UNIVERSITÀ DEGLI STUDI
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Energy saving room scheduling system for smart hotels

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1. Abstract

Energy management is one of the most important aspects treated in Engineering and sciences. Either a path planning problem or an energy harvesting field of wind turbines, the necessity to ensure optimality is always present when competitivity is desired. Optimisation at the service of Engineering is a broad field of development and deals with a very dynamic set of applications that can be present even in the normal life.

While technology is improving with time, new intelligence layers are being added to existing systems in order to make them reactive to predefined constraints [1]. Optimisation problems that were before only tangible for those having to do directly with the development of a product are becoming every day more popular and widely used by normal users.

Hotels and other accommodation providers deal with the problem of assigning booking requests in an optimum way. The majority of homologous systems attempt to forecast the energy consumption of the analysed buildings or to monitor it and propose alternative solutions to decrease it [8]. Others already go a step further in proposing systems that optimise tenants' comfort or energy consumption reduction by means of complex techniques like reinforcement learning [7] while at the same time adapting them to the usage pattern of the user.

While approaching in the same manner the multi objective problem of assigning the rooms to the guests in the most profitable way, this work deals also with the construction of an agent with an extra intelligence layer capable of choosing assignment sequences that ensure optimality in the sense of energy consumption. This framework can be envisioned as part of a smart building environment and chapter 2 introduces formally the problem formulation that motivates its creation. Chapter 3 analyses further the actual situation of the development field and gives an insight on the profitability of such a system in the actual environment. Chapters 4 and 5 describe more deeply the development and validation strategies adopted and finally, chapter 6 concludes on the topic and provides an outlook with possible future improvements.

2. Introduction and proposal

Even though energy consumption is penalised by governmental bodies with norms like DPR 412/1993 [2], it is also in the interests of hotel managers to ensure a lower energy consumption as it generates a more profitable situation for them. One could naively think that such a system would only be profitable for winter season, while in reality, in summer the problem happens in the same form as temperature regulation is needed. As an initial proposal, it is interesting to look for solutions that ensure profit maximisation as a first priority and then looks in the feasible set of assignments for those being energetically optimal.

In this context, the next assumptions were taken

1. Assume the existence of differed heat sources in every room of the building. This widens the research field and helps understand better the optimisation problem due to the variety in degrees of freedom.
2. Common areas like corridors or lounges should be heated up whenever new clients arrive.
3. Without losing generality, assignment of a room implies its direct heating given that its coupling relations with other rooms are to be considered.
4. A model predictive approach is to be used in order to broaden the degree of action of controls on the building to be considered.

An example that motivates this direction of research can be seen in Fig. 1. A lumped-parameter model of a hotel consisting of three floors and more than 80 rooms was designed and tested. A regular ON-OFF control strategy was adopted for its simulation, given that it is the common approach adopted for temperature management in the real life. As seen, while the first and third floor are heated up, the second floor finds itself already at the optimal temperature value, for which assigning a new booking request to any of the rooms in the middle would be a more intelligent solution from an incipient energy optimising approach.

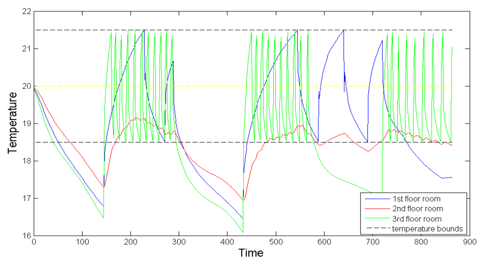

Figure 1: *Temperature of three rooms located one over the other having various customers along 6 days.*

Finally, it is important to say that the energetically optimal solutions are not necessarily predictable, and are expected to be dependent on several preconditions, among which the isolating performance of the hotel can be of interest. One attempts, however to exploit the adjacency relations of the rooms, the existence of natural heating sources like the sun radiation and a good estimation of the outer temperature to enrich a model in order to be able to forecast the energy consumption and to pick the best solution.

3. State of the art

This analysis is performed in two important directions: the commercial and the research ones. In the commercial field, only 20% of the hotel managers are used to looking for consistent demand statistics and use them actively for demand forecasting and profit management operations. The majority consider only the tourist information provided by specialized agencies instead of looking at past booking data to conclude on this. The existence of a software managing the whole bookings system is a common characteristic of many hotels.

The algorithms existing in the market either in specialized softwares or open source solvers, over all those being used in Italy require the owner of the building to load the prices and priorities of the rooms for making its decisions. These softwares, however, tackle mostly the point of revenue management optimisation (offer campaigns and calculation of optimal room prices) but do not direct its resources in determining the optimal booking out of a given booking request situation. Until today, random assignments and first book - first take policies have been implemented in order to achieve not only a profit but also convenient client satisfaction.

If a few quantity of the software market is directed to optimising the booking, one can imply that even a smaller one attempts to optimize the objective from different perspectives. A smart agent in this sense would be an attractive proposal for optimising decreasing the energy consumption while maintaining the revenue at a maximum level. As commented afterwards, the problem of client satisfaction and personalized use forecasting while ensuring feasibility on the final solutions determines also an important developmental direction and a allows to generate an intelligent framework capable of deciding on the assignment based on a more objective complexity level [9].

In the field of research, many works have attempted to manage the consumption of energy from a centralized point of view, in which small clients subscribe to a bigger entity in order to decrease the consumption by means of a closed communication mechanism [12]. Domotics is an area dedicated to the automation of environments and to the increasing of their receptiveness to human beings in order to perform tasks more optimally. One of the most salient topics in the present has been that of providing different frameworks with the awareness of energy consumption and with it generate even communication patterns that ensure optimality in request reception (e.g. turn off the lights and turn them on again)[11].

A framework like the one proposed in this work would therefore:

1. Represent a good opportunity to compete against softwares using other decision techniques.
2. Ensure the capacity of solving multi objective problems.
3. In both dimensions it implies improvements with respect to existing techniques

4. Previous analysis

The transference relationships of a building can be obtained in two forms: either by taking blueprints of the transmission surfaces and estimating the parameters with theoretical tables or by gathering enough information to perform a parametric identification with optimisation techniques. One could directly propose a first order differential model, corresponding to that in nature of a generalized thermal transmission system and accounting for continuity and energy conservation relationships. Eq. 1 shows how this model looks like.

$$
\begin{aligned}
q_{tot_t} &= \Sigma q_{k_t} + \Sigma q_{h_t} + \Sigma q_{vent_t} + \Sigma q_{sun_t} + q_{pump_t} \\
q_{tot_t} &= \rho V c_p \frac{dT}{dt}
\end{aligned} \quad (1)
$$

Where:

q_k is the thermal convection;
q_h is the thermal conduction;
q_{vent} is the ventilation flux according to the norm UNI/TS 11300 [3];
q_{sun} is the sun radiation took from weather forecast;
q_{pump} is the heat flux coming from the heat pump (if activated);
$\rho V c_p \frac{dT}{dt}$ is the time derivative of the internal energy.

4.1. Blueprint analysis strategy

Two hotels were proposed for means of validation of this work, a small hotel consisting on 12 rooms of the same size but of different classes (maybe due to their contents) and a bigger one with three kind of room according with their price and structure (25 m^2, 50 m^2, 75 m^2) and the same amount of customer kinds. Further parametrisations include the material of the walls (common bricks with density: 2000 $\frac{kg}{m^3}$; heat capacity: 0.9 $\frac{kJ}{kgK}$; thermal conduction: $8e^{-4}$ $\frac{kJ}{smK}$;) the exterior wall thickness is proposed to be 0.4 wide$m$, while the interior one is 0.1 m. Every room has at least a window and one door on the corridor. The windows are made of common glass (density: 2400 $\frac{kg}{m^3}$; heat capacity: 0.84 $\frac{kJ}{kgK}$; thermal conduction: $9.6e^{-4}$ $\frac{kJ}{smK}$), and their thickness is 0.04 m, while the doors are assumed to be like the interior walls. To run these initial set of experiments real Daikin Industries [4].

A parameter identification strategy would require of more software preparation but ensures from the beginning the addition of a first layer of intelligence capable of learning the parameters of the real building in time for posterior analysis. Differences from the theoretical model and the real model are taken into consideration by any error minimisation approach applied to a vector of parameters. The blueprint analysis strategy is faster than the system identification strategy, however if the company evaluating the building knows exactly every single part of the hotel.

4.2. Parameter identification strategy

At the first phase, the scheduling system must be robust enough to be put into operation with possibly little a priori information available. A fast revision of the construction conditions of the hotel motivates thence to the use of an initial model estimate of the linear time invariant form 1. This assumption is not inadequate at all given that the fundamental frequencies of the transference relationships are expected to be low.

However, it is required that the system acquires a good estimate on the real thermal performance of the building with time. An intelligent layer capable of learning the parameters characterizing its thermal isolating quality is then proposed. Consider an extended continuous abstraction of the form:

$$
\begin{aligned}
&c_i \dot{T}_i = -K_{i,e}(T_i - T_e) + \sum_{i \sim j}(T_i - T_j) + K_u u_i + q_i^S \\
&\forall i \mid 0 = 1 \ldots n_r
\end{aligned} \tag{2}
$$

with parameters c_i (conservation of energy) and transmittance (principle of continuity) parameters for inner adjacencies $K_{i,j}$ as well as those with the exterior (exogenous in nature) state T_e. Strictly adjacent rooms i and j are considered by emphasizing the coherence of their flux equality relations, described strictly by $q_{i,j} = K_{i,j}(T_i - T_j)$. Room control inputs u_i are also taken into account as well as the predictable solar flux q_i^S radiated into windows of each room. The characteristic discretisation is therefore given by the predictive form S_p:

$$
\begin{aligned}
&\hat{T}_{i,t+1} = \frac{1}{c_i}\left[\sum_{i \sim j \bigcup e}(\hat{T}_{i,t} - \hat{T}_{j,t}) + K_u u_{i,t} + q_{i,t}^S + \hat{T}_{i,t}\right] \\
&u_{i,t} = u_{i,t-1} + K_{u,i}(e_{i,t} - e_{i,t-1}) \\
&e_{i,t} = T_{sp,t} - T_{i,t} \\
&\forall i \mid 0 = 1 \ldots n_r \\
&\forall t \mid t = 1 \ldots P
\end{aligned} \tag{3}
$$

where already the exterior node is considered inside the whole set of adjacencies per room and a deliberate proportional control structure of the form $q_{u,i} = K_{u,i}(T_{sp,t} - T_i)$ is proposed for $T_s p$ desired temperature at the time a room is to be heated. A pure algebraic error state $e_{i,t}$ is also expanded determining the whole discretisation strategy. With initial parameter estimates $K_{i,j}^o$ and c_i^o from mechanical abstraction in Eq. 1, it is possible to solve a Nonlinear Least Squares optimisation problem with the aim of minimising predicting errors by means of the formulation

$$
\begin{aligned}
\theta^* = \arg\min_{\theta \in \mathbb{R}} \quad & (T_{i,t} - \hat{T}_{i,t})^2 \\
\text{s.t.} \quad & \theta \geq 0 \\
& S_p = 0
\end{aligned} \tag{4}
$$

returning the optimal parameter vector θ^* and performed over timespan P. Notice that one can warm up the optimisation routine with an initial first Linear Least Squares approach applied to an ARX-Model attempt. Nevertheless, in the scope of this work, it was demonstrated that the default trust-region-reflective algorithm implemented by **`MATLAB`** `lsqnonlin` solver could deal very well with this task.

For changes in the sampling rate at which the system can learn the parameters of the building, one could also start with a rough approximation and iteratively decrease the time differential in order to refine the solution. The analysis proposed here uses a sampling period of one hour and involves the use of more accurate simulations from the toolbox **`E-plus`**, providing the exogenous inputs of the optimisation problem and thence bounding the performance of the system up to the degree of mismatch of the toolbox itself.

In the real scenario, after put in operation, the scheduling system can be interfaced with the (probably) existing thermostats of the building and program itself e.g. once a week to improve the parametric estimation of the real structure and ensure more accurate results with time. Fig. 2 shows the obtained estimation.

4.3. Decision and control layers

For this work, two layers of intelligence are provided. One dealing with the revenue maximisation problem, which returns the assignment of clients to the rooms according to the booking characteristics and the commercial description of the rooms involved in the building. The second layer represents a lower level optimal control problem that ensures minimal

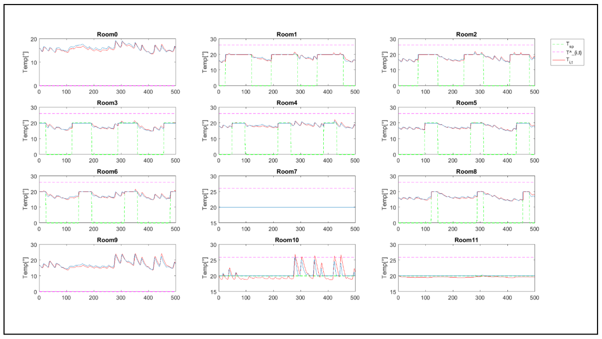

Figure 2: Forward simulation of the system after parameter identification.

energy consumption for an imposed maximum revenue and which depends on the topology and adjacency relationships within the rooms, exterior and ground.

With consideration of the sets:

$$
\begin{aligned}
& d \in D = \{0,1,\ldots n_d\} \\
& r \in R = \{0,1\ldots n_c, n_c+1\ldots n_s\ldots n_r\} = \bigcup\{R_c, R_s\} \\
& R_d \subseteq R \\
& R_{dn} = R_d \bigcup \gamma \\
& d \in D_d \subseteq Dnd \\
& t \in T_1 = \{1\ldots N\} \\
& t \in T_2 = \{1\ldots N+1\}
\end{aligned} \tag{5}
$$

described by booking requests set D, R available n_r rooms in building, out of which there are n_c client rooms and n_s service rooms or common areas (corridors and lounges), R_d compatible rooms to request d (in the case of considering the dummy node γ, one considers R_{dn}), the time sets T_1 and T_2 for revenue and energy consumption optimisation problems respectively and D_d competing requests of request d.

The corresponding constants defined for this step of development are:

$$
\begin{aligned}
& T_{sp} = 20 \\
& \hat{T}_{i,1} \\
& q^S_{i,t},\ T_{e,t} \\
& K_{i,j} \text{ and } c_i \forall i,j \mid i,j \in R,\ i \sim j
\end{aligned} \tag{6}
$$

where T_{sp} determines the temperature setpoint to be reached when a room is selected. The initial temperature states of each room are imposed to be $\hat{T}_{i,1}$. The exogenous inputs $q^S_{i,t}$ and $T_{e,t}$ correspond to the solar radiation through the windows of each room differentiated according to its position on the Earth and the external temperatures measured at every sample. Finally, the transmittance and capacitance parameters $K_{i,j}$ and c_i obtained either through initial theoretical estimate or parameter identification routines.

With this information, the decision variables used for the solution of both optimisation problems are:

$$
\begin{aligned}
& x_{d,r} \in \mathbb{B}\ \forall d \in D \text{ and } r \in Rd \bigcup\{\gamma\} \\
& z_{i,t} \in \mathbb{B}\ \forall i \in Rd \text{ and } t \in T \\
& T_{i,t} \in \mathbb{C}\ \forall i \in Rd \text{ and } t \in T \\
& u_{i,t} \in \mathbb{C}\ \forall i \in Rd \text{ and } t \in T
\end{aligned} \tag{7}
$$

The complete optimisation problem with emphasis on its linear multi objective nature is shown in Eq. 8.

$$
\begin{aligned}
Y^* = \max_{x_{d,r}} \quad & \textstyle\sum_{d\in D}\sum_{r\in R_d} Y_{d,r} x_{d,r} \\
\text{s.t.} \quad & \textstyle\sum_{r\in R_{dn}} x_{d,r} = 1\ \forall d \in D \\
& x_{d,r} + x_{k,r} \le 1\ \forall d \in D, \forall k \in D_d \\
& \text{ and } \forall r \in R_d \cap R_k \\
E^* = \min_{x_{d,r}} \quad & \textstyle\sum_{t\in T}\sum_{i\in R} u_{i,t} \\
\text{s.t.} \quad & \textstyle\sum_{r\in R_{dn}} x_{d,r} = 1\ \forall d \in D \\
& x_{d,r} + x_{k,r} \le 1\ \forall d \in D, \forall k \in D_d \\
& \text{ and } \forall r \in R_d \cap R_k \\
& z_{i,t} = \textstyle\sum_{\substack{d\in D \\ t_d^{in} \le t \le t_d^{out}}} x_{d,r}\ \forall r \in R, \\
& \forall t \in T_1 \\
& \hat{T}_{i,t+1} = \tfrac{1}{c_i}(\textstyle\sum_{i\sim j \bigcup e}(\hat{T}_{i,t} - \hat{T}_{j,t}) + \\
& K_u u_{i,t} + q^S_{i,t} + \hat{T}_{i,t}) \\
& T_{i,1} = \hat{T}_{i,1} \\
& u_{i,t} \ge 0 \\
& u_{i,t} \ge z_{i,t}(T_{sp} - T_{i,t}) \\
& z_{j,t} \ge \wedge z_{k,t}\ \forall j \in R_s \text{ and } k \sim j \\
& Y_t \ge Y^*
\end{aligned} \tag{8}
$$

The aim of this multiobjective problem is that of generating optimal energetically performing assignments once the revenue was maximised. With this a clear differentiation between actual solvers in the market and this scheduling system can be highlighted. For the development of this task, the work is divided into the next steps:

1. Solution of the revenue maximisation assignment problem (upper bound on revenue).
2. Generation of additional revenue-wise optimal solutions
3. Determination of the energy consumption of each of the obtained solutions. (Energy efficiency estimation).
4. Solution of the energy consumption minimisation problem (energetical lower bound on maximal revenue solution).

Notice than the profit is redefined to be depending on the kind of assignments $x_{d,r}$ performed instead of on attempting only to maximize income, which is also something that many easy solvers do. For this, six levels of profit were proposed, each for the compatible assignment of three levels of clients to three levels of rooms and accordingly to Table 1.

The profit was proposed in representative costs, not related to the real world and chosen with the proposal of a desired probability distribution to allow for approachability into a more

Table 1: Levels of profits used as a marketing strategy for this work

Request	Room type		
	Low	Medium	High
Low	9	7	2
Medium	0	22	17
High	0	0	72

real scenario. Notice that this profit definition does not suppress the possibility of assignment of high level rooms to low level requests, for which it is also possible to include an intelligent offer for the clients to ensure their pleasure as much as these profit values are tuned. As an example, one could consider the hotel in Fig. 3 with rooms 5 and 6 categorised as a high level rooms and rooms 9 and 10 with the biggest amount of solar irradiation (therefore energetically less demanding, at least in a direct sense).

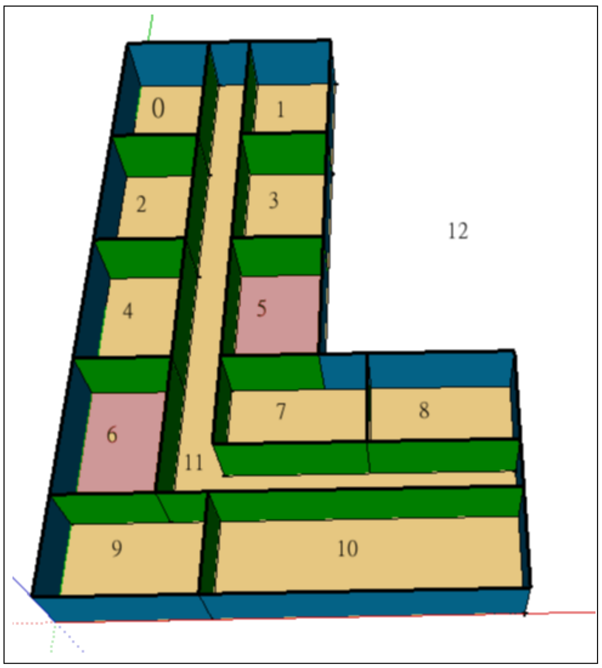

Figure 3: Forward simulation of the system after parameter identification.

After running the framework, one can find, among the several solutions, that by ensuring the optimum revenue value, it is possible to get energetically less demanding solutions preferring to start assigning rooms near rooms 9 and 10 than farther away. Notice that for this case, the fact that one room is occupied implies that the temperature of the central corridor (11) is also set to T_{sp} so that it might become more difficult to give a direct interpretation of the solutions. Nevertheless, the optimisation framework approach corresponds to a software robot capable of deciding for the owner of the building which rooms to assign by protecting the revenue, ensuring least energy consumption and learning the real parameters of the system for further proposals.

5. Data used and experimental campaign

5.1. Data

As said before, this work attempts to find optimal solutions in means of revenue and energy on two kinds of hotel. The first case corresponds to an easily found small scale hotel with one floor and with 20% of its rooms only dedicated to high level requests. In the scale commented before, six rooms where imposed as low level, 3 as middle range and 1 as high level. The bigger hotel, on the other hand counts with 23 rooms (15 low , 6 medium , 2 high), with 7 of them located on the first floor, and 8 on the other two. This information is necessary for planning the demand.

The optimal analysis should take place every time there is a new request, introducing the already occupied rooms as constraints. For analysis purposes, however, an optimisation horizon of two weeks was proposed. Fig. 4 shows the distribution used for planning the demand and based on information provided by a marketing analysis from ISTAT [5] in Liguria. Also, the weather parameters were taken from a Genova weather file, including those of the exterior temperature, ground temperature and solar radiation. [6]

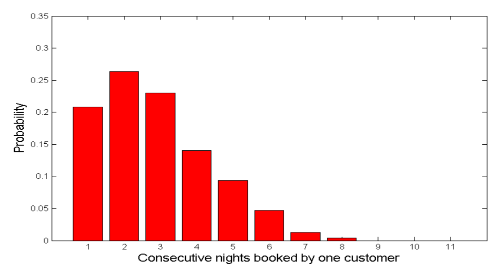

Figure 4: *Statistical distribution of the consecutive number of night asked by a customer.*

As explained before, the revenue is not just dependent on the price of the room, but also on the maintenance costs of the room which is about one tenth of the room's price (1, 3, 8 $[\frac{money}{night}]$). Finally, according to the formulation, a compatible costumer for a room can stay in a upper quality room paying the same price as offered during the booking request. So, since the revenue is the difference between price and maintenance cost of a room, the hotel can get 6 possible revenues according the combinations seen in Table 1.

5.2. Experimental campaign

A non-dimensional index was proposed in order to evaluate the performance of the scheduling system against that of common assignment approaches: The Relative Percent Deviation-RPD.

$$RPD = \frac{|X_o - X_r|}{X_o} \times 100$$

Where: X_o is a characteristic measure of the energy obtained by using any assignment ensuring maximum profit. X_r corresponds to the optimal energy solution with maximum revenue as constraint.

An important variable taken into consideration is the percentage occupancy of the hotel. If it were 100% occupied, there would not be any reason to optimize the assignment of customers. Characteristic rates of approximately 30%, 50% and 65%. Because the demand is generated before optimizing the revenue and some of the requests can be rejected during this step, some extra demand was added in order to remain about the above mentioned values.

Notice that the optimal energy consumption solution is not compared against any possible assignment given by any solver with non optimizing characteristics but rather against the heuristic solution of the solver used for optimisation (Gurobi). Moreover, to ensure robustness of the analysis form the statistical point of view, 10 instances per occupancy rate were generated for each of the two topologies and the optimisation process was run on five several solutions per instance and averaged. The RPD[%] can be then computed out of these comparison quantities.

6. Results and conclusion

Table 2 confirms the fact that for this optimisation run, energy is saved.

Table 2: Relative percentage difference

Occupancy	30%	50%	65%
Hotel 1-floor	5.68	8.88	4.27
Hotel 3-floor	11.27	8.73	4.27

In general, the obtained results prove that an increasing revenue is ensured for lower occupancy rates. However, the small hotel (30% occupancy rate) seems not to follow this expected behaviour. By analysing particular results, it was possible to propose possible causes to this event:

1. In many of the cases, more than one overlapping high quality rooms were proposed. The small hotel counts only with one high quality room and therefore the degree of compatibility in different assignments potentially decreases. Maximum revenue can therefore only be obtained by reassigning low and medium level rooms.

2. It was possible to notice that the solar radiation had an important effect on the dynamics of the system. Rooms facing the south side of the building are favoured with more solar radiation. For some cases, the energy consumption optimised assignment selected rooms near this location first, however the higher level rooms were located in unfavoured locations with respect to solar irradiation. This again constrained the capacity of assignation for which both energetic and revenue optimisation approaches were very similar in nature.

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