# Hyper-heuristics meet Controller Design: Improving Electrical Grid Performance through Microgrids

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***Abstract*—Microgrids stand as an alternative for incorporating Renewable Energy Sources into the electrical grid, but they require an adequate control scheme. Although the literature contains plenty of alternatives, it lacks implementations of hybrid controllers based on Hyper-Heuristics (HHs). Hence, we analyze whether they are of benefit. Our goal is simple: to alternate through diverse controllers as the simulation progresses. To this end, we consider some simple sequence-based selection HHs and test them across 13 scenarios. Instead of the customary low-level heuristics, we use predefined controllers that were previously tuned through a Genetic Algorithm. For the most part, at least one of the proposed models outperforms the best available controller. Thus, using HHs as an advanced control scheme seems feasible and should be explored more deeply in future works.**

***Index Terms*—Controller Design; Electrical Grid; Energy Quality; Hyper-Heuristics; Microgrids.**

## I. Introduction

The current climate crisis demands that we improve our lifestyle to adopt more environmentally friendly alternatives. Pragmatically, this implies that such alternatives offer the same benefits as existing technologies. One area of particular interest has been using Renewable Energy Sources (RESs). This idea can face the rising demand for energy and mitigate the dependence on fossil fuels for energy generation.

The electrical power system is a complex engineering system [1], that comprises three stages: generation, transmission, and distribution. Moreover, we can use RESs to create smaller independent systems, *i.e.*, microgrids, and help to mitigate the climate crisis. Microgrids (MGs) are electrical devices which features are similar to those of electric power systems. However, MGs perform in a distributed and decentralized manner, and at smaller scale. Furthermore, they are considered critical for modernizing traditional distribution systems into active distributed networks based on RESs. This is well-known as energy transition. Even so, the current challenge is to ensure the continuity of energy service at a minimum cost [2].

Although it would seem that the best alternative is to fully migrate to renewable sources, a high penetration, *i.e.*, high usage of such sources, leads to voltage variations in the electrical system due to their intermittency and uncertainty [3]. To overcome such issues, MGs require a proper renewable energy penetration index. Under such conditions, MGs offer an efficient solution that may enhance the power quality level of the distribution network while contributing to the decarbonization and decentralization of the electrical grid [4].

Various studies have established some of the effects of plugging MGs into the electrical grid. For example, Karimi *et al*. reviewed the state-of-the-art about issues related to photovoltaic systems and the distribution network, *e.g.*, voltage fluctuation, voltage rise, and harmonic content [5]. Additionally, intermittent meteorological conditions lead to unstable energy generation, which may compromise system performance. Therefore, renewable energies face challenges in technical aspects such as power quality, control strategies, and power system reliability [6]. In any case, it is paramount to enact a proper controlling scheme for the MG. Some examples include novel control structures for small-scale MGs powered by an electric vehicle-based energy storage management [7], a frequency controller that relies on a flywheel energy storage system for improving the reaction time of the MGs [8], and robust MG control techniques that aim to ensure system stability when plugging constant power loads to the grid [9].

Despite previous research efforts, there remains a knowledge gap: to determine the effect of using a hyper-heuristic model for enabling a cross-controller scheme. So, in this work, we analyze the feasibility of combining two control schemes through a sequence-based selection hyper-heuristic. In this sense, our main contribution stems from the fact that there is, indeed, a benefit from this combination, at least for our controlled testing conditions.

The remainder of this manuscript is organized as follows. Section II provides a brief description of fundamental ideas related to our research. Section III describes the model we implement and how it relates to the problem and the controllers. Then, we move on to the testing, which we describe in Section IV. We provide the resulting data in Section V and discuss the main highlights in Section VI.

## II. Fundamentals

We now present an overview of the application and hyper-heuristic model considered in this work.

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### A. Microgrids (MGs) and Power Quality

Generally speaking, MGs integrate an input (the RES), an energy conversion phase, a filtering stage, and a Static Disconnect Switch (SDS). It is precisely this switch the one that links the MG with the electrical grid through the so-called Point of Common Coupling (PCC). Hence, this component also allows an MG to operate under two schemes: tied or isolated. Moreover, the PCC serves to analyze the interconnected system under diverse scenarios. Microgrids also help reduce oscillatory electrical signals caused by unbalanced loads, which plague active distribution networks [10].

Since MGs supply energy, the overall electrical signal must conform to established specifications. This can be validated through several metrics related to power quality. An adequate signal requires that the voltage remains constant, the frequency remains close to the nominal value, and a quasi-sinusoidal waveform [11]. For this work, we focus on two metrics: harmonic distortion and current unbalance.

Harmonic distortion alters the waveform of current and voltage signals due to harmonic signals at several frequencies, which are multiples of the fundamental one. This alteration is mainly generated by nonlinear devices and can deteriorate electrical components while hindering the electrical grid's performance. There are some methods to attenuate the levels of this harmonic distortion, but they are often impractical and challenging to implement [12]. The metric associated with this phenomenon is the Total Harmonic Distortion (THD) [13],

$$\text{THD}_S = \frac{1}{S_1}\sqrt{\sum_{k=1}^{N} S_{2k+1}^2}, \forall\, k = 1, \ldots, N, \tag{1}$$

where $S$ is the signal of interest. Plus, $S_1$ is the signal at the fundamental frequency and $S_{2k+1}$ is the signal at harmonics of interest. At the low-voltage distribution level, the allowed limit for both, current and voltage, THD is 5%.

Current (and voltage) unbalance appears when the levels of the electrical system differ in magnitude and phase w.r.t. their nominal values. This is usually due to unbalanced loads connected to the electrical grid. As a result, the performance of the network and its components is hindered, which also affects end-users. One way of analyzing such a phenomenon is through the symmetrical components method [14]. Equation 2 presents the Current Unbalanced Factor (CUF),

$$\text{CUF} = \frac{|I_{\text{seq}(-)}|}{|I_{\text{seq}(+)}|} \times 100\,\%, \tag{2}$$

where $I_{\text{seq}(-)}$ and $I_{\text{seq}(+)}$ are the negative and positive sequence components of the current signal. The CUF is measured at the PCC between the MG and the distribution network and it should remain below 5% [11].

### B. Controllers

Conventional controllers, such as Proportional-Integral (PI) or Proportional-Integral-Derivative (PID), are widespread because of their straightforward implementation and efficient structure [15]. Nonetheless, they are sensitive to external variations (perturbations) and hard to tune when dealing with nonlinear systems. Literature offers different control techniques to tackle such a situation. The chief objective of such techniques is to achieve good performance when faced with perturbations while ensuring system stability. Among the most popular approaches, one finds H infinity control [16], Sliding Mode Control (SMC) [17], and the Linear Quadratic Regulator (LQR) [18], which are known as robust controllers.

In the first approach, controller design is stated as an optimization problem. Although, it is difficult to identify a suitable cost function that considers all available control specifications, such as settling time, overshoot, or energy consumption [19]. The second approach, SMC, can be interpreted as a special case of a hybrid dynamic control system since this system flows through a continuous space state and also moves in discrete control modes [20]. However, the resulting control action can provoke vibrations, energy losses, and other issues in applications involving commutation sequences. In contrast, the LQR algorithm provides an optimal control action through a couple of tuning parameters represented by $\boldsymbol{Q}$ and $\boldsymbol{R}$. The LQR algorithm also has the property of improving the dynamics of a system, allowing it to operate under a low-cost scheme. So, it is possible to improve classical controllers by incorporating these LQR features, as shown in Fig. 1.

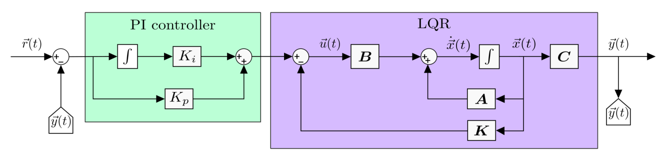


Fig. 1: Hybrid control scheme including a classical Proportional-Integral (PI) controller and a Linear Quadratic Regulator (LQR) approach.

From our perspective, a hybrid controller is a transfer element of a closed-loop control system that seeks to improve the operational features of conventional controllers. Such an improvement is achieved via robust controllers, and the literature contains many examples. One of them was proposed by Kumar and Jerome, where they tuned the PID gains through the poles placement method while using the LQR algorithm for tracking the trajectory of a magnetic levitation system [21]. Their main idea was to design the PID parameters dependent on the natural frequency, damping ratio, and LQR matrices.

Another application worth mentioning was developed by Kim *et al*. [22]. There, the authors used the LQR-PI controller as a compensation mechanism to improve the operational stability of a wind turbine. These works hint at the idea that a hybrid controller is a suitable approach for improving upon conventional controllers. However, such a methodology presents an issue related to the arbitrary assignment of its parameters, especially in the $\boldsymbol{Q}$ and $\boldsymbol{R}$ matrices. With this in mind, Das *et al*. employed an approach similar to the one from [21], but they used a genetic algorithm to select suitable parameters for the LQR [23]. Moreover, these authors presented a fractional-order fitness function that combined the Integral Time Squared Error and the Integral-Squared Controller Output.

### C. Sequence-based Selection Hyper-heuristics

A hyper-heuristic can be defined as a high-level automated search methodology that explores a search space of solvers and not the solution itself [24]. This means it seeks to propose a method that solves the problem, *i.e.*, a hyper-heuristic solves problems indirectly. A typical hyper-heuristic framework includes a high-level solver (*i.e.*, the hyper-heuristic) and a set of low-level solvers (*e.g.*, the heuristics).

Hyper-heuristics have been traditionally sorted into two classes: those that select existing heuristics and those that generate new ones [25]. Moreover, such heuristics can be constructive or perturbative, which leads to four classical groups. Nonetheless, hyper-heuristics is a broad subject, so it is difficult to provide a unified classification of all approaches. Hence, the classical grouping constantly evolves and nowadays covers diverse perspectives [24].

For this work, we are interested in a subgroup of selection hyper-heuristics that may be perceived as a niche and straightforward application. But, it paves the road for more complex models, such as those based on rules [26], [27]. Since we tackle a complex real-life application, we are confident that essential data can be provided for future research through sequence-based selection hyper-heuristics. Our idea is to develop a model that directly provides actions for taking when solving a particular problem instance.

As an example, consider Fig. 2. Here, we have a simple Hyper-Heuristic (HH) model given by a sequence with three elements. Each of these elements represents the ID of a low-level solver, and HH begins anew with each problem instance. So, the first decision (step) when solving any given problem instance will always be carried out based on heuristic $h_4$. Then, heuristic $h_2$ will be used, and the third decision will be made with heuristic $h_3$. Since most problem instances will probably require more than three decisions, one must define a way to reuse the sequence. That is, we must define a looping scheme. Do note that such a scheme affects some of the decisions, as indicated in the figure. In this case, decisions four and six change depending upon the selected looping scheme. Also, these schemes are only exemplary.

Albeit simple, this kind of model has been used in several works. This includes those from Kheiri *et al.*, which deal with the Nurse Rostering Problem [28], [29] and the Inventory Routing Problem [30]. Other examples include the work from Ahmed *et al.* about the Urban Transit Route Design Problem [31], as well as the one from Yates *et al.* about the effect of heuristic subsequences [32], the one from Sánchez *et al.* about the Balanced Partition Problem [33], and most recently, the one from Rodríguez *et al.* about the Traveling Thief Problem [34]. Even if though at a lower extent, one also finds sequence-based hyper-heuristics applied to automatic algorithm design [35]. We present the specifics of using this model with the electrical grid in the following section.

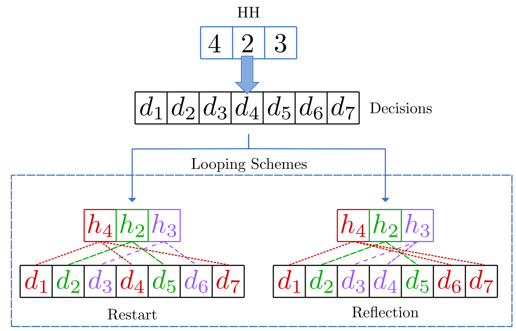


Fig. 2: An illustrative example of a sequence-based selection hyper-heuristic model with three elements, tackling a problem instance with seven decisions through two looping schemes. Note that decisions four and six change depending upon the selected looping scheme.

## III. Proposed Approach

In this work, our goal is to analyze the feasibility of using a sequence-based hyper-heuristic model for mixing controlling schemes. We consider this model over more complex ones (such as rule-based hyper-heuristics), since this a first attempt at using hyper-heuristics within this application. We selected an electrical system comprised of the electrical grid and a microgrid, as a testbed. Moreover, we measured performance based on two quality metrics: harmonic content and current unbalance reduction.

Let us begin by analyzing the hyper-heuristic model and how it operates. Such a model is given by a straightforward sequence of controllers, akin to the one we showed in Fig. 2. However, instead of low-level heuristics, we use controllers that have been previously tuned with a metaheuristic.

Each ID targets a different controller, which operates for a given time (see Section IV). In this way, hyper-heuristic HH1 $= [1, 2, 1]$ actually provides a control scheme that begins using controller C1, then moves on to controller C2, and finally returns to C1. In doing so, HH1 may perform better than C1 or C2. Also, notice that this model is not limited to a given length or pool of controllers. Instead, one may escalate it arbitrarily. So, one could have HH2 $= [4, 2, 3, 2, 1, 4]$, which will swap through four different controllers in a six-step sequence. Besides, such a sequence can be looped, so one does not require long sequences. Notwithstanding, we omit the looping scheme since the sequence covers the whole simulation time. We opt for this simplification as a first approach at the hybrid controller problem.

As we just mentioned, each controller must be applied for a given time. Hence, we require not only the sequence of actions but also a set of time values. Consider the general model shown in Fig. 3. The blank space represents that no control action is being applied, as it is customary in control-related applications. At time $t_0$, the hyper-heuristic begins to act by applying the controller indicated in its first step ($A_1$). Then, at time $t_1$, the signal is transferred to the controller indicated in the second step ($A_2$). This process continues until the sequence

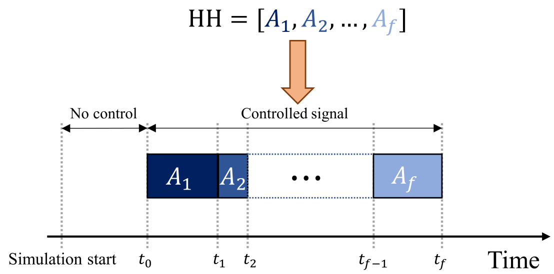


Fig. 3: Overview of the proposed hyper-heuristic model. Action $A_k$, $\forall k = 1, \ldots, f$, is a controller (repetitions allowed), which runs from time $t_{k-1}$ to $t_k$.

ends with $A_f$. After this point, the sequence may be reused based on a looping scheme, or the last controller may be used indefinitely. This decision would depend upon the simulation requirements and the time required to reach the steady state.

Since this work is exploratory, we analyze if simple combinations of specialized controllers lead to an improved performance. To this end, we considered two different architectures: C1 and C2. The former fuses a PI controller with an LQR approach. The latter integrates a resonant controller with the LQR approach, which we generate directly from the PI controller [36]. Hence, C1 and C2 share the same parameters. Despite this, they differ in performance.

Since random parameters may lead to poor performance, we selected previously trained controllers from the literature [37]. Such training is powered by a metaheuristic and targets the problem of minimizing (3),

$$J(\vec{k}, \boldsymbol{Q}, \boldsymbol{R}) = w_1 \left|(MO_{\text{shoot}} - O_{\text{shoot}}(\vec{k}, \boldsymbol{Q}, \boldsymbol{R}))\right| + w_2 \left|\frac{(MT_s - T_s(\vec{k}, \boldsymbol{Q}, \boldsymbol{R}))}{T_s(\vec{k}, \boldsymbol{Q}, \boldsymbol{R})}\right|, \quad (3)$$

where $w_1, w_2 \in [0, 1]$ are values that permit prioritizing the controller parameters. Moreover, $MO_{\text{shoot}}$ and $MT_s$ are the maximum overshoot and settling time values, respectively. Plus, $O_{\text{shoot}}(\vec{k}, \boldsymbol{Q}, \boldsymbol{R})$ and $T_s(\vec{k}, \boldsymbol{Q}, \boldsymbol{R})$ are the current values of the control response, which relate to the settling time and overshot, respectively. Additionally, $\vec{k} = (K_p, K_i)^\intercal$ are the proportional and integral gains of the controller, while $\boldsymbol{Q}$ is the state matrix penalization and $\boldsymbol{R}$ stands for the controller speed. For this work, we extract the values for $O_{\text{shoot}}$ and $T_s$ from a simulation of the response that the controller exhibits to a step input. The resulting controllers exhibit a settling time of 0.5245 ms and an overshoot of 4.4643%. They are represented by $K_p = 0.27084$, $K_i = 4289.9480$, $\text{diag}(\boldsymbol{Q}) = (1.7042, 8644.6, 7.4115)^\intercal$, and $\boldsymbol{R} = 0.0518$.

## IV. Methodology

In this work, we propose using a hyper-heuristic model for creating a mixed controller with better performance than its standalone components. To validate this idea, we lay out the electrical problem shown in Fig. 4, which includes the MG, the electrical grid, and a set of loads. Upon this set of loads, we define 13 different scenarios, which we summarize in Table I[1]. Such scenarios cover different combinations of loads and power quality events.

TABLE I: Experimental scenarios for this work. CCS: Controlled Current Source. CUF: Current Unbalance Factor.

| ID | Name | Description | CCS per phase [A] | CUF [%] |
|---|---|---|---|---|
| 1 | E1NLB | Nonlinear and balanced load | 20, 20, 20 | 0 |
| 2 | E2NLB | | 40, 40, 40 | 0 |
| 3 | E3NLB | | 30, 30, 30 | 0 |
| 4 | E1LU | Linear and unbalanced load | 0, 0, 0 | 40 |
| 5 | E2LU | | 0, 0, 0 | 45 |
| 6 | E3LU | | 0, 0, 0 | 50 |
| 7 | E1NLU | Nonlinear and unbalanced load | 20, 20, 20 | 40 |
| 8 | E2NLU | | 30, 30, 30 | 45 |
| 9 | E3NLU | | 40, 40, 40 | 50 |
| 10 | E4NLU | | 20, 40, 60 | 0 |
| 11 | E5NLU | | 50, 50, 20 | 0 |
| 12 | E6NLU | | 35, 40, 45 | 0 |
| 13 | E7NLU | | 20, 40, 60 | 40 |

We do not consider scenarios with linear and balanced loads since they do not represent a problem for the electrical grid. Moreover, we analyze two performance metrics. The first one is the ability of the controller to reduce the level of harmonic distortion, which appears when considering nonlinear loads. The second one is the ability to diminish the Current Unbalance Factor (CUF), mainly due to external factors. It is worth noting that some current unbalance appears when each phase has a different current value (*i.e.*, in scenarios 10–12), but this value is usually negligible.

We defined four handcrafted sequence-based models for combining the base controllers (Fig. 5). Each colored bar represents the usage of a particular controller for a given time frame. Hence, the base controllers (C1 and C2) stand as single bars. Then, we provided two straightforward models that combine C1 and C2 in opposing ways. Finally, we expand sequences to three steps, thus alternating between C1 and C2. In doing so, we sought to detect if there is a benefit from mixing controllers as one would mix solvers for combinatorial problems. We used an earlier starting time for the most extended sequences since we needed to accommodate more controller changes, and we wanted to preserve the total simulation time within 0.15 seconds. So, Fig. 5 indicates relevant time values in the abscissa for each controller. In any case, note that this approach requires no looping scheme since the sequence covers the whole simulation time.

### A. Nonlinear and Balanced Loads

As a first approach, we studied the effect of considering nonlinear loads within the system whenever the electrical grid behaves appropriately. This means that we disregarded external current unbalance due to grid failures. It also means that the current required by the load (as a whole) is the same for all phases. Although this may seem like an oversimplification, we do it for two reasons. First, ideally, the electrical grid should

[1] Data available upon request.

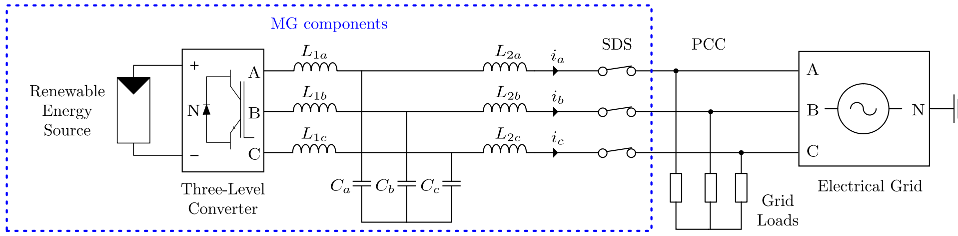


Fig. 4: Testing scenario assumed for this work. $C$ and $L$ are capacitors and inductors, respectively. A, B, and C are the three phases of the system. SDS: Static Disconnect Switch. PCC: Point of Common Coupling.

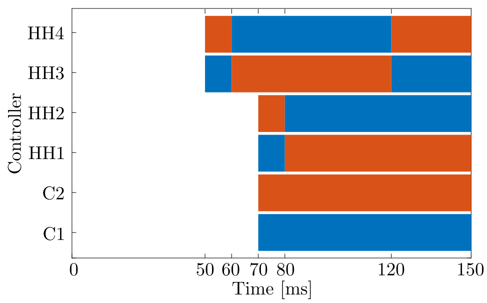


Fig. 5: Controller schemes proposed for this work. Hyper-Heuristics HH1–HH4 are given by a mixture of two base controllers, C1 and C2. Refer to Fig. 3 for more details.

perform properly (no failures and stable current output), so it is crucial to analyze the level of harmonics generated by the loads. Second, these scenarios provide a baseline for analyzing further data. To avoid overextending our testing at this point, we only consider three different conditions, which differ by the level of the current request. Hence, we analyzed the response when the loads demand 20 A, 30 A, and 40 A, respectively.

### B. Linear and Unbalanced Loads

We studied the opposite scenario as a second approach, *i.e.*, linear loads but with an external current due to a power quality event. However, bear in mind that we are not interested in simulating the effect of particular power quality events. Instead, we wanted to analyze the consequences of such events and how to mitigate them. To this end, we considered three relatively high current unbalance levels: 40%, 45%, and 50%. Do note that we did not include small values since it is akin to considering the simple scenario of linear loads with no unbalance. Plus, we disregarded higher values as they represent improbable events in real-life situations.

### C. Nonlinear and Unbalanced Loads

Finally, we analyzed some more complex scenarios. We started by considering both of the conditions mentioned above simultaneously. Hence, we assumed nonlinear loads that require the same current per phase but, at the same time, consider power quality events. Also, we considered increasing scenarios. So, we began with loads requesting 20 A per phase with power quality events that generate 40% of unbalance. Then, we implemented an intermediate scenario with 30 A per phase and 45% of unbalance, and finalized with a scenario of 40 A per phase and an external unbalance of 50%.

Afterward, we analyzed the effect of nonlinear loads with different currents per phase that summed 120 A. We started by providing three scenarios with different current values and no power quality events. Finally, we wrapped up our experimentation with a scenario with different current requirements per phase while simultaneously experiencing a power quality event that induces a 40% of current unbalance.

## V. Results

We now present the most relevant data associated with our work. For clarity, we preserve the structure from Section IV.

### A. Nonlinear and Balanced Loads

Let us begin by analyzing a simple set of scenarios. As we mentioned previously, such experiments only consider the effect due to the nonlinearity of the loads, with no power quality events whatsoever. Table II reveals an interesting pattern. For starters, one of the base controllers (C2) always provides the worst approach, albeit it reduces over 37% of the average harmonic distortion. Moreover, all sequence-based hyper-heuristics outperform such controllers in all scenarios, indicating that a hyper-heuristic approach may be feasible for this application. Additionally, hyper-heuristics with more elements seem to be more favorable since one of them always represented the best choice. It is noteworthy that although HH4 performed best for two of the instances, it ended up tied with HH3 in average performance. Besides, both rendered 5.5% and 0.7% more harmonic distortion reduction than the worst and best standalone controllers, respectively.

TABLE II: Percentage of harmonic distortion reduction achieved over scenarios with nonlinear and balanced loads. Hyper-heuristics HH1–HH4 are described in Fig. 5. Red and green values mean the worst and best per row.

| ID | Name | C1 | C2 | HH1 | HH2 | HH3 | HH4 |
|---|---|---|---|---|---|---|---|
| 1 | **E1NLB** | 41.72 | **36.71** | 41.37 | 41.64 | **42.28** | 41.48 |
| 2 | **E2NLB** | 44.02 | **39.45** | 44.31 | 44.16 | 44.96 | **45.30** |
| 3 | **E3NLB** | 41.61 | **36.80** | 41.95 | 41.91 | 42.20 | **42.66** |
| | **Average** | 42.45 | **37.65** | 42.54 | 42.57 | **43.15** | **43.15** |
| | **Ranking** | 5.00 | **6.00** | 4.00 | 3.00 | **1.50** | **1.50** |

### B. Linear and Unbalanced Loads

In contrast to the previous experiments, let us now observe some scenarios where it is only necessary to analyze the reduction of the electrical current unbalance. The reason is that scenarios E1LU–E3LU consider linear loads, which generate no harmonics. Table III shows the resulting data. Opposed to the previous experiments, this time, controller C2 always offers the best solutions (instead of the worst ones). In fact, this controller is so good that it mitigates virtually all current unbalance (99.93%). Even so, HH4 yields a similar response (99.91%). This is remarkable since HH4 uses controller C1 during 60% of the experiment, and C1 performs almost as severely as the worst choice (88.17% and 88.16%, respectively). More importantly, such a worst choice is given by a hyper-heuristic (HH2). This means that albeit hyper-heuristics can improve performance, they may also hamper it if not appropriately defined. Hence, it is important to refine their model for each application. This idea is reinforced by the fact that a simpler hyper-heuristic, such as HH1, offered almost 4% more unbalance reduction than a more complex one like HH3.

TABLE III: Percentage of current unbalance reduction achieved over scenarios with linear and unbalanced loads. Hyper-heuristics HH1–HH4 are described in Fig. 5. Red and green values mean the worst and best per row.

| ID | Name | C1 | C2 | HH1 | HH2 | HH3 | HH4 |
|---|---|---|---|---|---|---|---|
| 4 | **E1LU** | **88.15** | **99.92** | 99.24 | 88.18 | 95.20 | 99.90 |
| 5 | **E2LU** | 88.18 | **99.93** | 99.70 | **88.15** | 95.20 | 99.91 |
| 6 | **E3LU** | 88.18 | **99.94** | 99.71 | **88.16** | 95.22 | 99.92 |
| | **Average** | 88.17 | **99.93** | 99.55 | **88.16** | 95.21 | 99.91 |
| | **Ranking** | 5.00 | **1.00** | 3.00 | **6.00** | 4.00 | 2.00 |

### C. Nonlinear and Unbalanced Loads

As a final approach, we study the scenarios that target both issues and so we must analyze both performance metrics. First, we analyze harmonic distortion (Table IV). Once again, controller C2 performs worst in all scenarios. This is akin to the first test (*cf.* Table II). Hence, C2 works poorly when reducing harmonic distortion. Even so, it mitigates over 40% of the harmonics (on average), which is no small feat. Still, the best hyper-heuristic (HH4) outperforms this metric by 6.31% while also standing as the best overall controller.

Moreover, it is noteworthy that HH4 wins in six of the seven scenarios, with controller C1 being the only one who beats it in the E7NLU scenario. Despite this, HH4 exhibits an average harmonic reduction 0.65% higher than C1. Hence, it is evident that combining controllers is a feasible approach. Although, it also becomes clear that proper combinations are required. This can be seen in the performance achieved by the other hyper-heuristics (HH1–HH3). For all of them, the average performance was lower than for C1, representing poor sequences. Even so, HH2 outperforms C1 in some scenarios (such as E2NLU and E3NLU).

TABLE IV: Percentage of harmonic distortion reduction achieved over scenarios with nonlinear and unbalanced loads. Hyper-heuristics HH1–HH4 are described in Fig. 5. Red and green values mean the worst and best per row.

| ID | Name | C1 | C2 | HH1 | HH2 | HH3 | HH4 |
|---|---|---|---|---|---|---|---|
| 7 | **E1NLU** | 42.91 | **36.63** | 41.59 | 41.06 | 42.42 | **43.48** |
| 8 | **E2NLU** | 44.96 | **38.59** | 44.39 | 45.07 | 40.06 | **46.46** |
| 9 | **E3NLU** | 48.65 | **41.88** | 48.45 | 48.93 | 46.84 | **49.13** |
| 10 | **E4NLU** | 49.84 | **44.75** | 50.01 | 49.93 | 50.31 | **50.51** |
| 11 | **E5NLU** | 47.75 | **43.29** | 47.83 | 47.57 | 47.86 | **48.35** |
| 12 | **E6NLU** | 45.82 | **40.13** | 46.08 | 45.73 | 45.98 | **46.56** |
| 13 | **E7NLU** | **51.54** | **46.57** | 50.14 | 51.20 | 49.99 | 51.48 |
| | **Average** | 47.35 | **41.69** | 46.93 | 47.07 | 46.21 | **48.00** |
| | **Ranking** | 2.00 | **6.00** | 4.00 | 3.00 | 5.00 | **1.00** |

Let us now move on to the other metric (reduction of current unbalance), which we show in Table V. The first thing worth highlighting is that scenarios E4NLU–E6NLU provide no data. The reason is that such scenarios consider no power quality event. Thus, they exhibit a 0% of external current unbalance (*cf.* Table I). Moreover, the current that each load requires per phase differs. Although this can generate an additional current unbalance by itself, our experiments revealed that it was so small that it could be disregarded.

TABLE V: Percentage of current unbalance reduction achieved over scenarios with nonlinear and unbalanced loads. Hyper-heuristics HH1–HH4 are described in Fig. 5. Red and green values mean the worst and best per row. Dashed values correspond to scenarios with negligible values.

| ID | Name | C1 | C2 | HH1 | HH2 | HH3 | HH4 |
|---|---|---|---|---|---|---|---|
| 7 | **E1NLU** | **88.15** | 99.92 | 99.67 | 88.22 | 95.30 | **99.97** |
| 8 | **E2NLU** | **88.24** | 99.92 | 99.71 | **88.24** | 95.37 | **99.93** |
| 9 | **E3NLU** | 88.28 | 99.92 | 99.70 | **88.27** | 95.46 | **99.94** |
| 10 | **E4NLU** | – | – | – | – | – | – |
| 11 | **E5NLU** | – | – | – | – | – | – |
| 12 | **E6NLU** | – | – | – | – | – | – |
| 13 | **E7NLU** | **88.80** | 99.91 | 99.25 | **88.80** | 94.70 | **99.92** |
| | **Average** | **88.37** | 99.92 | 99.58 | 88.38 | 95.21 | **99.94** |
| | **Ranking** | **6.00** | 2.00 | 3.00 | 5.00 | 4.00 | **1.00** |

Another insight from Table V is that data for the worst controller is more spread out. This time, C1 and HH2 stand as the worst choice on one scenario each, and they tie on the remaining two scenarios. In fact, they offer virtually the same performance (as with linear, unbalanced loads, *cf.* Table III). The best controller is evident since HH4 won in all scenarios. We want to remark that although the average performance of HH4 and C2 only differ by a small amount (0.02%), HH4 beats C2 by 0.05% in scenario E1NLU. This means that there is indeed some benefit from combining C2 with C1.

Let us select some scenarios for detailing the change in harmonic content and current unbalance. Fig. 6 shows the magnitude of the original harmonic content and the best and worst controllers for E4NLU. It is evident that controllers perform better for lower frequency harmonics. Despite this, HH4 is noteworthy, as it performs properly for one more harmonic. Additionally, when both controllers fail (*i.e.*, for the 11$^{th}$ harmonic), the damage done by HH4 remains small.

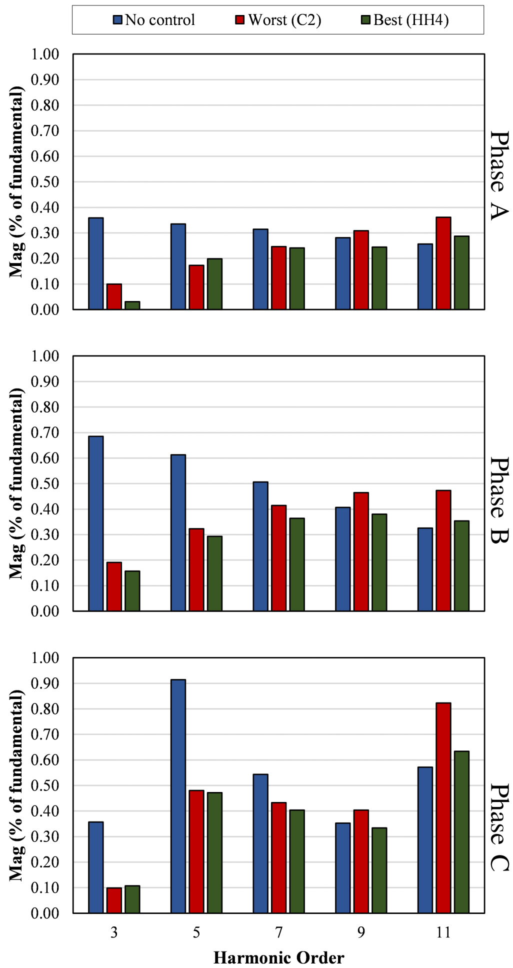


Fig. 6: Harmonic content of the original signal and the one generated when using the best (HH4) and worst (C2) approaches per phase and solving scenario E4NLU.

Similarly, Fig. 7 displays the evolution of the CUF throughout the simulation on scenario E1NLU. Once again, we display the best and worst controllers (HH4 and C1, respectively). Although the CUF sits below the allowed threshold (5%) in both cases, the one yielded by HH4 is several times smaller. This implies an electrical signal with better quality and, thus, a more robust electrical grid. Finally, we compare the performance of HH4 against that of a controller tuned by a metaheuristic while targeting harmonic content reduction and current unbalance mitigation, in scenario E7NLU. The controller tuned directly offers 1.19% more harmonic reduction but 12.17% less unbalance reduction. Hence, hyper-heuristics seem worthwhile for this application.

## VI. Conclusions

This article studied the feasibility of using sequence-based selection hyper-heuristics (HHs) to improve controller performance. To this end, we selected an application related to

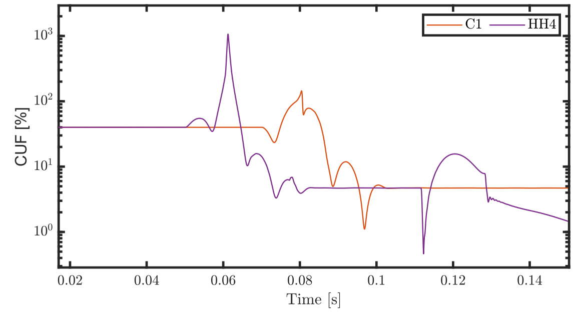


Fig. 7: Evolution of the Current Unbalance Factor (CUF) by controllers C1 and HH4 in the E1NLU scenario.

improving energy quality. Since this was exploratory work, we limited our testing to 13 scenarios and HHs with two and three elements. However, we analyzed two performance metrics: harmonic distortion reduction and current unbalance factor mitigation. We considered two base controllers (C1 and C2), which were previously tuned through a genetic algorithm [37].

Our data revealed exciting trends. We noticed that C1 worked best when dealing with harmonics, while C2 did so for current unbalance. Also, at least one of the proposed HHs outperformed the best-specialized controller in several experiments by up to 0.70%. Although this may seem small, it may have an crucial effect in real life, since a poorer energy quality increases power losses and heat generation and lowers the performance of electric devices. The remaining controller was outperformed by up to 11.74%. The main exception was for scenarios E1LU–E3LU, where the best HH (HH4) performed virtually equal to C2 (*i.e.*, 99.91% and 99.93%, respectively). The other exception was scenario E7NLU, where HH4 and C1 achieved 51.48% and 51.54%, respectively. In summary, combining traditional controllers with a different architecture through a hyper-heuristic approach leads to even better results and more robust controllers. For our data, this was reflected in HH4 performing best for 70% of the tests.

Although conservative in scope, our experiments hint that larger sequence-based hyper-heuristics may perform better. Even so, this must be carefully analyzed since it is not always true. For example, in scenarios E1LU–E3LU a simple model (HH1) yielded better performance than a larger one (HH3). A preliminary analysis revealed that the best hyper-heuristics were those that started with C1 and allowed the system to reach the start of the steady state.

We are confident that incorporating hyper-heuristics into control-related applications is a feasible and highly recommended alternative. Of course, more testing is required to validate the extent of this insight. Hence, several paths lie ahead. For starters, testing more varied scenarios regarding different loading conditions and more base controllers is paramount. One may also pursue a more exhaustive hyper-heuristic generation, *e.g.*, a training phase based on metaheuristics. Finally, it is worth exploring different hyper-heuristic models, such as those based on rules. In this sense, one would require a set of features related to the problem, which may prove challenging to identify. Still, using HHs may help improve controller performance for this application and future ones.

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