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# Using genetic algorithm for optimizing fuzzy logic controller for mode-based control algorithms of building automation systems

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*Abstract*— **The growing integration of renewable energy into building energy systems causes increasing complexity of energy conversion and distribution systems. This development creates the need for appropriate control algorithms implemented in building automation systems. We previously introduced the MODI-method to support structured development of mode-based control algorithms and allow simulation-based testing in early phases of the planning process. However, the control design concerns different aspects, such as efficiency and system lifetime. It is therefore challenging to determine the conditions of the transitions between operating modes. Furthermore, the control design process lacks an optimization approach for the generated control algorithms. In this paper, we investigate the application of a fuzzy logic controller to generate conditions for mode transition of control algorithms and transfer approximate human knowledge into the control design. We perform optimization based on genetic algorithm to improve the performance of the control system, considering several aspects. The case study presents structured development of a mode-based control algorithm for a cooling supply system and the functionality of a fuzzy logic controller implemented into the control algorithm. The optimization of the fuzzy logic controller is performed using genetic algorithm. As a result, the optimized parameters of the fuzzy logic controller are gathered, leading to improvement of the performance of the system.**

## I. INTRODUCTION

In recent years, the rapid growth of energy consumption in the building sector has attracted considerable attention in the context of substantial energy and emissions reduction [1]. The share of energy consumed in the building sector is approximately 20.1% of total energy consumption worldwide and is expected to rise further [2]. The building sector is believed to have a vital role in achieving reduction of energy consumption and emission [3]. However, only a part of the construction projects achieve the planning goal about energy efficiency. The study reports that unused efficiency potential reaches up to 30% of the calculated demand [4]. One of the main reasons may be faulty control design in the planning process. Increasing renewable energy is integrated into building energy system, which leads to increasing complexity of building energy systems and automation systems. This development has become a challenging issue in the classic planning. Regarding this problem, a method is needed to support control design and avoid errors in the planning process. In the previous work [5], the authors have introduced the application of the signal-interpreted Petri-Net (SIPN) for the description of control code. This SIPN-based description method is integrated into the so-called MODI-method (MODI), aiming at simplified and structured development of control algorithms [6]. The control algorithms generated by MODI can be modelled in the simulation environment Dymola using an SIPN-based modelling approach [7]. This approach allows testing of the control algorithm in early phase of planning process and presents the possibility to integrate MODI into the simulation-based planning process. Although MODI simplifies the process of control design, coordination of operating modes is a major difficulty, especially considering different design aspects, such as efficiency, system lifetime and comfort. New control algorithms are required to help determining mode transitions under different operating states and optimize the systems.

In this work, we use a fuzzy logic controller (FLC) to facilitate the development of mode-based control algorithms and genetic algorithm to optimize this controller. Fuzzy logic controller allows direct statements of control behaviour and linguistic rules to describe the mapping of the inputs to the output actions [8]. These features can support the determination of the operating mode in design of mode-based control algorithms. Genetic algorithm has been widely used to optimize fuzzy controllers and enable coordination of different design aspects by using a fitness function [9], [10], [11].

The rest of the paper is structured as follows: In section 2, we introduce the method applied in this paper. A case study presents the functionality of the applied method for a cooling supply system in section 3. The structured development of a mode-based control algorithm for this system is performed and a fuzzy logic controller is implemented to determine mode transitions. We optimize the fuzzy logic controller using genetic algorithm in this section. Finally, we conclude in section 4.

## II. METHOD

In this section, we briefly present MODI, which was introduced in previous work [6], [7]. Fuzzy logic controller will be integrated into the mode-based control algorithms generated by MODI in order to generate conditions for mode transitions. We demonstrate the optimization of the fuzzy logic controller using genetic algorithm.

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### A. Fuzzy logic controller for MODI-method

Fig. 1 depicts the basic strategy of MODI, consisting of decomposion and aggregation process. The building energy system is primarily transferred into its topological model, supporting the following decomposion process of the system. The complex system can be decomposed into simple subsystems, in which operating modes of actuators are considered. This procedure can previously simplify the complex control task. Subsequently, the operating modes of actuators are stepwise aggregated from subsystems to the total system. In a subsystem, all the possible combination of operating modes can be gathered for the further permissibility checking. A rule-based approach is defined to find unpermissble modes in the subsystem. Only permissible modes are considered for the next step of the aggregation process. Based on stepwise aggregation of subsystems, the total control system is obtained. In order to describe and model the control algorithm, we apply SIPN for formalized description of the algorithm. The hierarchical control model can be constructed according to the structure of the control algorithm. However, coordination and optimization of the mode transitions are still open issues. To address this problem, we apply FLC for determination of the mode transition on the highest control level.

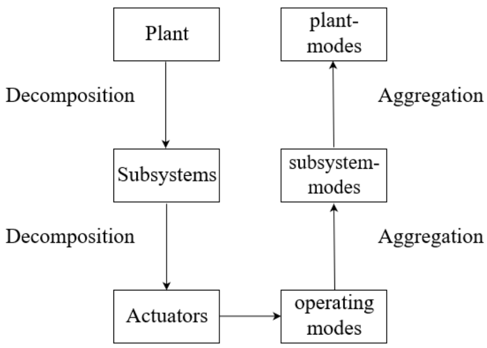


Fig. 1. The strategy of MODI-method.

FLC uses linguistic rules to describe the mapping of the inputs to the outputs and a mode of approximating reasoning to deal with uncertain knowledge. It also allows the integration of human knowledge into control systems. Based on these features, FLC is applied to MODI-method (FL-MODI) on the highest control level to decide the appropriate operating mode according to the actual operating conditions and the rule base.

The structure of FL-MODI is illustrated in Fig. 2, containing a fuzzy logic controller to determine the actual operating mode and a SIPN-based control system to set actuators in accordance with the mode. Inputs of FLC are relevant state variables describing the current operating condition. Theses inputs are represented by fuzzy sets in the fuzzifier. The context rules in the fuzzy rule base encode human knowledge about control design in linguistic form of IF-THEN. Output is the appropriate operating mode, which can be passed to the SIPN-based control system in the lower control level.

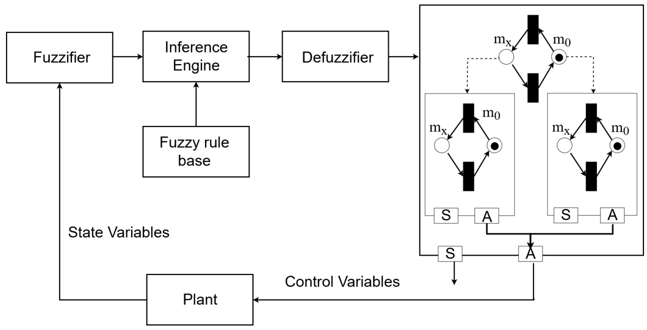


Fig. 2. Structure of FL-MODI.

We use the Modelica Fuzzy-Logic-Controller-Library [12] and Petri-Net-library [13] to create a FLC block and a SIPN-based control block in the simulation environment Dymola, which simplifies construction of the control model. In the following, we will describe genetic algorithm to optimize FLC.

### B. Optimization using genetic algorithm

In this section, we consider the optimization of membership functions of FLC using the genetic algorithm. By defining an appropriate fitness value, the genetic algorithm can optimize performance of the control system, concerning several design aspects.

The genetic algorithm is inspired by Darwins theory of evolution. Following the rule the strongest species that survives, populations are generated by iteration performing evolutionary biology of selection, crossover and mutation [14]. The individuals with higher fitness values are preferred being selected in the next population [15]. This procedure can finally approach a local optimum. As mentioned in section II-A, a fuzzy control rule is a conditional statement. The antecedent of a rule is the condition related with a linguistic term. Membership functions in the fuzzifier transform crisp inputs into fuzzy sets and specify the meaning of linguistic terms in antecedents of fuzzy rules. Therefore, the definition of parameters of membership functions has a significant influence on the performance of a control strategy. We use the genetic algorithm to tune parameters of membership functions and approach optimal solutions by comparing fitness values according to desired requirements.

In FLC, all considered parameters of membership functions are regarded as genes constituting a chromosome. According to the genetic algorithm, a chromosome is an individual and a collection of individuals is referred to a population. An initial population of individuals are usually created by means of a random function in the limitation of a desired range. Each individual is evaluated by a fitness function, whose value indicates the suitability of the corresponding individual. Then, the procedure named offspring is performed. According to the Darwinian evolution rule, the individuals with higher fitness values are selected to mate through the crossover process. These individuals called parents will pass on their genes to contribute to the population at the next generation. Some individuals in the next generation are to undergo a mutation process based on a definable mutation probability. Mutation provides possibilities to yield a better solution. Through this process, the new population is generated and the corresponding fitness values are cast. After several generations, the chromosome values are desired to converge to a range of values identifying appropriate controllers.

Fitness functions provide an approach to measure the suitability of control algorithms. Different aspects, such as energy efficiency and comfort, can be considered and weighted according to Eq. 1.

$$fitness\ value = \frac{\sum w_i I_i}{\sum w_i} \tag{1}$$

## III. CASE STUDY

In this section, we consider a system for cooling supply at the Center for Photonics and Optics in Adlershof, Berlin, Germany, as the case study [16]. We developed two control strategies focusing on the two different requirements of the control design for the cooling supply system and implemented in the simulation environment Dymola. We propose a fuzzy logic controller to consider both aspects during the control process. The genetic algorithm will be applied to improve the performance of the control system.

### *A. Development of mode-based algorithms for ZPO 3*

Fig. 3 shows a cooling supply station named ZPO 3 in Adlershof. This station consists of two chillers (chiller 6 and chiller 7), having the same capacities of 550kW and different efficiencies, and a heat exchanger supplying cooling energy to a network. According to MODI [7], this system is transformed into its topological model, as Fig. 3 shows. Based on this model, ZPO3 is decomposed into several subsystems according to their functions of the components. Fig. 4 illustrates the hierarchical structure of ZPO 3 after the decomposition process.

Stepwise aggregation of permissible operating modes is performed from the actuator-level to the system-level. In order to simplify the planning process, only two operating modes are considered, namely 0 (turn the components/systems off) and 1 (turn the components/systems on). Permissible operating modes of the system are summarized in Tab.1, where operating modes of actuators are shown in columns 2-4 in accordance with the modes of the system.

Two control strategies, namely the efficiency-based control strategy and the operating-time-based strategy, are feasible based on these permissible modes, as Fig. 5 shows. We utilize SIPN for the formalized description of these two strategies. In the efficiency-based control strategy, COPs of the two chillers are initially considered. If there is a demand, the chiller of higher COP is used to satisfy the demand. With increasing demand, another chiller is switched on. The load percentages of the chillers are used to indicate, whether one chiller can satisfy the cooling demands. This strategy ensures operation of the system with the higher efficiency. The operating-time-based strategy is similar to the efficiency-based strategy but considers the operating times of both chillers. The chiller having less operating time is preferred, aiming at compensation of the operating time difference between the two chillers.

### *B. Development of a fuzzy logic controller for ZPO 3*

Using the SIPN-based modelling approach [7], these mentioned strategies are modelled in the simulation environment Dymola. Based on the models, we construct FLC to determine which strategy should be used under the corresponding operating state, concerning both efficiency and compensation of operating time. The inputs of this controller are the normalized efficiency difference of the chillers and the normalized operating time difference. These crisp inputs are fuzzified into three groups (low, middle, high) using the membership function as Fig. 6 illustrates. The rules used by the controller are presented in Tab. II. With a high operating time difference, the operating-time-based strategy is used, while the efficiency-based strategy is preferred with a low time difference. With a middle time difference, we desire to compensate the time difference at low COP difference but ensure more efficient operation at middle or high COP difference. The output of the FLC is the strategy that is used.

### *C. Simulation-based optimization using genetic algorithm*

In this section, we apply the genetic algorithm for tuning the membership functions.

We define two genes $(e_{eff}, e_t)$ for each individual, namely parameter $e$ of the two membership functions, dealing with the efficiency and operating time difference. A generation consists of 24 individuals. The twelve individuals with the best fitness values are chosen as parents to generate offspring. The mutation occurs randomly during the crossover process with rate 50% of the new offspring in the range $\lfloor -0.05, 0.05 \rfloor$. Considering definition of the fitness value, the seasonal coefficient of performance (SCOP) of the system is used as the indicator of the efficiency and a piecewise function is defined to reveal the influence of the time difference. If the time difference is within 10% of the maintenance period, the influence of the time difference can be ignored. Otherwise, the influence grows quadratically, causing the significant increase of the maintenance cost. The weights of both indicators are $(w_{eff}, w_t) = (1, -1)$.

$$F = \frac{w_{eff} I_{eff} + w_t I_t}{w_{eff} + w_t} \tag{2}$$

$$I_{eff} = \frac{Q}{W} = \frac{\int q(t)\,\mathrm{d}t}{\int P(t)\,\mathrm{d}t} \tag{3}$$

$$I_t = \begin{cases} 0, & \Delta t < 0.1t \\ \frac{(\Delta t - 0.1t)^2}{0.1t^2}, & \Delta t \geq 0.1t \end{cases} \tag{4}$$

The simulation model is based on the following libraries: Modelica Standard Library and Aixlib [17] for the construction of the physical model, Fuzzy-Control-Library [12] for the modelling of a FLC and PNlib [13] for the modelling of the SIPN-based control model. The simulation time covers 20 days, including 5 typical days for each season. The simulated

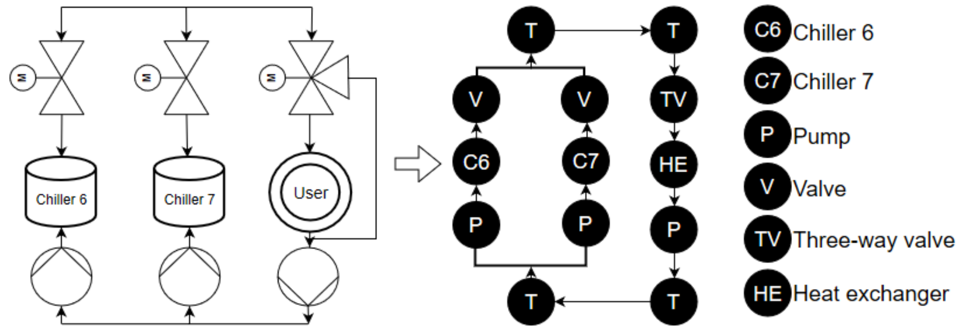


Fig. 3. System scheme and corresponding topological model of a cooling supply station named ZPO 3 in Adlershof, Berlin.

TABLE I
PERMISSIBLE OPERATING MODES OF ZPO 3.

| Mode | *GE1* (C1, P1, V1) | *GE2* (C2, P2, V2) | *Con* (HE, P, TV) | *Description* |
|---|---|---|---|---|
| M0 | (0,0,0) | (0,0,0) | (0,0,0) | There are no cold demands. |
| M1 | (1,1,1) | (0,0,0) | (1,1,1) | GE1 satisfies the cold demands. |
| M2 | (0,0,0) | (1,1,1) | (1,1,1) | GE2 satisfies the cold demands. |
| M3 | (1,1,1) | (1,1,1) | (1,1,1) | GE1 and GE2 satisfy the cold demands. |

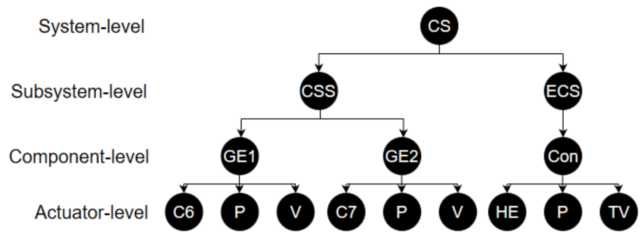


Fig. 4. Hierarchical structure of the energy system after decomposition. CS: cooling system; CSS: cooling supply system; ECS: energy consumption system; Con: Consumer; GE1 and GE2: generator 1 and 2; V: valve; P: pump; C1 and C2: Chiller 1 and 2; HE: heat exchanger; TV: three-way valve.

TABLE II
FUZZY RULES OF THE FUZZY LOGIC CONTROLLER USED BY ZPO 3, $M_{eff}$: THE EFFICIENCY-BASED STRATEGY; $M_t$: THE OPERATING-TIME-BASED STRATEGY.

| $\Delta COP$ / $\Delta t$ | low | middle | high |
|---|---|---|---|
| low | $M_{eff}$ | $M_{eff}$ | $M_{eff}$ |
| middle | $M_t$ | $M_{eff}$ | $M_{eff}$ |
| high | $M_t$ | $M_t$ | $M_t$ |

cooling demand of these 20 days is approximated by the local measured data as Fig. 7 illustrates, in which each period corresponds to a daily cycle.

Using the genetic algorithm, 5 generations are generated before a convergence is achieved. $(e_{eff}, e_t) = (0.43623059, 0.27500139)$ are the identified parameters for both membership functions. Fig. 8 shows the simulation results of C6 and C7 using the efficiency-based strategy and FLC. Only using the efficiency-based control strategy, C7 is always operated because C7 represents better operation than C6. This situation is changed by integrating FLC into the control that C6 can work not only satisfying large demands but also compensating the operating time difference. These results prove that FLC indeed enables mode changing between the two strategies and the two chillers are operated correspondingly.

Tab. III shows the simulation results of ZPO 3 using the efficiency-based strategy, the operating-time-based strategy and FLC. SCOP of the system is improved with FLC, comparing with the time-based strategy. Furthermore, the operating time difference of the FLC-integrated strategy is also within the allowed limitation, while the efficiency-based strategy results in a significant difference of the operation time between C6 and C7. It means the optimization approach using genetic algorithm can support the improvement of the control performance of FLC and find the optimal parameters for FLC.

TABLE III
SIMULATION RESULTS OF ZPO 3 USING THE EFFICIENCY-BASED STRATEGY, THE OPERATING-TIME-BASED STRATEGY AND THE FUZZY LOGIC CONTROLLER, $M_{eff}$: THE EFFICIENCY-BASED STRATEGY; $M_t$: THE OPERATING-TIME-BASED STRATEGY; $M_{FLC}$: CONTROL USING THE FUZZY LOGIC CONTROLLER.

| Strategy | SCOP | $\Delta t$/h | Fitness value |
|---|---|---|---|
| $M_{eff}$ | 3.92447 | 378.07 | -260.571045 |
| $M_{FLC}$ | 3.88502 | 13.95 | 3.88502 |
| $M_t$ | 3.8672 | 18.23 | 3.8672 |

## IV. CONCLUSION

The determination of transition conditions of mode-based control algorithms is a major difficulty in the process of control design. Control strategies are desired to consider different control aspects during the control process. This paper presented the development of FLC to organize transitions of

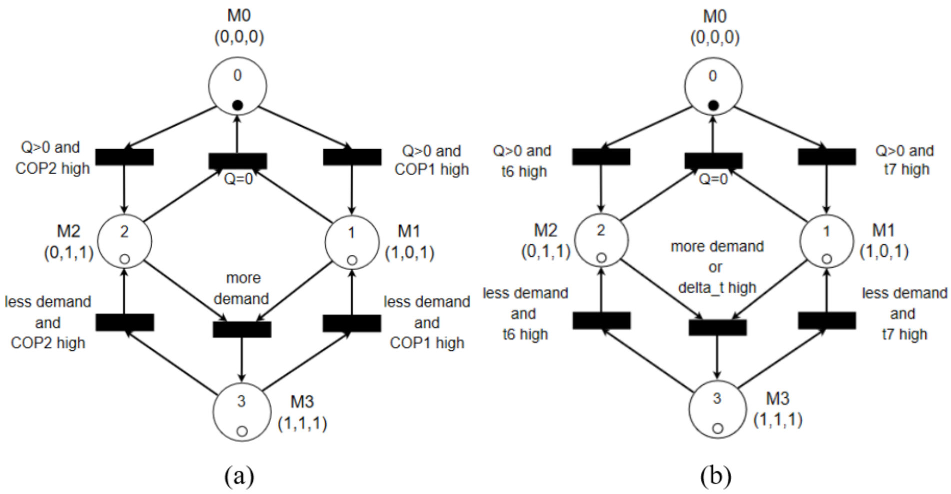


Fig. 5. SIPN-based models of the efficiency-based (a) and operating-time-based strategy (b). Q: cooling demand; COP1: COP of the subsystem GE1; COP2: COP of the subsystem GE2; t1 and t2: operating time of chiller 1 and chiller 2, respectively.

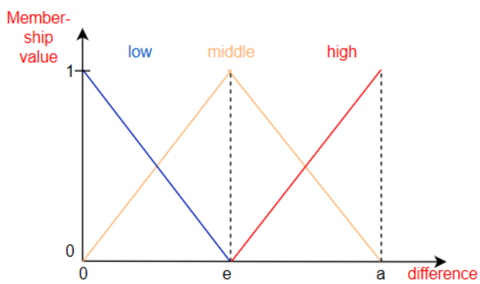


Fig. 6. Membership function of the fuzzy logic controller. For the normalized efficiency difference, a is 0.6; for the normalized operating time difference, a is 1.0; e needs tunning.

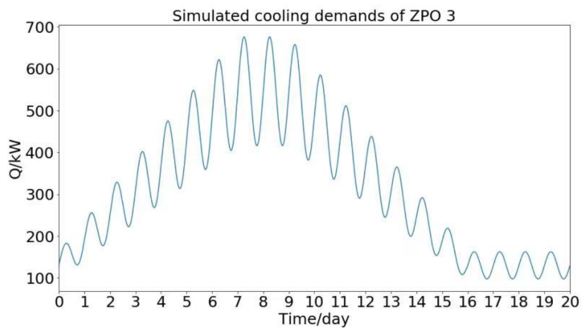


Fig. 7. Simulated cooling demands of ZPO 3 during the 20 typical days.

mode-based control algorithms, satisfying different control aspects. The genetic algorithm enables optimization of FLC, hence improvement of the performance of the control system. The results showed that FLC indeed simplifies the determination of mode transition in mode-based control algorithms and allows control systems to consider different aspects. The genetic algorithm was able to optimize FLC and improve the performance of control systems. Henceforth, future work will further investigate the application of FLC in the design of mode-based control algorithms. FLC is proposed not only to choose the strategy but also to decide about the operating modes directly. More control aspects will be considered and complex rules will be applied. Automation of this design process is also an important issue in future work.

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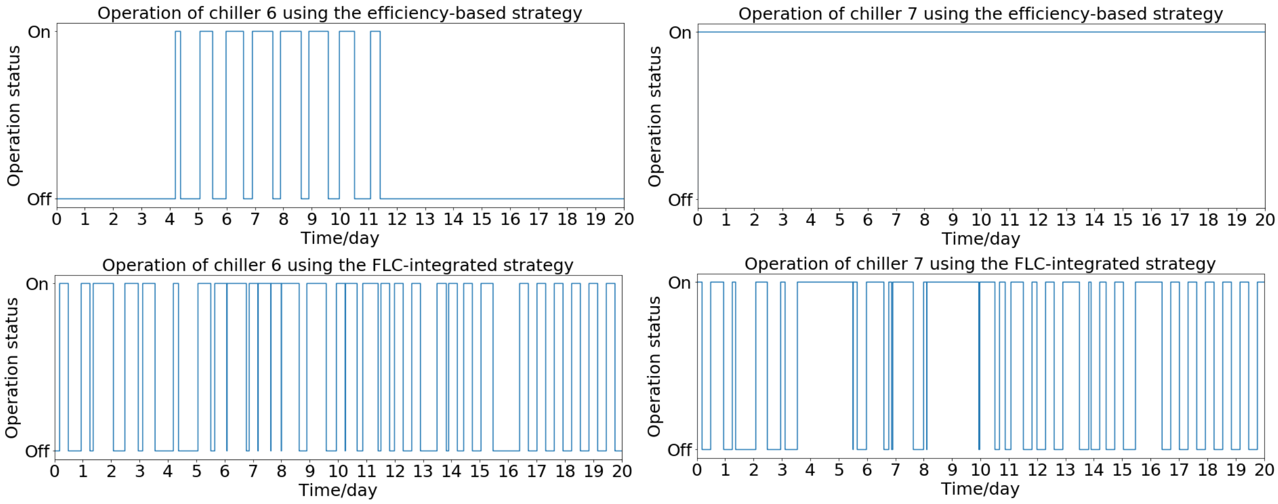


Fig. 8. The operation state of chiller 6 and chiller 7 controlled by the efficiency-based strategy and FLC in 20 days.

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