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A Peak Demand Control Algorithm for Multiple Controllable Loads in Industrial Processes

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ABSTRACT The peak demand or demand limit control is an important part of the actions that industries carry out to optimize their energy consumption and reduce the costs related to their electricity billing. Prioritized switching of multiple appliances is often needed in order to reduce demand and energy consumption during peak load periods. The present article describes a peak load limitation algorithm that estimates the optimal disconnection time for one or more electrical loads before the electric demand exceeds a preset limit. This algorithm uses parametric and variable load factors that vary dynamically depending on what loads are present at a given time. For its validation, a *software-in-the-loop* testbed was designed and developed, in which multiple electrical loads were simulated via LabVIEW software and connected to a PLC controller emulated through CODESYS software. In this environment, several test configurations were executed and evaluated to study the influence of variables such as the nominal power and the disconnection priority of loads in the algorithm output. The results showed that the control algorithm is effective for peak load limitation, the maximum demand value reached during simulations tests did not exceed the preset demand limit at any time interval. The performance of the algorithm could be improved when prioritizing the shutdown of loads with higher nominal power or when increasing the anticipation time used for the disconnection of the controllable loads.

INDEX TERMS Demand response, demand side management, load levelling, peak shaving, smart grid.

I. INTRODUCTION

One of the biggest operating costs for any company or industry is the cost of electric power. This cost is calculated based on several aspects related not only to energy consumption or efficiency but also to how and when the energy is used. One of these billable aspects is the electricity demand, which according to the Federal Commission for Electricity of Mexico is defined as ''the maximum coincidence of electric loads in a given interval of time'', and it can represent up to 30% of the value of electricity billing [1].

According to the National Commission for Energy Saving of Mexico, the control of electricity demand can be defined as ''the action of interrupting certain electrical loads during specific intervals of time in order to reduce energy consumption'' [2]. In this case, an energy behaviour in which there are occasional demand peaks must be observed, so that it is feasible to implement a peak demand control strategy and obtain economic savings [2]. For an effective demand control, it is necessary to know which are the electrical loads that are generating the peak demand, as well as to determine the duration and the time in which the peak demand occur. Subsequently, it is necessary to determine the specific demand of each load, as well as to establish its priority to decide which load can be turned off or deferred during the critical time period.

There are several approaches or methods to implement electrical demand control at an industrial level. In general, they can be classified among those who carry out the control in a deferred way, this is, the demand is planned before the start of the production tasks; these methods are defined as *offline* in [3]. In these methods, the ''control'' is based on

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the analysis and projection of future energy consumption values in order to control the demand in advance (prior to production) and thus prevent the demand value from increasing excessively. These types of methods are mainly based on anticipated production planning through optimization algorithms. The most popular techniques for this purpose are linear programming in its different forms: integer [4]; binary [5], [6]; mixed [7]–[9]; dynamic [10]–[13]. There are also other techniques such as: particle swarm optimization [14], [15]; evolutionary algorithms [16]; game theory [17]; stochastic programming [18]; or the approach in which a battery energy storage system (BESS) is coupled with the main energy source to optimize the peak demand as in [19], [20].

There are also those methods in which the control is performed reactively by turning off the loads based on the real-time demand value which are defined as *online* in [3]. These methods are based on the direct feedback of the demand value to make decisions based on dynamic control rules. In this category, it is possible to distinguish between two main approaches: *dynamic production planning* and *demand limit control*. The first one is a *time-based* approach that works through a dynamic planning of the electricity demand with respect to time (e.g., a day ahead planning) like in [21]–[24]. The second one is an *event-based* technique in which loads are shedded or shifted with the trigger of an event, e.g., that the electric demand value reaches a prescribed maximum limit. This type of control is usually performed by means of demand forecasting algorithms that normally require the modelling of the electrical loads as in [25], [26]; or the historical demand data as in [27]. This could be an inconvenient when implementing this type of algorithm on field because of the specific knowledge or extra time needed to model the loads. In [28], the authors addressed this issue by proposing a parametric algorithm that instead of modelling the load, it utilizes basic electrical parameters such as the load factor for computing the precise disconnection time before the maximum demand value is reached; however, such algorithm only works for single load scenarios, wherewith its applicability is very limited, as most industrial processes are composed of multiple electrical loads.

Taking into consideration the limitations of previous works, a parametric peak demand control algorithm for multiple load scenarios is proposed here. The novelty of this algorithm is not only that it does not requires the modelling of the electrical loads, but also, that it can handle more than one-single controllable load, with which its field of application can be more extensive. This algorithm was simulated and evaluated utilizing the CODESYS software which is based on the IEC 61131-3, and LabVIEW software. In this case, the CODESYS software executes the algorithm and communicates through Modbus protocol with the LabVIEW environment where loads and their parameters are simulated. Six different simulation tests scenarios were executed to evaluate its efficacy and performance. The test scenarios considered three controllable loads (loads that can be turned on and off by the controller) and two non-controllable loads (loads that cannot be turned off by the controller). The rest of the document is divided as follows: Section II describes some important parameters related to electricity demand, as well as the control algorithm. In section III, the *software-in-the-loop* testbed developed for the evaluation of the algorithm is described in conjunction with the different simulation tests and their parameters. Section IV comments the obtained results. Finally, section V presents conclusions and future work.

II. PEAK DEMAND CONTROL ALGORITHM

This section presents an explanation of how the electrical demand and the load factor are calculated, both concepts used within the control algorithm. At the same time, the control algorithm for one load and the proposed logic to operate multiple controllable loads is described.

A. ELECTRIC DEMAND AND LOAD FACTOR

The peak demand measurement is performed using the so called *sliding window* method, which is the most common method used by the energy suppliers to measure peak demand [25]. Through this method, pulses generated by an energy meter are added in run-time during a 15-minute interval divided in three 5-minute subintervals. The demand of every subinterval is registered and then added to the others, wherewith a demand measurement is obtained for the current 15-minute interval. The subsequent measurements are performed by adding the measurements of the last two subintervals (D_{10-15}, D_{5-10}) of the previous interval, to the value of the current subinterval (D_{0-5}), see Figure 1 and (1). This subinterval shifting is done through a synchronization pulse sent by the energy meter every 5 minutes, by which the end of every subinterval is specified, so a new complete interval can be reset.

$$D_k = D_{(10-15)} + D_{(5-10)} + D_{(0-5)} \tag{1}$$

where D_k is the electrical demand of the current 15-minute interval, D_{10-15} is the electrical demand of the last subinterval from minutes 10 to 15, D_{5-10} is the electrical demand of the last subinterval from minutes 5 to 10, and D_{0-5} is the electrical demand of the current subinterval from minutes 0 to 5.

Ultimately, the peak demand value will be the maximum demand value D_k registered at the end of any 15-minute interval occurring during the billing period (e.g., a month).

Another important parameter for controlling demand is the load factor (LF), which can be calculated for a whole plant or just for a single load. This parameter permits to know the efficiency in the use of the contracted electricity demand. This is calculated by dividing the average power value ($P_{average}$, kW) by the nominal power of the load ($P_{nominal}$, kW), see (2). Another way to calculate it, is by multiplying the average energy consumed ($E_{average}$, kWh) during a certain time interval, times the duration of the period in hours (h_{period}), divide it by the maximum electrical energy value that could have been consumed based on the peak demand value (D_{peak}) recorded

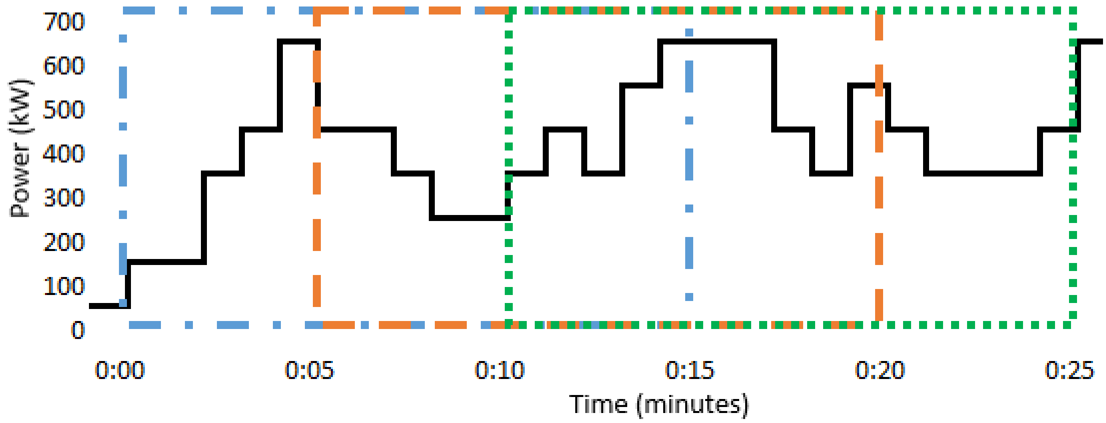

FIGURE 1. Demand measurement showing the sliding windows.

during the same period of time.

$$LF = \frac{P_{average}}{P_{nominal}} = \frac{E_{average} \times h_{period}}{D_{peak}} \quad (2)$$

A high LF value indicates a good use of the contracted electrical demand; while a low LF value would indicate that the contracted demand is not being used efficiently.

B. CONTROL ALGORITHM

The control algorithm presented in this work is an enhancement of the algorithm presented by Martell *et al.* in [28]. The contribution of the present algorithm is sustained in the fact that it adds functionality for the control by considering not one, but multiple loads through a dynamic computation of the multi-load parameters. This is relevant since most industrial processes involve two or more loads, reason why this improvement allows to extend the field of application of the control algorithm, hence outperforming the previous algorithm by adapting it to the needs of a greater and more diverse number of industrial processes.

The algorithm predicts the electrical demand value at the end of the measurement interval (15-minute window) by means of a geometrical projection, to determine the optimal time to disconnect a controllable load thus avoiding the surpass of a preset electrical demand limit. In this case, a controllable load could be any appliance, device, or machine with an intensive energy consumption, that is feasible to be disconnected at any time without compromising the task or batch process related to this load. Some examples of these loads can be electric furnaces, air compressors, pumps, refrigeration systems, fans, lighting, among others.

Figure 2 shows the graph for the accumulated demand value within a last control subinterval (10-15 minutes). It is observed that, before the disconnection time (t_d), the demand value increases at a fairly constant rate (m_T) so that if this trend continued the demand value would exceed the preset demand limit (D_L) before the end of the interval (t_I). However, it can be observed that at time t_d is when the control is exerted and the controllable load is turned off and the trend

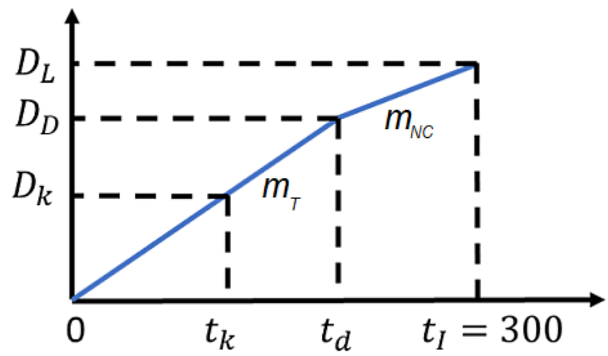

FIGURE 2. Disconnection time calculation.

changes to prevent the demand value from exceeding the D_L limit.

C. SINGLE LOAD CONTROL

The simplest scenario for demand control in an industry is the one in which there is a single controllable load and multiple non-controllable loads. Based on the graph plotted in Figure 2, (3) can be used to estimate the electrical demand value that will be reached at the end of the measurement interval.

$$D_L = D_k + m_T(t_d - t_k) + m_{NC}(t_I - t_d) \quad (3)$$

where D_L is the preset demand limit, D_k is the current demand value, t_d the disconnection time for the controllable load, t_k is the current time in seconds within the subinterval, t_I is the subinterval length in seconds (typically 300), m_T is the sum of the demand rate of change of every load (controllable and non-controllable), and m_{NC} is the sum of the demand rate of change of every non-controllable load. From the previous equation it is possible to calculate the exact time t_d when the load should be disconnected to avoid over-passing the preset demand limit, see (4). This t_d parameter will be used to generate the control signal of the controllable load: once the current time t_k reaches the value of the disconnection time t_d, then the controllable load will be shutted off.

$$t_d = \frac{D_L - D_k - m_{NC} t_I + m_T t_k}{m_T - m_{NC}} \tag{4}$$

The previous equation for the disconnection time can also be expressed by replacing the denominator with a demand rate of change parameter of the controllable load m_C, see (5).

$$t_d = \frac{D_L - D_k - m_{NC} t_I + m_T t_k}{m_C} \tag{5}$$

The demand rate of change parameters m_T, m_{NC} and m_C can be obtained either using the nominal power (in case of deterministic loads), or the average power, by means of the load factor LF (in case of loads with a lot of demand variation), see (6)-(8).

$$\frac{P_T \times LF_T}{t_t} < m_T < \frac{P_T}{t_t} \tag{6}$$

$$\frac{P_{NC} \times LF_{NC}}{t_t} < m_{NC} < \frac{P_{NC}}{t_t} \tag{7}$$

$$\frac{P_C \times LF_C}{t_t} < m_C < \frac{P_C}{t_t} \tag{8}$$

where P_T, P_{NC} and P_C are the nominal power value of the total, non-controllable and controllable loads respectively; LF_T, LF_{NC} and LF_C are the load factor values of the total, non-controllable and controllable loads respectively, while t_t is the time length of the complete interval control (typically 900 seconds). According to [28] this parametric approach is the principal advantage of the algorithm as it can improve the accuracy of the disconnection time computation depending on which of both parameters, nominal or average power, is used. When using the nominal power, the disconnection time can be shortened (over anticipated); while the use of the average power may imply exceeding the demand limit, due to the variation in the behavior of the loads. For this work, the second approach was selected, due to the almost deterministic behavior of the simulated loads used for testing the algorithm.

D. MULTIPLE LOAD CONTROL

To increase functionality and applicability to the single-load algorithm, a simple but effective approach is proposed here for scenarios in which there is the possibility to disconnect several electric loads without affecting the overall production process (examples of these loads were described previously).

Figure 3 shows a disconnection sequence for multiple controllable loads in which the calculations of the disconnection times for each controllable load (t_1 to t_n) can be done considering the sum of the demand rate of change of every controllable load (m_1 to m_n) that is turned on at each t_i time, see (9), (10), (11) and (12).

$$\begin{aligned} D_L &= D_k + m_1(t_1 - t_k) + m_2(t_2 - t_1) \\ &\quad + m_3(t_3 - t_2) + \cdots m_n(t_n - t_{(n-1)}) \\ &\quad + m_{NC}(t_t - t_n), \quad for\ t_k < t_1 \end{aligned} \tag{9}$$

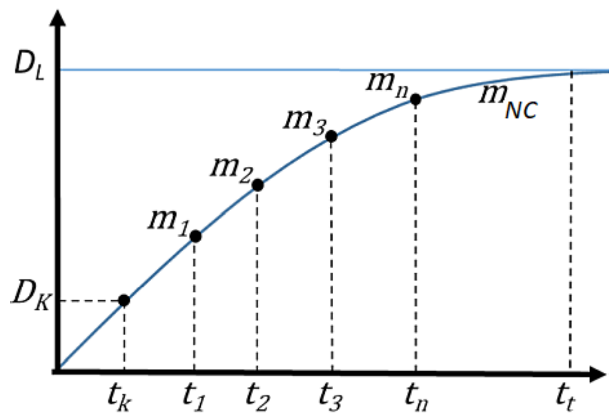

FIGURE 3. Demand control for multiple controllable loads.

After the first load is disconnected:

$$\begin{aligned} D_L &= D_k + m_2(t_2 - t_k) + m_3(t_3 - t_2) \\ &\quad + \cdots m_n(t_n - t_{(n-1)}) + m_{NC}(t_t - t_n), \\ &\quad for\ t_1 \le t_k < t_2 \end{aligned} \tag{10}$$

After the first two loads are disconnected:

$$\begin{aligned} D_L &= D_k + m_3(t_3 - t_k) + \cdots m_n(t_n - t_{(n-1)}) \\ &\quad + m_{NC}(t_t - t_n), \quad for\ t_2 \le t_k < t_3 \end{aligned} \tag{11}$$

Finally, when there is one load to be disconnected:

$$\begin{aligned} D_L &= D_k + \cdots m_n(t_n - t_k) + m_{NC}(t_t - t_n), \\ &\quad for\ t_{(n-1)} \le t_k < t_n \end{aligned} \tag{12}$$

If all the intervals between the disconnection times are set to be equal (t_c), this is:

$$t_c = t_2 - t_1 = t_3 - t_2 = \cdots = t_n - t_{(n-1)} \tag{13}$$

Then (9) can be expressed as in (14) and further simplified into (15):

$$D_L = D_k + m_1 t_c + m_2 t_c + \cdots m_n t_c + m_{NC}(t_t - t_n) \tag{14}$$

$$D_L = D_k + (m_1 + m_2 + \cdots m_n) t_c + m_{NC}(t_t - t_n) \tag{15}$$

Therefore, the demand limit equation for multiple controllable loads can be expressed as in (16) where m_{C_i} is the demand rate of change of the i-th controllable load:

$$D_L = D_k + \sum_{i=1}^{i=n} m_{C_i} t_c + m_{NC}(t_t - t_n) \tag{16}$$

The previous equations for a demand control of multiple controllable loads can be incorporated in an algorithm just by computing the demand rate of change of the total controllable load, and this can be done by adding up all the demand rates of change of each controllable load for the corresponding interval. See (17), where m_{C_T} is the demand rate of change of the total controllable load.

$$m_{C_T} = \sum_{i=1}^{i=n} m_{C_i} \tag{17}$$

If all controllable loads are in operation simultaneously, and if the control signal is sent to them to be all disconnected at the same time, then t_d can be calculated as in (18).

$$t_d = \frac{D_L - D_k - m_{NC} t_t + m_T t_k}{m_{C_T}} \tag{18}$$

If prioritizing the disconnection of certain loads with respect to others is needed, then it is possible to set an anticipation time t_{a_i} in seconds, to establish different disconnection times t_{d_i} for every different controllable loads, see (19). Considering that a measurement interval typically contains 900 seconds divided in 3 subintervals of 300 seconds each, then, an anticipation time t_{a_i} between 30 to 200 seconds (10 to 66 percent of a subinterval time) could be defined for the disconnection of each controllable load.

$$t_{d_i} = t_d - t_{a_i} \tag{19}$$

Once the current time t_k equals the disconnection time t_{d_i} of a specific controllable load, this load should be disconnected and remain off until the start of the new control subinterval. At the same time, the demand rate of change parameters of the current total load m_{T_k}, and the current total controllable loads m_{C_k} must be recalculated, considering only the currently connected (turned on) loads. Then, the new disconnection time calculation t_d should be made using (20) to avoid over anticipation and achieve more precision about the best time for disconnecting the next load.

$$t_d = \frac{D_L - D_k - m_{NC} t_t + m_{T_k} t_k}{m_{C_k}} \tag{20}$$

It is precisely this dynamic real-time computation of m_{T_k} and m_{C_k}, the principal advantage of the algorithm, as it permits the algorithm to be more precise about when to disconnect the loads and thus improving energy utilization of the total system.

It is important to emphasize that the main feature of the control algorithm is the computation of the exact time (t_{d_i}) when each controllable load should be disconnected so the current demand value (D_k) does not overpass the preset demand limit (D_L) by the end of the control interval. This calculation is based on the current demand rate of change of both, the controllable loads (m_{C_k}), and no controllable loads (m_{NC}) that are *on* at instant k. Finally, if the current time value (t_k) reaches the disconnection time value (t_{d_i}) for any controllable load, then, such load should be disconnected and remains like that until the end of the control interval when the current demand value (D_k) is recalculated using the *sliding window* method, and the current time value (t_k) is reset to zero. The flowchart in Figure 4 describes this sequence in a simplified manner assuming n controllable loads.

III. ALGORITHM TESTING AND EVALUATION

The objective of this stage was to evaluate the performance and efficacy of the algorithm when using different configuration criteria by means of a *Software-in-the-loop* testbed.

A. SOFTWARE-IN-THE-LOOP TESTBED

Part of the contribution of the present work was the design and development of a *Software-in-the-loop* (SIL) testbed architecture, specially conceived for the simulation, evaluation, and tuning of demand control applications. The testbed environment is divided into 2 main parts: 1) the load simulation environment, programmed in the LabVIEW software and 2) the controller application which is emulated through CODESYS software. Both executed at the same time on the same computer and communicated via Modbus TCP/IP protocol for data exchange.

The SIL testbed was developed with the following purposes:

- To provide a test environment in which it is possible to fine-tune the demand control algorithms prior to their actual implementation.
- To analyse the effectiveness of demand control algorithms when implemented by means of a programmable logic controller.
- To serve as the initial step for the creation of a distributed *hardware-in-the-loop* environment that serves the same purposes described above but with a hardware approach in mind.

In the SIL testbed, both, control hardware (controller) and plant hardware (electrical loads) are simulated by means of a software running on the same Windows 7 personal computer. Figure 5 shows a scheme of the testbed architecture.

The controller is emulated using CODESYS, which is a programming environment based on the IEC-61131-3 standard for PLC devices. The software permits to emulate a programmable logic controller with several of its functions. The control algorithm was programmed using two different programming languages. For the case of the load control signals, it was programmed in Ladder Language (LAD), which is a graphic language, while the equations of the control algorithm were programmed using the Structured Text Language (ST) which is a text language, both languages are included in the IEC-61131-3 standard. Data communication to and from the load simulator is carried out using a Modbus TCP/IP Slave communication module configured within the emulated PLC. Through this module, the emulated PLC receives 2 digital signals from the load simulator: the demand meter pulse and the synchronization pulse with which the total demand calculation is performed. For each demand meter pulse received, the controller adds 1 kilowatt-hour to the demand calculation of the current subinterval $D_{(0-5)}$. Ultimately with each synchronization pulse received (every 5 minutes), the shifting of the demand value for the 3 subintervals is executed using equations (21), (22) and (23).

$$D_{10-15} = D_{5-10} \tag{21}$$

$$D_{5-10} = D_{0-5} \tag{22}$$

$$D_{0-5} = 0 \tag{23}$$

The configuration of the emulated PLC includes some digital outputs by which it sends the control signals to the

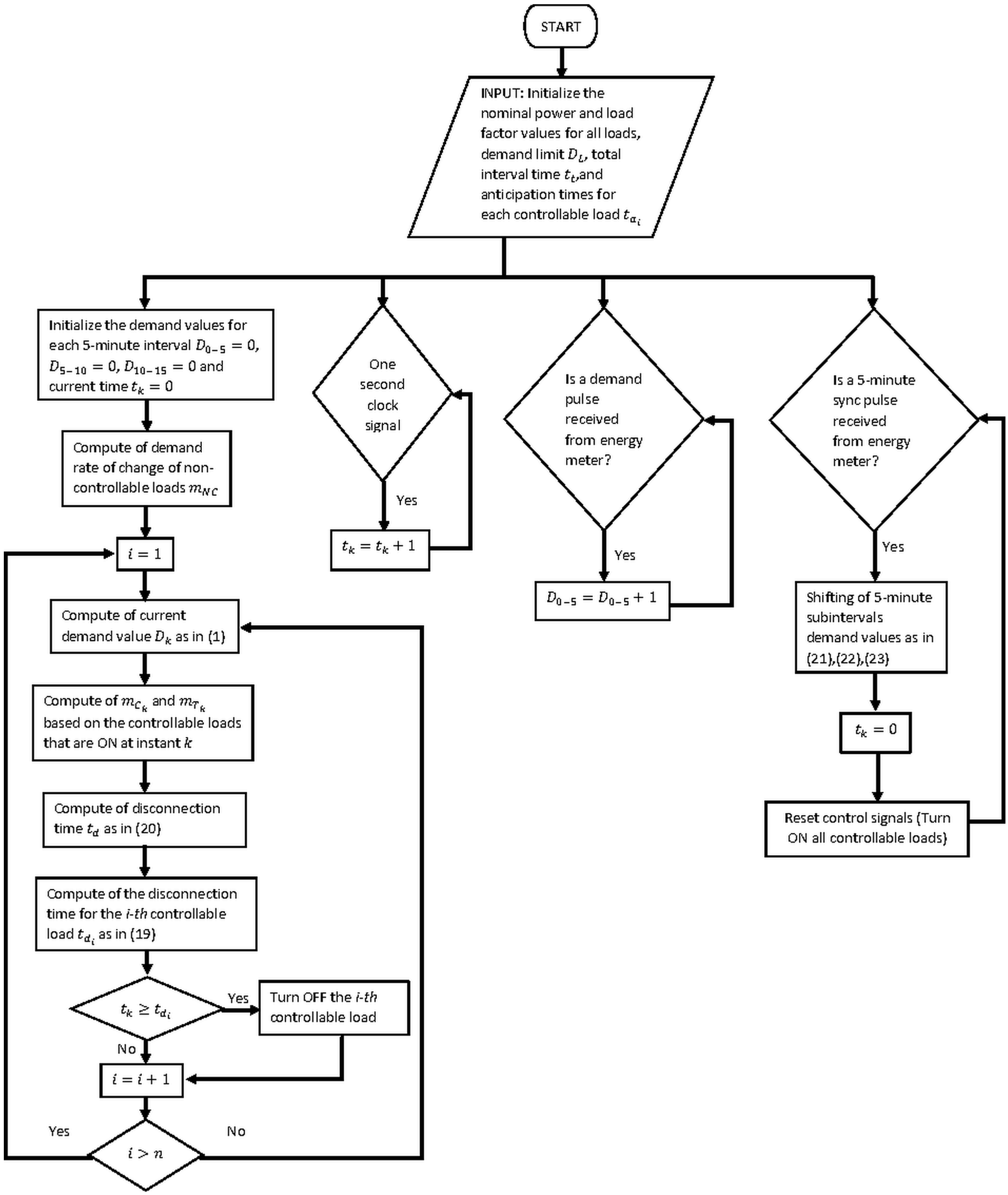

FIGURE 4. **Flowchart of the demand control algorithm.**

load simulator in LabVIEW. Utilizing these signals, the controllable loads are switched off when the algorithm detects that the demand limit could be exceeded, that is, when t_d is equal to or greater than t_k. Each of these control signals is linked to a specific controllable load, so that if this signal is high, the electrical load related to it must be turned off and maintained so until the end of the 300 second subinterval to avoid exceeding the demand limit.

Regarding the software developed in LabVIEW, it fulfills two main functions: the simulation of loads and the simulation of the energy meter. In the former, it allows the simulation of six controllable loads and four non-controllable loads. For each of these loads it is possible to modify its state (on-off), its nominal power (kW), its load factor (percentage), as well as a parameter called deviation (percentage), see Figure 6. This last parameter establishes the maximum and minimum

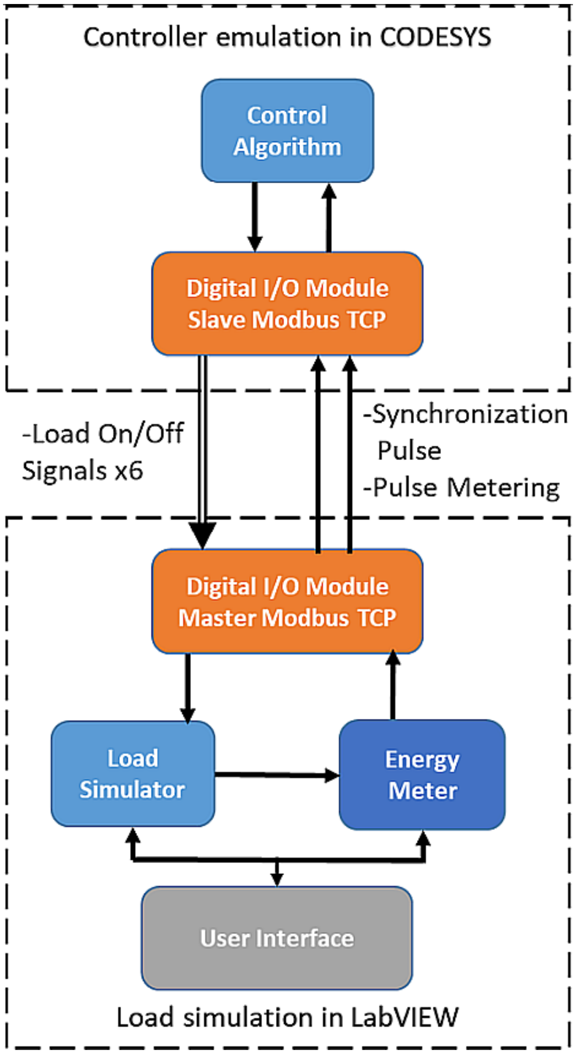

FIGURE 5. Software-in-the-loop testbed architecture.

deviation of the instantaneous power value for that specific load at a given time, see (24).

$$P_{k_i} = P_{n_i} \times LF_i \pm P_{n_i} \times LF_i \times dev_i \times RAND(1) \quad (24)$$

where P_{k_i} is the value of instantaneous power in kW for the i-th load, P_{n_i} is the value in kW of nominal power of the i-th load, LF_i is the load factor value of the i-th load, dev_i is the percentage deviation value for the i-th load and RAND (1) a function that can generate random values between zero and 1. In this way, the instantaneous power value of all loads is constantly changing with a frequency that is also possible to configure in the simulator interface itself. It is important to mention that this parameter allows adding some realism to the simulation since, in most cases, the instantaneous power value P_{k_i} of an industrial electric load will not behave so deterministically. Another function of this software is to simulate a pulse energy meter, which is connected to the control plant (load simulator) and is sending the energy consumption data to the demand controller programmed in CODESYS. This energy meter module receives the instantaneous total

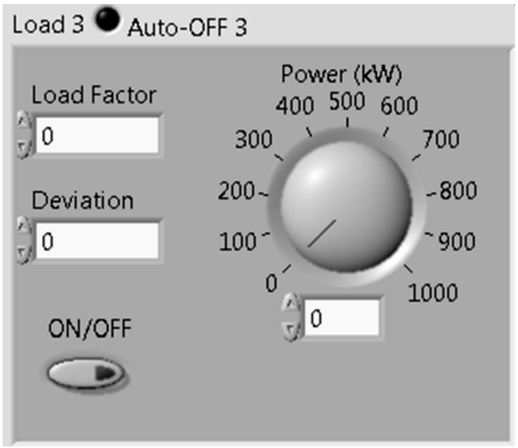

FIGURE 6. Load control interface in LabVIEW.

power value p_{t_i} of the load simulator and integrates the total energy value E_T second by second, see (25). For every kilowatt-hour recorded, the energy meter sends a pulse to the simulated controller in CODESYS. Also, a synchronization pulse is sent to indicate the end of a subinterval every 5 minutes. These pulses are sent via Modbus TCP / IP to the controller and allow it to perform the demand calculations described above.

$$E_T = \sum_{i=1}^{i=n} \frac{p_{t_i}}{3600} \quad (25)$$

Also, the graphical interface of the software in LabVIEW allows the monitoring and control of the parameters for the 10 simulated loads, as well as the visualization of the instantaneous power of each load (kW), the total instantaneous power (kW), the total energy consumption (kWh), and the total demand value (kWh). Additionally, it is possible to modify the refresh rate with which the random instantaneous power values of each load are recalculated. A graphical indicator was included within the LabVIEW environment interface for monitoring the system behavior. Figure 7 shows an example of the behavior of the system. It shows the demand limit set at 3000 kW, the instantaneous power value, as well as the real-time demand value. At the same time, it can be observed that the demand value does not exceed the established limit at any time, but also, that the instantaneous power value behaves at times in a staggered way due to the shutdown of the controllable loads executed by the controller.

B. SIMULATION TESTS

The aim of the testing phase was to evaluate the efficacy and performance of the algorithm when different configuration parameters are considered. For this purpose, 6 different simulation tests were established and divided into 2 categories depending on which parameter was to be configured. In a first category (A), the parameter that was set up in every simulation was the disconnection priority of the loads with respect to its nominal power. The goal was to determine the impact of prioritizing the shutdown of loads with

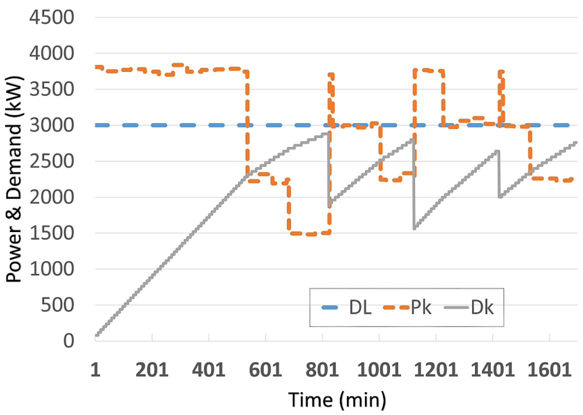

FIGURE 7. Simulated power (P_k) and demand (D_k) trend graphic.

higher or lower nominal power on the system efficacy and performance. In this case, the disconnection time between all simulations was the same, while the nominal power of all non-controllable loads was modified from simulation to simulation. See Table 1.

In the first simulation (1A), the order of priority is such that the load with the lowest nominal power would be the one that is first disconnected and so on. In the case of the second simulation (2A), the order of disconnection priority has no relation with the nominal power of the 3 controllable loads, as these 3 loads were set to an identical nominal power (1000 kW). In the third simulation (3A), the order of disconnection priority was such that, the load with a higher nominal power value would be the one that was disconnected first and so on. In a second category (B), another 3 simulation tests were established in which the configured parameter in every simulation was the anticipation time used to disconnect the load. The objective was to determine the impact of increasing or decreasing the anticipation time on the system efficacy and performance. In this case, all controllable loads had the same nominal power and same load factor value; only the disconnection times were modified through each simulation. See Table 2.

In the case of the simulation 1B, the disconnection times were t_{d-50}, t_{d-25} and t_d for controllable loads 1, 2, 3 respectively, which indicates that the controllable load 1 would be the one to be first disconnected. In the simulation 2B, the disconnection times were t_{d-100}, t_{d-50} and t_d. Finally, in the simulation 3B, the disconnection times were t_{d-200}, t_{d-100} and t_d. It can be noted that the disconnection times were incremented linearly from simulation to simulation.

It should be noted that, for all 6 simulations, the same total nominal power of non-controllable loads (2000 kW) and same total nominal power of controllable loads (3000 kW) were set, giving a total nominal power for the system of 3750 kW. In the same way, the demand limit value was set at 3000 kW for all simulation tests.

IV. RESULTS

Each of the 6 simulation tests described above were executed and evaluated through the SIL testbed. Both, the load simulation program in LabVIEW and the demand control algorithm in CODESYS were fed with the values applicable to each parameter for each simulation, to observe the performance of the algorithm under different conditions. For each test, the system was executed for an indefinite period of time. The test execution stopped only when counting 100 *5-minute* subintervals in which the system had to perform a control action to avoid exceeding the preset demand limit. In each of these subintervals, the maximum demand value reached in every subinterval was recorded, as well as the status (on/off) of each of the 3 controllable loads at the end of the subinterval. Then the maximum, minimum, average demand values, and the sum of the shutdown loads within the 100 subintervals were computed for each of the 6 simulation tests.

A. EFFICACY OF THE ALGORITHM

The efficacy of the algorithm was validated by means of the maximum demand value reached during every test which cannot exceed the preset demand limit. This efficacy was evaluated to answer two questions: how will prioritizing the shutdown of loads with higher or lower nominal power affect efficacy of the algorithm? (category A tests); and how increasing or decreasing the anticipation of the disconnection time affect the efficacy of the algorithm? (category B tests).

Figure 8 shows the maximum, minimum and average demand value reached during every category A test. It can be seen that the maximum demand value reached in the 3 tests was almost identical (around 2920 kW), so the preset demand limit (3000 kW) was not exceeded. It is also possible to observe that test 3A presented the lowest minimum demand value, which was predictable, given that the order of disconnection of the loads in this test prioritized the shutdown of loads with a higher nominal power value, which is also reflected in a slightly lower average demand value compared to the rest of tests. Besides, it can be seen that prioritizing the shutdown of loads with a higher nominal power has no significant effect on the reached maximum and average power demand values, that is on the efficacy of the algorithm.

As for the category B tests, Figure 9 shows the behavior of the system for each of the 3 tests in terms of maximum, minimum and average demand value. It is observed that, the reached maximum demand value remained below the preset 3000 kW limit and did not show a noticeable variation among the 3 tests, demonstrating that the increase or decrease in the anticipation of the disconnection time value had no significant effect on the efficacy of the algorithm. However, it is possible to appreciate that there was a decrement from test 1B to test 3B in the minimum and average demand values.

B. PERFORMANCE OF THE ALGORITHM

The algorithm performance was evaluated through the occurrence frequency of the shutdown of 1, 2 or 3 controllable loads during every control subinterval. Having less shutdown loads by the algorithm would be better because the process utilizing those loads will not result overly affected; additionally, less

TABLE 1. **Parameters for category A simulation tests.**

Simulation	Loads	Nominal Power (kW)	Load Factor (%)	Randomness (%)	Disconnection priority	Disconnection Time (s)
1-A	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	500	75	5	1	$t_d - 100$
	Controllable 2	1000	75	5	2	$t_d - 50$
	Controllable 3	1500	75	5	3	t_d
2-A	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	1000	75	5	1	$t_d - 100$
	Controllable 2	1000	75	5	2	$t_d - 50$
	Controllable 3	1000	75	5	3	t_d
3-A	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	1500	75	5	1	$t_d - 100$
	Controllable 2	1000	75	5	2	$t_d - 50$
	Controllable 3	500	75	5	3	t_d

TABLE 2. **Parameters for category B simulation tests.**

Simulation	Loads	Nominal Power (kW)	Load Factor (%)	Randomness (%)	Disconnection priority	Disconnection Time (s)
1-B	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	1000	75	5	1	$t_d - 50$
	Controllable 2	1000	75	5	2	$t_d - 25$
	Controllable 3	1000	75	5	3	t_d
2-B	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	1000	75	5	1	$t_d - 100$
	Controllable 2	1000	75	5	2	$t_d - 50$
	Controllable 3	1000	75	5	3	t_d
3-B	Non-Controllable 1	1000	70	5	NA	NA
	Non-Controllable 2	1000	80	5	NA	NA
	Controllable 1	1000	75	5	1	$t_d - 200$
	Controllable 2	1000	75	5	2	$t_d - 100$
	Controllable 3	1000	75	5	3	t_d

shutdown loads will lead to a better use of the contracted electrical demand. Based on this, having a higher percentage of subintervals with less shutdown loads would be preferable in terms of performance. Therefore, performance can also be evaluated with the two equivalent questions: How will prioritizing the shutdown of loads with higher or lower nominal power affect the performance of the algorithm? (category A tests); and How will increasing or decreasing the anticipation of the disconnection time affect the performance of the algorithm? (category B tests). Figure 10 shows the results for category A tests. It is possible to observe that for tests 1A and 2A, the occurrence of subintervals in which the algorithm resorted to the shutdown of all 3 controllable loads was superior to 80% and 60% of the total number of revised subintervals, respectively. While in the case of test 3A, this occurrence corresponded only to less than 5%. This demonstrates that prioritizing the shutdown of loads with a higher nominal power value will result in a smaller number of controllable loads disconnected within the controlled subintervals. It can also be observed that the occurrence of subintervals in which the algorithm resorted to the shutdown of at least 2 of the 3 controllable loads was superior to 90% of the control subintervals for all tests.

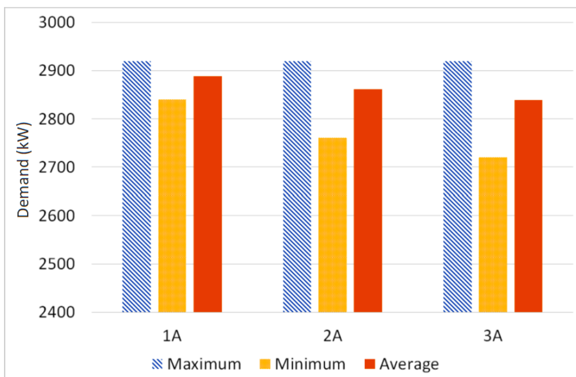

FIGURE 8. **Results for category A simulations.**

As for category B tests, Figure 11 shows that for tests 1B and 2B the occurrence of subintervals in which the control algorithm resorted to the shutdown of the 3 controllable loads was more than 75% and 50% of the control subintervals respectively; while in the case of simulation 3B, this occurrence corresponded only to less than 5%. This shows that increasing the anticipation time for disconnecting loads will lead to less controllable loads disconnected within the

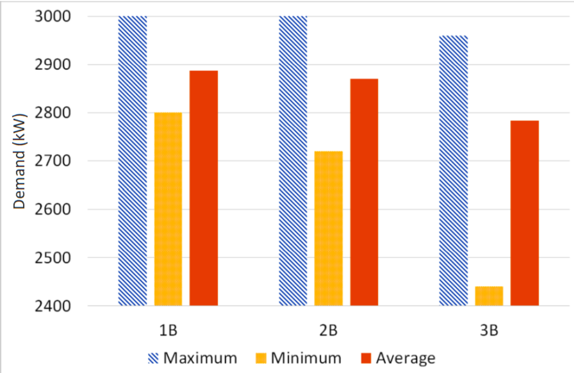

FIGURE 9. Results for category B simulations.

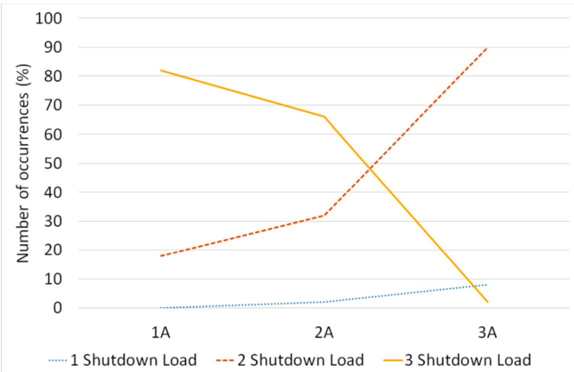

FIGURE 10. Number of shutdown loads for category A simulations (% of occurrence).

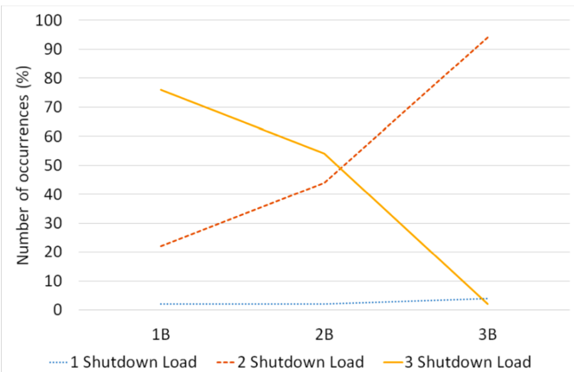

FIGURE 11. Number of shutdown loads for category B simulations (% of occurrence).

controlled subintervals. It can also be observed that the occurrence of subintervals in which the algorithm resorted to the shutdown of at least 2 of the 3 controllable loads was superior to 95% in all category B tests.

V. CONCLUSION

This research work presents the generalization of a demand control algorithm for multiple loads. Its novelty consists in that, unlike other demand control algorithms, the one proposed here is based on the estimation of a disconnection time for each of the multiple controllable loads by means of the real-time computation of equations with multi-load parameters, without the need of load modelling, thus facilitating its practical implementation. This parametric feature allows the control algorithm to be more precise about when to shutdown the controllable loads, thus improving energy utilization. The multi-load functionality is relevant since most industrial processes are composed of multiple electrical loads. In this sense, the presented control algorithm can be adapted to a greater number and diverse type of industries.

An additional contribution was the design and development of a *Software-in-the-loop* testbed architecture, specifically conceived for the simulation, evaluation, and tuning of demand control applications. In these sense, it can serve as a generic testing platform for any given demand control algorithm in the future.

The implemented testbed served to study the efficacy and performance of the presented algorithm when configuring and implementing it with different scenarios. Here, the results showed that the efficacy of the algorithm during all tests was satisfactory, given that the maximum demand value reached during these tests did not exceed the preset demand limit at any time interval. Results also showed that this efficacy was not affected when prioritizing the shutdown of the loads with lower or higher nominal power nor when increasing or decreasing the anticipation time used for the disconnection of the controllable loads. Moreover, it was demonstrated that the performance of the algorithm could be improved when prioritizing the shutdown of the loads with higher nominal power or when increasing the anticipation time used for the disconnection of the controllable loads.

The proposed algorithm can be implemented in any industrial environment in which the work-in-process is not to be affected when equipment is shutdown, for example: process where thermal inertia (electric furnaces, refrigeration systems) or fluid backup (air compressors or pumps with coupled tanks) can prevent the process to be interrupted.

Regarding future work, it is of interest to perform the simulation and evaluation of this control algorithm by means of a *Hardware-in-the-loop* environment where the control algorithm and the plant run on independent hardware systems. Additionally, it would be interesting to developed this test environment in a distributed and modular way, so that the load control can be executed remotely.

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