Abstract—This paper proposes an effective method for improving the flexibility of buildings as electrical loads to support the distribution grid operation. The buildings energy consumption is the result of the operation of the energy systems that are there to support its operation. As the buildings main purpose is to provide a safe environment, a great part of the buildings energy demand come from the operation of the comfort systems. Furthermore, the aim is always to use as less electrical energy as possible. In this paper, two conflicting objectives, i.e. maximization of comfort and minimization of energy consumption, are optimized to provide a Pareto optimal solution, taking into account the low voltage network operation. A Weighted Aggregation Approach is used in a combination with Particle Swarm Optimization to find this Pareto optimal. The model is tested on a low voltage distribution test feeder, and different weights are used to tune the flexibility of the building.

Keywords—Particle swarm optimization, comfort management, energy optimization.

I. INTRODUCTION

The Smart Grid (SG) has arisen as the concept to encapsulate the new electricity network targets, to involve customer participation for balancing supply and demand and network relief, and to include the different technologies required for those challenges [1], [2]. It is the result of the changes the electric power system has experienced in the past decades. It indicates a paradigm change from a centralized, unidirectional power flow system, to a decentralized supply with bidirectional power flows. The SG allows customers to become active part of the energy monitoring, generation and dispatch, with the integration of Distributed Energy resources (DER) at the consumer side. Thereby, the integration of the demand side of the power system, e.g. buildings, as smart and flexible loads able to support the grid operation. Among number of smart grid activities, demand side management (DSM), and demand response (DR) programs are two examples of this. The first refers to the long-term and short-term measures designed to influence the consumption pattern in such a way that it will influence the load shape of the utility, i.e. network or distribution operator. Whereas, the latter refers to the mechanisms designed to directly influence the demand of consumers in response to supply conditions, for instance through the use of market prices [3]. In general, they seek to increase energy efficiency and to control the effects of the loads of the grid [4].

Aligned with zero-energy objectives and intelligent building concepts, Building Energy Management Systems (BEMS) aim to increase energy efficiency and integrate DER while reducing energy cost and sustaining occupants comfort. Smart management of the building energy consumption offers a considerable potential for optimizing the electrical energy supply chain. As buildings are responsible for about one-third of the energy consumed in cities [5], their smart, i.e. flexible, behaviour within DSM and/or DR programs can facilitate Smart Grids functionalities to achieve the sustainable energy goals, while improving network and energy market reliability and efficiency. Although buildings differ in functions and structures, in general, their main goal is to provide the occupants with a comfortable environment, i.e. about 50% of the total electrical energy consumed is used for comfort management [6]. The application of advanced optimization methods is required to guarantee a global optimal solution, maximizing the welfare of both, the building users and building manager.

Traditionally, BEMS are classic and centralized control systems based on predictive and adaptive methods [7]. Increasing complexity and uncertainty in the built environment motivates alternative decentralized approach such as multi-agent system (MAS) to facilitate the intelligent control of large buildings [8]. Currently, MAS is also a widely accepted technology for different smart grid applications [9]. This creates an ideal environment for computational intelligence (CI) techniques such as Particle Swarm Optimization (PSO) to improve performance of BEMS [10], [11]. PSO applications have been demonstrated in a wide range, e.g. voltage control, economic dispatch, reliability assessment, generation expansion, state estimation, optimal power flow, and capacity management [12]–[14]. These applications are focussed on the generation, transmission and distribution domains of the energy supply chain, while the application of advanced optimization techniques on the customers side and their benefits in a smart grid environment is still lacking.

The aim of this paper is twofold. First, we propose the application of a multiple objective particle swarm optimization (MOPSO) to increase the buildings flexibility by maximizing both comfort and energy efficiency. Second, we evaluate the effects of the building operation in different optimization modes on the grid. Thus the ability of a building to support the grid operation by adapting its energy demand profile, while ensuring maximum comfort. Conflicting optimization problems are revealed internally within the BEMS but the resolved solution would be beneficial for the whole smart grid. The advantages of the proposed heuristic method will be demonstrated through a case of study of a typical Dutch low voltage test network.
The remaining of this paper is divided into four sections. Section II describes the formulation of both objectives, comfort and energy consumption, and the formulation of the multiple-objective optimization problem. Section III, describes the optimization methodology used for solving the multiple-objective problem. In section IV two cases of study are presented; first, the optimization of energy and comfort of a multi-zone floor; second, the operation of a LV network under the energy demand scenarios defined by the optimization strategy selected. Finally, the conclusions are outlined in section V.

II. PROBLEM FORMULATION

Buildings are complex and large-scale engineering systems determined by its structure, functions, and the required installations. BEMS aims to optimize the buildings operation to satisfy the occupants comfort requirements. Typically, this is done through the control of the Heating, Ventilation, and Air Conditioning (HVAC) systems. Which is normally done by controlling the inlet and outlet flow rates of the supplied fluid, e.g. air, and its temperature. However, these values are usually found in operation (heating or cooling) curves and depend mostly on the outdoor temperature, the number of occupants and type of space. Different standards and codes for building operation have been developed to guarantee the minimum comfort levels. Nonetheless, comfort is subjective and it’s perceived differently by people. It is usually measured using probability of dissatisfaction of people in a given space. Fig. 1 shows a visualization of comfort. It is conceptualized as a function of thermal comfort (i.e. temperature) [15] and extended to air quality (i.e. humidity)1. Both modeled through a Gaussian function representing the degree of satisfaction, with the average comfort value as the mean ($\mu$) and a standard deviation ($\sigma$), defined in equation (2). This guarantees the operation of the system in a range instead of a single value, which is closer to the subjective nature of comfort perception.

A. Comfort Optimization

As stated before, the first optimization problem is the maximization of comfort, which is equivalent to the minimization of discomfort, shown in the next equation:

$$f_1(x) = discomfort = 1 - comfort,$$  \hspace{1cm} (1)

$^1$The carbon dioxide is considered as a constraint of the optimization problem.

with,

$$comfort = \omega \cdot e^{\frac{-(T-\mu T)^2}{2\sigma_T^2}} + (1-\omega) \cdot e^{\frac{-(RH-\mu RH)^2}{2\sigma_RH^2}},$$  \hspace{1cm} (2)

where, $\omega$ is a weight factor, $T$ is the temperature, $\mu_T$ is the mean temperature, $\sigma_T$ the standard deviation for the thermal comfort, $RH$ the relative humidity, $\mu_RH$ the mean humidity, $\sigma_RH$ the standard deviation for air quality comfort.

Thermal comfort, i.e. the change in time of the temperature in a zone, can be modeled applying the energy conservation principle as shown in the next equation:

$$MC_p \frac{dT}{dt} = Q_{in} + Q_{HVAC} + Q_{heater} + Q_{loss},$$  \hspace{1cm} (3)

where, $M$ is mass of the air in the volume, $c_p$ the specific heat capacity of air, $Q_{in}$ represents the internal gains due to the heat generation rate per person$^2$. $Q_{HVAC}$ represents the heat contribution by the HVAC system operation as a function of the volumetric supply air flow rate ($V_s$) [16]. Due to the high costs involved in supplying the head demand only by an air system, i.e. HVAC system, a Heat Pump (HP) is used as the main heating system for this case. Therefore, $Q_{heater}$ represents the heat contribution of the HP used as a function of the water volumetric flow ($V_{s,h}$). Finally, $Q_{loss}$ is used to model the heat losses through the envelope of the zone [17].

The second part in equation (2) is the zone’s relative humidity. From the energy conservation principle, the dynamic model of change of enthalpy in the air is given in the following equation [16]:

$$M \frac{dRH}{dt} = V_s \rho_a (RH_s - RH) + M_c,$$  \hspace{1cm} (4)

where, $V_s$ is the volumetric supply air flow rate, $\rho_a$ the air density, $RH_s$ is the supply air enthalpy, $RH$ is the air enthalpy in the room, i.e. humidity ratio, and $M_c$ is the Moisture load.

As was mentioned, the CO$_2$ concentration levels are treated as a constraint of the system. Similarly to the dynamic model of temperature and humidity, the change in time of the CO$_2$ levels is given by [18]:

$$V_s \frac{d\Phi}{dt} = V_s (\Phi_s - \Phi) + N \Phi_{gen},$$  \hspace{1cm} (5)

where $V$ is the zones air volume, $\Phi$ is the CO$_2$ concentration at time $t$, $\Phi_s$ is the CO$_2$ concentration in the supply air, and $\Phi_{gen}$ is the CO$_2$ production rate per person. The supply air concentration is a function of the supply air flow and the return air flow $V_s$ as shown in next equation.

$$\Phi = \frac{(V_s - V_r) \Phi_{out} + V_r \Phi}{V_s}$$  \hspace{1cm} (6)

B. Energy efficiency optimization

In this work, we consider only the energy consumed by the comfort systems, i.e. the HP for heating purposes and the HVAC for air quality and supplementary heat, as expressed in the following equation:

$$f_2(x) = E_{total} = E_{HVAC} + E_{heater},$$  \hspace{1cm} (7)

$^2$The solar gains are neglected in this work.
The energy consumed by a typical HVAC ($E_{HVAC}$) is function of the supplied air temperature and flow rate. In turn, air temperature and flow rates are functions of the individual systems that conform the HVAC system (see equation (8)). Supply and return fans move the air in and out of the building zone, while the heating and cooling coils are responsible for the air temperature.

$$E_{HVAC} = E_{fan,s} + E_{fan,r} + E_{heating coil} + E_{cooling coil}.$$  \hspace{1cm} (8)

where, $E_{fan,s}$ and $E_{fan,r}$ are the energy consumed by the supply and return fans, which are proportional to the supply ($V_s$) and return ($V_r$) air volumetric flow rate [19]. The energy consumed by the heating coil ($E_{heating coil}$) and the energy consumed by the cooling coil ($E_{cooling coil}$) are a function of the air flow rates (supply and return), the difference in the indoor and outdoor temperatures, and their respective efficiencies. The energy consumed by the heat pump, ($E_{heater}$) is a function of the Coefficient of Performance COP of the machine and the required heat power. The COP of the heat pump is used to describe the ratio between the useful heat produced and the work input.

C. Multiple objective optimization problem

$f_1(\vec{x})$ and $f_2(\vec{x})$ defined in equations (1) and (7), and with equations (3) to (8) the complete optimization problem can be defined as follows:

Minimize

$$f(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}))$$ \hspace{1cm} (9)

Subject to

$$\Phi_{CO_2}(t) \leq \Phi_{max}$$

$$\text{comfort} \geq \text{comfort}_{min},$$ \hspace{1cm} (10)

where, $f_1(\vec{x})$ and $f_2(\vec{x})$ are two conflicting optimization problems; $\Phi_{max}$ is the maximum $CO_2$ levels allowed in the zone; and $\text{comfort}_{min}$ is the minimum comfort level acceptable. This last constraint is used to not allow the comfort satisfaction fall below a defined threshold, so a minimum user’s satisfaction is guarantee at all times.

III. METHODOLOGY

The control parameters of these systems are $V_s, V_r, T_s$ for the HVAC and $V_{sh}, T_f$ for the Heat pump. Where $T_s$ and $T_f$ represent the temperature of the supplied air and water, respectively. For the sake of simplicity, only the flow rates of the supply air, the return air and the water are considered here as the control space. The constraint of the systems is a $CO_2$ maximum concentration of 1000ppm and a minimum level of comfort of 0.661 which corresponds to one standard deviation.

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) has been proven to be an alternative solution to deal with the non-linear and non-stationary systems with noise and uncertainties [12]. PSO is a stochastic-based optimization method that has its roots in artificial life, social psychology and computer science. It uses a population of particles to search over a hyperspace. The particle’s velocities and directions are stochastically adjusted based on the historical data available [12]. In each iteration, the swarm particles update their flying trajectories in order to find new feasible solutions. Every time a best solution is found for each particle $p_i^k$, and a new leader, i.e. the best particle of the swarm, is selected $p_g^k$. This is done until either certain conditions are met or the maximum number of iteration has been reached. The rules of PSO are described in equations (13) to (14). The velocity is updated according to equation (13), and based on this updated velocity, each particle can now update its position according to equation (14).

$$v_i^{k+1} = v_i^k + \phi_1 \text{rand}_1(p_g^k - x_i^k) + \phi_2 \text{rand}_2(p_g^k + x_i^k),$$ \hspace{1cm} (13)

$$x_i^{k+1} = x_i^k + v_i^{k+1},$$ \hspace{1cm} (14)

Here, $v$ is the inertia weight used to enhance the searching process, given by equation (15); $\phi_1$ and $\phi_2$ are two positive constants; $\text{rand}_1$ and $\text{rand}_2$ are two random numbers with uniform distribution in the range [0 1]; $p_g^k$ is the best position of the particle $i$ achieved based on its own experience; $p_i^k$ is
the global best position based on overall swarms experience; and $k$ is the iteration index.

$$u = u_{max} - \frac{u_{max} - u_{min}}{iter_{max}}$$

(15)

The methodology used for the optimization is described in Fig. 3. The PSO algorithm is run in time steps of 15 minutes. Furthermore, the PSO algorithm is modified to allow the update of $p^g_k$ if the constraints of the problem are also met.

![Flow chart of the particle swarm approach](image)

**Fig. 3.** Flow chart of the particle swarm approach

### B. Multiple objective particle swarm optimization

In multi-objective (MO) problems, the objective functions are usually in conflict, thus challenging to find out a single optimal solution. However, a set of solutions which represents the best trade-off and the best compromise can be found instead. These are known as Pareto-optimal solutions. There are several different approaches to solve MO problems [20]. Here the weighted aggregation approach is used. This approach aggregate all the objectives of the problem into a single one through a weighted combination. Thus equation (9) is replaced by:

$$W \cdot discomfort(V_s, T) + (1 - W)\sigma E_{total}(V_s, V_r, T),$$

(16)

By replacing equations (2) and (7) in the previous one, the complete objective function is obtained as:

$$W \left[ 1 - \left( \omega e^{-\frac{(T - T_{ref})^2}{2\sigma_T^2}} \right) + (1 - \omega) e^{-\frac{(RH - RH_{ref})^2}{2\sigma_{RH}^2}} \right]$$

(17)

$$+(1 - W)\sigma \left[ E_{fan,s} + E_{fan,r} + E_{heating} + E_{cooling} + E_{heater} \right],$$

where $W$ is a non-negative weight. The main advantage of this method is that it allows the use of the conventional

**Fig. 4.** Zone’s comfort variation

PSO algorithm. However, it only allows to find one solution, requiring the algorithm to be applied repeatedly to find the desirable number of nondominated solutions. Finally, $\sigma$ is a normalization factor that allows the two objectives to be treated equally.

### IV. CASE STUDIES

#### A. Building Optimization

The optimization is done in 15 minutes intervals. Three optimization (control) scenarios are simulated: A: No PSO; B: PSO with dynamic weight; and C: PSO with constant weight. The first scenario, i.e. normal operation, uses an on-off control of the heat pump and constant operation of the HVAC system to operate the zone. The second scenario uses two weight values, one for no occupancy, i.e. $N = 0$, and one for occupancy, i.e. $N > 0$. The last scenario uses one weight for the entire simulation time.

**Fig. 4.** shows the comfort in the zone over the simulation period. As can be seen, for scenarios B and C, the comfort was improved, 0.63 and 0.85 in average respectively. The average comfort level for the scenario without PSO is 0.58. Although there is not a big difference between scenario A and B, the comfort levels of scenario B during the occupancy period is higher, with the exception of two points. Fig. 5, summarizes the PSO results for a constant weight aggregation, i.e. scenario C, on an hourly basis. Where $V_s$ is the supplied air flow rate, $V_r$ the returned air flow rate and $V_{sh}$ is the supplied water flow rate, all in $m^3/s$.

![Swarm results for a constant weight aggregation](image)

**Fig. 5.** Swarm results for a constant weight aggregation

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3This interval corresponds to the Program Time Unit (PTU) period adopted by the Dutch TSO TenneT, for scheduling and settlement of the electricity market participants. However, it can be extended to different time horizons.
Fig. 6. Zone's power and energy consumption

Fig. 6. shows the power [kW] and the accumulated energy [kWhr] consumption of the zone for the whole day. In this figure, it can be seen that the three scenarios have different energy consumption profiles, which can be used to support the grid operation. Despite the fact that scenario B has the lower energy consumption, it also has lower comfort values, which means that in this scenario comfort is being sacrificed for energy reductions.

Fig. 7 shows the zone's thermal and air quality response. As can be seen in the upper graph of the figure, the temperature is only allowed to drop to undesired levels in scenario B (T with PSO dynamic weight), this is due to the fact that during the time of no occupancy, the weight, i.e. importance of comfort, is reduced significantly in order to obtain higher energy reductions. Furthermore, the concentration constraint is met (middle graph) in all the cases, with lower levels in scenario A. This is due to the constant operation of the HVAC system. Finally, regarding humidity (bottom graph) in all scenarios it was kept around 50% percent, except for scenario A, in which the constant operation of the system resulted in higher reductions.

B. Power system operation support

Based on the system’s power consumption output of the three scenarios (see Fig. 6), the operation of a low voltage (LV) distribution network was tested. Using the PowerFactory software of DiGSilent, a time sweep analysis was made of the LV network shown in Fig. 8. This typical Dutch LV network has 383 customers with 7 feeder of around 500 meters. The cable model used is a 150mm4 conductors PVC sheathed cable, and the transformer is 10kV/0.4kV 630kVA Delta – Yn11. In the figure more details of the characteristics of the LV network are given. The number of loads and length of each feeder is indicated in the boxes at the bottom of the figure.

The load profiles for a typical day are shown in Fig. 9. It is based on measured data at the beginning points of each feeder and distributed equally over the loads of each feeder. 40% of the total feeder load is replaced by the building load to represent the total share of energy consumed by large buildings in cities. Fig. 8 shows the number of buildings connected to each feeder. Each building was connected in different parts of
each feeder as also shown in the figure.

![Fig. 9. Feeders load profiles without buildings](image)

Each building load was defined based on the three scenarios identified in the previous section. As before, scenario D, corresponds to all the buildings with no PSO; scenario E, corresponds to all the buildings with dynamic weight PSO; and scenario F, correspond to all the buildings with constant weight PSO. A time sweep power flow analysis was carried out on a 15 minutes interval.

![Fig. 10. Power losses variations in the LV feeder](image)

Fig. 10 shows the losses fluctuations for one day simulation. With the exception of Scenario E in which comfort is allowed to drop during the periods of time when occupancy is not detected, the building load profile is quite constant over time. With, 60% of the energy demand coming from household loads, the result is that the highest consumption is during the evening times. Scenarios D and F with a similar load pattern, the energy losses are increased over the whole day. Whereas, the scenario E increases them mostly during the day period, resulting in lower energy losses, as it can be seen in the figure.

Fig. 11 shows the voltage variations in the LV feeder over a day. Although, the voltage limits are not violated (i.e. +/-5%), it can be appreciated that in both cases, the optimization of the building energy consumption results in an increase of the voltage levels. Furthermore, The voltage variations were also studied for each feeder, showing feeder 5 as the most critical one, due to the higher number of loads and length of the feeder. Fig. 12 to 14 show the feeder voltage profile, for each scenario, as a function of time and the distance of the feeder. In this feeder, three building loads are connected at 152, 359 and 421 meters from the LV bus bar (see Fig. 8).

![Fig. 11. Voltage magnitude variations in the LV feeder](image)

![Fig. 12. Voltage variation over the feeder with the scenario (a)](image)

![Fig. 13. Voltage variation over the feeder with the scenario (b)](image)

Fig. 12 shows the voltage profile for the scenario D, i.e. normal operation. This figure shows a decrease of the voltage as the distance increases and a deeper drop during the evening time, when the households load is maximum. However, it also shows a more steady behavior in time.

Fig. 13 shows the voltage profile for the scenario E, i.e. PSO with dynamic weight. It shows less decrease of the voltage over the distance, compared to the results from scenario D and F. However it shows lower voltage levels during the day time, with a deep at around 15hr.

Fig. 14 shows the voltage profile for the scenario F, i.e. PSO with constant weight. It shows a major decrease of the voltage over the distance, compared to the results from scenario E, but less when compared against scenario D. It also shows a higher voltage and more steady during the day voltage time, with a deep, also, at around 15hr.

From these figures, it can be observed, that there is not a clear winner scenario. Each scenario behaves better at some
In this paper, an optimization strategy was presented for building energy management system, which optimizes both, energy and comfort in a zone. Two approaches were used, constant weight MOPSO and dynamic weight MOPSO. This two approaches were compared against a scenario without optimization. From the results obtained, it can be concluded that the PSO algorithm offers a great potential for energy savings and comfort optimization. Different energy profiles were obtained, while the minimum comfort level was kept.

Furthermore, the results were tested in a low voltage grid network, and the positive effects of energy efficiency in the built environment were evaluated, while keeping the minimum comfort levels. In this work, the weight value, i.e. dynamic weight scenario, was changed based on the detection of occupancy. However, if the network needs would be included here, the optimization strategy can be tuned to benefit also the grid. The building could switch from multiple operation modes according to the status of the grid and the comfort levels. In this paper it is shown, that by sacrificing comfort, i.e. scenario F, higher energy reduction is obtained which result in a better grid operation. However, for some cases, higher energy consumption is required. In these cases the building could opt for a different optimization strategy, e.g. scenario E or D, and in that way, providing support for the grid operation. Although, more energy consumption might not be a desired option due to the financial implications, under a dynamic price electricity scheme, the building can benefit from storing energy in itself, i.e. thermal mass and storage systems, in such periods.

V. Conclusions

In this paper, an optimization strategy was presented for building energy management system, which optimizes both, energy and comfort in a zone. Two approaches were used, constant weight MOPSO and dynamic weight MOPSO. This two approaches were compared against a scenario without optimization. From the results obtained, it can be concluded that the PSO algorithm offers a great potential for energy savings and comfort optimization. Different energy profiles were obtained, while the minimum comfort level was kept.

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