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Genetic Algorithm Optimization of the Economical, Ecological and Self-Consumption Impact of the Energy Production of a Single Building

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***Abstract*—This paper presents an optimization method based on genetic algorithm for the energy management inside buildings developed in the frame of the project Smart Living Lab (SLL) in Fribourg (Switzerland). This algorithm optimizes the interaction between renewable energy production, storage systems and energy consumers. In comparison with standard algorithms, the innovative aspect of this project is the extension of the smart regulation over three simultaneous criteria: the energy self-consumption, the decrease of greenhouse gas emissions and operating costs. The genetic algorithm approach was chosen due to the large quantity of optimization variables and the non-linearity of the optimization function. The optimization process includes also real time data of the building as well as weather forecast and users habits. This information is used by a physical model of the building energy resources to predict the future energy production and needs, to select the best energetic strategy, to combine production or storage of energy in order to guarantee the demand of electrical and thermal energy. The principle of operation of the algorithm as well as typical output example of the algorithm is presented.

***Keywords*—Building's energy, control system, energy management, modelling, genetic optimization algorithm, renewable energy, greenhouse gases, energy storage.

I. Introduction

THE design of an efficient management of the energy production and consumption of individual buildings is a challenge in the perspective of greenhouse gases emissions reduction. The existing solutions for the optimization of the local renewable energy production does not allow an energetic independence with respect to external resources. A major obstacle to this independence comes from the temporal shift between the energy production and users demand. In order to give the energy independency a major focus is increasing the energy efficiency. Several projects and commercial products concentrate on the increase of the energetic production efficiency and the improvement energy regulations methods. In Fribourg, several projects are dealing with this topic mainly on the optimization of the energy self-sufficiency: "Carbon correlation experiment" [1] and "Prototype for predictive, autonomous and innovative energy management for buildings" [2]. There are also commercial products with optimization algorithms coupled to predictive models like Neurobat [3], Loxone [4] or Siemens [5]. Products like Gridsense [6] couple the operating cost with the energy consumption in the control system of the building. Research projects as "Carbon correlation experiment" project [1] bring a new approach with a control systems which has for only purpose the decrease of the CO2 emissions of the building.

The present project aims at the development of a regulation which takes into account three pillars of the sustainable development [12]: the energy independence, economy (decrease of operating costs) and ecology (decrease of CO2 emissions) by using genetic optimization algorithm and a physical model based on weather forecast. Most commercial products and projects performed in Fribourg use decisions trees as individual building energy control method [1], [2], [7]. This work wants to implement a more flexible strategy of optimization based on in-house algorithm and weather forecasts [8]–[11].

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II. Optimization Algorithm Principle

The algorithm structure is presented in Fig. 1. The initial input data consist in real time physical parameters of the building system (room and outside temperatures, electrical needs, etc.) and the users set values. These data are sent to the optimization loop. This part simulates different scenarios for the energetic time evolution of the building based on weather forecasts and physical models and selects the best energetic strategy. The optimization method is based on genetic algorithm. The principle of the genetic algorithm method consists in trying a set of randomly generated solutions, sorting them according to a mathematical criteria called the score function and mixing them to find better solutions. In our case, a solution is a set of coefficient that tells the percentage and time of use of the different energy resources of the building. For example, if the simulation lasts a total of 48 hours with time steps of 1 hour, the algorithm will generate 48 random coefficient for each technology. In addition, the state of the energy resources during these 48 hours is predicted using a physical model of the electrical and thermal production, storage system and users needs. The random coefficients are constrained to fulfill the needs with the available energy at each time. At the end of the simulation a score is attributed to each energetic scenario based on a combination of the three optimization criteria :

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energetic independence, CO_2 production and costs. At this state the algorithm generate a new set of scenarios based on a combination of the previous scenarios and the simulation is launched again in order to obtain new improved solutions. The algorithm optimization runs for a given number of loops and allow to get the best scenario found corresponding to the best score. At the end, the coefficient of use of the best scenario is used to regulate the entire building energy system. By this method, the solution that is used is based on the future evolution of the global system and will find solutions that are different from an optimization based on single time system state.

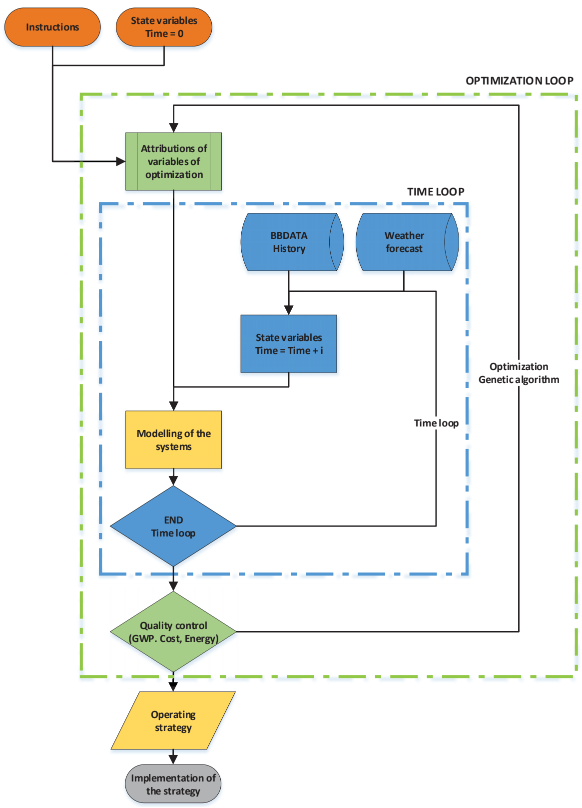

Fig. 1 Algorithm structure

A. Genetic Algorithm

The choice of the genetic algorithm method is motivated by the large number of variables of the optimization function, and by the non-linearity of the latter. Conventional method use the function gradient to find the minimum or maximum of a function but here the gradient is non-linear due for example to the abrupt change of score when an energy source becomes empty. In addition, the large number of variables (one for each energy technology) make the optimization space to be too large to scan in a pure random way. The optimization algorithm is written in the Python 3.6 programming language. All functions used for the genetic algorithm optimization come from the pyevolve Python framework [13]. The method requires a so-called score function, given by the user, that allows to rank different solutions. In this work the score function is a combination of three criteria: the energy production costs, the CO_2 equivalent ecological impact and the energetic independence. The score of each criteria can be weighted in order to favor a particular one. However, for the moment and in the example presented in this paper, the score function only minimizes the CO_2 equivalent value.

B. Optimization Criteria

The optimization function combines three criteria for the global energy management. The first criteria is the building's self-production and self-consumption. Commercial solutions are usually dedicated to one specific energy subsystem (for instance the heat pump). The global approach use in this work aims at using the thermal and electrical storage to reduce the use of external energy resources (power grid) and non-renewable energy resources (wood, gas or oil). The second criteria is the carbon footprint or the Global Warming Potential (GWP). When using non-renewable energy sources or the power grid, the building increases its carbon footprint. As shown in Fig. 2, the carbon footprint of the swiss power grid [14] is varies in time, these variation being due to the electricity production type (nuclear, hydraulic, etc.). The ecological criteria tends to use the grid when its GWP is the lowest, and thus store it in advance in batteries.

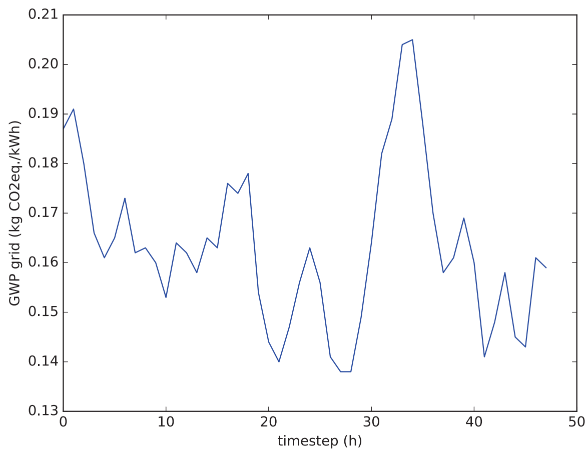

Fig. 2 Variation of the carbon footprint (GWP) of the power grid [16]. The GWP value fluctuatation is of the order of $\approx \pm 20\%$

The third criteria is the operating costs. The algorithm is feeded with the selling and purchase prices of energies like the power grid. This information is included in the optimization function in order to increase the equipment profitability. Consequently, as for the ecological criteria, the algorithm allow to anticipate the purchase/sell of electricity to the power grid at the best rate. With the opening of the swiss energy market [15] to the public market, it is essential to take into account this criterion.

C. Predictions of Future Production and Consumption

In order to anticipate disadvantageous situations, a physical model of the time evolution of the different energy resources (for instance, the domestic hot water) is used. This model predicts the future state of each energy resource by using the weather forecast and users habits. The weather forecast is used to predict the photovoltaic and thermal solar energy production and the building thermal energy needs and losses. Thanks to presence sensors and to the building energy consumption database history, the average users habits are statistically determined . The algorithm will, for example, anticipate inside building heat-up before the usual presence of people.

III. Example of Algorithm Optimization with Real Data

This section presents an example of optimization using real data as inputs. The data comes from the Laboratory of Renewable Energies Integration (LIRE) [17], located on the site of blueFACTORY [18] in Fribourg, Switzerland. This building is equipped with several energy resources devices like thermal and electrical solar panels, an air-water heat pump, an electrical battery, etc. These devices are connected to sensors that deliver real time physical information (temperature, power, presence, etc.) which is stored in a database. This data will be used to test the algorithm. The mathematical functions used to model the time evolution of the state of each subsystem are simplified in order to deliver a correct physical behavior but need to be refined in the future for more precise calculation. In this example there are 5 different subsystems to optimize : the charge/discharge of the electrical battery, the heat pump use, the charge/discharge cold of the thermal storage, the hot thermal storage use and the power grid use. However in practice however, the number of free parameters is only 2 because of the dependence between each subsystem. In the future, more technologies will be added, thus increasing the number of free parameters.

A. Algorithm Input Data

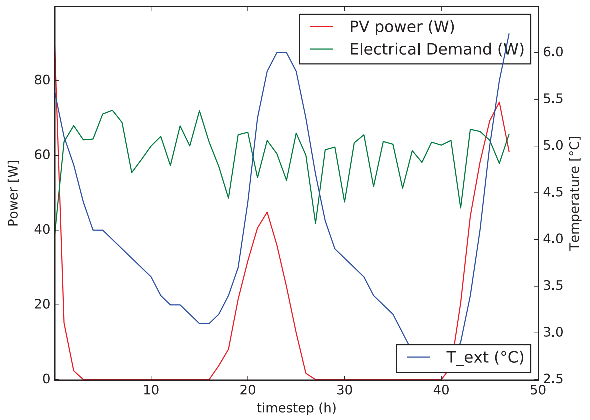

Fig. 3 Example of algorithm predicted data for 48 hours. The daily variation of the solar pannel production and outside temperature are determined by weather forecast and the building energy needs is computed from the physical model. In this example the users power need is limited to the devices standby mode (60 W continuously)

Fig. 3 shows an example of the algorithm predicted data for 48 hours: the photovoltaic pannel power production, the outside temperature and the building energy demand. The first data value, at the beginning of the series, are measured in real-time and the rest of the data are computed from the physical model for the next 48 hours. The outside temperature and solar energy comes from weather forecast and are used to compute the photovoltaic power and building energy demand. The building energy need varies also with the people presence (variation between night and day) but, in this example the users demand consists only in the standby mode of device (60 W continuously).

B. Algorithm Optimization Results

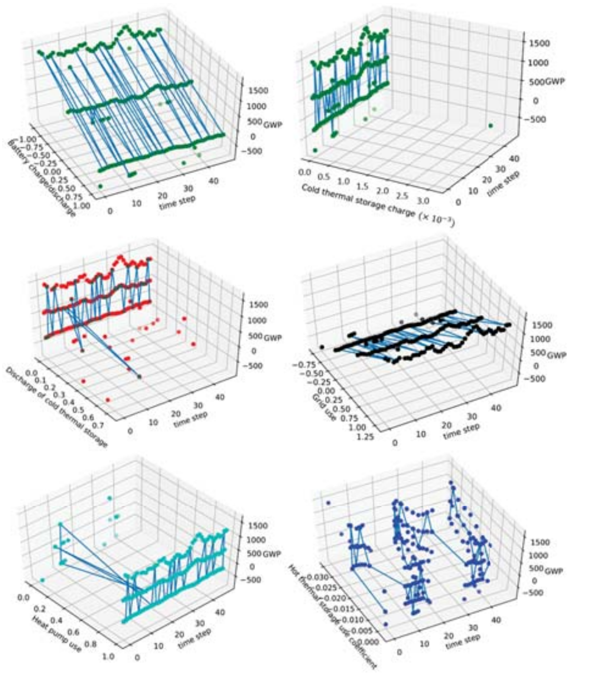

Fig. 4 The 6 plots show all the 100 strategies tested by the algorithm. The best strategy is shown by a solid line connecting the coefficient values

The optimization process tries to find the best strategy to use the different technologies for a given period of time. For the results presented here, the total prediction duration is 48h with an hourly rate of use profile allowing thus makes a total of 48 coefficients to optimize for each technology. The genetic algorithm method starts with a set of random solutions for the first generation (here 10), and rank them according to the defined score function. Presently, the score function only optimizes the CO_2 equivalent, but in the future will include the two others criteria. For the second generation of solutions the algorithm mixes different solutions of the first generation with each other and evaluate them with the score function. For the results presented here the algorithm has performed ten consecutive generations of results.

All 100 solutions tested by the algorithm are presented in Fig. 4. On each of the six plots there is a ensemble of data points. Each data point corresponds to the value of a given coefficient at a given time during the 48h of simulation. One strategy for the 48 hours corresponds to 48 points in two of these plots, i.e. 96 values. All other coefficients can be computed from these 96 free values. The best strategy is indicated by the data points linked with solid lines. A quick look at the plots reveal that the entire space is not scanned by the algorithm. The reason for the empty parts of the plots is the physical constraints included in the algorithm. For example, when there is a heating demand, the cold thermal storage discharge is forbidden and the coefficient of cold thermal storage discharge remains zero. An other example is the correlation between the coefficient of the electrical battery charge-discharge (which can take the discrete values -1, 0, or 1) and the use of the power grid. Since in the previous example, the user power demand is very low (its value is at present only the standby demand of devices of ~ 60 W), the electrical energy is exchanged between the power grid and the battery, explaining why the two sets of data have mainly opposed values. The battery is feeding the power grid and vice versa.

C. Results of the Best Strategy

Based on the optimization presented in Section III-B a best strategy is obtained. Fig. 5 shows the 48 hours prediction of a few building state variables for the best strategy. The internal temperature follows the user set value of 20 °C during the day when people are present (red line equal to 1) and goes down below 10 °C during the night (when the building is empty red line equal to 0). In practice the presence is anticipated and the warming of the room starts in advance. Once the room temperature has reach the user set value, the temperature is regulated by a proportional-integral-derivative method or cooled down by the thermal cold storage.

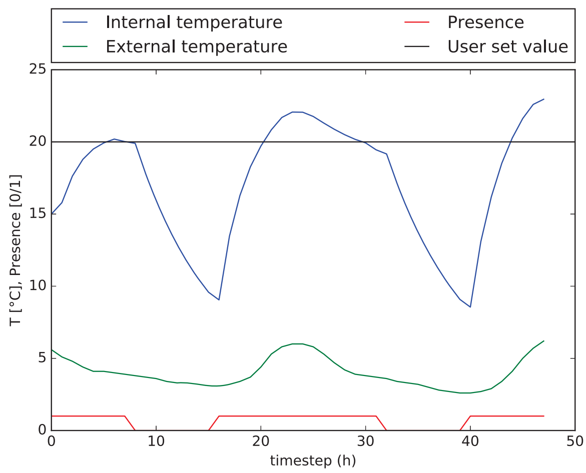

Fig. 5 Example of the time evolution of the building room temperature and three parameters for the best strategy found in Section III-B. The variation of the internal temperature depends on the external temperature, the user set temperature value and the presence of people in the building. During the night, the room is naturally cools down and is only heated up when people comes in

Fig. 6 shows the time evolution of the battery level, the photovoltaic power, the building energy demand and the use of the power grid. In this example, the strategy given by the algorithm suggests to empty the battery gradually to minimize the purchase of electricity on the grid. Thus, the carbon footprint (GWP) is decreased (objective fixed to the algorithm in this case).

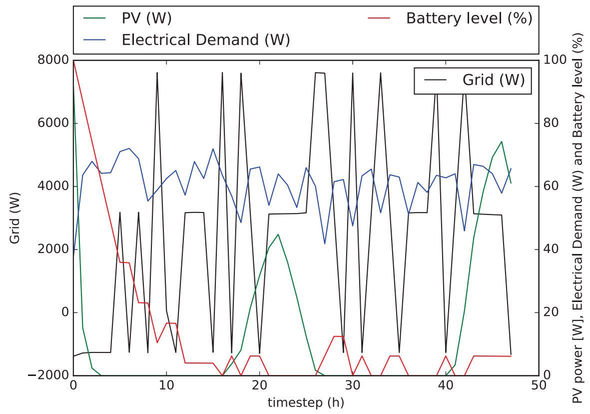

Fig. 6 Example of 48 hours time evolution simulation of the photovoltaic power, the battery level, the power grid use and the user electrical demand for the best strategy found

IV. Conclusion

The research on building energy consumption and self-production efficiency is crucial for the CO2 emissions reduction. The current commercial approach is based on the optimization of individual energy subsystems performances. This paper proposes an approach which allows to optimize all energy resources at the same time while taking into account their couplings/interactions. The algorithm performs a real time optimization of the production, consumption and energy storage. The genetic optimization algorithm uses three criteria to select the best energetic strategy: the energy independence, the ecology (decrease of carbon footprint) and the economy (decrease of operating costs). It uses real time data of the building environment (temperature, people presence, etc.) and evaluate the best strategy by predicting the future evolution of the resources based on the users habits and weather forecast thanks to a physical model. A case study is presented with focus on GWP which includes the real application on a test laboratory in Switzerland. This case study allows the identification of the best scenario for this parameter and proves the correct excecution of the genetic algorithm. At present the algorithm uses one criterion (minimization of the carbon footprint) for the optimization to find the best two free parameters for a duration of 48 hours. The algorithm will be tested on the data provided by the Laboratory for the Renewable Energies Integration in Fribourg (Switzerland) in order to improve the energy systems modeling. Once the algorithm completely validated more technologies and energy systems will be included.

References

[1] T. M. Schafer, G. Magnin, D. Vuarnoz and E.-L. Niederhäuser, *Development and Validation of an Intelligent Algorithm for Synchronizing a Low-Environmental-Impact Electricity Supply with a Buildings Electricity Consumption*, University of Applied Science of Fribourg and Swiss Federal Institute of Technology of Lausanne, proceeding of the 4th International Conference on Renewable Energy Technologies, January 2018.

[2] L. J. Favre, T. M. Schafer and E.-L. Niederhäuser, *Prototype for predictive, autonomous and innovative energy management for buildings*, University of Applied Science of Fribourg, unpublished, 2017.

[3] Neurobat AG, *products and technologies aimed at reducing HVAC-related CO2 emissions and energy costs*, Neurobat products NOL and NIQ: http://neurobat.net/fr/produits/, read in December 2017.
[4] Loxone Electronics GmbH, *smart home product*, Miniserver: http://shop.loxone.com/dech/miniserver.html, read in December 2017.
[5] Siemens AG, *HVAC control system for small and medium-sized multipurposed buildings*, Synco product: http://www.buildingtechnologies.siemens.com/bt, read in December 2017. /global/en/buildingautomation-hvac/building-automation/building-automation-for-small-applications-synco/pages/hvac-building-automation.aspx, read in December 2017.
[6] Alpiq InTec Suisse SA, *intelligent energy control*, Gridsense: https://www.gridsense.ch/en/home.html, read in December 2017.
[7] G. Magnin, M. Rouge, V. Liblin and E.-L. Niederhäuser, *Photo-PAC: Optimization of the use of the coupling heat pumps - solar photovoltaic thanks to the predictive management*, University of Applied Science of Fribourg, unpublished, 2015.
[8] F. Oldewurtel, A. Parisio, C.N. Jones, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, M. Morari, *Use of model predictive control and weather forecasts for energy efficient building climate control*, 2012, Energy Build., 15-27, 2012.
[9] F. Oldewurtel, A. Parisio, C. Jones, M. Morari, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, K. Wirth, *Energy efficient building climate control using stochastic model predictive control and weather predictions*, 2010, American Control Conference (ACC), 5100-5105, 2010.
[10] M. Killian, M. Kozek, *Ten questions concerning model predictive control for energy efficient buildings*, 2016, Building and Environment vol. 105, 403-412, 2016.
[11] Binghui Si, Zhichao Tian, Xing Jin, Xin Zhou, Peng Tang, Xing Shi, *Performance indices and evaluation of algorithms in building energy efficient design optimization*, 2016, Energy vol. 114, 100-112, 2016.
[12] Sustainable development, FSO, Federal Administration: https://www.bfs.admin.ch/bfs/en/home/statistics/sustainable-development.html, read in December 2017.
[13] Pyevolve: A Python Open-source Framework for Genetic Algorithms. Perone, C. 2009. 1, November 2009, SIGEVOlution, Vol. 4, pp. 12-20, November 2009.
[14] D. Vuarnoz and T. Jusselme, *Temporal varitation in the primary energy use and greenhouse gas emissions of the electricity provided by Swiss grid*, submitted, 2017.
[15] Energy Act (EnA), Swiss Federal Council: https://www.admin.ch/gov/en/start/documentation/votes/Popular%20vote%20on%2021%20Mai%202017/Energy-Act.html, read in December 2017.
[16] D. Vuarnoz, T. Jusselme, S. Cozza, E. Rey and M. Andersen, *Studying the dynamic relationship between energy supply carbon content and building energy demand,*, 2016, PLEA conf. Los Angeles, 2016.
[17] H. Brülhart, D. Vionnet, M. Boesiger and J.-P. Bacher, *Smart Living Lab: Laboratoire d'intégration des énergies renouvelables*, University of Applied Science of Fribourg, 2017., unpublished, 2017.
[18] blueFACTORY, *the neighbourhood of the innovation of Fribourg*: http://www.bluefactory.ch/fr/home, read in December 2017.