lambda} - \underline{d_\lambda}$, and $\Delta d_\alpha = \overline{d_\alpha} - \underline{d_\alpha}$. Here, $\Delta d_\lambda = \overline{d_\lambda} - \underline{d_\lambda}$ indicates how long a task should be executed if we want the matching degree between the user's knowledge, and if the demand of the task is not less than λ. In addition, $\Delta d_{\alpha} = \overline{d_{\alpha}} - \underline{d_{\alpha}}$ indicates how long the task should be executed if we want the matching degree to be not less than α.

The execution time of the work unit is not only concerned with the knowledge structure of the work unit, but also with related tasks and the knowledge requirements of these tasks. In this paper, we assess the execution time of the work unit based on the similarity between calculating the knowledge structure of the task and the demand knowledge.

Definition 2: The Knowledge Unit (KU) represents the smallest independent unit of the product knowledge.

Definition 3: The Knowledge module (KM) is a set of KUs, and represents a tuple:

$KM(ku, w) = \{(ku_1, w_1), (ku_2, w_2), \ldots, (ku_i, w_i)\}$, where w_i is the knowledge weight.

Definition 4: The Knowledge Unit Similarity (KUS) shows the similarity between the knowledge demanded by the task and the knowledge structure of the work unit. A task has a demand knowledge module $KD(kd, w) = \{(kd_1, w_1), (kd_2, w_2), \ldots, (kd_i, w_i)\}$. So we get the task's demand knowledge vector is $V_d = \{w_1, w_2, \ldots, w_i\}$. In this vector, w_i indicates the proficiency required for the requirement knowledge for kr_i.

The matching degree $S(V_d, V_s)$ between a task demanding knowledge and the knowledge structure of the work unit is presented through the cosine of V_s and V_d. This cosine shows the work capacity of the finishing tasks of the work unit.

$$S(V_r, V_s) = \frac{V_d \times V_s}{\|V_d\|\|V_s\|} = \frac{\sum_{j=1}^{i}(w_i \times s_i)}{\sqrt{\sum_{j=1}^{i} w_i^2}\sqrt{\sum_{j=1}^{i} s_i^2}} \text{ (formula 1).}$$

TASK COMPLETION TIME CONSTRAINTS BASEDD ON KNOWLEDGE SIMILARITY

The work unit is a reusable resource assigned to the relative task during a given time. The work unit is released at the end of the task. Some allocation rules are given for a complex task allocation problem. Every task is composed of a work unit, and cannot be interrupted when started. Assigning collaborative tasks to the same work unit is a type of non-preemptive model.

Time constraints are the key to building the task allocation function. The design efficiency of a complex product is one of the important criteria for assessing a task allocation scheme. In a task allocation scheme, Task T_i is conducted by work unit K_x, which will take execution time $\Delta t(T_i, K_x)$ to finish. Suppose that the start time is $St(T_i)$ and the end time is $Et(T_i)$.

$$St(T_i) = \max(\max_{T_{pro} \in PRO}(Et(T_{pro})), Et(PRE(T_i))) \text{ (formula 2)}$$

$$Et(T_i) = St(T_i) + \Delta t(T_i, K_x) \text{ (formula 3).}$$

When $PRE(T_i) = \phi$, $Et(PRE(T_i)) = 0$. The results must meet this formula when all tasks are completed, which means $f(S) = Et(S) = \max_{T_x T}(Et(T_x))$.

The closer $f(s)$ is to $f_{\min}$, the better the allocation scheme.

TASK ALLOCATION METHOD USED BY GENETIC ALGORITHM

Complex product task allocation is a non-deterministic polynomial (NP) problem. We designed a new task allocation strategy based on a genetic algorithm. Task allocation constraints can be deduced from task allocation initial population evolution to finally populations. We designed a tuple gene (T_i, K_j), which indicates that task set T_i will be finished through work unit K_j. Initially, we provide certain parameters and initial conditions. A random initial population generation method based on the task depth is presented. The initial population must meet the relationships among the tasks to improve the efficiency. Some of the parameters are given in advance. Here, T is the task set, matrix $RT_{n \times n}$ indicates the constraint relationships among the tasks, K is the work unit set, and S is the final allocation scheme. The task allocation is thus as follows:

Step 1: According to constraint relationship matrix $RT_{n\times n}$, we compute depth T of every task set . The tasks are sorted according their depth. Thus, we obtain the task sequence $T_{x1}, T_{x2}, \cdots, T_{xn}$. For each task, we randomly select a work unit from work unit set $K_1, K_2, \cdots, K_m$ and assign it to the task. Therefore, task allocation scheme $S_n = [(T_{x1}, K_{y1}), (T_{x2}, K_{y2}), \cdots, (T_{xn}, K_{yn})]$ is obtained.

Step 2: The method of individual choice in our paper is roulette selection method. Thus, the individual fitness function is defined as $p_i(s) = F_i(s)$. The possibility of an individual being selected is $p(s) = F(s) / \sum_{j=1}^{n} F_j(s)$.

Step 3: Execute the crossover operation. Two known distribution schemes are indicated by S_i and S_j. Given a random integer $p\,(0 \le p \le n)$, two parts are split by p, where each part contains one allocation scheme, S_i and S_j. A new allocation scheme, S_i' and S_j' is commutated through the old S_i and S_j, respectively. Individuals and cross individuals have the same crossover probability, which is not beneficial for maintaining good genes and eliminating poor genes. Thus, we define the adaptive crossover probability as follows:

$$p_k = \begin{cases} \dfrac{0.9 - 0.3 \times (f - \overline{f})}{f_{\max} - \overline{f}} & f \ge \overline{f} \\ 0.9 & f \le \overline{f} \end{cases} \quad \text{(formula 4)}$$

where f is the cross individual fitness, and $\overline{f}$ and $f_{\max}$ are the average and maximum fitness of the generated group, respectively.

Step 4: For a mutation operation, any individual can be selected with a predefined mutation probability. The work unit is re-assigned in a roulette manner as probability random integer p.

TASK ALLOCATION METHOD USED BY GENETIC ALGORITHM

For this paper, we took a custom development project of a 5 MW variable-speed constant frequency (VSCF) wind turbine for a large wind power generation company as an example, which validates the task allocation of a customized product. The entire project is divided into 20 design tasks using 11 work units. Under the same initial conditions, three algorithms were used to calculate the instance. The population is 100 for the genetic algorithm, with 100 iterations. The number of ants for the ant colony algorithm is 100, with 100 iterations. The results are shown in figure 1 to 3. All results are from the same population size, number of evolution iterations, and other initial conditions. From figure 1 to 3, the task allocation scheme proposed in this paper showed the shortest execution time and can achieve rapid convergence. The basic genetic algorithm and ant colony algorithm were unable to converge after 100 iterations. Meanwhile, the task allocation method based on a fuzzy set theory and similarity knowledge reduces the amount of cognitive assessment errors and mistakes compared with a traditional assessment.

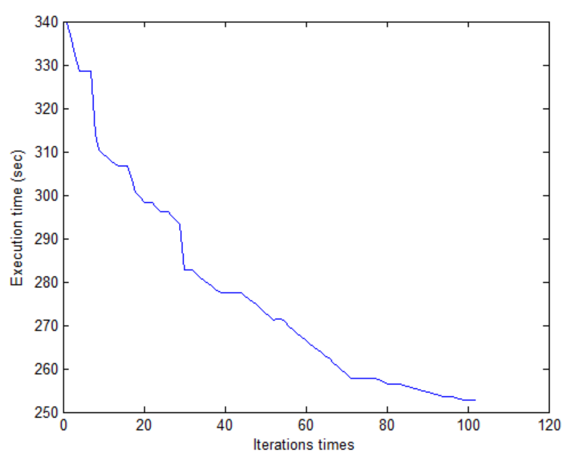

Figure 1 : Genetic algorithm based on similarity.

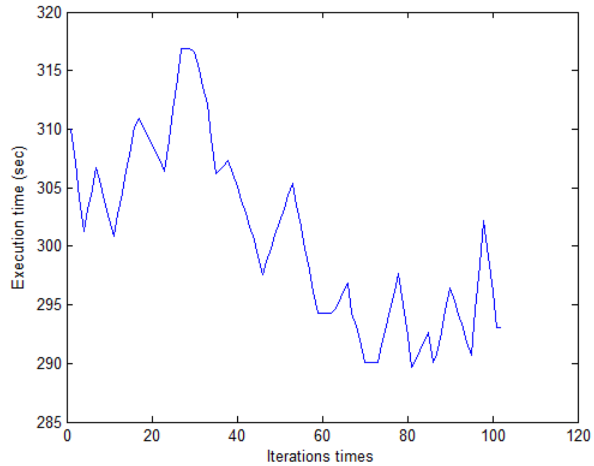

Figure 2 : Basic genetic algorithm

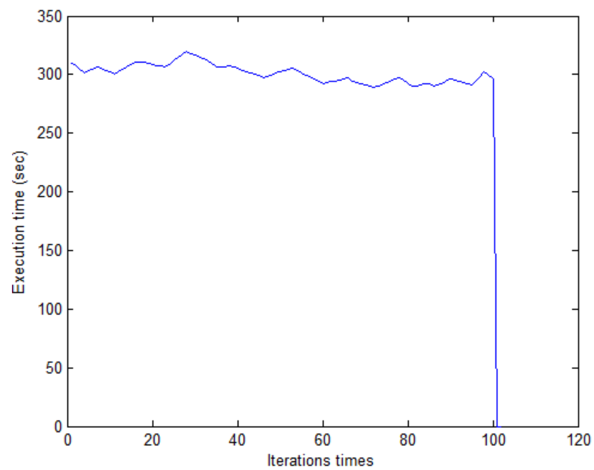

Figure 3 : Ant colony algorithm

CONCLUSIONS

Task allocation for a large comprehensively customized product has always been subjected with many difficulties, such as a lack of historical experience and reference data. Herein, we presented a complex task allocation method based on the work unit similarity that fully considers the work unit capacity, experience, and dependencies. We defined the task execution time based on the fuzzy set theory and proposed a genetic algorithm for calculating the task execution time based on similar tasks in the knowledge database. The results show the feasibility of the newly proposed method.

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