# Multi-objective optimization methods applied to a residential solar combisystem

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## Abstract

Solar heating systems for domestic hot water and space heating have been used to reduce primary energy consumption for residential buildings; however, the performance of such systems, known as combisystems, depends on their sizing. In this paper, two multi-objective optimization methods are applied to a combisystem in Montreal, Quebec, Canada, using the life cycle cost and life cycle energy use. The multi-objective particle swarm optimization (MOPSO) method is compared to the weighted sum method (WSM) using the hybrid particle swarm optimization/Hooke-Jeeves (PSO/HJ) algorithm. The results show that MOPSO outperforms the WSM in terms of computing time, but provides dominated solutions.

**Keywords**: multi-criteria problems, solar combisystems, weighted sum method, multi-objective particle swarm optimization, Hooke-Jeeves

## Résumé

Les systèmes solaires thermiques pour le chauffage et l'eau chaude sanitaire ont été utilisés afin de réduire la consommation d'énergie primaire des bâtiments résidentiels ; cependant, la performance de tels systèmes, communément appelés « systèmes combinés », dépend de leur dimensionnement. Dans cet article, deux méthodes pour les problèmes d'optimisation multi-objectifs sont appliquées à un système combiné situé à Montréal, Québec, Canada, via le coût et l'énergie du cycle de vie. Les méthodes « multi-objective particle swarm optimization (MOPSO) » et « weighted sum method (WSM) » utilisant l'algorithme hybride « particle swarm optimization/Hooke-Jeeves (PSO/HJ) » sont comparées. Les résultats montrent que MOPSO est plus rapide que la méthode WSM, mais fournit des solutions qui sont dominées.

**Mots clés** : problems multi-objectifs, systèmes solaires combinés, weighted sum method, multi-objective particle swarm optimization, Hooke-Jeeves

## 1. Introduction

This first section provides an overview of the context in which this research was conducted. Since this paper focuses on the multi-objective optimization of a residential solar combisystem, previous studies related to the optimization of solar combisystems are also presented.

### 1.1 Solar thermal combisystems

Among all renewable energy sources, solar energy appears to be one of the most suitable sources for residential buildings. The most common use of solar energy is for the direct heating of air and water [1], which explains why solar water heating (SWH) is the most widely used solar energy application in the world [2]. Solar water heating systems have known a significant deployment over the past decade; however, they are designed to meet only the domestic hot water (DHW) needs. Solar water heating systems for combined space heating (SH) and domestic hot water needs are usually known as “solar combisystems”. Through several studies, solar combisystems have proved to be efficient at reducing primary energy consumption for houses; however, all solar combisystems do not have a high level of performance [3]. Therefore, special attention must be paid to the design of solar combisystems in order to enhance their performance.

The Solar Heating and Cooling (SHC) Programme has devoted one of its projects, named Task 26 [4], to solar combisystems. Task 26 was an exhaustive project conducted by a group of 35 experts and 16 solar industries from nine European countries and the USA, from 1998 to 2002, so as to analyze and optimize solar combisystems [5]. The aim of Task 26 was to find the best technically feasible designs to maximize the thermal performance of solar combisystems. From 2001 to 2003, the European Alterner Programme Project studied more than 200 solar combisystems installed in seven European countries [6]. Since then, many independent studies have been related to solar combisystems to improve their cost and/or thermal performance. The review of those former studies reveals that most of them were conducted by using building performance simulation (BPS) programs, which provide key indicators such as temperature or energy use to assess different design alternatives. Although hundreds of BPS tools have been developed, the two most popular ones are [7]: EnergyPlus [8] and TRNSYS [9]. The next section presents some previous optimization studies of solar combisystems.

### 1.2 Optimization of solar thermal combisystems

Although optimization studies applied to building systems have known a substantial increase over the past decades, more than half of them used only one objective function at a time [10]. Yet, most of the real-world problems involve conflicting objectives, which compete against each other such as technical, financial, environmental, and social issues. The optimization of the solar combisystem design is a multi-objective problem (MOP); therefore, multi-objective optimization techniques should be used. According to [11], two approaches have been mainly used for multi-objective problems. The first approach reduces MOPs to single objective problems (SOPs). To do so, a weight is assigned to each normalized objective function, and then all are added up into one global objective function. This approach, named the weighted sum method (WSM), is one of the simplest approach. The second approach is based on the concept of Pareto optimality, which implies the use of multi-objective algorithms.

## 2. Multi-objective model and method

A generic optimization process can be divided into three phases [7]: (i) pre-processing, (ii) optimization phase, and (iii) post-processing. The first phase comprises the creation of the mathematical model, formulation of the optimization problem, and selection of a suitable algorithm, which can be coupled with a BPS software. The pre-processing phase in this study contains:

- The development of the residential solar combisystem model in the TRNSYS program;
- The selection of two objective functions;
- The selection of eight design variables, which are constrained to avoid unrealistic solutions;
- The selection of an optimization algorithm.

The next sections focuses on the first three steps of the pre-processing phase of the residential solar combisystem.

### 2.1 Residential solar combisystem model

The net zero energy house (NZEH) model as well as that of the solar combisystem used in this current study were developed in [12] using the TRNSYS 16 environment. This NZEH model was a modified version of a typical 1994 house built in Montreal. This two-story house, with a heated floor space of 208 m², was equipped with a solar combisystem whose schematic layout is reported in Figure 1. The residential solar combisystem configuration has two thermal storage tanks; one is dedicated to the DHW preparation and the other storage tank to the SH needs. Both storage tanks are charged by solar energy through the solar collectors array, and electric heating elements.

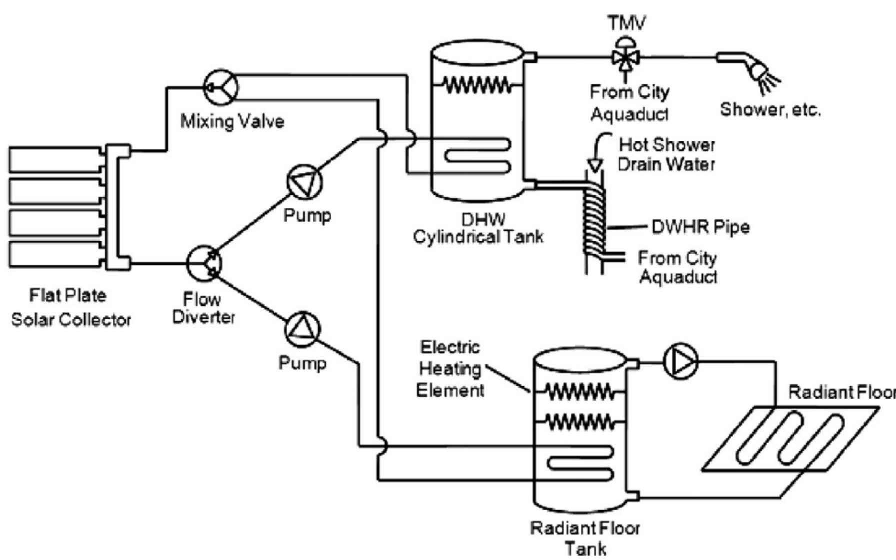


**Figure 1. Schematic diagram of the residential solar combisystem [12]**

In order to assess the solar combisystem shown in Figure 1 in terms of cost and energy use, two objective functions are used. The next section focuses on these two objective functions.

### 2.2 Objective functions

Any optimization problem must comprise at least one objective function, which is improved (i.e., maximized or minimized) during the optimization search process. This paper focuses on the financial and environmental aspects of a residential solar combisystems.

#### 2.2.1 Life Cycle Cost (LCC)

Although the simple payback period has been used in several studies as a financial metric of such systems [13], it does not take into account the cash flows beyond the payback period [14]. The life cycle cost (LCC) approach is more thorough. The LCC objective function of the residential solar combisystem of this paper comprises three components: (i) the initial cost of all components, (ii) their replacement cost, and (iii) the annual operating cost. Minimizing the LCC value can lead to a set of values of the design variables where the solar combisystem is not able to ensure the desired thermal comfort of occupants. A metric named HUSP, which stands for Hours Under the heating Set Point, is added as a penalty function to ensure that the number of hours in each zone, under the heating set point, throughout the year is not above 550. Thus, the LCC objective function, in present-value dollars, is formulated as follows:

$$LCC = InitialCost + PWrepl,\cos t + PWenergy,\cos t + 200{,}000 \times lt(550, HUSP); \quad (1)$$

where $InitialCost$ is the initial cost of the combisystem; $PWrepl,\cos t$ is the replacement cost of the solar combisystem components; and $PWenergy,\cos t$ is the energy cost. The electricity rate of Hydro Quebec [15] of $0.0776/kWh was used in this study.

2.2.2 Life Cycle Energy Use (LCE)

The life cycle energy use is formulated as follows:

$$LCE = EE_{col} + EE_{RFT} + EE_{DHWT} + LCE_{operating} + 200{,}000 \times lt(550, HUSP); \quad (2)$$

where $EE_{col}$ is the embodied energy of the solar collectors; $EE_{RFT}$ is the embodied energy of the radiant floor tank; $EE_{DHWT}$ is the embodied energy of the domestic hot water tank; $LCE_{operating}$ is the operating energy of the residential solar combisystem.

### 2.3 Design variables

The design variables of the solar combisystem to be optimized, and their acceptable design range are reported in Table 1.

**Table 1. Design variables of the solar combisystem**

| Design variable | Range |
|---|---|
| Number of solar collectors | 1-22 |
| Collector slope (degrees) | 0-90 |
| Collector fluid flow rate (kg/hr/$m^2_{collector}$) | 10-115 |
| DHW tank volume (L) | 100-1,000 |
| Radiant floor tank volume (L) | 300-30,000 |
| DHWT auxiliary power (kW) | 0.5-5 |
| RFT auxiliary power high (kW) | 0.5-10 |
| RFT auxiliary power low (kW) | 0.5-15 |

## 3. Multi-objective optimization of the residential solar combisystem

This section focuses on the last step of the pre-processing phase presented in Section 2 that is the selection of a suitable optimization algorithm. This section gives a short overview of the weighted sum method (WSM) and multi-objective particle swarm optimization (MOPSO) method.

### 3.1 Weighted sum method (WSM)

The weighted sum method (WSM), as presented in [16], minimizes the global objective function $Z_{global}$ that is obtained from the objective functions $f_i$, as follows:

$$Z_{global}(x) = \sum_{i=1}^{k} w_i \times f_i(x); \tag{3}$$

where $w_i \in [0,1]$ is the weight of the i-th objective function $f_i(x)$ and $\sum_{i=1}^{k} w_i = 1$.

If one or more objective functions are considerably different in terms of magnitude, their impact on the results would be substantial, regardless of the weights assigned by the decision maker. For this reason, the objective functions must be normalized. Since the LCC and LCE objective functions are used to optimize the residential solar combisystem, the global objective function *($Z_{global}$)* is computed as follows:

$$Z_{global} = w_1 \times \frac{LCC - LCC^{\min}}{LCC^{\max} - LCC^{\min}} + w_2 \times \frac{LCE - LCE^{\min}}{LCE^{\max} - LCE^{\min}} \tag{4}$$

Where $w_1$ and $w_2$ are the weights assigned to LCC and LCE, respectively; while $w_2 = 1 - w_1$.To provide more than one solution and approximate the Pareto frontier, the weights are varied from 0 to 1, with a step of 0.1. A hybrid algorithm, composed of particle swarm optimization (PSO) and Hooke-Jeeves (HJ), is used to minimize the $Z_{global}$ objective function. This algorithm, which has already proved to be effective in [17], offers a good trade-off between computing time and accuracy. In addition, PSO/HJ is available in GenOpt [18] that is coupled with TRNSYS in this study for the WSM method. The two algorithms composing the hybrid algorithm are shortly presented in the two next sections.

#### 3.1.1 Particle swarm optimization (PSO) algorithm

Particle swarm optimization (PSO) is a stochastic population-based computational method [19]. Inspired by the behavior of schools of fish searching for food, PSO uses a number of particles (i.e., candidate solutions), whose position (i.e., their design variables' value) is modified iteratively to find the minimal or maximal value of an objective function. All these particles form a swarm, which migrates in a search space based on the best solution found by each particle, but also the one discovered by the whole group.

#### 3.1.2 Hooke-Jeeves (HJ) algorithm

The Hooke-Jeeves (HJ) algorithm [20] operates by changing the values of one variable at a time, examining the objective function value at each iteration, and then comparing each trial solution with the minimum (or maximum) value obtained up to that time. When no decrease (or increase) of the objective function is obtained, then the step size of each design variables is reduced. Unlike the PSO algorithm, HJ is efficient at searching for local minima (or maxima).

### 3.2 Multi-objective particle swarm optimization (MOPSO) method

As stated in [21], multi-objective evolutionary algorithms usually derive from a single-objective version. Knowing the capabilities of PSO for single-optimization problems, a multi-objective version of PSO was proposed in [22], then improved in [23]. This multi-objective version, named multi-objective particle swarm optimization (MOPSO), appeared promising. MOPSO uses the concept of Pareto optimality to store, in a repository (i.e., an archive for non-dominated solutions), the best solutions found during the optimization search process. To the best knowledge of the authors, no open-source optimization program has implemented MOPSO. Therefore, the MOPSO version presented in [23] was implemented in MATLAB by the authors. For practical reasons, some studies have used the coupling of different computer programs such as MATLAB with GenOpt [24]. Herein, the MOPSO algorithm implemented in MATLAB was coupled with TRNSYS as illustrated in Figure 2.

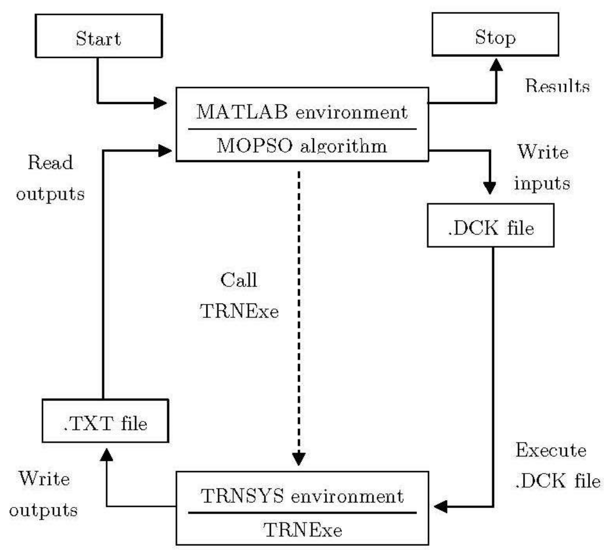


**Figure 2. Framework of the optimization process**

MOPSO starts by writing the value of each design variable to the deck file of the residential solar combisystem, which is a text file containing all inputs for TRNSYS. Then, MATLAB calls the TRNSYS executable (i.e., TRNExe) to run the deck file. Once all TRNSYS simulations are performed for one generation, MOPSO reads from the TRNSYS output text file the LCC and LCE values for the given set of values of design variables. Based on the LCC and LCE values, a new set of values for the design variables is calculated and written on the deck file. This process continues until the maximum number of generations is reached. Subsequently, the optimization results are displayed.

## 4. Results

This section presents the results obtained by the WSM and MOPSO method for the multi-objective optimization of the residential solar combisystem. Both approaches started with the same solar combisystem sizing (i.e., the same set of values of the design variables), which was selected from [25]. Since PSO relies on its memory (i.e., the archived results) to optimize an objective function, the first set of values of the design variables was chosen to give relatively expensive objective functions (see Table 2). Thus, the first values of the design variables were not optimum.

**Table 2. Initial values of the design variables and corresponding objective functions**

| Design variable and objective function | Value |
|---|---|
| Number of solar collectors | 20 |
| Collector slope (degrees) | 25 |
| Collector fluid flow rate (kg/hr/$m^2_{collector}$) | 70 |
| DHW tank volume (L) | 700 |
| Radiant floor tank volume (L) | 25,000 |
| DHWT auxiliary power (kW) | 2.5 |
| RFT auxiliary power high (kW) | 4 |
| RFT auxiliary power low (kW) | 7.5 |
| Life cycle cost (k$) | 40 |
| Life cycle energy (MWh) | 337 |

## 4.1 WSM

To approximate the Pareto front, the weight $w_1$ used in the WSM method was changed from 0 to 1, with a step of 0.1, and the optimum solution was recorded for each value of $w_1$. Figure 3 shows the LCC and LCE values obtained by the 11 optimization runs, which approximated the Pareto front; however, only six solutions out of 11 were distinct Pareto solutions.

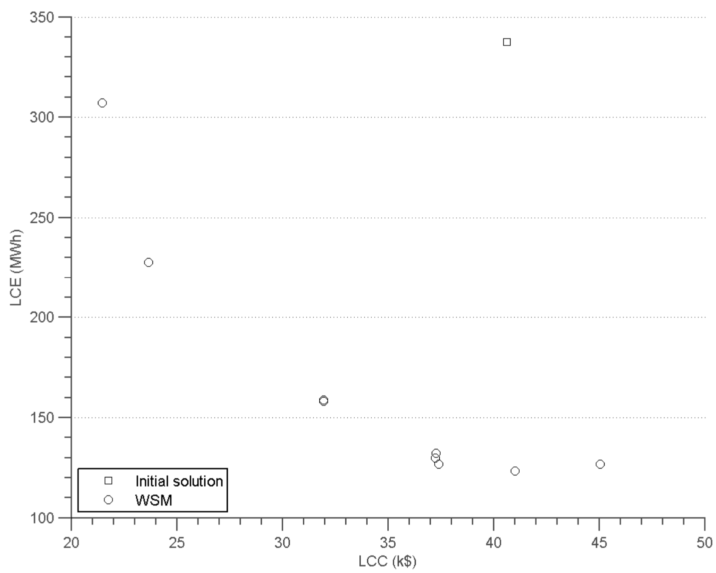


**Figure 3. Results of the WSM using the PSO/HJ algorithm**

The characteristics of three of the optimization runs using the WSM are reported in Table 3. Since PSO used six particles over 25 generations, the number of TRNSYS simulations was 150 for each value of $w_1$ (i.e., 1,650 TRNSYS simulations for the PSO portion). In the case of the HJ portion, the search stops when no improvement of the global objective function can be achieved, so the total number of TRNSYS simulations was not the same for each optimization run. For instance, the HJ portion called 155 TRNSYS simulations for $w_1 = 1$. The total number of TRNSYS simulations for the HJ portion was 2,054, which implies a total of 3,714 calls of TRNSYS for all Pareto solutions. The average computing time for an optimization run (i.e., for one value of $w_1$)

was around 86 hours using a 6 cores Intel Xeon @ 2.40 GHz. Therefore, more than 39 days were necessary to approximate the Pareto front depicted in Figure 3.

**Table 3. Characteristics of three optimization runs using the WSM**

| $w_1$ | 1 | 0.8 | 0 |
|---|---|---|---|
| Number of solar collectors | 1 | 8 | 13 |
| Collector slope (degrees) | 60 | 73.75 | 72.5 |
| Collector fluid flow rate (kg/hr/$m^2_{collector}$) | 18.5 | 15 | 10 |
| DHW tank volume (L) | 100 | 100 | 100 |
| Radiant floor tank volume (L) | 300 | 300 | 300 |
| DHWT auxiliary power (kW) | 0.5 | 1.25 | 1.5 |
| RFT auxiliary power high (kW) | 2.5 | 1 | 0.5 |
| RFT auxiliary power low (kW) | 8 | 1 | 0.5 |
| Number of TRNSYS simulations performed with PSO | 150 | 150 | 150 |
| Number of TRNSYS simulations performed with HJ | 155 | 144 | 267 |
| LCC final value after PSO (k$) | 24 | 33 | 117 |
| LCE final value after PSO (MWh) | 316 | 172 | 172 |
| LCC final value after HJ (k$) | 21 | 32 | 41 |
| LCE final value after HJ (MWh) | 307 | 158 | 123 |

Although the use of WSM resulted in a discrete Pareto front covering different values of LCC and LCE objective functions (i.e., the design solutions are diverse), it was time consuming. In addition, when more Pareto solutions are desired, the computing time increases. Hence, a faster optimization search method is needed.

### 4.2 MOPSO method

Unlike the WSM, MOPSO needs only one optimization run, which implies 150 TRNSYS simulations, to approximate the Pareto front related to the bi-objective optimization of the solar combisystem. This optimization run, using six particles during 25 generations (i.e., 150 TRNSYS simulations) lasted for 18 hours, on the same computer as the WSM. MOPSO is therefore much faster than the WSM. However, as depicted in Figure 4, the WSM found better solutions (i.e., having lower LCC and LCE values) than MOPSO, when using 25 generations as a termination criterion. Increasing the number of generations performed by the MOPSO algorithm can result in a Pareto front with lower LCC and LCE values, as shown in Figure 4; however, it increases the total computing time. In addition, more generations do not necessarily lead to lower objective function values (e.g., the algorithm can get stuck in a local minimum). For comparison, the WSM method used the hybrid PSO/HJ algorithm to overcome the main weakness of PSO (i.e., a weak local search) by adding the HJ algorithm.

The characteristics of three of the optimization runs using MOPSO are reported in Table 4. As a result, the lower the LCE value is, the higher the number of solar collectors. The lower the LCC value is, the smaller the number of solar collectors.

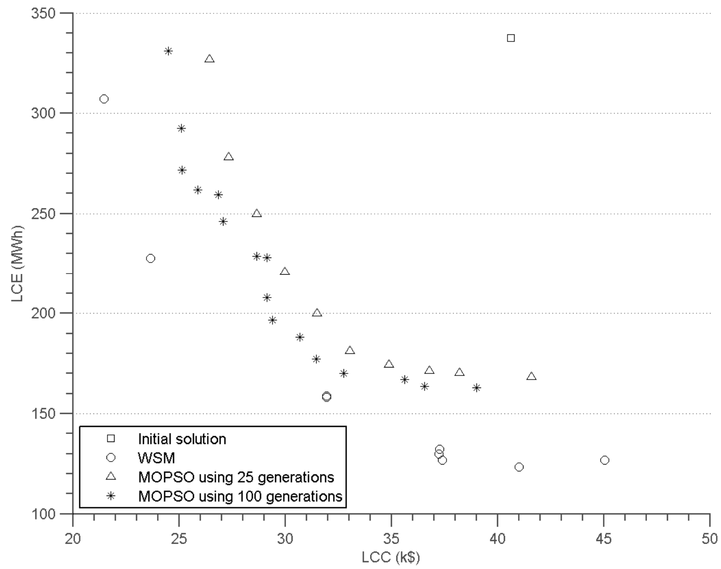


**Figure 4. Results of the MOPSO and WSM approaches**

The optimum values of the design variables, obtained from the WSM and MOPSO methods, are quite different, except for the radiant floor tank volume, that is 300 L. For instance, for the MOPSO method, the electric heater of DHW tank is between 2.5 and 5 kW; while for the WSM method is between 0.5 and 1.5 kW. Those differences are due to the fact that MOPSO performing 25 generations might converge to local minima.

**Table 4. Characteristics of three optimization runs using MOPSO**

| | | | |
|---|---|---|---|
| Number of solar collectors | 1 | 6 | 11 |
| Collector slope (degrees) | 70 | 55 | 50 |
| Collector fluid flow rate (kg/hr/$m^2_{collector}$) | 50 | 20 | 10 |
| DHW tank volume (L) | 1000 | 1000 | 800 |
| Radiant floor tank volume (L) | 300 | 300 | 300 |
| DHWT auxiliary power (kW) | 5 | 3 | 2.5 |
| RFT auxiliary power high (kW) | 2.5 | 0.5 | 0.5 |
| RFT auxiliary power low (kW) | 8 | 7 | 8 |
| LCC final value (k$) | 26 | 33 | 42 |
| LCE final value (MWh) | 327 | 181 | 168 |

The solutions having the highest number of solar collectors found by the WSM and MOPSO method have almost the same value of the LCC objective function (i.e., 41 vs 42), whereas the values of the design variables are different. The WSM solution has more solar collectors, which leads to higher initial cost; however, its electrical consumption is lower than that of the MOPSO solution; hence a balance was reached between both solutions. Thus, two different solar combisystem configurations can have the same LCC value.

## 5. Conclusion

Two methods for solving multi-objective problems have been applied to a residential solar combisystem. Although the WSM found better solutions than the MOPSO method in terms of LCC and LCE values, its computing time was too high for practical applications such as in consulting firms. The MOPSO method is much faster, but its local search needs to be improved in order to achieve better results.

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## 8. Biography

Anthony Rey is a PhD student at Concordia University in Montreal, whose research interests lie at the intersection of solar thermal combisystems and multi-objective optimization methods.

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