System Analysis and Design of Task Allocation for Human-Automation Symbiosis in Smart Manufacturing

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Abstract

Since Industry 4.0, development in automation technology cases a transformation in many industries to integrate the latest technology and reinforce human-automation collaboration in cyber-physical systems. It is expected such collaboration can leverage the capabilities of both human and automation agents and achieve team synergy. To achieve this objective, this paper proposes dynamic task allocation considering human factors for human-automation symbiosis. In this paper, analysis and design of the team cognition-aware task allocation system are elaborated. The task allocation problem is formulated with team cognitive performance in the optimization objective function. A two-dimensional genetic algorithm is proposed to solve this allocation problem. An application case of medical product assembly is presented to validate the proposed solution.

Keywords
Human-automation symbiosis, task allocation, team cognition, human trust, genetic algorithm

1. Introduction
Recent years have witnessed rapid development in automation technology since Industry 4.0, which not only enhances the operational capabilities of automation agents through advanced hardware technologies and control theory, but also facilitates the cognition capabilities using artificial intelligence and data analysis techniques. Within this process, the importance of human operators in the automation system is changing, too (Endsley 2017). In the beginning, the role of human operators is to monitor and intervene the automation system when hardware or software cannot complete its tasks. As the communication techniques advance, there is a trend for keeping the human in-the-loop and thus operators take more responsibilities (Sahinel et al. 2021). The objective of such involvement is to enable the

collaboration between human agents and automation agents, so the overall operation system can achieve better performance by leveraging the advantages of different agents. Furthermore, by augmenting team cognition, human and automation agents can achieve better collaboration for team synergy (Jiao et al. 2020).

To achieve this objective, much research has been conducted regarding how human agents should interact with automation agents. Human-automation interaction is such domain that studies how to optimize the interactions to help improve overall performance, and there are several directions: function and task allocation between human and machines, human trust modeling and incorrect use, team cognition modeling, and so on (Janssen et al. 2019). Since it involves modeling human beings in the decision-making process, human-related research can help provide theoretical foundations for mathematical modeling (Jiao et al. 2022). In the meantime, some research studies the concept modeling of human-automation interaction to find the relationship between different factors in the human-automation interaction system (Sanchez 2009). Formulating the system in a mathematical approach brings benefits for understanding how the system performs in different scenarios. Among these research questions, task allocation is the most direct decision-making process that influences human-automation team performance. It not only includes modeling human-related factors but also incorporating them into the task allocation problem.

In this regard, this paper studies dynamic task allocation for human-automation symbiosis. There are several differences between human-automation task allocation and conventional multi-robot task allocation problems. Firstly, conventional multi-robot or human-robot task allocation does not consider human-related factors in the problem formulation (Ham and Park 2021). For example, human trust implies the risk attitude towards the automation agent, and this factor can reflect operators' confidence for collaborating with an automation agent at a certain level of automation (Lee and See 2004). Secondly, conventional task assignment will not be changed until they are reallocated, and it cannot assign tasks based on real-time status of related agents. Thirdly, the conventional approach is not human-centric and fails to manage human workload from both physical and cognitive perspectives.

To address the above problems, this paper proposes dynamic task allocation considering human factors to facilitate human-automation symbiosis with an emphasis on design, problem formulation, and solution of task allocation. There are several challenges. (i) System analysis and design. One significant feature of human-automation task allocation is the consideration of human factors. Selection of key human factors and applying their influence on task allocation decision-making process should be studied during system design. (ii) Problem formulation for human-automation task allocation. To achieve human-automation symbiosis, team cognitive performance should be considered during task allocation in the objective function. Therefore, evaluation of cognitive performance should be studied. In this way, task allocation can allow mutual adaptation between human and automation agents. (iii) Optimization algorithm for task allocation. The optimization objective function should consider conventional task performance measures, including time and cost, and team cognitive performance. Considering the modeling of human factors involves prediction algorithms and theoretic foundation of human behavior theory and cognitive theory, calculation of cognitive performance may be non-linear. Therefore, the task allocation algorithm should accommodate optimization for non-linear objective functions.

The rest of this paper is organized as follows. Section 2 discusses related work for task allocation, human-automation symbiosis, and human factor modeling. Section 3 demonstrates system analysis and design for dynamic task allocation in human-automation teams. Section 4 formulates the task allocation problem. The solution of two-dimensional genetic algorithm (GA) is introduced in the Section 5. An application case of medical product assembly is presented to validate the 2D GA solution in Section 6. Managerial implications are discussed in Section 7. Finally, conclusions are made in Section 8.

2. Literature Review

2.1 Multi-robot Task Allocation

Multi-robot task allocation studies how to perform collective behavior in a multi-robot system to achieve designed goals where one single robot cannot (Khamis et al. 2015). Such planning can benefit resolving complex tasks, increasing overall performance and reliability. The task planning problem is often seen as an optimal assignment problem to optimize the overall system performance, which can be studied as a basis to understand how to incorporate human factors in human-automation interaction. For this type of problem, the objective is to assign a set of tasks to a set of robots, where each robot conducts only one task (Nam and Shell 2014), and the objective function is to maximize the overall profit. Based on this framework, several problem variations can be formulated, and here are some examples

(i) the single-task versus multi-task: each robot can conduct only a single task or multiple tasks; (ii) single-robot versus multi-robot: one task can be performed by either one robot or several robots; (iii) task execution: if a task can be finished at once or be executed over time (Gerkey 2004; Dasgupta 2011). Optimization solutions to these questions include heuristics and mixed integer programming solutions (Gong et al. 2019), and they can be categorized into distributed methods and centralized methods based on the implementation approach (Ham and Park 2021).

2.2 Human-automation Interaction

With the development in robotic systems, there shows strong economic motivation to include human into automation operations for collaborative tasks (Cheng et al. 2021). Much research has focused on the interactions that enable performance improvement for the human-automation team, and the major challenges are the integration of human factors, situation awareness, and task allocation. Task allocation between human and automation agents is often formulated as an optimal control problem with the objective to maximize system performance while minimizing the cost (Wu et al. 2017). Therefore, interactions between human and automation agents need to be modeled during task allocation, which suggests the integration of task analysis (Sheridan 1997), human trust, team cognition, team performance, automation system, and operator system into the task allocation model. Since complex operations may constitute of multiple steps, dynamic allocation should find the assignment policy that optimizes the probability of achieving overall high performance while minimizing the cost (Jiao et al. 2020).

In a conventional human-automation system, one important role for human operators is to monitor and intervene in situations when the autonomous system fails to handle, because most automation systems are designed to work in a range of situations (Woods and Cook 2017). The concept of situation awareness is firstly proposed by Endsley (1995) where it is categorized into three levels: perception, comprehension, and projection. Perception emphasizes detection of environment event or information, comprehension refers to the understanding of the information, and projection is to extrapolate information forward to determine its influence in the future. Since the concept is developed, much research focuses on measuring and improving situation awareness. Previous studies focus on several aspects, including situation awareness measurement or assessment (Endsley 2021), situation awareness-oriented design (Endsley 2016), and different approaches to improve situation awareness (Munir et al. 2022; Zhu 2019), including sensing techniques and internet of things, artificial intelligence and image analysis, intelligent reasoning (Wang et al. 2019; Wang et al. 2021), and so on.

2.3 Human Behavioral Modeling

Human factor modeling has been identified as the primary challenge for human-automation symbiosis. Two important factors are team cognition and human trust. (i) Cognition is defined as the process of coming to know or the act of knowing, particularly using reasoning as opposed to feeling or willing (Stahl 2013). In the context of HAI, team cognition targets at both human-human and human-automation teams, and the objective is to measure it to estimate team status and use its prediction to analyze the decision-making process (Cuevas et al. 2007). For measurement, it can be done through behavioral observation, operator feedback, or physiological measurement. On the other hand, modeling or prediction of team cognition, including attention management and decision-making performance prediction, is the important topic to model human-automation interaction. Since team cognition shall be extended beyond the average or sum of cognition for individuals, statistical learning approaches prove to be useful for cognition prediction regarding task requirements at the team level (Jiao et al. 2020).

Common approaches include Bayesian network model, Markov decision process, non-parametric Gaussian processes, and so on. Overall, cognition modeling requires interdisciplinary knowledge in cognitive science, psychology, human factors, and computer science. Studying theoretical framework can facilitate representation and simulation of team cognition process and performance. (ii) Human trust reflects the willingness of operators' using automation, and too high or too low of trust will result in either overuse or disuse of automation (Parasuraman 1997). Such characteristics can be modeled by prospect theory to suggest operators' attitudes towards the automation agents (Zhou and Jiao 2013; Wang and Jiao 2022). Moreover, human trust can be a dynamic value influenced by the discrepancy between what operators observe and what they expect from the automation agent (Sadrfaridpour et al. 2016), making it necessary to formulate the trust as a dynamic process (Muir 1994; Jiao et al. 2020).

3. System Analysis and Design

3.1 Functional Analysis

The main challenges of human-automation task allocation lie on the modeling of related human factors as well as synthesizing and integrating them into the conventional task allocation workflow. In this regard, this section presents a system design for human-automation symbiosis through dynamic task allocation considering team cognition, including functional analysis and system architecture.

The functional analysis for the proposed system is displayed in Figure 1. The procedure can be decomposed into seven activities: the first three activities are modeling of key human factors, then team cognition and situation awareness are accessed to provide real-time inputs for task allocation. After task allocation is complete, performance is analyzed again for task allocation strategy adjustment. Details of each activity are elaborated below.

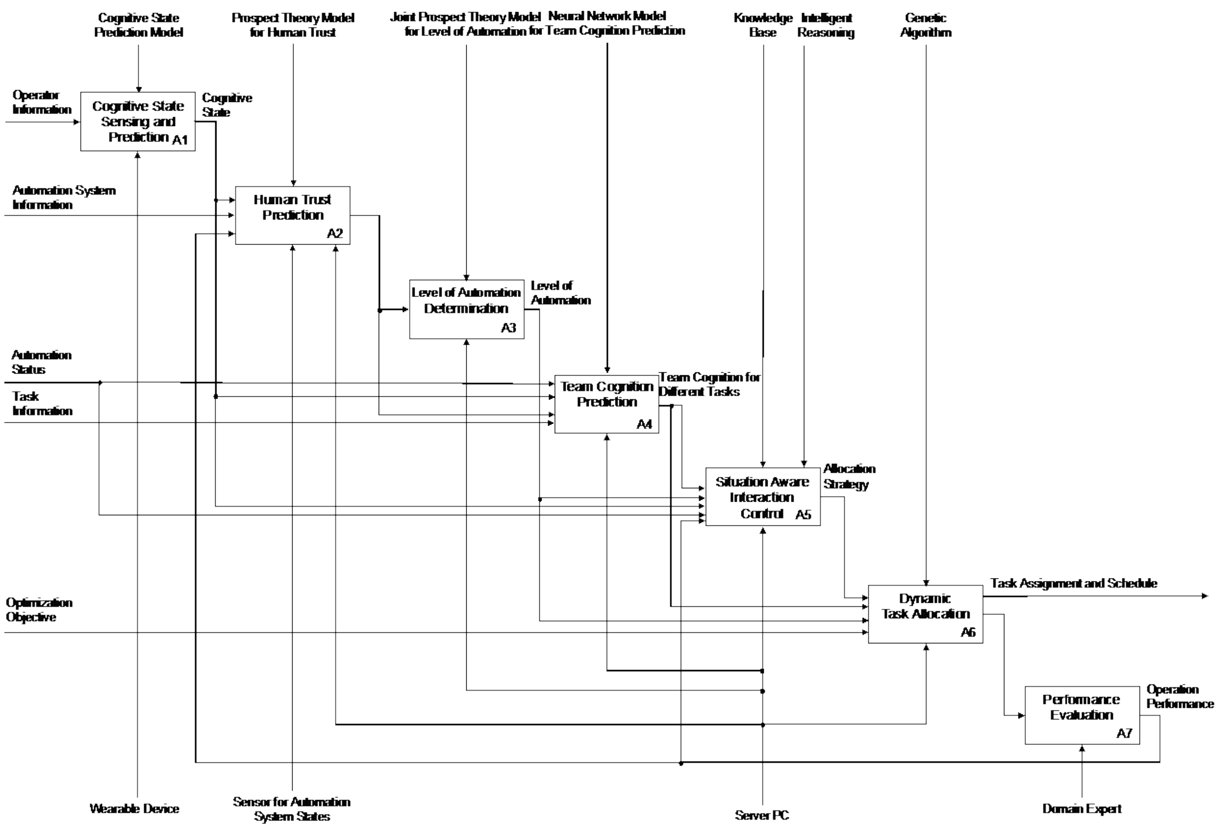

Figure 1. Functional Analysis for Dynamic Human-automation Task Allocation

The first activity is cognitive state sensing and prediction for human operators (Activity 1). The objective of this step is to access operator cognitive state in real-time and provide basis for further analysis, including human-automation mutual adaptation, human trust calibration, and cognitive load evaluation. Prediction can be done through physiological measurement from wearable device, where the collected measurement is fed into a pretrained model for cognitive state prediction. It can also be analyzed through human behavior interpretation. After accessing the cognitive state, human trust can be modeled using prospect theory, where the predicted cognitive state influences the shape of the prospect value function (Activity 2). Human trust reflects the risk attitude of one operator towards one automation agent at a certain level of automation, which can be modeled as the human agent's confidence towards automation agents for team cognition evaluation. Individual differences can be characterized by the function shaping parameters. Level of automation is another important human-related factor in human-automation teams, which influences the usage of automation agents and thus can be used for human workload adjustment. Determining level of automation can be modeled as the trade-off between operator's preference and manager's preference (Activity 3). On the one hand, human trust and workload reduction influences the operator's preference towards certain level of automation.

On the other hand, choosing certain level of automation influences the task cost, time, and quality from the manager perspective. Joint prospect theory can model this decision-making through estimating the prospect function value from two groups of people separately (Wang and Jiao 2022). Once decision is made, it can influence the preference for how team performance is measured in task allocation objective function.

Team cognition prediction aims to map the human-related factors into team cognitive performance as part of the performance measurement during task allocation (Activity 4). Using the preferred level of automation for each task, along with human trust, automation agent information, and task information, team cognitive performance can be estimated using statistical learning with the prediction results being reported values from observations. Cognition performance evaluation is an important step in human-automation symbiosis which emphasizes the interaction design is human-centered. The next activity is situation aware interaction control (Activity 5). This step is to enable situation awareness of interaction coordination, which is to comprehend the context of special events during operation or a sudden change of team states. Its implementation relies on intelligent reasoning mechanism and the knowledge base. It also can adjust the optimization objective function for task allocation problems to control the interaction between human and automation.

Dynamic task allocation is to find the optimal task assignment that maximizes the overall system performance, where the performance is evaluated by both task performance and cognitive performance (Activity 6). In this study, task performance is measured by financial cost and completion time, and cognitive performance uses the team cognition prediction model. The proposed solution to the optimization problem is genetic algorithm. Finally, after tasks are completed, the overall system performance will be evaluated in multiple perspectives (Activity 7). To characterize the dynamic feature and situation awareness of human-automation symbiosis, the system performance is provided to both human trust prediction and situation aware interaction control as feedback. Human trust can change by time, and its dynamic property is due to the discrepancy between the expected performance of an operator and the actual performance he observes. The performance will also be analyzed through situation awareness to find potential changes that can improve performance.

3.2 System Architecture

To enable intelligent interaction between human and automation agents, the system should have supporting function modules and models. The design of the system architecture is presented in Figure 2.

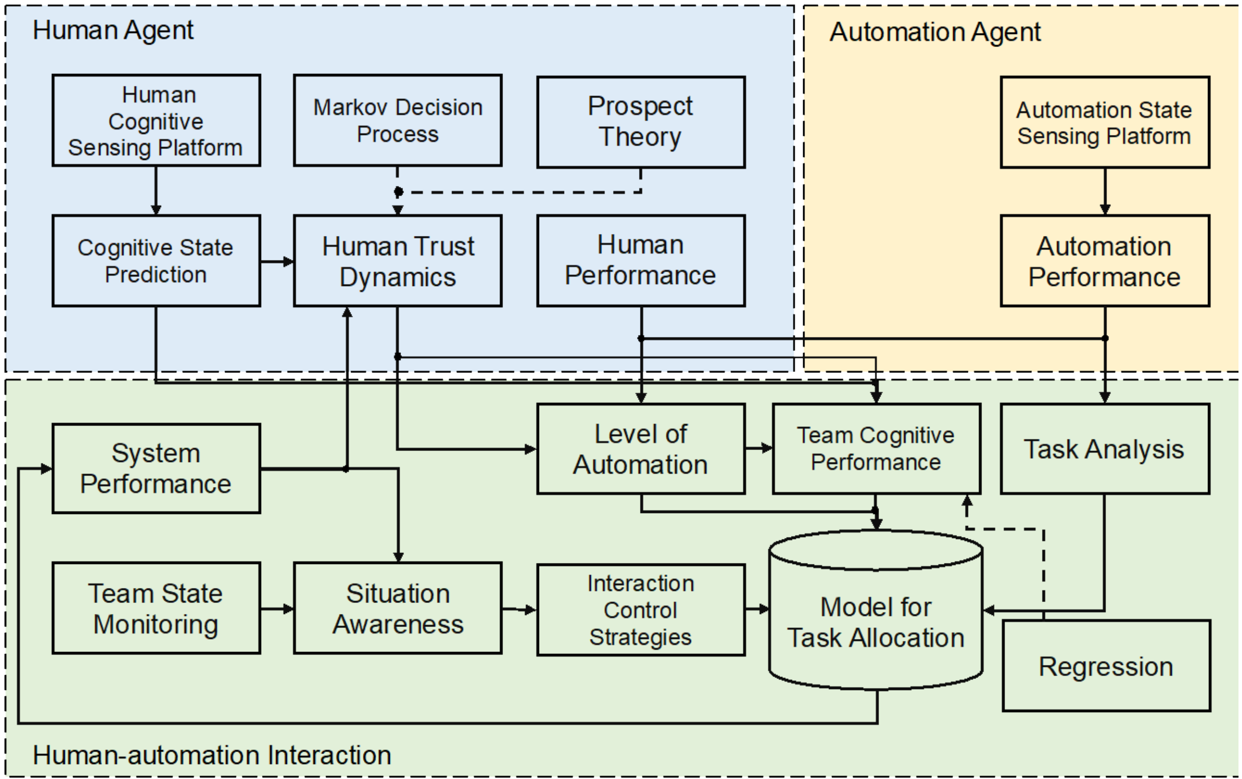

Figure 2. System design for human-automation symbiosis

The enabling mechanism can be categorized into three sections: human agent, automation agent, and human-automation interaction. In the human agent section, three function modules should be addressed: prediction of cognitive state, modeling of human trust dynamics, and human performance evaluation. Cognitive state can be estimated with cognitive sensor data using statistical learning or other prediction algorithms. Human trust dynamics can be modeled with prospect theory along with the Markov decision process. Human performance can be evaluated in several perspectives, including operator skills (qualification), cognitive capabilities, task conduction speed, salary, and so on. For the automation agent, the required feature is to understand the automation capabilities as well as its states. This can be supported by an automation state sensing platform. For human-automation interaction, there are several function modules that should be implemented. (i) Determination of level of automation for adjusting team performance evaluation strategies; (ii) Predicting team cognitive performance for team performance evaluation; (iii) Task requirement analysis for understanding the capabilities of different agents towards different tasks; (iv) Team state monitoring for detecting state change or pattern change inside the human-automation team; (v) Situation awareness that conducts inference to map an unexpected scenario or event to a set of actions; (vi) Intelligent control that modifies the allocation strategy based on the analysis of situation awareness and observed team performance; (vii) System performance evaluation.

4. Problem Definition and Mathematical Model

4.1 Problem Context of Human-automation Task Allocation

Task allocation aims to allocate tasks to proper agents with the objective of maximizing operation performance. For conventional multi-robot task allocation, selection of one automation agent will not influence the performance of the other human agents. However, in the context of human-automation symbiosis, different human operators may have different collaboration efficiency with automation agents at different level of automation, thus resulting in different task performance and cognitive performance. In this study, this characteristic is modeled in the optimization objective function.

Assume $A^M = \{a_m^M\}$ represents the set of available automation agents, and $A^H = \{a_i^H\}$ represents the set of available human agents. The operation requires conducting several operation tasks $\Omega = \{\omega_j\}$. For each human agent a_i^H or automation agent a_m^M to conduct the task ω_j, it has a corresponding financial cost $d_j(a_i^H)$ or $d_j(a_{ml}^M)$, and a time cost $t_j(a_i^H)$ or $t_j(a_{ml}^M)$, where l is the level of automation for one automation agent. Agent usage is enumerated by $\Gamma = \{\gamma_q\}$, which specifies all potential selection of a human agent or an automation agent working at different levels of automation.

This paper proposes to include cognitive performance B in the objective function. The cognitive performance is predicted from multiple human factors: (i) human trust $v_i(a_{ml}^M)$, which refers to the trust of human agent a_i towards the automation agent a_m^M at the level of automation l; (ii) individual cognitive performance of a human agent β_i, which is the prediction from human cognitive sensor data; (iii) the preferred level of automation l^*, which determines the weights for different performance factors. Apart from these human factors, task condition ω_j and agent information a_i^H and a_m^M are also the inputs. Therefore, cognitive performance can be illustrated as $\mathrm{B}(a_i^H, a_m^M, \omega_j, \beta_i, v_i, l^*)$.

In this regard, the objective function consists of three factors: financial cost, completion time, and team cognitive performance. The cost structure and priority can be adjusted through situation awareness for controlling the human-automation interaction in different applications and scenarios.

4.2 Mathematical Formulation

The formulation of human-automation task allocation originates from the conventional multi-robot task allocation problem (Kuhn 2005):

$$\max \sum_{i=1}^{n} w(r_i \omega_i) \tag{1}$$

where r_i and ω_i are robots and tasks, and $w(r\omega)$ represents the profit. Therefore, the objective is to maximize profit.

In the context of human-automation symbiosis, team cognitive performance is added to the cost function, along with the completion time and financial cost:

$$\min \sum_{\gamma \in \Gamma} c_\gamma^{cost} x_\gamma + c^{time} \sum_{\gamma \in \Gamma} t_\gamma x_\gamma - c^{cog} \sum_{\gamma \in \Gamma} \mathrm{B}_\gamma x_\gamma \tag{2}$$

$$s.t. \quad \sum_{\gamma \in \Gamma} o_{\gamma\omega} x_\gamma = 1, \forall \omega \in \Omega \tag{3}$$

$$x_\gamma, o_{\gamma\omega} \in \{0,1\} \tag{4}$$

Equation (2) is the objective function, where c^{time} and c^{cog} represents the weights for time cost and cognition cost. x_γ is the decision variable describing if an agent is chosen. $c_\gamma^{cost}, t_\gamma, \mathrm{B}_\gamma$ represents the measurement for financial cost, time cost, and cognitive performance separately. Equation (3) is the constraint for task fulfillment, requiring each task should be fulfilled once. $o_{\gamma\omega}$ is the variable that describes if the allocation γ conducts the task ω_j. If $o_{\gamma\omega} = 1$, it means the allocation γ conducts task ω, and 0 otherwise. Equation (4) is the integer constraints. Team cognitive performance B can be a measurement reflecting cognitive load, operator attention, and confidence.

With the above formulation, this optimization problem can be solved by genetic algorithm. The implementation details are introduced in Section 5.

5. 2D Genetic Algorithm for Human-automation Task Allocation

Genetic algorithm is a common approach to solve the task allocation problem. The conventional one-dimensional encoding approach is to encode the chromosome with assigned agent to each task. One issue for one-dimensional encoding is its computing efficiency for calculating the objective function and the equality constraint. In this regard, a two-dimensional genetic algorithm is proposed to increase the computing efficiency through matrix multiplication. The crossover and mutation operators for the 2D genetic algorithm are also presented.

To accommodate the variability of task allocation and level of automation, a two-dimensional gene encoding approach is proposed. The chromosome is a 2D matrix $[\mathbb{C}]_{|\Gamma| \times |\Omega|}$, where $|\Gamma|$ is the number of all possible agent selection (human agent a_i^H and automation agent at different automation level $a_{i,l}^M$) and $|\Omega|$ is the number of tasks. The gene $g_{\gamma\omega} \in \{0,1\}$

represents the allocation of task to an agent. Corresponding, there are two matrices, $\mathcal{F}_{\gamma\omega}$ that represents the financial cost for an agent to conduct a task, and $\mathrm{T}_{\gamma\omega}$ that represents the corresponding time cost. For an infeasible allocation, the financial cost and time cost can be set at an enough large number to avoid being selected. The team cognitive performance can be obtained through the pretrained prediction function.

The workflow for genetic algorithm optimization is shown in Figure 3.

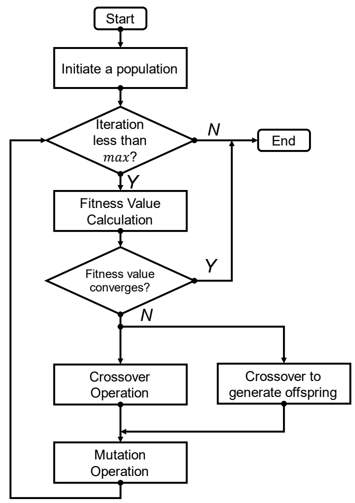

Figure 3. Genetic algorithm workflow

Crossover and mutation are two important genetic operators to genetic algorithm. In the context of 2D genetic algorithm, the operations also need to be modified.

Crossover is to exchange parents' chromosomes to produce child chromosome. The operations for crossover include selection of parent entities, determination of gene segments, and gene exchange. Figure 4 represents one example of crossover in the proposed 2D genetic algorithm. By choosing a random point on the chromosome, the crossover operation can divide the parent chromosome horizontally or vertically to form the child chromosome.

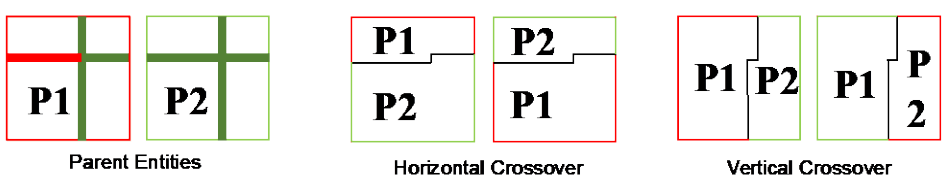

Figure 4. 2D Chromosome Crossover

Mutation operations can help increase diversities during crossover. Conventional 1D mutation usually randomly changes one gene from one random position. In the context of 2D genetic algorithm, mutation can be done by swapping and perturbation (Gong et al. 2019). To control the algorithm convergence, the mutation rate is at a very small value. Figure 5 shows how the mutation operation is done.

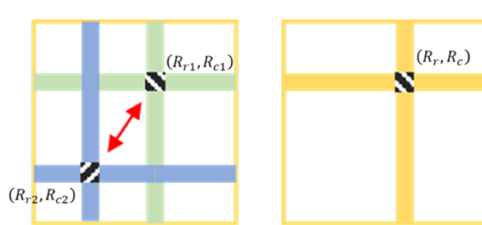

Figure 5. Mutation Operations on 2D Chromosome

6. Case of Medical Product Assembly Task Allocation

In this study, an example case of medical product assembly is presented. Figure 6 presents the case layout of different workstations. Medical products have high requirements for product quality, and practitioners have serious attitudes about using automation solutions. Thus, the operations are usually a mix of manual and automatic workstations. With the development in automation technology, there is a trend to let human operators to work with automation techniques to increase the assembly efficiency and reduce the cost of poor quality from purely manual operations.

Figure 6. Medical Product Assembly (Image from Internet)

To validate the feasibility and effectiveness of the proposed genetic algorithm, a task allocation case for the assembly line is used. In this example, there are 12 steps for product assembly, and each step happens in one workstation and by sequence, as shown in Table 1. Each step requires either a human operator or an automation machine. In some stations, there are multiple agent states can be selected for the operation, including operators with different experience and automation machines at different levels of automation.

Table 1. Workflow and Agent Type for Assembly Operations ("Auto" stands for automation agent)

Operation Number	Type	Operation Number	Type	Operation Number	Type
Op1-Attach	Manual	Op5-Inspection	Manual	Op9-Inspection	Auto
Op2-Heat	Manual	Op6-Glue	Auto	Op10-Cut	Auto
Op3-Cut	Auto	Op7-Heat	Manual	Op11-Attach	Manual
Op4-Straighten	Auto	Op8-Cut	Auto	Op12-Inspection	Manual

For the operation that uses automation machines, like Operation 9 – inspection, multiple levels of automation are considered. Also, for some manual operations, like operation 12 inspection where the inspector will refer the results from the machine inspection in operation 9, operator's preferred level of automation will influence the team cognitive performance. Meanwhile, automation agents at different level of automation and different operator agents are modeled to have different cost and time performance.

In this example case, data for cognitive performance are artificially made based on real-world understanding of the process. Time and cost metrics are from statistical analysis of production activities. After preparing the inputs, the optimization problem is solved by the proposed 2D genetic algorithm. The optimization results provide the optimal task allocation solution based on the defined objective function. The minimum and average objective function values representing the best candidate and average candidate in each iteration are displayed in Figure 6. This application case demonstrates the feasibility and effectiveness of the proposed genetic algorithm.

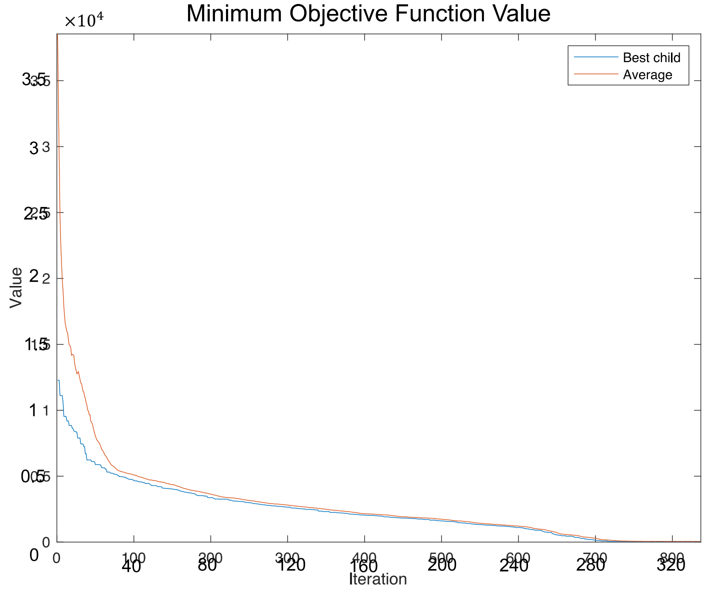

Figure 7. Fitness Function and Iteration Curve

7. Managerial Implications

There are many practical benefits and profound significances for studying and implementing human-automation symbiosis. Firstly, it could facilitate the design and operation of practical applications in different environment. Secondly, it can improve team performance, increase operation safety and avoid human errors. Thirdly, it proposes solutions to allocating tasks appropriately to leverage advantages of different agents and to increase operator satisfaction, so that the industry can maintain the operation level when there are not enough operators. Fourthly, it can help prepare human operators for new techniques by understanding how automation agents influence human cognition, behavior, and required skills. Nowadays artificial intelligence has made huge breakthroughs, and some generative artificial intelligence and large language models have already been applied to real-world problems. Understanding human-automation symbiosis can better utilize the cognitive capabilities from these techniques.

8. Conclusions

This paper presents the system design and methodology for dynamic task allocation considering team cognitive performance to achieve human-automation symbiosis. It proposes the approach to modeling human-related factors, including cognitive state, human trust, level of automation, and team cognition. These factors are integrated into the task allocation problem, which is formulated as an optimal assignment problem with the objective function being the sum of financial cost, time cost, and team cognitive performance. A 2D genetic algorithm approach is proposed to solve the formulated problem. It also presents an application case of medical product assembly for validating the feasibility and effectiveness of the proposed solution.

There are several contributions of this work. Firstly, it proposes the comprehensive system analysis and design for task allocation decision-making towards human-automation symbiosis. Secondly, it formulates the dynamic task allocation problem between human and automation agents with human factors considered. Thirdly, it proposes a 2D genetic algorithm to solve the optimization problem.

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Biography

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Dr. Jiao joined the Woodruff School in December 2008. Prior, he was an Assistant Professor and then Associate Professor in the School of Mechanical and Aerospace Engineering at Nanyang Technological University, Singapore. Before his career in Singapore, he was a Visiting Scholar in the Department of Industrial Engineering and Engineering Management at Hong Kong University of Science and Technology from 1998 to 1999. From 1993 to 1994, he was a Lecturer of Industrial Engineering in the School of Management at Tianjin University, China, and from 1988 to 1990, he worked as an Associate Lecturer in the Department of Industrial Design at Tianjin University of Science and Technology, China.