Intelligent Controllers based on Genetic Algorithms for Reducing Energy and Water Waste

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***Abstract*— A significant amount of water, energy and time are often wasted, before someone gets the desired water temperature in a bathroom or a kitchen. In this paper, we propose a novel electro-mechanical device for mixing the water intelligently, which is effective for saving water, energy and time. The problem that we intend to solve can be seen as a multi-objective optimization problem in which we require to optimize water's flow and temperature. To achieve this task, we consider both the single-objective and the multi-objective optimisation variants of the problem. NSGA II is then used to solve each of these variants. In order to assess the effectiveness of each approach, a case study has been conducted, where controllers are applied to control a dynamic number of users within a house. The results suggest that multi-objective optimization outperforms single-objective optimization, in terms of quality of the returned solutions.**

I. INTRODUCTION

In many countries, despite the advancement in engineering and technology, a significant amount of water and energy are wasted. This is particularly noticeable in modern homes and residences where there is no cost-effective devices to improve efficiency and save energy. A typical example is when someone needs to set a desirable water temperature before taking a bath. This often requires a high amount of water waste, before the preferred temperature is reached. Moreover, preserving the preferred temperature does not work as needed, due to changes in the input flow of hot and cold waters. Another challenge is when users are added/removed dynamically, which requires the management of different objectives and constraints for different taps. Some efforts have been conducted to reduce the water and energy wastes in water taps. However, these works have limitations such as design lacking the proper electronic system [1], or design without the proper mechanical device [2]. Other attempts have been conducted to save energy but these are not aligned with the scope of the problem we stated [3], [4]. In [5], we have proposed a new mixing device which addresses some of the issues listed above. More precisely, our mixing device, relies on a multi-objective heuristic optimization solution to automatically control the adequate mixing amount of hot and cold water, in order to satisfy a given user's preference.

Following on our previous work, and in order to deal with dynamic users for different taps, we propose the following. First, we redesign the mechanical device. The new proposed mixing device has a number of new features including a smaller size that is easy to install. The device is very compact and can be installed in any traditional water system. The second contribution is related to the controlling method that is used in the mixing device. In order to come with the adequate controlling method, we conducted a study of several controllers. Each controller relies on a different solver. Indeed, we represent the problem as a multi-objective optimization problem [6], where constraints need to be met while optimising some objectives. To solve this optimization problem, we consider both the single-objective and the multi-objective optimization approaches.

The rest of the paper is structured as follows. In the next Section, the problem formulation is stated, The proposed device and controllers are then presented in Section 3. The experimentation conducted to compare the different controllers, in terms of computation cost and quality of the solution, is reported in Section 4. Finally, concluding remarks are listed in Section 5.

II. PROBLEM FORMULATION

As stated in the previous Section, our goal is to develop a new mixing device that will be installed on each house tap. The device acts as a controller on the tap to which it is attached. The controller optimizes the performance in the related tap, as well as the other taps inside the house. The house is assumed to be equipped with a heating source. During the optimization of the water's flow and temperature, a number of possible conditions might take place including low temperature in hot pipes, low flow rate of water, and a varying number of users. These conditions may affect the overall performance of all the taps within the house. The first and the second conditions might happen due to a high number of users or may result from an issue in the heating source. The third condition relates to an abrupt change in the number of users. We assume that each user has a specific preference, and each mixing device is intended to optimize the overall performance. To do this, the device sets the water flow and temperature according to the preference of the user, as a first priority, while as a second priority, the device considers other taps and the overall performance.

We present the mathematical formulation of the problem as follows. For the heater we have:

$$e_s = \tau_s E_{max} \tag{1}$$

where e_s is the current consumed energy in the heating source (in kcal/hour), τ_s is the tuning factor of the source controller ($0 < \tau_s \leq 1$), and E_{max} is a constant (see Table I).

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The following formulation is based on the fact that the energy that dissipates through the pipes is related to the length of the pipe. Similarly, based on the travelled length in the pipes, the water's flow rate dissipates accordingly. In addition to this, the flow rate dissipation may relate to the flow rate in both the heating source and other mixing devices. In this problem formulation, if a house has N taps on use, the total available energy for the taps can be written as:

$$e_{o_i} = e_s - \sum_{i=1}^{N} L_i \tag{2}$$

where L_i is a coefficient related to the amount of reduction in energy, as follows:

$$L_i = W d_i \tag{3}$$

Here, the temperature of the water drops in proportion with W (W is a constant in kcal/hour). In addition, d_i is the total length, in meters, between the source and tap i. Furthermore, in proportion with D, the flow rate of the water in the pipe will be reduced. The flow rate is measured in litre/min.

$$f_i = F - \sum_{i=1}^{N} D d_i \tag{4}$$

where F is the source flow rate and f_i is tap i's flow rate.

$$S_i = a_i f_i (h_d - h_i) \tag{5}$$

where S_i is the wasted water, h_d is the desired temperature, and h_i is the current temperature. The temperature is measured in Celsius.

To compute the time that is needed to set the water to the preferred temperature, we have to minimize t_i :

$$t_i = \frac{(h_d - h_i)}{(f_i - f_d)(h_s - h_d)} \tag{6}$$

where f_i is the current flow-rate in the tap, the desired flow rate is f_d, h_s is the heating source water temperature, h_d is desired temperature, and h_i is the current temperature of the hot pipe. To set the desired flow rate (f_d), we minimize the following term:

$$k_i = f_i - f_d \tag{7}$$

According to the above equations, the cost functions can be formulated as:

$$c_1 = \sum_{i=1}^{N} a_i e_{o_i}^{-} 1 \tag{8}$$

$$c_2 = \sum_{i=1}^{N} a_i S_i \tag{9}$$

$$c_3 = \sum_{i=1}^{N} a_i t_i \tag{10}$$

$$c_4 = \sum_{i=1}^{N} a_i k_i \tag{11}$$

where a_i refers to the given priority of tap i. Hence, the Multi Objective Optimisation (MOO) considers the priority coefficients in the costs optimization. In other words, if we assume N taps in the house, we will have N priority coefficients as follows:

$$\sum_{i=1}^{N} a_i = 1 \tag{12}$$

where $N \geq 1$, $a_i > 0$.

In addition, in the place of each tap, the flow-rate of hot water pipe is calculated as follows:

$$F_i = F_{max} \frac{h_d}{h_i} \tag{13}$$

where F_i is the flow-rate of tap .

1) Heater controller: As it was shown in Equation (1), in the heating source, τ_s regulates the amount of consumed energy. τ_s may vary within a given range ($0 < \tau_s \leq 1$). The controller of the designed system sets a proper value for τ_s, between a partial load ($\tau_s < 1$) and a full load ($\tau_s = 1$). In case of existing many users, the heater will choose to work on full loads, while , in partial load, the system will set the load when there are no or a few users.

A. Constraints

In the above-mentioned problem, we have to meet a few constraints. These constraints relate to mixing device, heater, and pipeline.

1) Mixing device constraints: Each tap is able to set the desired temperature h_d with the following constraint:

$0 < h_d \leq h_{max}$ where h_{max} is defined according to the specifications of the pipeline and the heating source. In our simulation, h_{max} is assumed to be 80^oC . Furthermore, the desired flow in the tap (f_d) is constrained to $0 < f_d \leq f_{max}$.

2) Heater constraints: The total consumed energy (e_o) in the heating source is a combination of used energy in the heater, lost energy in pipes e_i, and used energy in the taps by users (e_c):

$$e_s - e_i - e_c = (e_s - \sum_{i=1}^{N} L_i - e_c) \tag{14}$$

in which $0 < e_o \leq E_{max}$. In addition, the heating source also pose a few constraints. The heating source's flow and temperature is constrained to $H_{min} < h_s \leq h_{max}$ and $F_{min} < f_s \leq F_{max}$ respectively (See Table 1).

3) Pipeline limits: The pipeline is constrained to a specific flow and temperature: $F_{p_{min}} < f_p \leq F_{p_{max}}$ and $H_{p_{min}} < h_p \leq h_{p_{max}}$.

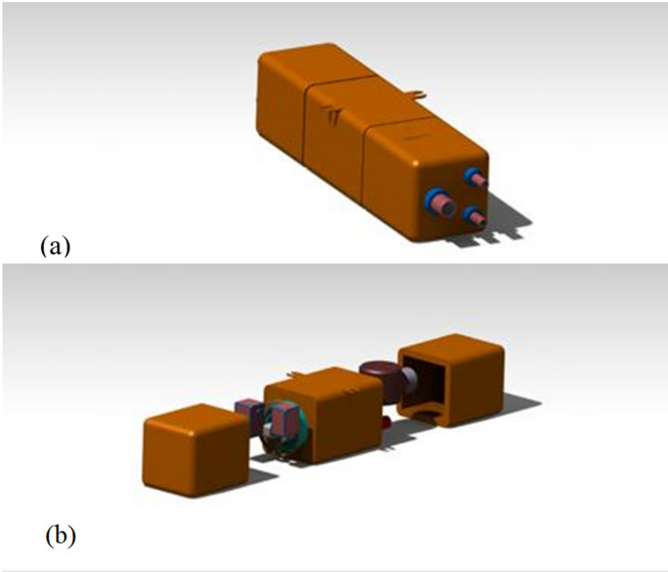

Fig. 1. The design of the mixing device. (a) The outside view. (b) The inside view.

III. Proposed Device and Controllers

In this section, a new mechanical system is developed as a mixing device, which can be inserted close to the taps. The mixing device includes two main parts: mechanical and electrical parts. The mechanical part is mainly working as an actuator to control the mixing amount of water coming from hot and cold pipes. The electronic part primarily comprises sensors, servomotors, a wireless communication module, and a processor. The redesigned device is shown in Fig. 1. The key duty of the processor is controlling the actuators to set a proper follow and temperature of the output. This is done according to sensors and communicated data. In the following, the implemented controllers are defined. Each device is run the controller locally considering the user's preference, heating source, and other taps that are in use. The installment of the device is shown in Fig. 2.

The mixing device includes flow meter and temperature sensors, and the mechanical mixing part that works with two servo motors. The flow and the temperature of the water in the output are set by servomotors. For proper control of two servo motors, a low-level control is required.

The overall system comprises two levels of control: high-level and low-level controllers. The high-level controller is the main part of the system, which finds out the best solutions for each in-use mixing device as well as the hot water level in the heater. The low-level control is applying the fuzzy controller to produce a proper water flow and temperature in the output (see Fig. 3). This paper focuses on the high-level control when the low-level controller is studied in detail in [7].

A. *Multi-Objective Optimizer*

The multi-objective optimizer optimizes the tap performance as well as the overall performance inside the house.

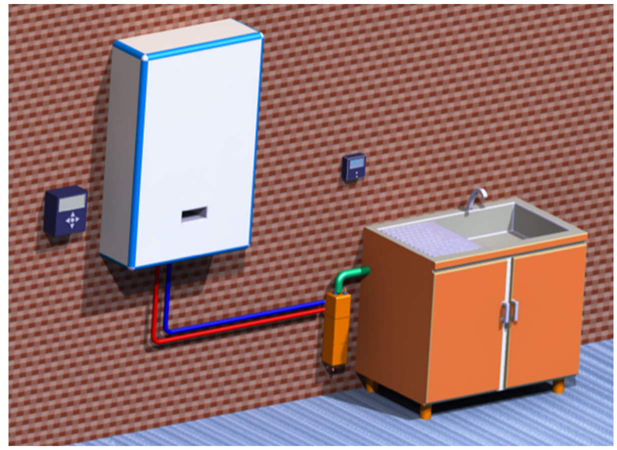

Fig. 2. The location of the prototype with a user input interface.

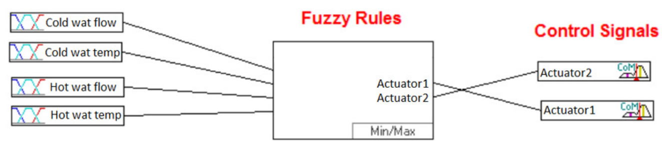

Fig. 3. Fuzzy controller on layer 1: Inputs are flow-rate and temperature of the water in both cold and hot pipes.

The optimization is done using the following objectives to minimize.

c_1= the overall consumed energy,

c_2= the overall water wast,

c_3= the delay time between the current water and the user' s preferred water

c_4= the difference between the preferred and the current flow.

For each tap, the mixing device runs the solver, which optimizes the above defined conflicting objectives. The aim here is to provide a set of Pareto optimal solutions (Pareto front) minimizing the objectives. As shown in the next subsection, the decision maker will then choose the best solution among the set.

NSGA-II is used here to solve the problem and returns several Pareto fronts. In the literature, NSGA-II is well-known for rapid convergence with acceptable prediction. NSGA II is the multi-objective version for Genetic Algorithms (GAs), which can optimize various objectives simultaneously. In this algorithm, each front contains a set of optimized solutions. The first front is made of a completely non-dominant set, the second front is dominated only by the individuals in the first front, and so on. Details of NSGA-II settings are shown in Table II. Since NSGA-II obtains a set of non-dominated solutions, a final solution should be chosen out by a decision maker. In this regard, apply a vector-based decision maker which is described in the next section.

1) Implementation of NSGA-II: First, in each tap, NSGA-II produces a uniform population of size 2, which are water flow rate and temperature. Then, online information of other taps is received over IoT network. This information includes the flow rate and temperature of current in-use taps.

TABLE I

SETTINGS FOR THE SPECIFIC PARAMETERS

Parameter	Value
Max heating capacity (E_{max})	2100 kcal/hour
Max water flow (F_{min})	1 litre/min
Max output water flow (F_max)	10 litre/min
Max gas usage	2,5 $\frac{m^3}{hour}$

Meanwhile, the device receives information about the current temperature of the water on the heater. More precisely, we follow the procedure below:

1) The objectives of each individual are calculated using Equations (15), (16), (17) and (18). Then population are evaluated and sorted based on the non-domination. For non-domination sorting, each solution has a special rank using the non-dominated sorting.
2) A binary tournament selection is adopted. To create an initial population of off-springs (P), two genetic operators including Binary Crossover and Polynomial mutation are selected [8].
3) A new population is then generated by combining off-springs and parents.
4) Next, the new combined population is sorted based on a non-dominated rule.
5) Crowding distance is used to ensure the diversity of solutions, which helps to avoid convergence in a particular direction. If we have three adjacent points on the Pareto front including $\{z-1,z,z+1\}$, the crowding distance (ψ) is computed with the following equations that are two distances in a cuboid:

$$\psi_1 = \|f_1(x_{z+1}) - f_1(x_{z-1})\| \tag{15}$$

$$\psi_2 = \|f_2(x_{z+1}) - f_2(x_{z-1})\| \tag{16}$$

The crowding distance is $\psi = \psi_1 + \psi_2$.
6) If there is active user in the tap, update the iteration α=α+1 after β seconds. This time delay (β) helps to improve the life-time of the mixing device. In addition, time delay results in avoiding too much oscillation in the device. To calculate β, the following formula is used:

$$\beta = AC(1/(1+\kappa)) \tag{17}$$

where the value of A is 1 if the tap is in use, and is 0 otherwise. C is a constant, and κ is the output difference which is computed as follows:

$$\kappa = X(f_i - f_d) + K(h_i - h_d) \tag{18}$$

where X and K values coefficients are tuned to their best.

2) Decision Maker: The MOO process finishes with a set of non-dominated solutions which corresponds to the Pareto front. According to the nature of the problem, some of these solutions may work better. In this sense, the decision-maker is interested in only some of the solutions of the Pareto front. The process of selection of a subset of these Pareto optimal follows the known selection approaches. Each of these approaches have some limitations, for example, the knee based method requires at least four solutions, while the vector-based approach can make decisions with any number of solutions. Since, in real-word applications, we cannot guarantee to have a minimum number of solutions, the vector-based decision-maker is chosen for this work. The method is applied when the vector passes from the point called Reference. Reference vectors provide a preference for the designer in the solution space. Each solution is compared with the perpendicular distance, while improving the diversity [9]. The preference value is as follows:

TABLE II

SPECIFIC SETTINGS FOR NSGA-II

Mutation Rate	0.02
Cross-over percentage	0.7
Mutation percentage	0.4
Mutation Step Size	0.3

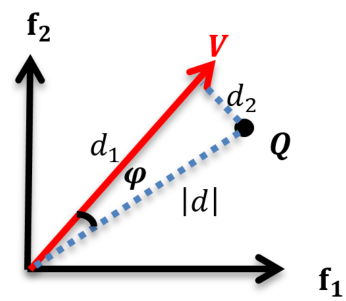

Fig. 4. Vector based preference decision making where Q is the point that we compute the preference value, and $\vec{V}$ is a reference vector.

$$g = (1 + p(\phi))|d| \tag{19}$$

where $p(\phi)$ is a penalty function and is similar to [9], and

$$p(\phi) = O\frac{\phi}{\Gamma} \tag{20}$$

$\vec{V}$ is a reference vector and $\vec{P}$ is a vector connecting the centre to the point Q as shown in Figure 4. In addition, Γ is the minimum angle between $\vec{V}$ and other $\vec{P}$ for all objectives, and O is the total number of objectives while ϕ refers to the angle between $\vec{V}$ and $\vec{P}$.

B. Single-Objective Optimizer

To produce a single-objective from multiple objectives, scalarization has been applied. In this method, the objectives are represented in a single function, where a weight is associated to each. Proper weights may be found considering trial and error as well as priorities from the problem definition. More formally, the single objective is defined as follows:

$$H = \tau_1 c_1 + \tau_2 c_2 + \tau_3 c_3 + \tau_4 c_4 \tag{21}$$

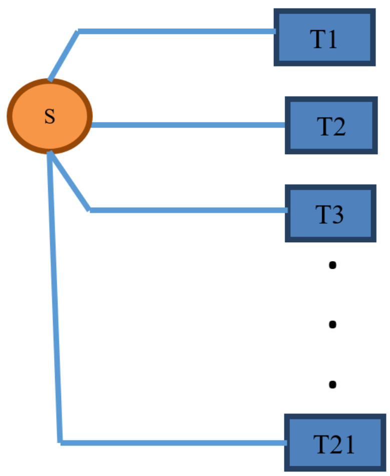

Fig. 5. First setup, where S is the source and Ti are the taps

TABLE III
SETTINGS FOR THE SPECIFIC PARAMETERS

	τ_1	τ_2	τ_3	τ_4
SOO1	0.3	0.15	0.4	0.15
SOO2	0.25	0.25	0.25	0.25

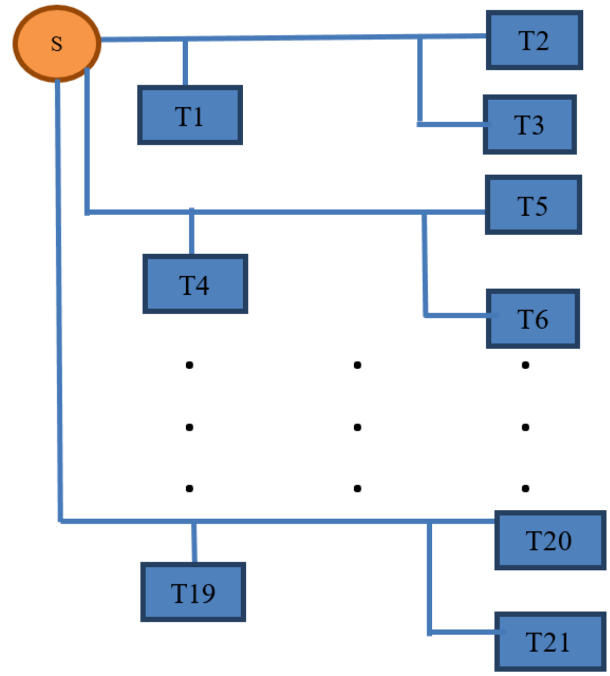

Fig. 6. Second setup

where H is the objective that is optimized, and $\tau = [\tau_1, \tau_2, \tau_3, \tau_4]$ is set of weights for multiple objectives. Also,

$$\tau_1 + \tau_2 + \tau_3 + \tau_4$$

is equal to one.

Genetic algorithms (GAs) are used to solve the single-objective optimisation variant of the problem. GAs are developed based on natural selection of living species. In GAs, selection of best fitted solutions is done for producing best offspring in the next generation. This process relies on three main operators: mutation, cross-over, and selection.

IV. Experimentation

A. System Setup

To test the above-mentioned controllers, two configurations are studied: parallel and series configuration. These configurations are shown in Figure 5 and Figure 6, respectively. Since the system is stochastic, each experiment is repeated for 30 times, and the average result is taken and presented. To show the difference between controllers, and to assess the effectiveness of each, we require a high number of taps with dynamic usage of the taps. In this sense, two set-up configurations are considered with 21 taps, and all taps have equal priority. In these setups, after water passes from the l length of the pipe (where l is assumed to be one meter), the water flow is reduced in proportion with D (D =0.15 lit/min). Similarly, the water temperature drops in proportion to W (W=148 kcal) per l length of the pipe.

Mathworks Matlab 2018b has been used on a PC with a Core I5 processor and 8 Giga bytes of RAM. A random change in the number of users is simulated. In the first experiment, the configuration of Figure 6 is simulated. Here, all 21 taps are acting simultaneously according to different users' preferences (in terms of temperature and water flow). The total time corresponds to 60 iterations which simulates 30 seconds in practice. From a practical point of view, since each mixing device runs a GA or an NSGA-II controller on its processor, according to the literature, ARM or FPGA embedded processors can work properly in real-time [10]. Internet of things (IoT) as an alternative approach can be used for this application. IoT technology provides a cloud computing option, which enables the designers to use a low-cost device with effective power of computing. In addition, this technology makes histories of each device usage available online on the Internet. On the other hand, all devices can communicate with each other and the heater using the Internet.

B. Results

Since we are dealing with 21 taps, there is not enough space to show the completed performance for each. For this reason, we selected a few samples among others. In Figure 7, a Single-Objective Optimisation (SOO) is listed with two different weighted-sum, compared in terms of performance in both temperature and flow. Table III shows the different settings of τ. The different values for τ are set based on trial and error. In theory, the optimal values can be predicted more precisely with mathematical approaches, while, in practice, since there is no precise mathematical model for the device, one may require to use trial and error to set the proper values for τ. The configuration is set to series. As it can be seen, the performance is highly related to the proper tuning of the different values of $\tau = [\tau_1, \tau_2, \tau_3, \tau_4]$. This is justified by

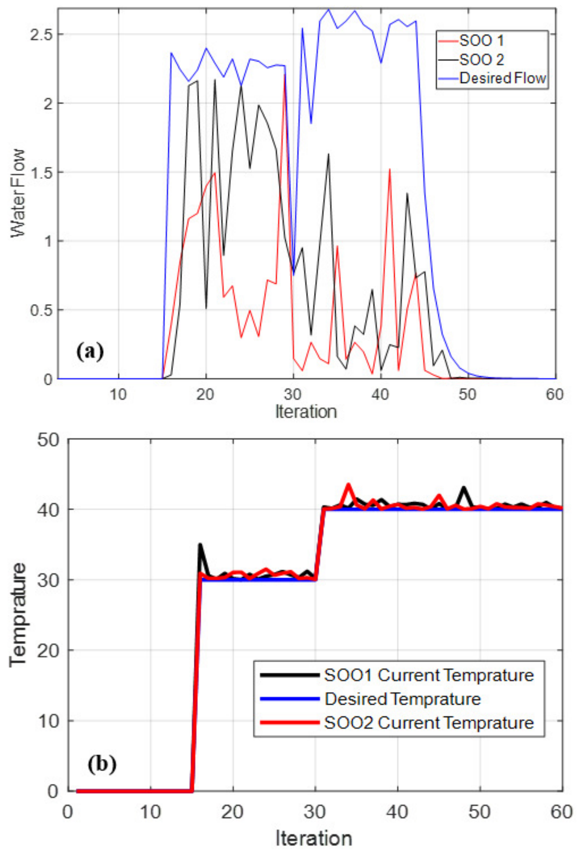

Fig. 7. Water flow (a) and temperature (b) of tap 3 in series configuration using the SOO controller. The performance is highly related to the weighted-sum coefficients.

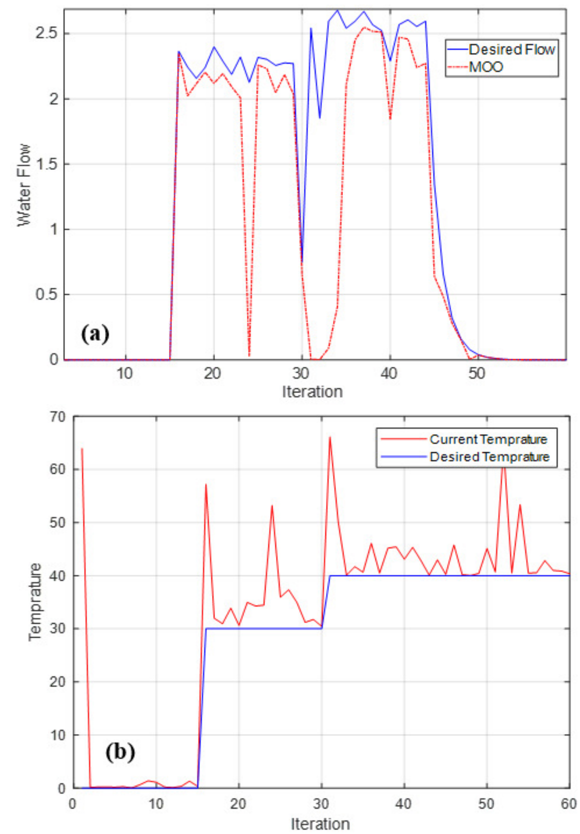

Fig. 8. Water flow (a) and temperature (b) of tap 3 in a configuration in series using MOO controller.

TABLE IV
SOO AND MOO PERFORMANCE

	SOO1	SOO2	MOO
Temperature	-0.28	-0.31	-0.6
Flow	-0.38	-0.44	+30.630

the fact that SOO cannot handle several values of τ. On the other hand, MOO can optimize the objectives in a timely manner.

In Figure 8, the same tap with the same desired flow and temperature in the 21 taps is tested with the MOO controller in a series configuration. As can be seen, the performance of the flow rate is better than the one of SOO. Additionally, the water temperature remains higher than in Figure 8 (b). The reason behind is the MOO's ability to deal with conflicting objectives. In other words, MOO keeps the temperature higher than the desired one to improve the total performance.

We compute the temperature values and water flow during all iterations for all taps. Table IV shows that, in terms of temperature, MOO's total output temperature is 0.6 degrees less than the user preference, while the flow is higher than the user preference. Similar results are obtained in the case of parallel configurations as shown in Figures 9 and 10.

Finally, according to our experience on Matlab, MOO's computational cost is about 10 times higher than SOO. it is clear that MOO requires a higher amount of computational cost than SOO. However, as can be shown in Table IV, MOO does not really perform better than SOO in highly dynamic situations. In all, MOO can be seen as more flexible optimizer which is robust against abrupt change of each objective, which is not the case of SOO, even for one objective. We believe that MOO can outperform SOO if we have a more complicated configuration, which we leave as a future research.

V. CONCLUSION

Efficient taps with minimum energy and water waste motivated us to design a new electro-mechanical device. This device can be installed at any location with ease. The device is controlled on two levels. The high-level controller that improves the efficiency of all taps in use and the heating source, and the low-level controller that translates the high-level controller outputs to proper commands in servomotors. We have compared two optimization control approaches for high-level control, namely, single-objective and multi-objective optimizations. The results suggest that multi-objective control is superior in terms of performance, while it requires more computational power. The results also show that multi-objective control is more flexible in dealing with highly dynamic situations when a high number

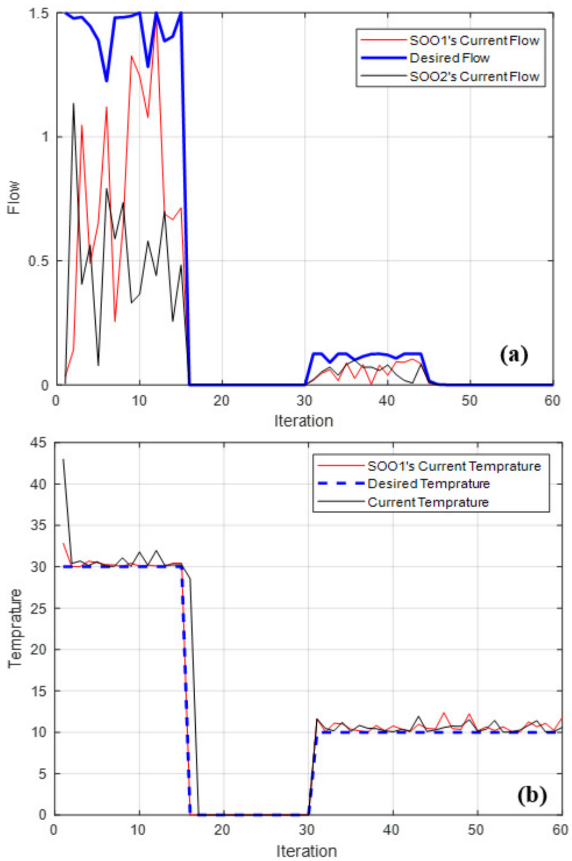

Fig. 9. Water flow (a) and temperature (b) of tap 1 in parallel configuration using SOO controller.

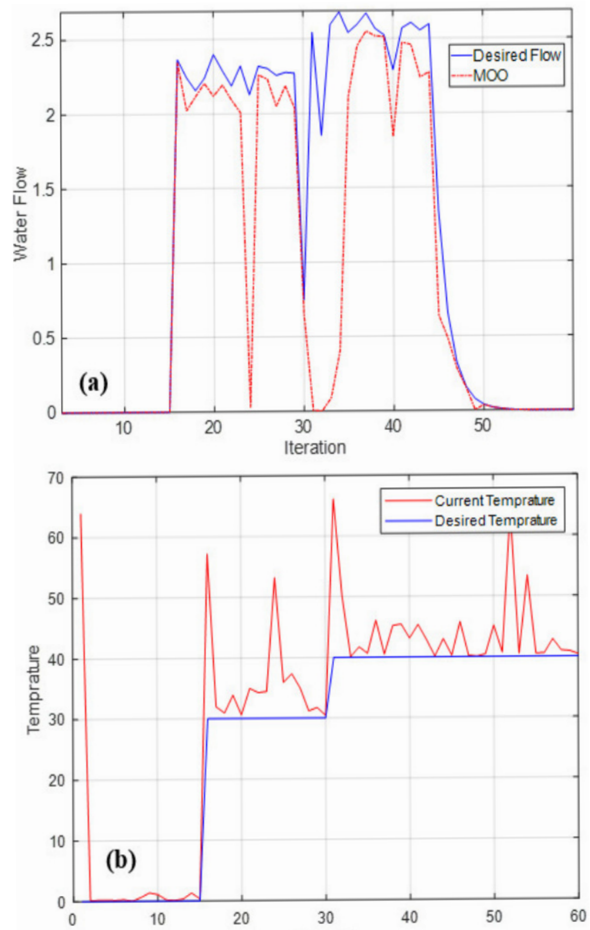

Fig. 10. Water flow (a) and temperature (b) of tap 1 in the parallel configuration using MOO controller.

of users use the taps in a dynamic manner. As a future work, we intend to control the proposed device using many-objective optimization approaches, i.e., multidisciplinary design optimization, as well as relying on other nature-inspired techniques [11], [12], [13], [14], [15], which can help the system to be usable with current commercialized smart house systems.

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