Modularization in Dual System and Occupational Self-governance Concerns Employing the Fuzzy Control Algorithm in Vocational Education Personnel Training

Jinyuan Li
College of Electrical Engineering
Guangzhou Railway Polytechnic
China
lijinyuan188@outlook.com

Yuqi Cheng
College of Intelligent Manufacturing
Guangzhou Panyu Polytechnic
China
chengyuqi_edu@outlook.com

Abstract: *Vocational education enhances traditional education by providing students with the advanced information and skills necessary for career success. Based on the traditional course structure, vocational education places equal emphasis on self-governance and occupational skills. This article proposes a Modularization-based Training Control Optimization (MTCO) approach to leverage the adaptability of vocational education training for market skills. This optimization approach classifies the training and its adaptability for the occupational and self-governance skills of the students. Based on the demand, the modular priority for skill-based training is pursued to provide better training efficiency. As optimization is induced for the personnel training, standard interchangeable modules based on the skills and agenda are optimized for maximum efficiency and the minimum swapping between the training sessions. The optimization uses fuzzy control to consider the current demand for personnel for modularization. This optimization relies on the modularization process's minimum swapping criterion for maximum training efficiency in consecutive and distinct training sessions. Based on this minimum swapping, the new fuzzy control criteria are designed to prevent modularization failures and time demands.*

Keywords: *Fuzzy control, modularization, personnel training, vocational education.*

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1. Introduction

Vocational education or Vocational Education and Training (VET) is an education system that prepares people to be skilled in a particular field or area [3]. VET provides various non-academic, traditional, occupational, and trade-related activities to gain more knowledge over fields [6]. The main goal of vocational education is to give the knowledge to succeed in career growth. VET programs are conducted among personnel or employees. The actual concept of VET is that it produces effective practices and training sessions for the employees [15]. A quantitative approach is used to train the employee efficiently. The system provides innovative ideas and strategies to the employees, decreasing difficulties in learning. Pedagogical principles are also used to produce the optimal information and services for the employees [31]. The pedagogical principle improves the training systems' efficiency and the functionalities range [22]. An effective technique is used to train the employees, providing communication and interaction skills to the users. The practical approach enhances the training systems' performance and feasibility levels [10].

Modularization is a process that divides the system or product into interchangeable modules. The modularization process creates a flexible and optimal system that enables the functionalities of creating a module [16]. Modularization training is provided to personnel during self-governance programs. The fundamental concept of modularization training is to improve an employee's quality and assurance levels [5]. Modularization's main aim is to avoid the unwanted problems that occur during the self-governance processes. A theory-based technique is used in the modularization training systems [27]. The theory-based strategy identifies the essential features required to divide the content into modules. The specified data produces feasible information for the modularization training process [14]. The theory-based technique achieves high accuracy in training the self-governance personnel and improves the feasibility level of the organizations [20]. The theory-based approach reduces the unnecessary modules that are created by personnel. Modularization training also produces practical vocational skills and knowledge for the learners [1]. Modularization training enhances the feasibility level of the occupational self-governance personnel [25].

The fuzzy control optimization technique is a controlling measure used in the vocational education systems. Various methods and techniques are used for the optimization process [29]. The Grey Wolf Optimization (GWO) algorithm is used for the fuzzy control process in the vocational education systems. The GWO algorithm identifies the objective function containing sensitive data performed in the training sessions. The GWO algorithm reduces the parametric sensitivity level in vocational education, which controls the learners' overall training period. GWO solves the problems faced during the optimization and reduces the computation cost range in the education systems [18, 23]. A Fuzzy Logic-Based Model (FLBM) is also used to control and optimize the vocational education training modularization process. FLBM uses a fuzzy definition to understand the exact key role of the variables. The FLBM changes the modules based on the characteristics that minimize the latency in the computation process. The FLBM maximizes the vocational training systems' overall performance and efficiency [24, 29, 30].

Contributions

The contributions of the articles are listed below:

1. Designing a fuzzy control optimization-based on a modularization system for improving the training efficiency of the vocational education courses.
2. Validating and mitigating the constraints in vocational course adaptation in self-governance and occupational efficiency.
3. Performing a modularization swapping suppression process using the fuzzy optimization for training efficiency maximization.
4. Performing a data and comparative analysis using the multiple considerations, metrics and methods from the previous works.

1.1. Introduction to Fuzzy Control Optimization

Training programs' flexibility and effectiveness are critical in vocational education to guarantee that students gain current and applicable skills. Conventional training approaches frequently find it difficult to adapt quickly enough to meet the changing needs of learners and the changing demands of the labour market. This is where FLBM and the GWO algorithm emerge as beneficial fuzzy control optimization strategies.

1.2. Rationale for Fuzzy Control Optimization in Vocational Education

- **Dynamic adaptability**: because uncertainty and imprecision are frequent in vocational training, fuzzy control systems are naturally built to handle them. Fuzzy systems, as opposed to inflexible old techniques, may dynamically adjust to the shifting skill requirements of various industries, guaranteeing that training stays applicable and efficient.
- **Enhanced Decision-Making**: in complex and uncertain contexts, fuzzy control techniques offer a reliable foundation for decision-making. This is especially important for vocational education since learners' input and industry trends must be considered while adjusting the instruction. Fuzzy logic makes it possible to make more complex decisions, which can raise the general standard and effectiveness of training initiatives.
- **Optimizing modular training**: fuzzy control techniques can help achieve more effective modularization of vocational training. This implies that training materials can be instantly modified and reorganized in response to learner input and performance indicators. As a result, students receive a more tailored education that suits their requirements and learning styles.
- **Efficiency and performance**: strategies such as the Grey Wolf Optimization (GWO) algorithm optimize training settings to reduce session swapping and increase training efficacy. This results in a more effective use of time and resources, enabling a stronger emphasis on skill development rather than administrative tweaks.
- **Scalability**: because fuzzy control optimization is scalable, it can be used in various contexts related to vocational education, from primary institutional settings to small-scale training initiatives. This scalability guarantees that more students and educational institutions can benefit from optimized instruction.

1.3. Comparison with Traditional Methods

The labour market's demands are changing quickly, and traditional vocational education methods frequently use linear progression models and static curricula. Alternatively, fuzzy control optimization has several benefits: it allows for real-time adaptation, which keeps training up to date and applicable; guarantees precision by making targeted adjustments based on learner needs and industry feedback; and it offers flexibility by incorporating new information and adjusting training programs with ease. Thanks to these advantages, fuzzy control systems outperform conventional techniques regarding effectiveness and responsiveness.

A significant development in the discipline is incorporating fuzzy control optimization techniques into vocational education. These methodologies' qualities, which include dynamic flexibility, enhanced decision-making, modular training optimization, efficiency, and scalability, can significantly improve vocational training programs. This methodology guarantees that students have the most pertinent and efficient instruction possible, better equipping them to meet the needs of the contemporary labour market.

1.4. Problem Statement

Traditional vocational training methods are not easily adapted to rapid changes in market demand. Most of these methods are not flexible and do not optimize training efficiency. Challenges such as module switching, training delays, and mismatched skill development hinder effective learning outcomes. There is a need for a dynamic and adaptive approach that will link vocational training to market requirements while decreasing inefficiencies.

1.5. Research Objectives

- Develop a modularization-based approach to improve training adaptability and efficiency.
- Apply fuzzy control to reduce module switching and training failures.
- Evaluate the effectiveness of the MTCO approach in addressing the limitations of traditional vocational training.

1.6. Significance of the Study

The research is essential because it provides a practical solution to improve vocational training systems. Combining modularization with fuzzy control, the MTCO approach will overcome the shortcomings of traditional methods, ensuring learners acquire relevant skills, enhance training efficiency, and align education with industry needs. This innovation can transform vocational education by creating flexible and effective training systems.

1.7. Methodological Overview

The MTCO approach combines the techniques of modularization and fuzzy control to improve training efficiency. Modularization provides training in flexible units adaptable to the learners' competence and market demand. Fuzzy control is introduced to handle uncertainty, optimize training sequences, and minimize module switching. The test using this approach used accurate training data from 31 fields of observation and 711 records. Evaluation metrics considered in the assessment of the training sessions included efficiency, frequency of switching, and adaptability.

1.8. Key Terms

- **Fuzzy Control**: mathematical approach for dealing with uncertainty, making decisions based on imprecise input.
- **Modularization**: breaking up training into smaller, interchangeable units for greater flexibility and adaptability.

1.9. Key Results

- Occupational-Based Training: improved through modular tailoring of job-specific skills and reduced switching delays.
- Self-Governance Training: improved personal skills such as discipline and flexibility, with reduced failures in training.
- Comparative Study with Traditional Methods: achieved a 10.07% increase in training effectiveness and a reduced module switching by 8.86% over traditional methods.
- Scalability and Flexibility: adaptability to diverse learner needs and market conditions.

These results validate the effectiveness of the MTCO approach in addressing the challenges of traditional vocational training systems.

2. Related Works

2.1. Frameworks for Advanced Vocational Training

Romero-Gázquez *et al*. [26]: IN4WOOD combines the most innovative technologies for Industry 4.0 vocational training. It increases the productivity of workers and managers with hands-on learning and task performance tools. It is not concerned with flexibility for different industries and individual learners. Billert *et al*. [4]: 360-degree Learning Environment workshop-based approach simplifies vocational topic learning and improves workers' performance. Experimental evidence shows that it enhances competitiveness and boosts effectiveness. Its drawback is reliance on physical workshops, hence a limitation regarding scalability and accessibility.

2.2. Conceptual Models and Lifelong Learning Systems

Dogara *et al*. [9]: Work-based learning (WBL) integrates vocational topics with soft skills to enhance the knowledge and adaptability of students in technical colleges. However, it lacks real-time adaptation to the industry's rapidly changing needs. Georgescu and Gliga [13]: The Forestry Training Framework focuses on continual vocational training for forestry. It identifies workers' needs and consequently develops specific practical training for them. While this model is good for forestry, it cannot be replicated for other sectors. Besides, it may not support interdomain competency development. Chukwuedo *et al*. [8]: Lifelong Learning System, a self-directed learning model that reinforces engagement and academic performance in vocational and adult education. The system's limitation lies in its dependency on learner initiative, which may not work for the less motivated student.

2.3. Digital Competence and Vocational Identity

Findeisen and Wild [11]: VET Model for Digital Competence is a beginner-oriented model that improves digital competence and self-assessment, optimizing learning outcomes. However, it does not provide advanced training for learners with higher skill levels. Keijzer et al. [19]: Vocational Identity Framework analyses the relation of school engagement with vocational identity and helps learners target their difficulties in identifying specific interventions. It remains limited as it is not embedded with market-oriented vocational competence.

2.4. Optimization Skill Identification

Chukwuedo and Ohanu [7]: Vocational Optimization employs career-related practical life skills to monitor and enhance students' job-search effectiveness. However, occupation-seeking remains skill-based, not competencies in vocations in general. Shamzzuzoha *et al*. [28]: Skills for Green Innovation identifies core skills for vocational excellence in innovation and improving education outcomes. However, it is limited in addressing non-green sectors or general vocational training.

2.5. Advanced Educational Models

Huang and Liu [17]: Technology Acceptance Model (TAM) proposed a STEAM education model that enhances logical thinking and positive mindsets in vocational students. Its limitation is the narrow application to STEAM fields, which excludes other vocational areas. Findeisen *et al*. [12]: Persistence in VET uses social cognitive career theory to increase persistence intentions, leading to lifelong vocational success. The model does not articulate how to deal with a diverse group of learners with varying degrees of engagement.

Modularization is novel for vocational course training and has implications for professional courses. Training efficiency will be improved with the maximum adaptable modules based on the available inputs. Specifically, vocational course training is required to meet the agenda and extract the trainee's skills. The methods discussed above rely on limited metrics for preventing training failures. Therefore, the proposed optimization approach focuses on maximizing efficiency using maximization and minimum swapping.

Agarwal *et al*. [2] suggested the Intelligent Adaptive Neuro Fuzzy Method for Component-Based Software System Reusability. This paper utilizes the Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) approach to evaluate reusability, with Interface Complexity (IC), Understandability (Un), Customizability (Co), and Reliability (Re) as input variables. These two approaches are commonly used for evaluating quality factors. An online poll was used to gather opinions from academics and researchers, and one case study was conducted to develop criteria for evaluating reusability based on four distinct aspects. For 10 distinct input variable values, reusability was evaluated. According to the experiment, the findings generated via the ANFIS approach were more in line with the original values. Applying the ANFIS technique lowered the Root Mean Square Error (RMSE) of 6.05% of the FIS findings to 2.20%.

Kurre *et al*. [21] proposed the Self Tuning Fuzzy Control Dual Input Nine-Level Self Balancing Switched-Capacitor Inverter for Induction Heating Applications. Various quantization parameters in FLC must be set according to the system needed to achieve this purpose. The author built STIFLC to manage the induction heating temperature and execute it in real time after carefully analyzing all the quantization elements, which allows us to overcome this issue. The system's efficiency is determined by deriving power loss equations and comparing the control performance of regular FLC with STIFLC. Lastly, experimental and simulation testing on a 5kVA inverter prototype that included the IH system confirmed the suggested system's efficacy. The results show that the controllers' flexibility and control capabilities were greatly enhanced by the suggested STIFLC, including the multilevel inverter.

2.6. Discussion of Findings

Together, the examined studies demonstrate the beneficial effects of information technologies on vocational education, pointing out that e-learning platforms and Learning Management technologies (LMS) significantly improve student engagement, knowledge retention, and skill development. Additionally, digital platforms improve accessibility, increasing vocational education's time and geographical flexibility. Furthermore, developing practical skills and augmenting learner confidence are particularly successful outcomes of interactive tools such as simulations. However, the literature also points out several difficulties, including technological impediments like poor infrastructure and low levels of digital literacy among teachers and students. Additionally, there is a frequent reluctance to change, with teachers and students favouring the conventional approaches to instruction.

2.7. Research Gaps

Notable gaps persist despite much study on the application of information technology in vocational education. Most research is done in the short term and does not examine how information systems affect vocational education outcomes over the long run. Furthermore, little research has been done on how information systems might be customized to foster career skills. Additionally, a few studies examine efficient methods for teaching instructors how to use information technologies in vocational education.

2.8. The Unique Contribution of the Study

This work seeks to close these gaps by implementing a Modularization-Based Training Control Optimization (MTCO) strategy. Using fuzzy control optimization techniques, the MTCO approach develops a flexible and dynamic vocational training program. This methodology, in contrast to previous methods, may adapt continuously to the changing demands of the labour market and individual learner requirements. The MTCO approach offers a holistic solution that addresses the constraints noted in the literature by emphasizing both occupational and self-governance abilities.

3. Modularization-based on Training Control Optimization (MTCO) Approach

Mainstream course design for vocational education modularization is adaptable based on the growing student demands and interest in vocational education personnel training sessions. Amid the challenges in the training sessions, occupational and self-governance are the accurate and appropriate demands that satisfy students of different vocational education. The students from the other vocational education personal training sessions are observed to identify their skills and the agenda. Hence, regardless of the mainstream courses and strength of the students, optimal training and adaptability for the students based on modularization are identified as prominent considerations. The proposed MTCO approach focuses on this by providing better vocational education training efficiency based on the student's skills through an accurate modularization process. In this approach, the adaptability of modularization is administrable for personal training, and the student skills and agenda with the current modularization demand for a set of personnel is considerably using the fuzzy control by the proposed optimization. A schematic illustration of the proposed approach is given in Figure 1. The figure shows the MTCO approach, its process of modularization, and features of adaptability. It illustrates the interplay between personnel training, modular priorities, and fuzzy control for maximizing training efficiency and minimizing swapping.

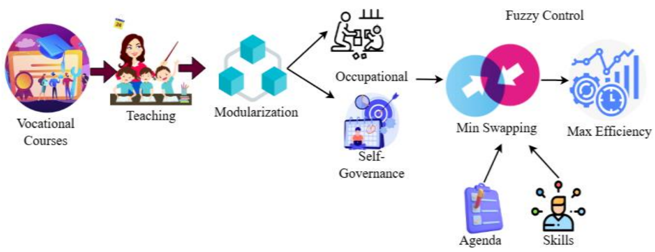


Figure 1. Schematic illustration of MTCO approach.

Vocational education supports the diverse mainstream courses to meet the current market skills with better knowledge for maximizing personnel training efficiency. The adaptability of vocational education training based on market skills is achieved through the proposed MTCO approach using fuzzy control optimization. The MTCO approach operates between the personnel training sessions and the modular priority for maximizing efficiency and minimizing swapping. In this proposed approach, the proposed optimization classifies the training and its modularization adaptability for the available students, and extracting the occupational and the self-governance features are feasible for improving the student skills for the swapping modular priority. Further, this approach aims to provide minimum swapping of the modularization process and maximize the current personnel training efficiency. The proposed approach functions in two forms: concurrent training and adaptability for the occupational and self-governance skills of the students. The modularization process is adaptable for the occupational and self-governance skills to handle a diverse density of students. The initial data observed from the vocational education training sessions are analyzed, and the acute modularization process for the time interval is computed as:

$$\left.\begin{array}{c} \max\limits_{s\in t} VET_s \ \forall\ OC_p = SF_g \\ \min\limits_{s\in VET_s} Trn_t * Adp_t \\ where, \\ Trn_t = OC_{p_t} - SF_{g_t} \\ and, \\ \min\limits_{s\in t} \exists_{\emptyset}\ \forall\ t \in Trn_t \end{array}\right\} \quad (1)$$

In Equation (1), the variables $VETs$, OC_p, SF_g, t used to represent the vocational personnel training sessions s, occupational and self-governance skills of the students were also computed in the different time intervals t. In the next mainstream course design, the variables Trn_t and Adp_t, used to denote training and adaptability for improving vocational training practices. The third objective is to maximize the training efficiency and minimize swapping of the modularization process, which is represented using the constraint, $\exists_{\emptyset}\forall t\in Trn_t$. If $Stud^N=\{1, 2, \ldots, N\}$ means the set of students attending vocational education personnel training. Then the number of training sessions may increase based on the demand is $Trn_t\times s$ whereas its adaptability is $Stud^N\times Trn_t$. From the current market skills of $Trn_t\times s$ and $Stud^N\times Trn_t$, is the considerable factor computed to meet the mainstream courses. The optimization approach classifies the occupational and self-governance skills of the students based on their demands. Analyzing the training and its adaptability for the upcoming needs are feasible. In these instances, the classification of the training and its modularization adaptability is prominent in identifying the interchangeable modules for personnel training based on the student's skills and agendas. The demanding requirement ($\Delta Stud^N$), of the students between the different training sessions depends on the optimized student skills and agenda for maximum efficiency, and minimum swapping is achieved for successful training. The remaining time needed for adaptability is the factor for improving vocational education training. Before discussing the modularization concept, the data used for MTCO assessment is introduced.

The proposed MTCO is analyzed using the data from (https://data.world/city-of-ny/fgq8-am2v). This source provides VET course inputs for training grants. The inputs include 31 personal, professional, and grade-based observation fields as 711 record entries. The maximum number of training hours is 600, split into 60 sessions. The skills and the training elements are illustrated in Figure 2. The figure groups training components into occupational and self-governance skills. It indicates how skills are measured and their relationship to agenda fulfilment metrics.

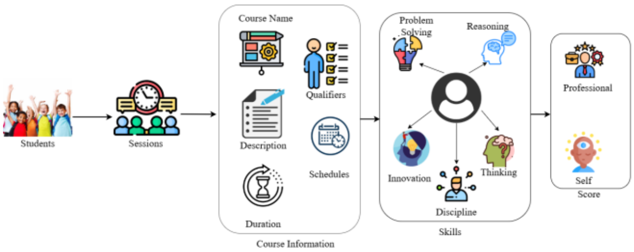


Figure 2. Skills and training information.

The session is equipped with course information and the exact output skills. Based on the course information, the skills are split into occupational efficiency (Profession) and self-governance. The agenda fulfilment is verified based on the available scores (assessment). Therefore, this requires criteria based on assessments for the new score updates (Figure 2).

The classification of the occupational and self-governance skills of the current training session students is pursued, identifying the modular priority by the fuzzy control optimization. Later, depending upon the classification process, the modular priority is the augmenting feature here. From this classification, the modularization process's personnel training and swapping criterion is the fuzzy control instance for defining the consecutive and distinct training sessions. The pre-modeling of the training and its adaptability for the modularization process are described in the following cases.

- **Case 1:** occupational-based Modularization Training
  - Analysis 1: in this modularization process, the demand of $Stud^N \times Trn_t$, all the students in the vocational education training are analyzed based on $\Delta Stud^N$, is the considering feature. This considering metrics is pursued to achieve the maximum efficiency and minimum swapping between the different training sessions are using the fuzzy control. The probability of identifying an accurate modularization model for occupational skill-based training (ρoc_p) sequentially is computed as:

$$\rho_{OC_p} = \left(1-\rho_{\exists_\emptyset}\right)^{t-1} \forall s \in t \tag{2}$$

Where,

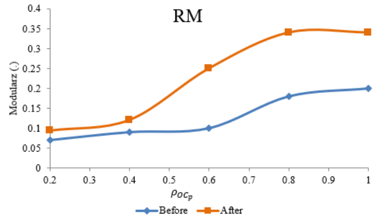
$$\rho_{\exists_\emptyset} = \left(1 - \frac{Trn_t \in Stud^N}{Trn_t \in s}\right) \tag{3}$$

As per the Equation (2) and (3), the sequential performance of the modularization-based on training follows the occupational skills of $Stud^N$, such that there is no mainstream course. Hence, the fuzzy control optimized skills and agenda of the students with the maximum training efficiency and the minimum swapping of modularization process is computed as in the above Equation (1). Therefore, the modular priority for skill-based training for ρoc_p follows:

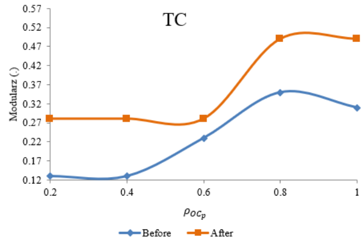
$$Modularz\,(Stud^N) = \frac{1}{|Trn_t - OC_p + 1|} \cdot \left(\rho_{OC_p}\right)_t \forall s \in t \tag{4}$$

However, the modularization process depends on the student's skills and agenda, as in Equation (4) is to satisfy both the constraints of ($Trn_t \times s$) and ($Stud^N \times Trn_t$) for ensuring maximum training efficiency. The interchangeable modules are optimized between the different personnel training sessions in different T intervals to minimize the swapping with the constraint ($Trn_t \times s$) and ($Stud^N \times Trn_t$), modularization is adaptive using the classification process. Therefore, the considerable constraint of $Stud^N > Trnt$, and less to satisfy Equation (1). Contrarily, case 1 identifies the minimum training efficiency and the maximum swapping from the instance. Hence, the available modularization process outputs failures and time demands. The modularization outputs on occupational efficiency from the data source post the optimization are presented in Figure 3. From the given input source, the occupational efficiency of the Resource Management (RM), Task Completion (TC), and Instructor (IT) positions are analyzed. The analysis considers ρoc_p and $\rho_{\exists\emptyset}$, concurrently before and after optimization, as in Figure 3. The figure illustrates the comparison in occupational efficiency before and after optimizing fuzzy control. It indicates improvements in resource handling, task delivery, and instructor roles.

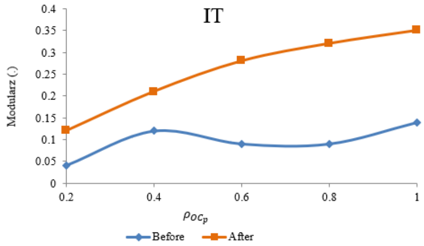
The before and after modularz (.) for the three occupational skills (RM, TC, and IT) are validated for efficiency. The maximum swapping is suppressed using constraints in the fuzzy process. If the skill expressed by the trainees exhibits a new improvement in efficiency, then OC_p, is high. It is estimated for consecutive $\rho_{\exists\emptyset}$, are presented in Figure 3.



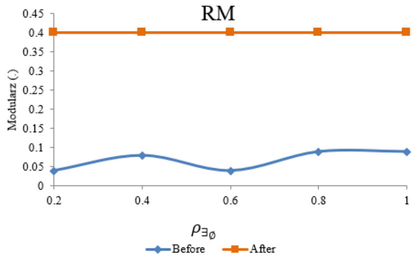
a) Resource Management (RM) under probability of occupational modularization model accuracy $\left(\rho_{OC_p}\right)$.



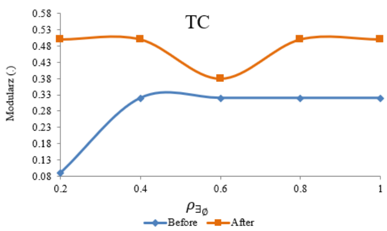
b) Task Completion (TC) under probability of occupational modularization model accuracy (ρ_{OC_p}).



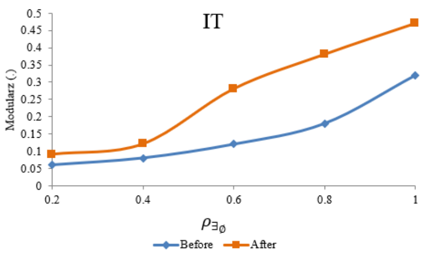
c) Instructor Training (IT) under probability of occupational modularization model accuracy (ρ_{OC_p}).



d) Resource Management (RM) under probability of effective task-based modular training realization ($\rho_{\exists_\emptyset}$).



e) Task Completion (TC) under probability of effective task-based modular training realization ($\rho_{\exists_\emptyset}$).



f) Instructor Training (IT) under probability of effective task-based modular training realization ($\rho_{\exists_\emptyset}$).

Figure 3. Modularization output for occupational efficiency.

- **Case 2:** self-governance based modularization training.

- Analysis 2: in this modularization process, the self-governance-based skills of the students are identified using the constraint $Stud^N > Trnt$, and hence, the modularization for a training session is swapped. Along with the optimization for personnel training of $Stud^N$, the constraints identified using the fuzzy control are the modularization failures and time demands. The probability of identifying the accurate modularization for the self-governance skills based on training (ρ_{SFg}) is computed as,

$$\rho_{SF_g} = \frac{\rho_{OC_p}.Modularz\,(Stud^N).\left[\left(\Delta_{Stud^N - Trn_t}\right)\rho_{\exists_\emptyset} - \left(\frac{\Delta_{Stud^N - Adp_t}}{s}\right)\frac{VET_s}{OC_{p_t}}\right]}{M(F).Stud^N} \quad (5)$$

Where,

$$M(F) = \int_0^t VET_{s_{t-1}}(1 - Trn_s)^{t-1}\,dt \quad (6)$$

$$M(F) \in Modularz\,(Stud^N) = \int_1^s VET_{s_{t-1}}.\frac{\rho_{\exists_\emptyset}}{Trn_t}\left(1 - \rho_{OC_p}\right)^{t-1} ds \quad (7)$$

The above Equations (5), (6), and (7) estimates the modularization function of $M(F)$, for the student skills and agenda observed in the vocational training sessions. For all the modularization processes, the difficulty in meeting the current market skills for the $Stud^N$ is the failure of this proposed approach. As in the above equation, the modular priority for the student skill-based training requires maximum training efficiency, thereby minimizing the swapping process. The common interchangeable modules are used for personal training based on the skills and agenda of the students in vocational classes, which is increased to improve student knowledge. The modularization output for the skills exhibited is tabulated in Table 1. The table shows the quantification of output from modularization in various skills, such as problem-solving, reasoning, and innovation, pre- and post-optimization, with emphasis on improvements in skill adaptability.

Table 1. Modularization output for the skills.

Skills	Min modularz (.)	Max modularz (.)	ρ_{SFg}	*M(F)*
Problem-Solving	0.065	0.16	0.032	0.0805
Reasoning	0.032	0.25	0.021	-0.069
Thinking	-0.062	0.32	0.063	0.071
Innovation	-0.058	0.18	0.058	0.003
Discipline	0.012	0.25	0.019	0.112
Adaptability	0.035	0.32	0.036	0.1415
Sensible	0.014	0.41	0.041	0.187
Governing	0.054	0.44	0.025	0.222

The modularization output is validated based on the available skills and its min-max values in $\rho_{\exists\emptyset}$. If the modularization requires the least possible Trn_{eff}, modifications, then it is minimum else the maximum possibility of ρ_{SFg}, is considered. Based on this consideration, maximum variation suppression is induced. Using the fuzzy control, the agenda and skills constraints are updated. This update, therefore, intends to maximize $M(F)$ for the missing $\rho_{\exists\emptyset}$. Hence, the adjustments between (within) min-max modularz (.) are performed for the variation analysis (Table 1). From the above process of case 1 and case 2, the swapping of the modularization based on $Stud^N > Trnt$ and $Stud^N$, training and adaptability are the identifiable constraints for improving personnel training efficiency. The above limitations are addressable using the proposed MTCO approach to mitigate the modularization failures and the time demands through the fuzzy control optimization method. The following section represents the optimization performed for the current modularization demand to minimize the discussed issues using fuzzy control.

4. Modularization Process using the Fuzzy Control Algorithm

The decisions for classifying training and adaptability rely on the MTCO approach. It aids in supporting the mainstream courses for the students' occupational and self-governance skills in the personnel training sessions. Case 1 (Occupational) and case 2 (Self-governance) skills and agenda are optimized with the resolving instances using a Fuzzy Control Algorithm (FCA). The FCA is a powerful instrument for enhancing and modernizing vocational instruction. Because it is built on fuzzy logic, a mathematical foundation for dealing with uncertainty and imprecision, it can be beneficial when working with indistinct or qualitative data. FCA uses the membership functions to symbolize the variables inside a linguistic set, with the degree of the membership being defined by the function's return value. These operations are necessary for assigning the numerical values to the linguistic concepts. FCA additionally depends on the fuzzy rules, which explain the connection between the input and the output variables, utilizing "if-then" statements to turn input data into meaningful output. This all-encompassing breakdown of FCA's ideas, components, methods, and application is crucial for grasping its utility in this research. By utilizing the FCA, the Modularization Process seeks to improve the efficacy and flexibility of the vocational education and training. Fuzzification, problem definition, fuzzy control rule establishment, application to fuzzily the input data, and defuzzification are all part of the process. The FCA inference engine uses these rules to analyze the input data and determine how well each direction fits the data.

The FCA improves modularization by evaluating aspects such as students' talents, training efficiency, and swapping criteria, seeking to design a plan that reduces the swapping and maximizes efficiency. As a bonus, it saves time by adapting your training to your business's and pupils' needs. FCA guarantees that students acquire training when needed by monitoring the time-demand restrictions and avoiding overloading time resources. Finally, FCA detects the possible failures and takes action to prevent them. This results in an increasingly reliable training process by identifying situations where modularization fails or the training process does not reach the required goals. However, the classification depends on the different training sessions used to determine the modularization failure and the time demand probabilities at the minimum swapping. Hence, the modularization process cases are other for all the vocational education personnel training, which follows the modularization processes through an optimization approach. The classification is performed for both cases by validating the first training session modular priority based on the requirements, the available probability and the modularization intended time demand. The first modularization relies on maximum training efficiency (Trn_{ef}) and $M(F)$ is computed as,

$$M(F, Trn_{ef}) = \left[\Delta_{Stud^N} - \left(\frac{VET_s}{OC_{p_t}}\right) \times \frac{1}{Trn_t}\right] - Modularz\,(Stud^N) + \frac{\rho_{\exists_\emptyset}}{Trn_t}\left(1 - \rho_{OC_p}\right)^t + 1$$
$$\textit{such that}$$
$$\sum_{s\in t}\sum_{s\in Trn_t} \exists_{\emptyset_t} - \sum_{s\in Stud^N} \Delta_{Stud^N} \tag{8}$$
$$\textit{and}$$
$$Stud^N = \sum_{s\in t} Modularz\,(Stud^N)_t - \left(\rho_{SF_g}\right)_t$$

In Equation (8), the training efficiency depends on the modularization process for case 1 as per ρ_{SFg}. and *modularz*($Stud^N$). In this instance, the chances of achieving the occupational training are given as in Equations (9) and (10).

$$\rho_{OC_p}\left(\frac{t}{Trn_{ef}}\right) = \frac{1}{\sqrt{2Stud^N \nabla^\theta}} experssion\left[\frac{VET_s - \rho_{\exists_\emptyset} \times Trn_t}{\nabla^\theta}\right] \tag{9}$$

Where,

$$\nabla^\theta = \Delta_{Stud^N} - \rho_{\exists_\emptyset} * t \tag{10}$$

Where the variable ∇^θ, represents the modularisation process's minimum swapping criterion for maximizing personnel training efficiency. Table 2 outlines the swapping criteria and their corresponding training efficiency metrics. It compares efficiency before and after modularization across different skills.

Table 2. Swapping criterion and training efficiency.

Skills	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Trn_{ef}	
	$\nabla^\theta = Modularz\,(Stud^N)$	$\rho_{OC_p} = (1 - \rho_{\exists_\emptyset})^{t-1}$	$M(F) = \int_0^t VET_{s_{t-1}}(1 - Trn_s)^{t-1}\,dt$	$Stud^N > Trn_t$	Before	After
Problem-Solving	√	X	X	X	0.622	0.463
Reasoning	√	√	X	X	0.489	0.524
Thinking	X	X	√	√	0.398	0.791
Innovation	X	√	X	√	0.405	0.654
Discipline	√	√	√	√	0.399	0.621
Adaptability	√	X	X	√	0.581	0.512
Sensible	X	√	√	X	0.523	0.698
Governing	√	X	X	X	0.621	0.451

As presented in Tables 2 and 4 criteria are analyzed, namely swapping and modularization are balanced:

1. The occupational probability is the same as the skill sequence.
2. Modularizations is the VET score leaving out the previous efficiency.
3. The training sessions are less than the students
4. The swapping requirements for the conditions rely on the criteria satisfaction (represented as √) and the failures (denoted as X).

If the criteria fail, swapping is required; swapping if it exceeds the fuzzy threshold, then efficiency loss occurs. It enhances the $\rho_{\exists\emptyset}$ he upcoming instances require a new fuzzification process based on agenda or skills or both (constraints). Therefore, if maximum criteria fail, then modularz (.) is required to prevent the efficiency loss. In the modified fuzzy process, the requirements using multiple skills are verified if they satisfy the maximum agenda provided (Refer to Table 2). In the above probability assessment, the goal is to balance $Stud^N$ and Trn_s, to reduce the modulation failures. Hence, the accurate modularization process A_{MP} for consecutive and the distinct training sessions are given as in Equation (11).

$$A_{MP} = \max\left[\frac{\left(\rho_{OC_p} + \rho_{SF_g}\right) \times Trn_t}{Modularz\ (Stud^N) - \rho_{\exists_\emptyset} * \nabla^\theta}\right] \quad (11)$$

Therefore, the minimum swapping constraint is $\left[1 - \frac{\left(\rho_{OC_p}+\rho_{SF_g}\right)\times Trn_t}{Modularz\ (Stud^N)-\rho_{\exists_\emptyset}*\nabla^\theta}\right]$, and this swapping criterion is the time-demand overloading instances in the training sessions. The excluding students in personnel training are analyzed using $[Stud^N * M(F, Trn_{ef})]$, is the occupational and self-governance skills requiring the training sessions; hence, the time demand is high. In this approach, there are two possible constraints for maximizing the training efficiency and minimizing the swapping criterion of the modularization process as per the following equations. This constraint is given as:

$$Stud^N = \nabla^\theta = Modularz\ (Stud^N) - \rho_{\exists_\emptyset},\ least\ prossible\ constraint \quad (12)$$

Maximum possibilities are equated from the RHS of Equations (9) and (2),

$$\left(1 - \rho_{\exists_\emptyset}\right)^{t-1} = \frac{Stud^N - \nabla^\theta + Trn_{ef}}{M\left(F, Trn_{ef}\right)}\ \forall\ s \in t \quad (13)$$

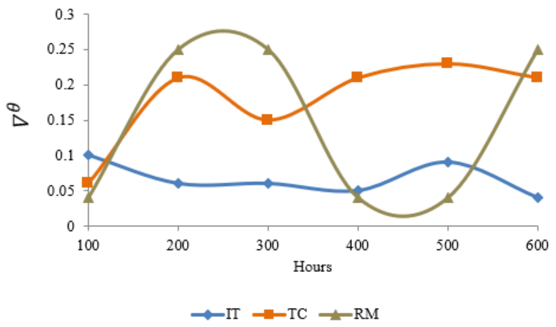
$$\Delta_{Stud^N} = \rho_{\exists_\emptyset} * Stud^N - (1 - \nabla^\theta)^{t-1} + Modularz\ (Stud^N) + 1 \quad (14)$$

Finally,

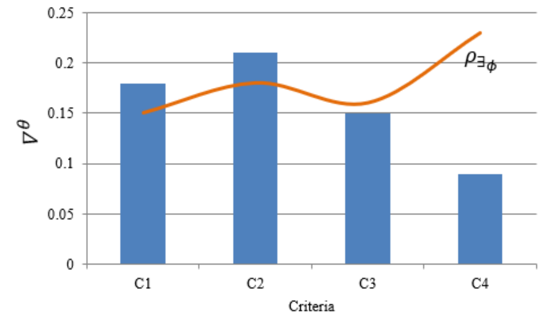
$$\left.\begin{array}{ll} \rho_{\exists_\emptyset} = 0, \Delta_{Stud^N} = \sqrt{2\pi}\nabla^\theta = \sqrt{2\pi}\,(Trn_t)^2, & least\ possible\ constraint \\ & and, \\ \rho_{\exists_\emptyset} = 1, \Delta_{Stud^N} = VET_s, & maximum\ possible\ constraint \end{array}\right\} \quad (15)$$

From the above Equations (12) to (15), the changing time demand as per the student's skills and agenda is either ∇^θ or $Stud^N$, for maximizing the training efficiency. In this case, $\rho_{\exists\emptyset}$=0, then $\nabla^\theta = \Delta_{Stud^N} = \sqrt{2\pi}\nabla^\theta$, is the maximum swapping condition for the modularization process, whereas $\rho_{\exists\emptyset}$=1, $\Delta_{Stud}{}^N = VETs\text{-}Stud^N$ or $\Delta_{Stud}{}^N = VETs$, is the minimum swapping condition. Therefore, the occurrence of $\Delta_{Stud}{}^N = VETs$, is an optimal result in this approach. The time demands for all the personnel training sessions without the modularization failures are given in Equation (1). The modular priority is analyzed for the students' occupational and self-governance skills based on the demand in this scenario, where all the training and its adaptability are balanced, and the time demand is compact as per the above Equation (1). Here, the training efficiency of all vocational education is the sum of students and training that does not improve $Stud^N \in \rho_{\exists\emptyset}$. Therefore, the modularization failures are shared between the different training sessions without increasing the time demand and reducing efficiency other than swapping in t intervals. It is based on the condition; the new fuzzy control criteria are designed to minimize the issues. Figure 4 presents the swapping instances for the occupational efficiency extracted from the data source. The figure illustrates the frequency and impact of swapping instances in the training sessions and how the fuzzy control approach could minimize the number of unnecessary module transitions.

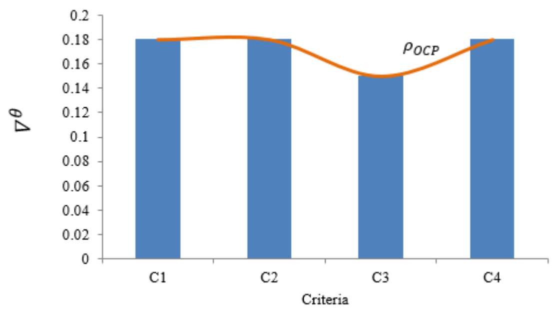
The swapping rates for the different training hours and the criteria ($\rho_{\exists\emptyset}$, ρ_{ocp}) are diagrammatically analyzed in Figure 4. The available $M(F)$ for training efficiency improvement relies on the fuzzy control using $\rho_{ocp}(t/Trn_{ef})$. This verification requires $M(F,Trn_{ef})$ over the individual $M(P)$ as in Equations (6) and (7). Considering the differences between $M(F)$ and $M(F,Trn_{ef})$ the ∇^θ, suppression is performed. If this is to be achieved, then the consecutive $\rho_{\exists\emptyset}$, is to be updated. Therefore, the available criteria (as in Table 2) satisfaction is expected to meet the constraint in Equation (12) such that the least and maximum possible constraint satisfaction is focused. If this is achieved, then ∇^θ, is less, regardless of the training hours or building criteria. Figure 5 analyses the least and maximum possible constraints observed for the varying hours and skills. The figure shows training time constraints and skill acquisition and proves the optimization obtained by using fuzzy control.



a) Over time (Hours).

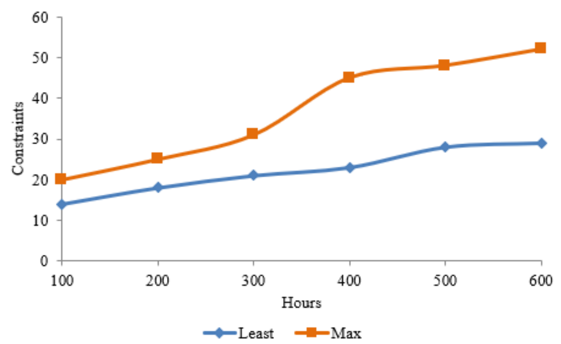


b) based on criteria.

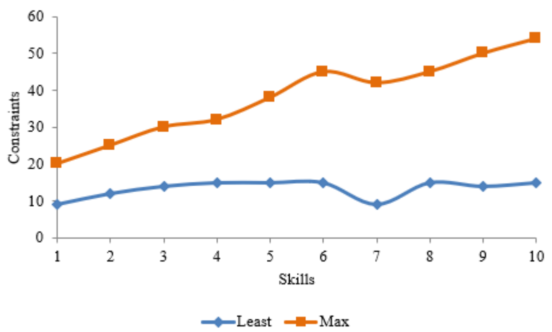


c) Based on criteria using the probability of effective task-based modular training realization ($\rho_{\exists_\phi}$).

Figure 4. Swapping instances analysis.



a) Over time.



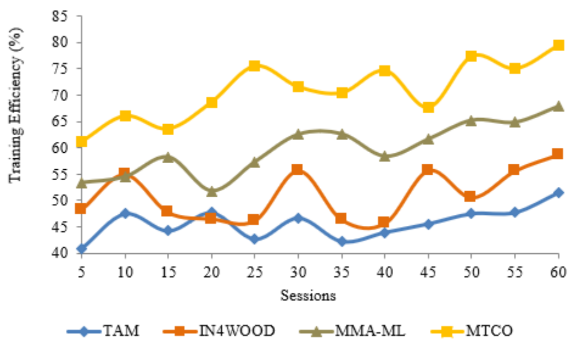
b) Over skills.

Figure 5. Constraint analysis for hours and skills.

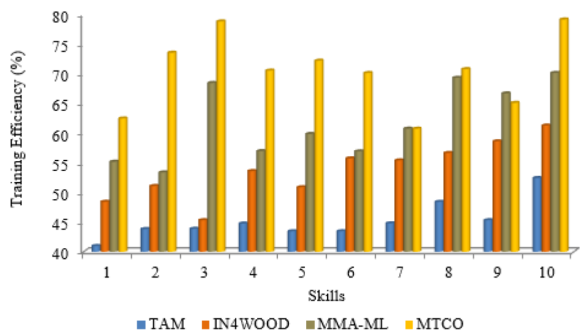
The constraints that are satisfied in t forms the least and that require consecutive $\rho_{\exists\emptyset}$, is the max. Based on the fuzzy control for Modularz ($Stud^N$) and $M(F, Trn_{ef})$, the hourly constraints are suppressed. Contrarily, $stud^N D=\nabla\phi$ and $\rho oc_p(t/\ Trn_{ef})$ are the constraints required for skill-based validation. Therefore, the available $M(F)$ sequences are merged with the consecutive intervals to improve the efficiency. This improvement is verified using the swapping criteria pursued in the following training sequence and the agenda imposed. Therefore, the fuzzification level is varied across $M(F)$ alone other than $M(F,\ Trn_{ef})$, preventing the new constraints (Refer to Figure 5).

5. Discussion

The discussion is presented using the metrics of training efficiency, modularization, swapping, failures, and time demand. To analyze the above metrics, the number of sessions (60) and the skills from the data source (10) are varied. The methods TAM [17], IN4WOOD [20], and MMA-ML [9] from the related works section are used along with the proposed approach for comparison.



a) Over sessions.

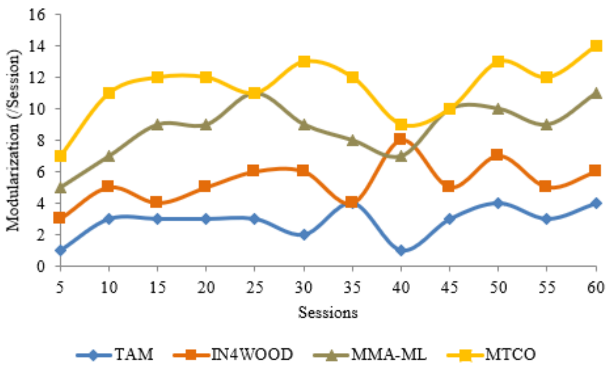


b) Over skills.

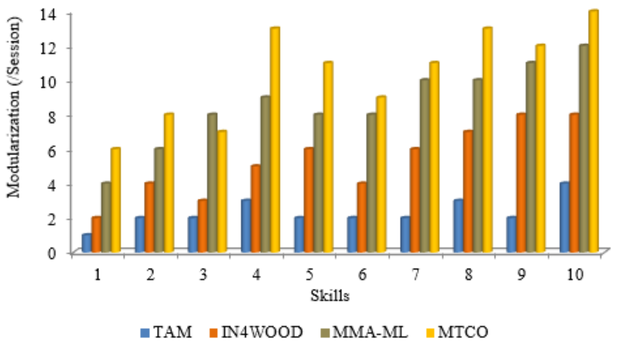
Figure 6. Training efficiency.

Figure 6 compares the training efficiency of different methods, such as TAM, IN4WOOD, MMA-ML, and MTCO, with the proposed approach. In Fig. 6, the observed data from the vocational education training for improving the training and its adaptability for the occupational and self-governance skills of the students are performed using the proposed optimization. Modularization in dual systems requires additional training and swapping to compute the time demand using a less fuzzy control method. The students achieve high personnel training efficiency based on the skills and agenda in that vocational education is analyzed for performance analysis to identify better training modularization. The maximum efficiency and the minimum swapping lead to successful vocational education training, and then the teaching modularization is updated with the current market skills and demands, preventing failures. The fuzzy control considers the current modularization demand for extracting the specific features and reduces the swapping in the modular priority computation. The identification of swapping occurrences in vocational education is pursued through MTCO to improve the training and adaptability of the students to the current market skills. This proposed approach satisfies the high training efficiency for computing skill-based training and prevents failures.

Figure 7 shows the effectiveness of the modularization process, with increased adaptability and efficiency in training sessions.



a) Over sessions.

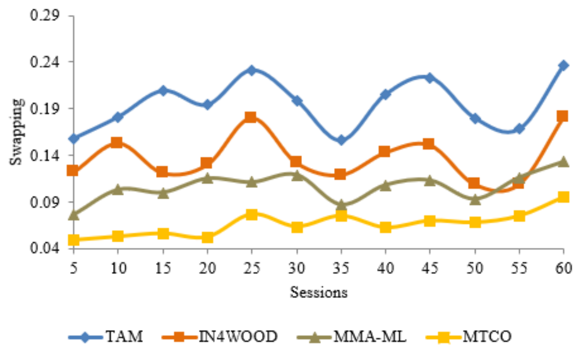


b) Over skills.

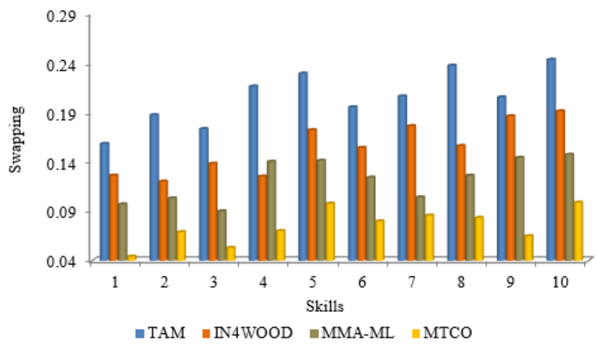
Figure 7. Modularization.

This proposed optimization approach is used for maximizing the training efficiency based on the occupational and self-governance skills based on the personnel training is provided for achieving the high modularization for the time intervals (Refer to Figure 7). The data observed from the student training is analyzed for the available mainstream courses to meet the current market skills with better knowledge. The increasing chances of personnel training and interchangeable modules based on the student skills and agenda are processed using the fuzzy control for a set of personnel. The proposed optimization optimizes the swapping and the time demands depending on the mainstream course design for maximum efficiency and the minimum swapping between the training sessions. The modular priority for skill-based training is to ensure better training efficiency using the fuzzy control method. The modularization failures in the vocational education support are identified using the fuzzy approach, which determines the training and its adaptability for all the training sessions, preventing computation complexity and the time demands. Therefore, the market skill-based training is pursued for improving the vocational education training without failure, and therefore, high modularization is used in this article.

Figure 8 shows the reduction in switching instances over time, thanks to fuzzy control optimization in modularization processes.



a) Over sessions.

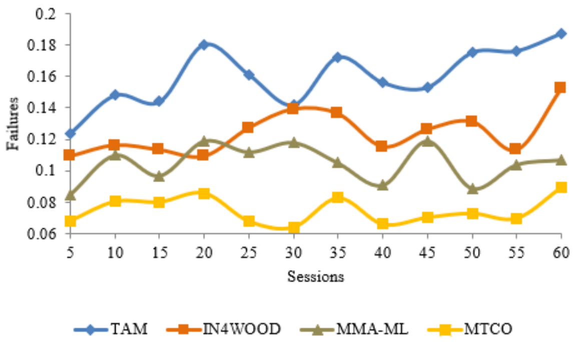


b) Over skills.

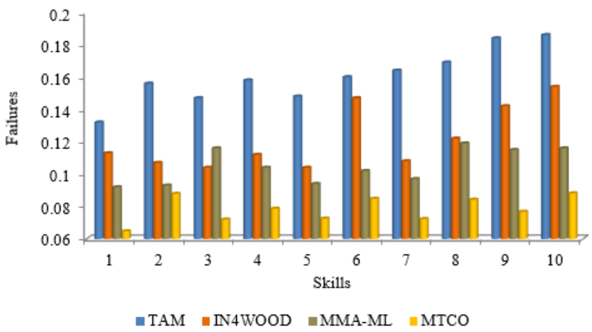
Figure 8. Swapping.

The currently observed skills of the students are compared with the previous information using the fuzzy control for achieving a high swapping factor for instances; the new fuzzy control criteria are designed to improve training efficiency, as illustrated in Fig. 8. In this proposed approach, the interchangeable module for personnel training satisfies less swapping and failures using the fuzzy optimization are performed at different time intervals. It is based on the skills and the agenda. This article identifies the failures, and the time demands for designing the new fuzzy control criteria for the modularization process. It is based on the analysis of student skills. The linear output of the occupational and the self-governance features are to maximize the training and the adaptability. Leveraging the adaptability of vocational education training is to meet the current market skills. The proposed approach's modular priorities require additional training and a modularization process to improve training efficiency without failure. In this proposed approach, the multiple modularization process is used for the different training sessions, and the fuzzy control identifies the current modularization demand for a set of personnel. It is based on this sequential analysis of the student market skills; the swapping factor is less compared to the other metrics.

Figure 9 shows that the MTCO approach has reduced the occurrence of training failures significantly, improving modularization and adaptability.



a) Over sessions.

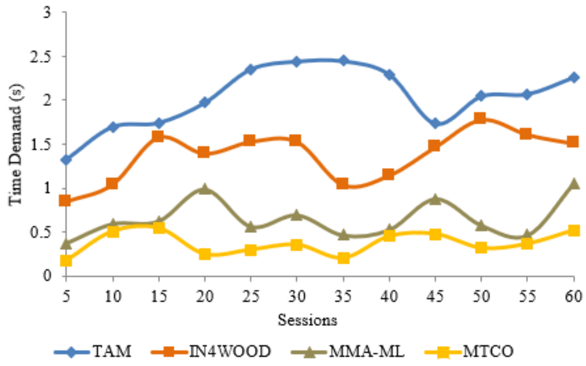


b) Over skills.

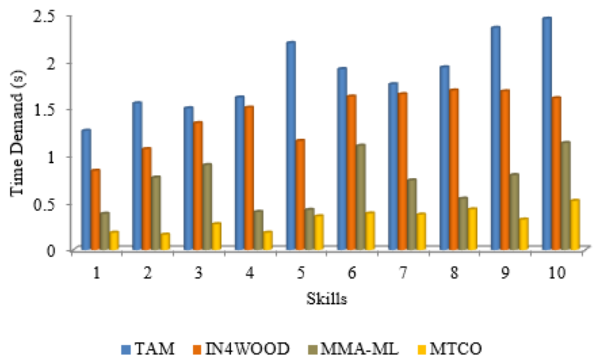
Figure 9. Failures.

In Figure 9, the fuzzy control output and the final modularization process based on production provide better training efficiency. The feasible training and its adaptability for occupational and self-governance are identified for all the students in training sessions at different time intervals. The modular priority for student's skill-based training is processed based on the demands and analyzed using the fuzzy control optimization to prevent failures, and swapping in different instances improves the student's adaptability to the current market skills with vocational education training. Accurate modularization is identified for the training sessions using fuzzy optimization to improve vocational education training in any interval. The current modularization demands are considered for personnel to reduce the failures, and time demands for augmenting the training efficiency by generating the new fuzzy control through the proposed approach. The observed student skills and the agenda data are identified for improving the failure-less modularization. It is based on the minimum swapping; the new fuzzy control is designed in which the proposed approach satisfies less failure.

Figure 10 analyzes the reduction in time demand by optimized modularization, which proves the effectiveness of the proposed fuzzy control method.



a) Over sessions.



b) Over skills.

Figure 10. Time demand.

The proposed modularization based on the training control optimization process for the multiple modularization verification is analyzed based on the market demands for reducing the computation complexities and time demand for improving the training efficiency. Therefore, the fuzzy control and the personnel training output are used to enhance the training and the adaptability without the failures. Hence, the modularization process is pursued based on the occupational and self-governance skills of the students, which are computed using (Trn_{ef}) and $M(F)$, preventing failures and swapping. The classification process relies on different training sessions to identify the modularization failure, and the time demand based on the minimum swapping factor. Hence, the modularization process constraint differs for all the vocational education personnel training, which follows fuzzy control for identifying market demands through an optimization approach. The proposed method is used for improving student interest in vocational education. The new fuzzy control criteria are designed to achieve less time demand, as represented in Figure 10. Tables 3 and 4 present the comparative analysis summary for sessions and skills with the discussion.

Table 3. Comparative analysis summary of sessions.

Metrics	TAM	IN4WOOD	MMA-ML	MTCO
Training Efficiency (%)	51.55	58.64	67.88	79.49
Modularization (Session)	4	6	11	14
Swapping	0.236	0.181	0.133	0.0947
Failures	0.187	0.152	0.107	0.0895
Time Demand (s)	2.265	1.508	1.059	0.5239

The proposed MTCO improves the training efficiency and modularization by 10.07% and 8.3%, respectively. This approach reduces the swapping, failures, and the time demand by 8.86%, 11.83%, and 11.25%.

Table 4. Comparative analysis summary of skills.

Metrics	TAM	IN4WOOD	MMA-ML	MTCO
Training Efficiency (%)	52.42	61.26	70.12	79.116
Modularization (Session)	4	8	12	14
Swapping	0.243	0.191	0.147	0.0987
Failures	0.186	0.154	0.116	0.0882
Time Demand (s)	2.449	1.607	1.133	0.5202

The proposed MTCO improves the training efficiency and the modularization by 8.92% and 7.14%, respectively. This approach reduces the swapping, failures, and time demand by 9.5%, 12.76%, and 11.65%.

Tables 3 and 4 provide a comparative analysis of training efficiency, modularization, swapping, failures, and time demand with respect to the different methods, underlining the advantages of the MTCO approach.

5.1. Results Interpretation

The proposed research results demonstrate that MTCO provides an effective way of improving the effectiveness of vocational training. It resulted in a 10.07% increase in training effectiveness and an 8.86% reduction in module switching compared with the traditional way. The presented methodology effectively tailors training toward meeting occupational requirements and improving self-governance skills by reducing failures by 11.83%. Moreover, the MTCO approach offered scalability, allowing it to fit diverse learner needs efficiently and proving useful in both high- and low-density training environments. These results demonstrate the feasibility and adaptability of the MTCO approach in modern vocational education systems.

5.2. Implications

These findings bear significant implications for the field of vocational education. Integrating modularization and fuzzy control optimization techniques makes it possible to make training programs more efficient and adaptive to the changing market demands. This study also lays a foundation for policymakers to consider revising the vocational education framework to include adaptive and learner-centred training methodologies. Moreover, the realized gains in the scalability of training and resource efficiency mean that this could be one of the best leading models for other educational systems, balancing flexibility with effectiveness.

5.3. Future Directions

Future research can explore several areas to build on the present study's findings. Only longitudinal studies will be able to determine the long-term effect of the MTCO approach on learners' career success and skill retention. Further optimization of the modular approach for the unique needs of each sector could be done through sector-specific adaptations. Moreover, advanced AI methods can be integrated to further enhance the modularization process by dynamically predicting training needs and customizing the content accordingly. Lastly, future research should focus on strategies for equipping educators with the wherewithal to implement modular and fuzzy control systems, ensuring successful adoption and sustained impact.

5.4. Potential Problems in Implementing the Proposed Strategy

While the MTCO approach promises considerable benefits, significant challenges associated with its implementation need to be addressed. First and foremost, the process of modularization itself is inherently challenging to scale for a large student population and highly variable training environments since the computational and infrastructural requirements to support the system could be vastly different. An essential factor is that the fuzzy control algorithms can deal with the scale without creating a performance or accuracy issue.

Another challenge lies in the adaptability to diverse curricula, especially in multidisciplinary settings where vocational training programs differ significantly in content, goals, and delivery modes. Tailoring the modularization process to the different domains and aligning it with the varying market demands and pedagogical goals may require iterative development and testing.

Another significant barrier is the resource constraints of institutions, where access to advanced technology and funding is limited. Implementing fuzzy control optimization and modularization techniques calls for investment in computational tools, training of educators, and development of adaptive content modules. Such requirements might hinder implementing this approach, especially in resource-constrained settings.

Scalable algorithm design, flexible frameworks for curriculum adaptation, and cost-effective solutions will address these and make the approach accessible to institutions with varying levels of resources. Therefore, future research should examine these aspects to make the proposed MTCO approach more applicable and practical for broader use.

5.5. Practical Applications of the Proposed Method

The MTCO approach may be illustrated effectively through hypothetical and real-world scenarios. One such hypothetical scenario is a vocational training program for workers in the manufacturing industry. The curriculum includes modules on operating machinery, safety protocols, and quality control. In this way, the MTCO approach dynamically adjusts the modularization process based on trainee feedback and changes in market demands, such as introducing advanced machinery. For example, when a new machine is installed, the fuzzy control algorithm focuses on the training modules most important to the workers so they can be trained quickly and with the least disruption of ongoing courses.

An efficient example is vocational training in health care, such as training for nurses. The MTCO method would focus training modules on meeting the emerging requirements of caring for patients, including adopting telemedicine practice. The fuzzy control system can dynamically adjust the training content by analyzing student performance data and real-time industry requirements. This ensures that the nurses will efficiently acquire foundational and emerging skills. It will also save resources from wasted on repetitive or redundant modules by aligning the training with the practical demands of jobs.

These scenarios show how the MTCO method can enhance adaptability, efficiency, and relevance in vocational training programs. It can better prepare learners to meet industry expectations while optimizing the use of available resources.

6. Conclusions

6.1. Summary of Findings

The MTCO approach, which combines the concepts of modularization and fuzzy control, has resulted in several significant findings. A 10.07% improvement in training efficiency proves that the modular approach makes learning more effective and less time-consuming. Also, there was an 8.86% decrease in module switching, meaning learners can move more smoothly from one training module to another without unnecessary interruptions or confusion. This has also improved the adaptability of the approach given individual learner needs and market demands, thus making it easier for training to change in line with individual learning progressions and shifting industry requirements.

6.2. Implications for Practice

The MTCO approach to vocational training has several critical implications. These include revolutionizing the training process and making it more flexible and efficient so learners can focus on relevant skills without being restricted by rigid, traditional training formats. It reduces the switching of modules, creating a flow in the learning experience and contributing to better learner outcomes. The approach will also enable training to be increasingly tailored to industry needs and individual learner profiles so that participants acquire skills relevant to current market demands.

6.3. Future Research Directions

The MTCO approach can be further optimized with some future research directions. One promising way is to explore advanced optimization algorithms in depth, which can further improve the adaptability of the training system in responding to both learner's needs and external changes in the job market. Another line of inquiry could extend the MTCO approach to other vocational sectors and industries, asking about its feasibility and scalability by applying it. Lastly, real-time monitoring and feedback systems would yield even more significant gains in efficiency, as they provide immediate insight into the learners' progress and allow dynamic adjustments to be made to the training material to fit individual needs more closely.

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Jinyuan Li, born in August 1988, male, Han nationality, currently serves as a lecturer at Guangtie Vocational and Technical College in Huainan City, Anhui Province, with a master's degree. His main research areas include Psychological Crisis, Innovation and Entrepreneurship, Employment, etc.

Yuqi Cheng, born in March 1991 In Jingdezhen City, Jiangxi Province, Is A Female Han Chinese with A Master's Degree. Currently an Associate Professor at Panyu Vocational and Technical College in Guangzhou, Her Main Research Areas Include Psychological Crisis, Innovation and Entrepreneurship, Employment, Etc.