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Dynamic fuzzy logic elevator group control system for energy optimization

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High-rise buildings with a considerable number of elevators represent a major logistic problem concerning saving space and time due to economic reasons. For this reason, complex Elevator Group Control Systems are developed in order to manage the elevators properly. Furthermore, the subject of energy is acquiring more and more industrial relevance every day as far as sustainable development is concerned.

In this paper, the first entirely dynamic Fuzzy Logic Elevator Group Control System to dispatch landing calls so as to minimize energy consumption, especially during interfloor traffic, is proposed. The fuzzy logic design described here constitutes not only an innovative solution that outperforms usual dispatchers but also an easy, cheap, feasible and reliable solution, which is possible to be implemented in real industry controllers.

Keywords: Elevator, Energy Optimization, Fuzzy Logic, Sustainable Development, Vertical Transportation.

1991 Mathematics Subject Classification: 22E46, 53C35, 57S20

1. Introduction

An Elevator Group Control System (EGCS) [1] manages multiple elevators in a building in order to efficiently transport passengers. Performance of EGCS is measured through different criteria parameters like average waiting time, percentage of waits longer than 60 seconds and power consumption.

Usually, an EGCS assumes the following statements during its performance: (1) each landing call is answered by only one elevator, (2) maximum number of passengers being transported in the cabin is bound by its capacity, (3) elevators can stop at a floor only if there is a landing call or a car call on that floor, (4) car calls are sequentially served in accordance with the elevator trip direction, (5) an elevator carrying passengers cannot change its trip direction. Therefore, most common controllers designed to manage groups of about two or three elevators in not very high buildings implement dispatch rules based on an IF-ELSE logical command set. In this sense, the computer-aided design suite Lift Simulation and Design (LSD), implemented at the elevator systems: the algorithm named THV collects most of the above mentioned common rules in duplex or triplex systems and assigns the landing call to the nearest elevator in the correct trip direction. Other modern examples of different rules of logic have been proposed in [2] or [3] where a general set of rules is defined and particular norms prevail over them for specific moments.

However, a snapshot elevator dispatching problem has been shown to be NP-Hard. In fact, in a building with n number of elevators where k floors need elevators, the number of solutions to be considered is n^k. Therefore, the complexity of the problem becomes huge in modern skyscrapers and other high-rise buildings in general. In this sense, once a certain grade of optimization is reached, it is impossible to satisfy all criteria at the same time. The EGCS is, therefore, designed to satisfy each one to a certain level depending on the tenant's preferences. However, each criterion optimization is also limited not only to inverse correlations of other criteria but also to physical constraints regarding the inherent to the system effects and elements such as acceleration/deceleration [4] or doors [5].

In this paper, a novel fuzzy logic elevator group control system that minimizes power consumption is proposed and, as far as the authors are aware, it constitutes the first complete dynamic fuzzy logic elevator group control system. The following section presents a literature review for the elevator group control system. The third section describes consumption in an elevator hoisting system and details some energy aspects. The fourth section describes the global idea of the dynamic algorithm that allocates landing calls minimizing the energy employed, while in section five the assignment criteria is clearly stated and extensively described. The fuzzy procedures are well detailed in the following section six and some aspects concerning the dispatch problem are described in section seven together with a practical methodology developed to integrate the energy algorithm with a time optimizer algorithm. Finally, section eight presents the simulation results and in section nine the main conclusions are highlighted.

2. Elevator group control system literature review

An EGCS mainly consists of hall call buttons situated on every floor, car call buttons inside each cabin and a group controller. In common systems there is a considerable amount of uncertainty, as usually neither the quantity of passengers behind a landing call nor the exact destination until they press the car button inside the cabin is known [6]. Apart from complexity and data shortage, the system also has to deal with unknown possible future calls. As a result partial mathematical approaches are very complicated ([7], [8] and [9]). Therefore, modern heuristics usually has to be employed in order to solve the problem (sometimes helped by technological measures [10] that contribute to reduce uncertainty): Algorithms based on Prioritized A* Search (pruning a solution tree) [11] or the employment of Linear Programming [12] have shown certain accurate performance. Usually, artificial intelligence like genetic algorithms [13] - [17], immune algorithms [18], particle swarm [19] - [20] or viral systems [21] show acceptable results, but the time employed in obtaining a solution or convergence problems do not make them efficient enough solutions. Other techniques like neural networks [22] need too much training time to work properly, as well as they are sometimes difficult to implement and do not show desirable results at all when adapting to fast unforeseen variations. Methodologies like ant colony optimization (ACO) show fast convergence but are tedious to implement and they are usually integrated with other methodologies in an attempt to merge advantages: in [23] they combined neural network and fuzzy logic (Fuzzy Neural Network) with Ant Colony Optimization and in [24], they joined the principles of genetic algorithm and neural network in a Genetic Network Programming with ACO transition considerations, but their respective deficiencies are not overcome at all by this combination. The more complex design became a serious obstacle for the actual implementation of the system. On the other hand, fuzzy reasoning logic has been designed to represent very complex models difficult to depict ([25] - [31]) and combines both fast performance and cheap implementation. The fuzzy EGCS depicted in [32] constitutes a typical example, where, as is usual, the fuzzy design does not benefit from complete dynamic dispatching.

All these artificial techniques bring about problems concerning the tuning of the parameters. Usually the parameters are just specially optimized for each concrete design. However, on some occasions the designs are developed in a self-tuning way like [33] or [34] where a way to integrate both advantages of the most widely employed techniques ("the nearest car algorithm" and "the earliest car algorithm") is offered, and takes into account different factors such as velocity profiles, number of stops and time to arrival. This, therefore, accurately estimates the most suitable car to reduce overall waiting time.

Another vertical transport research line is aimed at providing reliable simulation software for the design problem [35].

Currently, with the rise in importance of sustainable development, the problem of energy consumption is becoming one of the most important features in technology [36] along together with other environmental issues like pollution [37] or CO_2 levels [38]. The total percentage of electricity wasted by the group of elevators in a building goes from 2% to 8% [39]. However, although the total amount of power is considerable, it is not an issue which has often been researched. Apart from some early studies, few serious proposals have been developed: [32] proposes a fuzzy model but the energy performance is not based on actual resistors capable of recuperating part of the energy employed, [40] designs a combination that integrated a bi-objective genetic algorithm and the control of its performance due to a PI controller, but the design has to know information about its possible performance in advance (expected waiting time).In this paper, we implemented a fuzzy logic controller to deal with the energy consumption minimization in EGCS showing how the use of such techniques can be added to other successfully implemented industrial problems (for other industrial examples of fuzzy techniques implementation see for example the works described in [41-45]).

3. Energy consumption in an elevator hoisting system

Nowadays with the fall into disuse of the hydraulic elevator, all the modern elevator systems placed in buildings can be represented as a counterweight plus cabin and ropes system. From this situation a mathematical model with its implications can be inferred.

3.1. *Mathematical energy model consumption for an elevator hoisting system*

Normally, the design is made to be in equilibrium every time the deck load is equal to half of the maximum load allowed, as shown in fig. 1.When a cabin moves towards a height h_2 from a height h_1, its potential energy changes, and as a result so does the whole potential energy of the system:

$$\Delta E = mg\ (h_2 - h_1) = mg\Delta h \qquad (3.1)$$

Where m represents the static balance of the system and the mass of ropes could be disregarded in relation to those others elements:

$$m = m_{Deck} + m_{Load} - m_{Counterweight} = m_{Load} - (1/2) m_{Maximum\ Load} \qquad (3.2)$$

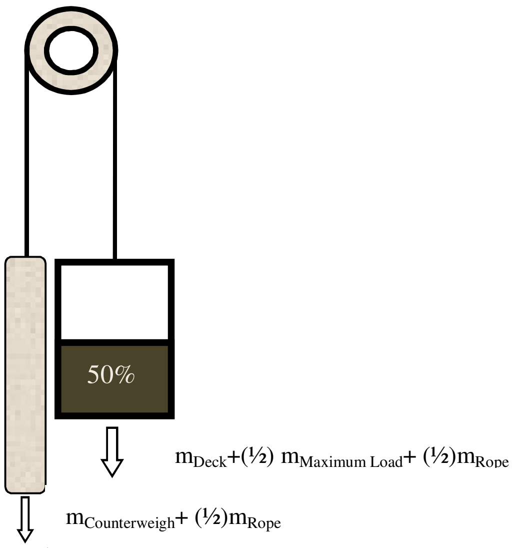

Fig 1. Balanced elevator system.

From those descriptions it can be concluded that elevator systems do not use energy during every movement. In fact, when an elevator moves downwards with less load than half the maximum allowed or upwards with more load than half the maximum allowed, the hoisting system wastes energy. But *vice versa*, every time the deck moves downwards with more load than half the maximum allowed or upwards with less load than half the maximum allowed, the hoisting system gains energy. Current brakes use resistors that can recuperate the energy gained, however due to reasons of mechanical friction not all the energy can be restored. In this scenario, energy system consumption depends strongly on efficient dispatching.

3.2. *Deductions from the energy model consumption for an elevator hoisting system*

From the previously explained model, the following deductions can be obtained concerning certain energy aspects.

3.2.1. *Avoiding unnecessary stops*

When dispatching for average waiting time optimization, it is typical to sometimes employ a policy to avoid unnecessary stops, such as in the cases when it could be predicted that there is no space available for all the passengers making the landing call so another stop will have to be made in the future to collect the passengers left. The elevator would thus make two stops in the end instead of just one making the overall performance worse, especially during highest traffic demands. However, strictly from a purely energy point of view, two stops instead of one could be profitable. It just depends on the snapshot situation.

3.2.2. *Sectoring techniques*

Also when dispatching to optimize time, it is common in periods such as interfloor traffic to distribute the elevators among some defined zones of the building made up of consecutive floors. The aim here is to minimize the space a cabin has to move to respond to a landing call and therefore reducing waiting time.
On the other hand, when dispatching to optimize energy, such a division has no sense at all because it could limit the amount of energy that can be recuperated, as longer distance to the landing call when the elevator is generating power would be better from an energy efficiency point of view.

3.2.3. *Unpredictable future*

Without hall call allocation panels situated on every floor, it is impossible to know the destination of each passenger before entering the cabin, nor know exactly the number of passengers that will alight or board on both car and landing calls. However, as far as energy is concerned, it is of vital importance to estimate the future mass carried by the cabins to estimate approximately the possible energy to be gained or lost and thus allocate the cabins to the landing calls accordingly.

If every cabin has a simple scale in its floor, it is possible to estimate the average number of people behind a future landing call based on recent history. If a time interval

Δ_t (minutes) is defined, the average number of future passengers attempting to board the cabin could be estimated every time the cabin stops at a floor. The alighting and boarding moment of passengers could be detected through the sign of the parameter Δ_m, as passengers alighting nearly always step outside the cabin before passengers boarding step in:

$$\Delta_m = m_{Actual} - m_{Previous} \tag{3.3}$$

The following fig. 2 is provided as an example.

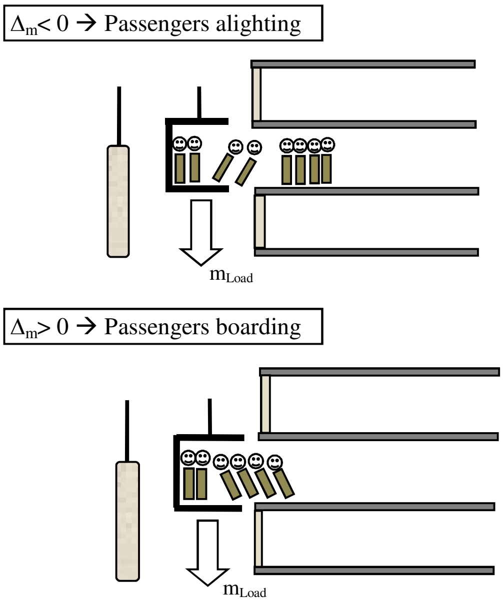

Fig 2. Estimation of the number of passenger boarding.

If the average passenger weight is considered to be 75Kg, the number of passengers behind a landing call (*LCall*) is obtained from the difference between the minimum load reached while unloading and the total mass inside the deck once the doors are closed:

$$Num\ of\ \ Passengers\ Behind\ a\ LCall = \left(m_{final} - m_{minimum}\right)\Big/ 75Kg \tag{3.4}$$

It is also possible to employ better detection technologies such as special cameras, laser beams or a good mass transducer that can detect each passenger from the moment he steps inside the cabin. However, sometimes the increase in cost that is involved does not improve the performance enough to justify their installation. It usually depends on the features of the building and the tenant.

From the number of passengers behind each *LCall* made during a predefined time interval Δt, it is possible to obtain the average number of people behind a "future" *LCall* for a specific moment (a "future" *LCall* is taken to mean every *LCall* that already exists for a specific moment that has not been answered yet):

$$E\left[N.\,Passengers\ Future\ LCall\right] = \sum_{i=1}^{N.\,LCalls\ in\ \Delta t} Passengers\ Behind\ LCall_i \Big/ Num.\,LCalls\ in\ \Delta t \qquad (3.5)$$

Where *NumLCall in* Δt is the number of landing calls that happen during a predefined time interval Δt.

Moreover, it is also possible to estimate the average number of people carried in the cabin during consecutive trips answering the number of car calls produced, landing calls assigned and the total weight inside the cabin. The predicted number of passengers alighting for a specific deck could be easily obtained every time:

$$E\left[Num\ of\ \ Passengers\ Alighting\right] = M_{Load}/75Kg \cdot Num.\,Car\ Calls \qquad (3.6)$$

The following fig. 3 is provided as an example:

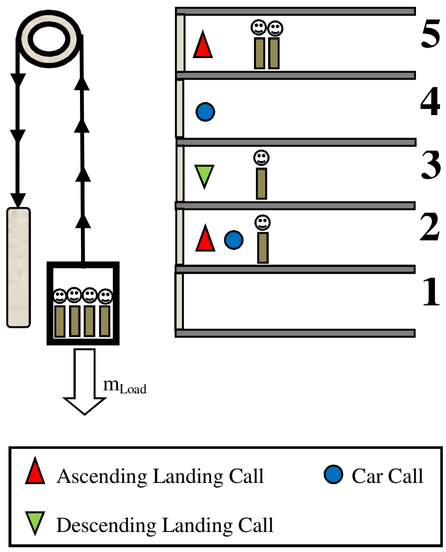

Fig 3. Estimation of number of passenger alighting.

The elevator is moving upwards and is assigned to the two ascending landing calls and must answer the two car calls. If we take the estimated number of people behind a landing call to be four for the calculation detailed above, the estimated number of passengers alighting on every car call would therefore be:

$$E\left[Num\ of\ \ Passengers\ Alighting\right] = \left(\square\ 4x75kg/75kg\right)\Big/2\ Car\ Calls = 2 \qquad (3.7)$$

Therefore, the estimated number of passenger in the cabin throughout the trips for this specific snapshot problem is calculated as follows:

Trip 1 (from floor 1 to 2): 4 passenger already aboard.

Trip 2 (from floor 2 to 4): 4 passenger already aboard + 4 passengers estimated boarding – 2 passengers estimated alighting = 6 passengers on board.
Trip 3 (from floor 4 to 5): 6 passenger already aboard – 2 passengers estimated alighting = 4 passengers on board.
Trip 4 (from floor 5 on): 4 passenger already aboard + 4 passengers estimated boarding = 8 passengers on board.

Every time a new landing call appears or the elevator stops again at a new floor, each calculation must be redone. Employing these techniques, the EGCS is able to estimate the total amount of passengers throughout the trip and the consequent energy implications.

3.2.4. *Energy Considerations about traffic pattern*

Classical theory [6] describes four traffic patterns for a typical day in a workers' building according to whether the main flow is significantly ascending, significantly descending, both or none of them. See our work in [46] for a fuzzy logic controller predicting traffic patterns.

As mentioned in the introduction, some intelligent dispatchers make their decisions based on different criteria: average passenger waiting time and the most advanced, energy or percentage of long waits.

Destination or starting floors are usually known in downpeak or uppeak periods respectively, and this also occurs in the lunchpeak period, (which constitutes a mixture of both) reducing the dispatching options. Besides, there is a considerable amount of passengers in these periods so waiting time is critical. As a consequence, it is usually during the interfloor pattern when dispatching options are higher and traffic lighter (so the waiting time problem does not have the same importance as in other periods), when the EGCS is able to dispatch landing calls taking the energy problem into account more than other factors.

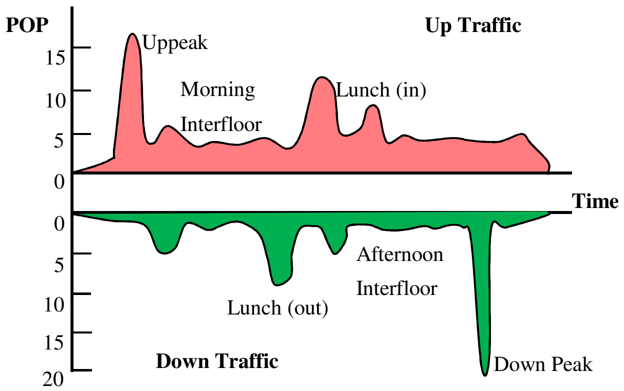

Fig 4. Traffics patterns occurring through the day in a typical workers' building.

3.2.5. *Adjoining landing calls*

Proximity between landing calls should be a decisive factor to take into account when dispatching. Adjacent landing calls must be assigned to the same or different cabins according to the energy state of the elevator. For example, a cabin that is moving downwards with a total load inferior to half its maximum load should answer a number of landing calls in a row to increment its inside weight to reduce energy wastage or even to start generating energy as it is shown in Fig. 5.

On the other hand, for example, cabins moving upwards with a total load inferior to half its maximum load, should answer the least number of landing calls possible as every passenger will reduce the gain in energy as it is shown in Fig. 6.

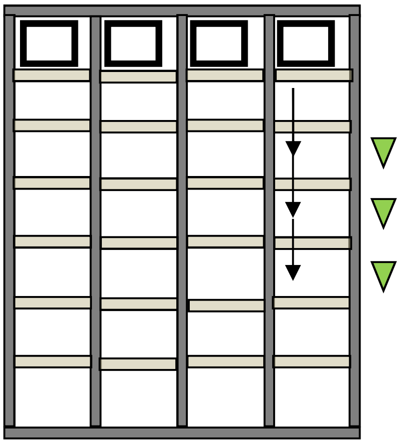

Fig. 5. Trivial Example: An Elevator should answer the most number of adjoining calls as possible.

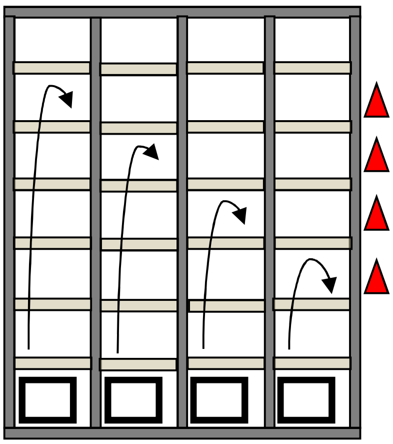

Fig. 6. Trivial Example: Elevators should answer the least number of adjoining calls.

Real situations involve artificial intelligence methodologies to deduce an optimal dispatching solution.

3.2.6. *Promote loading passengers depending on cabin direction*

As an alternative to the adjoining landing calls consideration, EGCS could prompt or not loading passengers into the same cabin for the same reason as stated previously. However, in an attempt to not make this multi-criteria design redundant, promoting loading passengers was not considered in favor of answering adjoining landing calls, as the latter makes a simple complete dynamical dispatching in a fuzzy logic system possible.

4. Dynamical dispatching feature of the proposed fuzzy logic EGCS

The algorithm is based on the statement that dynamic dispatching produces better results than a static one. So every time the system detects a change (cabin load or a new landing call appears), the whole set of landing calls are re-allocated. This allows the system to optimize the allocations. However, common fuzzy logic methods are not able to process the information in a parallel form or to calculate solutions in the way other methodologies do, such as genetic or tabu algorithms. Therefore, it is necessary to establish an optimal sequential order to evaluate the landing calls properly according to certain criteria. Few fuzzy logic elevator group controllers have been proposed (as [46] refers) in the past years, but the following Fuzzy Logic Elevator Group Control System constitutes the first one, which is completely based on dynamic dispatching. This has never been seen in the elevator industry before.

5. Principles of the fuzzy logic algorithm for energy optimization

The fuzzy logic-based algorithm for energy consumption optimization proposed here can be characterized by the flow-chart diagram shown in fig. 7. It works as follows: in a facility with n number of elevators and p number of active landing calls, the algorithm evaluates $n \times p$ fuzzy procedures, each one representing the possibility for a cabin i to respond to a landing call j. In view of the above, landing calls are allocated in an optimized order to the best desired elevator among all the possibilities according to the final estimated figure $S_E[i][j]$ obtained for each i-j pair.

This final figure $S_E[i][j]$ is evaluated in agreement with a set of weights $[v_1, v_2, v_3]$ and three fuzzy-inferred evaluation criteria defined for each i-j pair: possible absolute energy ($E_{ABS}[i][j]$), possible relative energy ($E_{REL}[i][j]$) and possible adjacent energy ($E_{ADJ}[i][j]$):

$$S_E[i][j] = E_{ABS}[i][j] + E_{REL}[i][j] + E_{ADJ}[i][j] \tag{5.1}$$

Each of the different evaluations contributes to examine a partial and non-related aspect of the energy problem.

At the beginning there are no landing calls assigned to any cabin at all as allocation is dynamic, so all parameter values are zero. The whole set of $n \times p$ procedures that represent the fitness of each i-j dispatch option has to be calculated only once in its entirety (for the first I-J assignment). The following times, only the related figures that have changed as a consequence of the previous I-J assignment need to be recalculated to reflect the new state (cabin I assigned to *LCall* J). There is no need to recalculate the rest of the figures as their values have not changed since the first calculation (this feature gives the controller a very fast performance). The only parameters that need to be updated are:

- The values of $E_{ABS}[i][j]$ for the specific wining cabin i and the whole set of active landing calls.
- The values of all $E_{REL}[i][j]$ figures for all the i cabins and the p active landing calls.
- The values of E_{ADJ}[i][j] for the cabin i and the entire set of landing calls j.

6. Dispatch option evaluation

The three assignment criteria shown in the flow-chart diagram in fig. 7 in the fifth section constitute the main body of the dispatch option evaluation concerning saving power. Their calculation for each dispatch option *i-j* let us obtain the final energy fitness figure $S_E[i][j]$ for each *i-j* pair and therefore, to establish an optimal sequential order for assigning the set of active landing calls, as well as the optimal cabin for each one of the landing calls.

All three criteria represent fuzzy inference processes that are calculated according to some input parameters. In this section each set of inputs is listed and a theoretical definition is also given for each criterion (the next section is fully-detailed with descriptions about the fuzzy procedures). The aim is to put forward and justify the nature of the developed energy evaluation.

6.1. *Absolute energy evaluation*

The absolute energy evaluation ($E_{ABS}[i][j]$) estimates the total amount of power wasted by cabin i if it attended landing call j. The definition of the absolute energy evaluation depends on:

- The *possible flight* made by the cabin.
- The *unbalanced* weight compared to the equilibrium-balanced state.
- The *current direction* of the cabin (which at the same time depends on the car calls and landing calls already assigned to the cabin).

Absolute evaluation acts as a measurement of the objective energy employed in the action without considering the snapshot problem conditions.

6.2. *Adjacent energy evaluation*

The adjacent energy evaluation ($E_{ADJ}[i][j]$) estimates if a landing call j should be allocated to a cabin i according to the landing calls already assigned to cabin i. The definition of the adjacent energy evaluation depends on:

- The *proximity* of the landing call j considered with the nearest landing call already assigned to cabin i.
- The *unbalanced* weight with respect to the equilibrium balanced state.
- The *current direction* of the cabin (which at the same time depends on the car calls and landing calls already assigned to the cabin).

Adjacent estimation contributes to whether a group of nearby landing calls should be assigned to the same cabin with regards to saving energy as described in the previous section 3.2. This evaluation combined with the relative evaluation acts as a measurement of the overall snapshot problem situation.

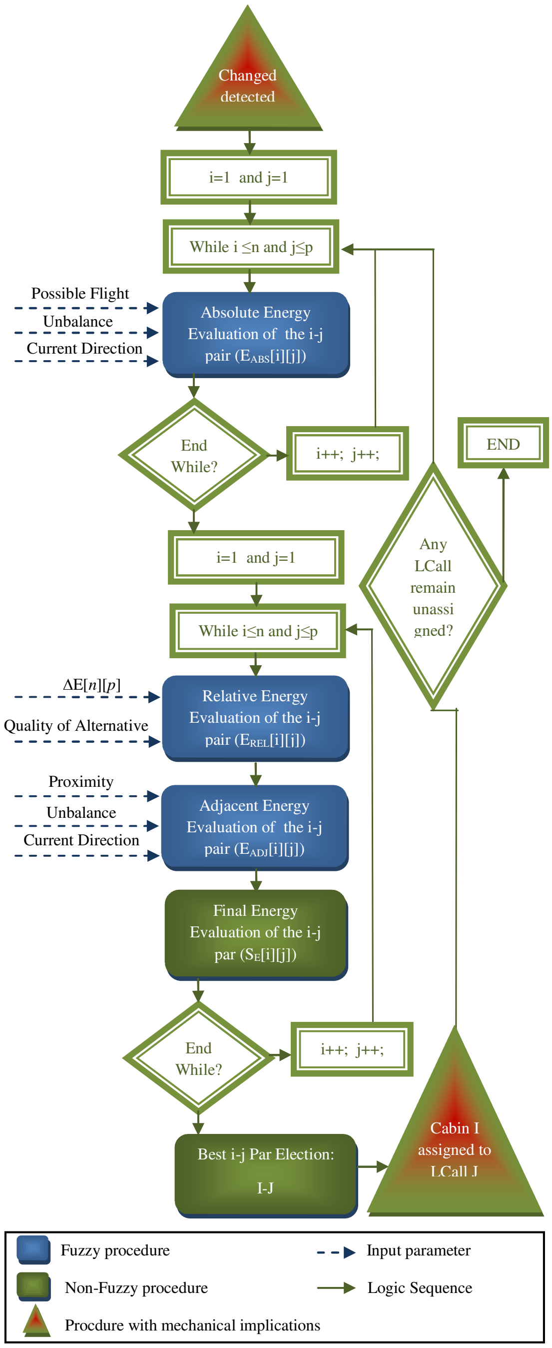

Fig 7. Flow-chart showing main steps for a complete dispatch of a set of *p* active landing calls in a building.

6.3. *Relative energy evaluation*

Relative energy evaluation ($E_{REL}[i][j]$) makes a quality comparison between the total amount of power wasted by the cabin *i* if it answered the landing call *j* ($E_{ABS}[i][j]$) and the energy wasted by the rest of *n*-1 deck possibilities for answering the specific landing call *j*. The definition of the relative energy evaluation depends on:

- $\Delta E[i][j]$: It measures in number of average deviations the difference between the absolute energy of the *i-j* pair decision and the average of the whole set of *n* elevator possibilities to answer the specific landing call *j*:

  $$\Delta E[i][j] = E_{ABS}[i][j] - \bar{E}_{ABS}[j] / S_{ABS} \tag{6.1}$$

  Where:

  $$\bar{E}_{ABS}[j] = \sum_{k=1}^{n} E_{ABS}[k][j] \Big/ n \tag{6.2}$$

  $$S^2[j] = \sum_{k=1}^{n} \left(E_{ABS}[k][j] - \bar{E}_{ABS}[j]\right)^2 \Big/ n \tag{6.3}$$

  $S[j]$ is the standard deviation and $E_{ABS}[j]$ the average energy consumption for all possible assignations for a fixed landing call *j*.

- The *quality of the best alternative* to cabin *i* to answer the specific landing call *j* ($Q[i][j]$):

  $$Q[i][j] = E_{ABS}[i][j] - E'_{ABS}[l][j] / E''_{ABS}[k][j] \tag{6.4}$$

Where $E'_{ABS}[l][j]$ is the best alternative to $E_{ABS}[i][j]$ for a fixed landing call *j* and $E''_{ABS}[k][j]$ the best option among all the possibilities (including $E_{ABS}[i][j]$) for a specific landing call *j*.

Relative evaluation acts as a measurement of the environmental situation. This lets the dispatcher sets out decisions on the suitability of *n* possibilities for answering a specific landing call *j* and by extension, lets the dispatcher set out decisions on the quality of the $n \times p$ possibilities in general.

In fact, relative evaluation affects the order in which landing calls are answered. The $\Delta E[i][j]$ measurement can detect whether an option is profitable enough in the sense that it exceeds the average cabin marks or not. And jointly with $Q[i][j]$,the dispatcher can find out if the *i* option constitutes a critical dispatching decision for the specific landing call *j*. This allows the dispatcher to resolve difficult situations satisfactorily. For example, when there is not optimal cabin to assign to a landing call *j,* in the sense that all choices would waste a considerable amount of power but one cabin would employ less significant energy than the others (or even produce a gain in energy). Therefore, this critical cabin option could be assigned to the landing call *j* before being allocated to another landing call which does not have this vital cabin choice and which would also make the cabin not ready to answer landing call *j*.

In Fig. 8, elevator 3 and 1 are especially well situated to answer the ascending landing call at floor 6. Elevator number 3 is located at the same distance as elevator number 1 but moving upwards partially loaded (still carrying less load than half the maximum allowed so acting as a generator) to floor 5. While elevator number 1 is empty so it would, therefore, produce a slightly higher amount of power in the case of responding to the landing call at floor 6. However, there is not critical difference in magnitude of the energy recovered. However among all the elevators, elevator number 1 is by far the best option to respond to the landing call located at floor number 2 because while wasting some energy doing it, it is located only one floor above it while the others are further (elevator number 3 has to arrive to floor 5 first before it could answer it due to direction constrictions).

Without $\Delta E[i][j]$ and the *quality of the best alternative* criteria ($Q[i][j]$),elevator 1 could be assigned firstly to the landing call at floor 6 because it produces a slight gain compared to elevator 3 (and elevator1 also wastes energy answering floor 2 and therefore it is behind it in the serving order) so there would not be any optimal cabin to answer floor 2 in the sense that all of them would use a considerable amount of power (elevator 1 would be higher than floor number 6 and elevators 3 and 4 would be at floor 5 before they could attend it). However, $\Delta E[i][j]$ and $Q[i][j]$ criteria allow the dispatcher to detect such a situation as it considers cabin 1 option for attending landing call at floor number 2 as a vital one and is, therefore, given preference in the allocation order. With preference in the serving order, the landing call at floor 2 would firstly be assigned to elevator number 1 and, after estimating the number of passenger that would board the cabin based on recent history, the landing call at floor 5 would be assigned to elevator number 1 or 3 depending on the gain in energy.

In the same way, through $\Delta E[i][j]$ and $Q[i][j]$, some other complicated situations could also be detected and, therefore, solved correctly. For example, when there are not one but two (or more) critical decisions, in the sense that their marks for answering a specific landing call j strongly exceed the others, assigning the first one to another landing call j does not involve losing the energy bonus opportunity since the other cabin with a similar mark remains unassigned. However, once the latter cabin is the only one that remains as a crucial choice, it cannot be assigned to another landing call if that makes it impossible for it to respond to landing call j.

Fig. 9 shows an example similar to the previous one. In this case, the three cabins 1, 3 and 4 are well situated to answer the landing call at floor 6 with similar energy results. Cabins 1 and 4 are also well-placed to answer the landing call at floor 2. They both constitute critical decisions if standing alone but $Q[i][j]$ criteria let the dispatcher detect the situation. It is therefore possible to allocate one of the two cabins to floor 6 while the other remains as a critical decision (in case there are more landing calls).

In short, relative criteria evaluation allows the dispatcher to detect the situations when an optimal decision for attending a specific landing call j does not produce the best overall performance.

Note that in the above examples the decisions about criticality of every option seem to appear as an abrupt dichotomy, but this has been done for reasons of simplicity and comprehensibility, while in the real model the criticality of a decision is defined implicitly along a continuous range through $\Delta E[i][j]$ and the $Q[i][j]$ criteria as detailed before.

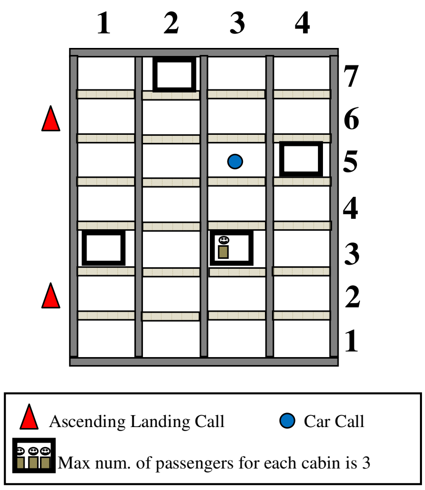

Fig. 8. Dispatching example with a crucial cabin option.

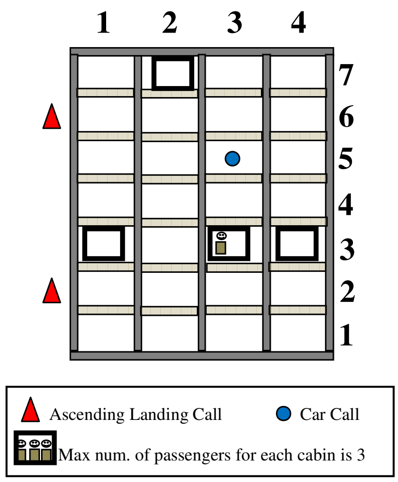

Fig. 9. Dispatching example with 2 crucial cabin options

7. Computation of fuzzy parameters

Each one of the triple energetic evaluations represents a typical fuzzy procedure (fuzzification, inference and defuzzification).

The fact that it does not require previous knowledge about its performance, as occurs in other designs ([38]), constitutes one of the main characteristics of the proposed design: membership functions are solely based on building and elevator features.

It has to be noted that energy consumption functions are provided by the manufacturer, which link the power used by a cabin with the flight and quantity of passenger carried along the trip.

7.1. *Input data*

Input data is only made up of basic information:

- Mass load of each cabin (*Kg*) measured by scales installed in the cabin floor.
- Current direction of each cabin (upward, downwards or stationary).
- Position of every cabin and landing floor (meters above reference).
- Registry of the car calls.

7.2. *Linguistic variables*

As shown in previous Fig. 7, only some and not all the linguistic variables form part of a determined criteria calculation. Although some of them also contribute to more than one calculation. The design handles the following linguistic variables:

- Possible flight
- Unbalanced
- $\Delta E[i][j]$
- $Q[i][j]$

- Proximity

7.3. *Fuzzification*

Fuzzification of linguistic variables is carried out via Mamdani's method [47] according to the membership functions depicted in Fig. 10.

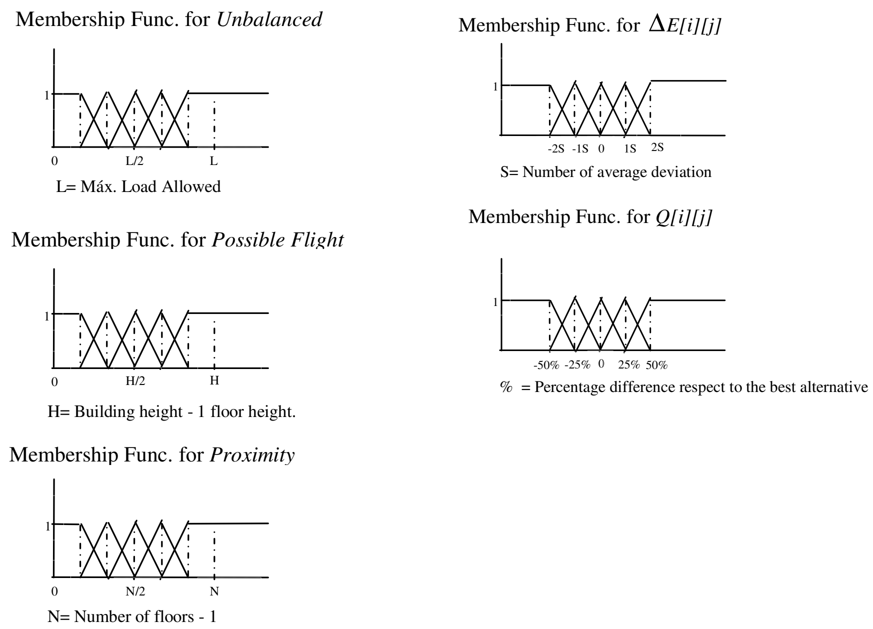

Fig. 10. Membership functions defined for linguistic inputs.

7.4. *Fuzzy inference*

Each energy evaluation is worked out from fuzzy variables according to a set of logical rules. Each rule, that is represented in the following tables follows a general structure as it is shown in the next example:

IF Actual Direction is Up THEN→**R1:** PF_{VS}&&U_E= Good

IF NOT→**R1:** PF_{VS}&& U_E = Bad

Where the logic product *AND* (*&&*) represents the minimum between factors.

The following Table 1 shows the logical rules representing the deduction on the quality of absolute energy for a specific *i-j* pair ($E_{ABS}[i][j]$).

Table 1. Logic Rules for absolute energy criteria.

	PF_{VS}		PF_S		PF_A		PF_L		PF_{VL}	
U_E	R_1	↑G / B↓	R_6	↑G / B↓	R_{11}	↑VG / VB↓	R_{16}	↑VG / VB↓	R_{21}	↑VG / VB↓
U_{NE}	R_2	↑A / A↓	R_7	↑G / B↓	R_{12}	↑G / B↓	R_{17}	↑VG / VB↓	R_{22}	↑VG / VB↓
U_{EQ}	R_3	↑G / G↓	R_8	↑G / G↓	R_{13}	↑A / A↓	R_{18}	↑A / A↓	R_{23}	↑B / B↓
U_{NF}	R_4	↑A / A↓	R_9	↑B / G↓	R_{14}	↑B / G↓	R_{19}	↑VB / VG↓	R_{24}	↑VB / VG↓
U_F	R_5	↑B / G↓	R_{10}	↑B / G↓	R_{15}	↑VB / VG↓	R_{20}	↑VB / VG↓	R_{25}	↑VB / VG↓

PF: Possible Flight	VL: Very Large	E: Empty
U: Unbalanced	L: Large	NE: Near Empty
	A: Average	EQ: Equilibrium
VG: Very Good	S: Short	NF: Near Full
G: Good	VS: Very Short	F:Full
A: Average		
B: Bad		
VB: Very Bad		

Next Table 2 shows the logical rules representing the deduction on the quality of relative energy for a specific *i-j* pair ($E_{REL}[i][j]$). And following Table 3 shows the logical rules representing the deduction on the quality of adjoining energy for a specific *i-j* pair ($E_{ADJ}\,[i][j]$).

Table 2. Logic Rules for relative energy criteria.

	ΔE_{VB}		ΔE_{B}		ΔE_{A}		ΔE_{G}		ΔE_{VG}	
Q_{VB}	R_1	B	R_6	A	R_{11}	G	R_{16}	VG	R_{21}	VG
Q_{B}	R_2	B	R_7	A	R_{12}	G	R_{17}	VG	R_{22}	VG
Q_{A}	R_3	VB	R_8	B	R_{13}	A	R_{18}	G	R_{23}	VG
Q_{G}	R_4	VB	R_9	B	R_{14}	A	R_{19}	G	R_{24}	VG
Q_{VG}	R_5	VB	R_{10}	B	R_{15}	A	R_{20}	G	R_{25}	VG

Q: Quality of the best alternative

ΔE: Energy Deviation from Energy average

VG: Very Good
G: Good
A: Average
B: Bad
VB: Very Bad

Table 3. Logic Rules for adjoining energy criteria.

	P_{VS}		P_{S}		P_{A}		P_{L}		P_{VL}	
U_{E}	R_1	↑G / B↓	R_6	↑G / B↓	R_{11}	↑VG / VB↓	R_{16}	↑VG / VB↓	R_{21}	↑VG / VB↓
U_{NE}	R_2	↑A / A↓	R_7	↑G / B↓	R_{12}	↑G / B↓	R_{17}	↑VG / VB↓	R_{22}	↑VG / VB↓
U_{EQ}	R_3	↑G / G↓	R_8	↑G / G↓	R_{13}	↑A / A↓	R_{18}	↑A / A↓	R_{23}	↑B / B↓
U_{NF}	R_4	↑A / A↓	R_9	↑B / G↓	R_{14}	↑B / G↓	R_{19}	↑VB / VG↓	R_{24}	↑VB / VG↓
U_{F}	R_5	↑B / G↓	R_{10}	↑B / G↓	R_{15}	↑VB / VG↓	R_{20}	↑VB / VG↓	R_{25}	↑VB / VG↓

7.5. *Defuzzification*

The defuzzification is carried out through a typical center of gravity method to obtain a unique decision value between zero and one.

Once the value of each rule is computed, the strength of each component is obtained calculating the root sum squared of all the rules associated to the component. For example, if the direction of the cabin is upwards, the strength of each component for the evaluation of the absolute energy (please see table 1) would be obtained as follows:

$$\text{VG Strengh} = \sqrt{\left(R11^2 + R16^2 + R17^2 + R21^2 + R22^2\right)}$$

$$\text{G Strengh} = \sqrt{\left(R1^2 + R3^2 + R6^2 + R7^2 + R8^2\right)}$$

$$\text{A Strengh} = \sqrt{\left(R2^2 + R4^2 + R13^2 + R18^2\right)}$$

$$\text{B Strengh} = \sqrt{\left(R5^2 + R9^2 + R10^2 + R14^2 + R23^2\right)}$$

$$\text{VB Strengh} = \sqrt{\left(R15^2 + R19^2 + R20^2 + R24^2 + R25^2\right)}$$

Once each component strength is calculated ($f(x_i)$) and taking into account each respective center ($c(x_i)$), the final output ($S_{ABS}[i][j]$) for each option $[i][j]$ is obtained as follows:

$$S_{ABS}[i][j] = Output\_RSSCentroid = \frac{\sum_i f(x_i)x_i}{\sum_i f(x_i)}$$

Where the values of $c(x_i)$ are:

- -1 for the center of VG.
- -0.5 for the center of G.
- 0 for the center of A.
- 0.5 for the center of B.
- 1 for the center of VB.

8. Experimental results

Elevator systems are designed mainly according to classical theory [6] in the sense that a system that can handle the logistic transport during uppeak is also able to transport passengers efficiently during the rest of the periods. Above all, this gives a large extra handling capacity during interfloor interval, as shown in the previous section, which allows the dispatcher to focus exclusively on the problem of energy. In this aspect, the fuzzy based elevator group control designed is able to dispatch the landing calls efficiently.

The most common dispatch algorithm actually implemented by most companies is the “nearest call algorithm” (which is self-descriptive: it dispatches the landing call to the nearest elevator following the collective principle) because of its reliability and short processing time. In this sense, it has been proposed as a benchmark for testing the proposed algorithm.

Simulation has been carried out through ELEVATE software. The example building has 19 floors and has been designed to accomplish the vertical transportation requirements ([6]) so it possesses 7 elevators for a total population of 1520 workers equally distributed throughout the facility. Therefore, while different demands for interfloor traffic occurred (Percentage Of Population requiring service, POP), the following average results were obtained (Fig. from 11 to 14 and Table 4):

Fig. 11 represents the Average Wasted Power (AWP) per second depending on passenger demand (Percentage Of Population, POP) for both dispatching algorithms so that the total amount of energy saved by the proposed dispatching method can be observed.

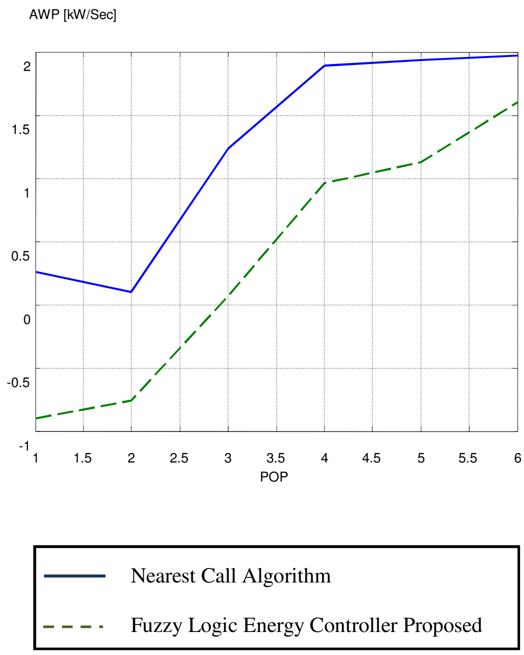

Fig. 11. Function relating the Average Wasted Power (AWP) per second and the Percentage Of Population demanding service (POP).

Fig. 12 complements Fig. 11 and relates the Average Wasted Power (AWP) per trip made by an elevator and the Percentage Of Population demanding service (POP). Although the total number of trips made by the elevators in a time interval depends on the dispatching algorithm, in practice this number is very similar. Therefore, the consumption per trip can be compared to provide a very approximate idea of the total amount of energy wasted or gained by each algorithm.

By looking at the energy saving for each trip and that the total amount of trips performed by each elevator every five minutes goes from approximately 30 to 120 during interfloor (depending on demand), a specific idea on the vast amount of energy that can be saved without deteriorating the time service can be calculated.

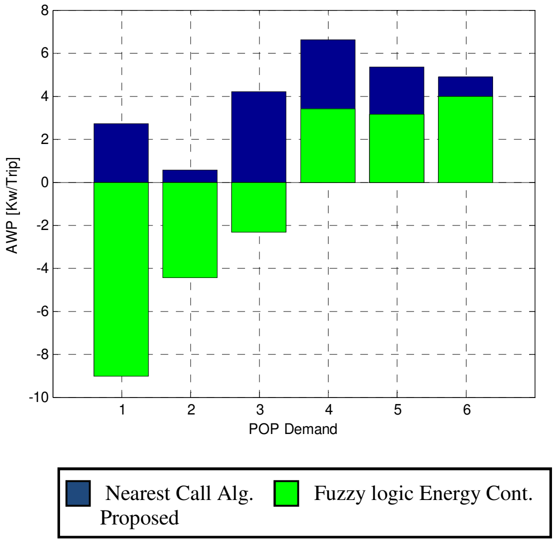

Fig. 12. Function relating the Average Wasted Power (AWP) per trip and the Percentage Of Population demanding service (POP).

The results summarized in Table 2 are conclusive: for low demand, the total amount of energy wasted in the movement of the elevator can be extensively decreased and even produce a gain in energy for the system with a slight disadvantage to Average Waiting Time (AWT) (Fig. 13) and practically keeping the Average Transit Time (ATT) constant (Fig.14).

Table 4. Simulation result showing the absolute and relative power gain by employing the proposed EFLGCS

POP	NC Alg.	EFLEGCS	Difference	%Improve
1%	0.26	-0.90	1.16	- 446%
2%	0.10	-0.75	0.85	- 850%
3%	1.23	0.07	1.16	- 94%
4%	1.89	0.96	0.93	- 49%
5%	1.93	1.13	0.80	- 41%
6%	1.97	1.61	0.36	- 18%

EFLEGCS: Energy Fuzzy Logic-based Elevator Group Control System.

POP: Percentage of Population.

NC Alg.: Nearest Call Algorithm.

As traffic demand raises so do the marginal costs, reducing the advantages of decreasing average time in favor of energy consumption. When the demand is considerably high, around 6% POP, (interfloor traffic rarely exceeds the 4% POP level), the disadvantages of increasing waiting time surpass the advantages of reducing consumption, producing waiting times that become unacceptable and involving an energy gain which is not worthwhile enough.

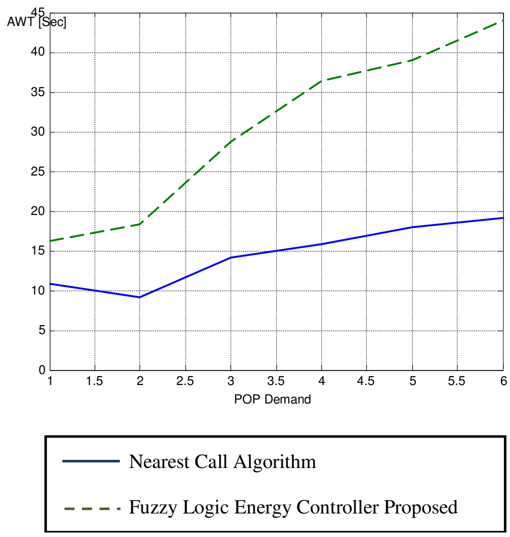

Fig. 13. Function relating the Average Waiting Time (AWT) and the Percentage Of Population demanding service (POP).

In this sense, it should be considered to combine the proposed energy dispatcher with one related with waiting time minimization for allocating demands higher than 6% POP. From next Fig. 14 it can be observed that whereas it exist a difference in the performance for higher demands while considering waiting times, there is no significant results for the average transit time marks.

Fig. 15 points out the variation in the energy consumption depending on the size of the time interval (Δt). It can be seen that different time intervals (from time intervals long enough to consider a significant number of *LCalls*) produce only slightly different AWPs. This is probably due, apart from the random nature of the simulations, to the fact that employing a larger interval, and as a consequent taking the distant past more into account, does not provide the elevator group controller with better information because, during interfloor traffic, demand is quite random. A little more dispersion between the AWPs values is obtained for higher demands. In fact, as demand raises the dispersion of the incoming probability also gets higher, and passengers often arrive in bunches.

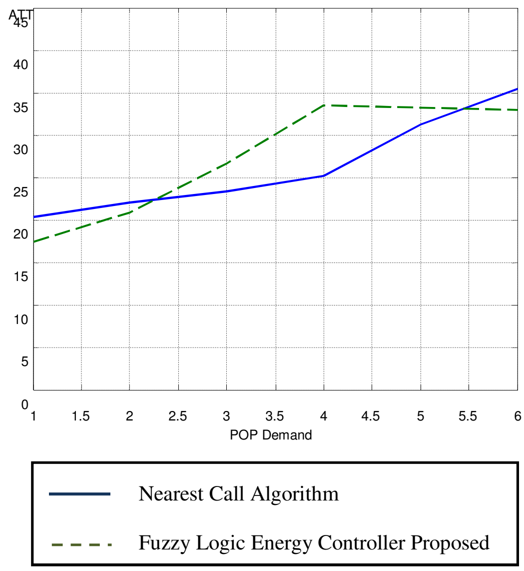

Fig. 14. Function relating the Average Transit Time (ATT) and the Percentage Of Population demanding service (POP).

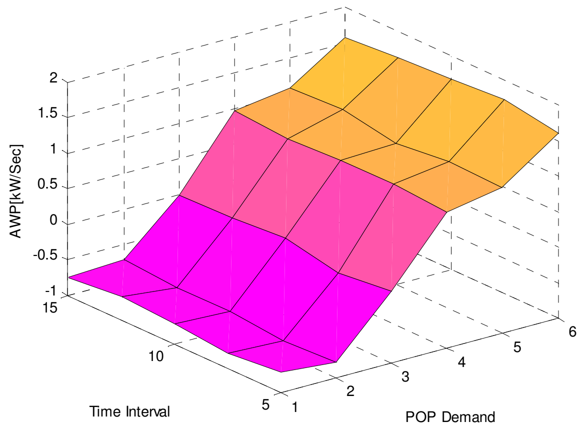

Fig. 15. Function relating the Average Wasted Power with the Time Interval and the Percentage Of Population demanding service (POP).

9. Conclusions

In this paper a novel Fuzzy Logic Elevator Group Controller for energy consumption optimization that employs complete dynamic dispatching for the first time in the elevator industry has been presented: the dispatcher reallocates all the landing calls still not attended every time a change is detected.

Dispatching is carried out according to three criteria: an absolute energy evaluation, a relative energy evaluation and an adjoining of landing calls evaluation. The evaluation of each parameter is made by a fuzzy process (employing triangular memberships functions), this allows us to obtain an optimal "reasoned" solution in practically an instant at the same time that complicated designs and computational-expensive algorithms are avoided.

The self-sufficiency for working during light and medium traffic periods such as during interfloor has been proven conclusively and the energy profit has been numerically estimated through a simulation on different demands during interfloor traffic and by a comparison against the most employed dispatcher in the industry. The results show a desirable performance, widely surpassing the other dispatcher on the problem of energy while maintaining a more than acceptable mark as far as waiting time is concerned.

Natural future research lines for the developed and tested design appear to be a controller that allows connecting an energy dispatcher with a time dispatcher, as well as providing a smooth transition between energy dispatching and time dispatching.

It is also deduced from the proposed model that some figures, like the ones in the membership functions, may need some calibration for achieving the best possible performance (which is a common feature in AI designs). This observation leads to a second future line of research which could be the development of some kind of self-calibration system, based for example in an artificial intelligence design like neural networks that can "learn" through as time pass by.

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