DESIGN DAY SELECTION BASED ON MULTIOBJECTIVE OPTIMIZATION

*Sara Khelil (1), Fatma Zohra Haridi(2), Alla Eddine Khelil (1), Berkouk Djihed (1), Bouzir Tallal Abdelkrim (3)

(1) University of Biskra
(2) University of Guelma
(3) University of Blida

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ABSTRACT

Assuring interior comfort in the attempt to realize an energy economy is a very important task, without which, the design of a new modern building is not even conceivable. The annual climatic variations have a big influence on the energy consumptions of buildings, where it is necessary to know how is the building's energetic behavior through a whole year providing an important basis for the design. The building's behavior simulation becomes valuable technique to understand and optimize enormous challenges. It depends on the values of yearly meteorological parameters variations. However in this case we have to do a lot of simulations, which is a time consuming process. In this work, we present an overview on the design day notion and we propose a new method for selecting the design day, to study the building comfort, using the nondominated sorting genetic algorithm II "NSGA-II" for optimizing simultaneously the climatic criteria.

Keywords: Design day, Multiobjective optimization, Pareto approach, NSGA-II, AMY, Building comfort, Performance simulations, Hot and arid regions.

1- INTRODUCTION

Computer simulations have been well recognized over the years, where different approaches and methods have been developed and used for studying and predicting behaviors of complex systems such as wildfires, urban traffic, buildings studies and infectious disease spread. Many different approaches and methods have been developed. Data used in the simulations and fidelity of the simulations models affect the accuracy of these simulations. Weather data sets have big influence on simulated annual energy use and cost, Crawley had compared the influence of the various weather data sets in (Crawley, 1998)

Recently, building related engineering have big interest in computer simulations, where many simulation programs have been developed to resolve a number of challenges including: sizing equipment, monitoring and troubleshooting installed equipment, estimating long-term behavior and energy consumption, simulating equipment behavior. Designers need to make key design decisions in the early design stages, in order to provide better guidance for building design. By using performance simulations and exploring the short and long-term dynamic behavior of the designs and for understanding the cause and relationships of the weather phenomena, they become valuable technique to understand and optimize enormous challenges.

Buildings simulations depend mainly on thermophysical properties and the values of yearly meteorological parameters variations. Users of energy simulation programs often have a wide variety of weather data from which to choose from locally recorded, measured data to typical data sets. The use of multiple year measured meteorological data is a time-consuming method. Therefore, it is necessary to derive a weather dataset, an alternative reduced weather data as "the design day", extracted from yearly weather information, is able to represent the climate of a location that can ensure shorter time and less complex simulation. Design days are used to visualize the designs performance during a precise period, it can be revealing about the designs strengths and weaknesses.

Previously, the weather data used in performance simulations were carried out through a statistical processing to extract extreme values for each weather criterion over the previous ten years or so. The extracted values are then linked and used as one-day design weather data, which leads to overestimation and unrealistic results. **(7days)**

The aim of this research is presenting the notion of the design day and proposing a new method for selecting the design day, to study the building comfort, using the nondominated sorting genetic algorithm II "NSGA-II"; for optimizing simultaneously the climatic criteria and helping the buildings designers with an alternative reduced weather data extracted from yearly weather information that can ensure shorter time and less complex simulation. In order to clarify this new method, we apply it into a case of study of the natural ventilation in a typical medium rise residential building located in a semi-desert region (Biskra South East of Algeria) under a hot and dry weather. It has a rigorous climate characterized by very hot, dry summer and cold winter. Its characteristics are unfavorable for achieving thermal comfort.

2- DESIGN DAY OVERVIEW

The design day is a real historical day, which reflects the natural hourly variations of meteorological parameters. We select it from a complete set of weather data for a single day chosen from the meteorological year. Theoretically, the design day is ~~to be~~ the day having the most adverse set of weather conditions to enable the design to meet the indoor comfort criterion all over the year when performing at their maximum capacity **(Tianzhen, 1999)**. Design days are used to visualize the designs performance during a precise period, it can be revealing about the designs strengths and weaknesses. An important characteristic of a worst-case meteorological period is that it can be representative of a class of meteorological conditions that occur in a region and can effect human comfort. This kind of days are known as prototype days.

Design days consist of 24 hourly values of climatic criteria parameters. Because of the significant thermal inertia of a building and its internal structure, the effects of the hour-by-hour fluctuation of the weather are not immediately felt but are distributed over several hours of the day. It is important that a better understanding of a region's meteorological conditions is established to aid in the design of building's ventilation and energy systems **(IOLANDA, 2008)**.

Colliver et al proposed a method for determining design weather sequences that uses the mean value for a certain weather element over a given period of time as an index in order to select several days of extreme weather (Colliver et al,1998).

In the other hand, O'Brein et al (SDD), in order to evaluate the passive solar house design has proposed a method for selecting solar design days SDD by identifying the most appropriate days by visually inspecting the weather data. He was interested by dry bulb temperature, direct solar radiation and horizontal diffuse radiation to define the solar design days as follows: cold sunny day, cold cloudy day, warm sunny day, mild sunny day. While Hisaya Ishino (7days) has presented a proposal of seven day design weather data for HVAC peak load calculation which is the most critical (SDD). The method consists of reviewing data from 20 years of weather observations and selecting a seven days period during which the weather conditions were extreme and matching the human weekly working cycle because, in the author's view, the weather is affected by urban heat generation, exhausted gaz and weather characteristics on holidays may be different from those on weekdays.

3- SIMULATIONS WEATHER DATA

Over the past 20 years, several organizations have developed weather data sets (Hong, 2000; Crawley, 1997). California Energy Commission (CEC), National Renewable Energy Laboratory (NREL), the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) and WATSUN Simulation Laboratory have developed typical weather data sets to use for simulating building energy performance (Drury, 1998). Where all groups intended their weather data sets to be usable with energy simulation programs. For instance, EWY, TRY-US, TRY-ROW, TMY, TMY2, TMY3, IWEC, WYEC2, CWEC, and AMY, which are typically, single year compilations for specific locations. Each year is assembled from 8,760 hourly records for the wanted data parameters (**Piotr, 2013)**. There are two primary sources for climate data: Direct Observations (Weather Stations), which generally accurate but measure a limited number of variables (5 – 10); or modeled data: Reanalysis data (free data uniformly distributed across region or globe with all variables).

There are three general approaches to selecting weather years.

- The first approach selects a contiguous year where the monthly means and standard deviations for that year match the means and standard deviations for a longer period of record – often 15 to 30 years. Examples of this approach include EWY and TRY-US.

- The second approach involves creating composite years using representative months from different years. Examples of this approach include TRY-ROW, TMY, TMY2, TMY3, CWEC, WYEC2, and IWEC. Data selection therefore emphasized 'typical' years that are representative of these longer-term durations (e.g. 30 years) **(Skeiker, 2007)**.
- The third approach includes Actual Meteorological Years (AMYs), which represent hourly weather data from a single contiguous year that is not necessarily representative of a greater span of time. This approach is favored when examining a typical or extreme years.

Below we describe some of the major types of climate datasets used in energy modeling. The developers used standard methodologies to determine which data would be used from the actual weather data period of record. The methods were virtually the same; the true differences are related to the different weights applied to weather variables in the selection process.

- **TRY (TRY-US) – Test Reference Years**

The TRY datasets were first created in 1976 by NOAA's National Climatic Data Center. They entail hourly data from 60 locations in the United States. The data include dry bulb temperature, wet bulb temperature, dew point temperature, wind direction, wind speed, barometric pressure, relative humidity, cloud cover, and cloud type. However, no measured or calculated solar data are included. When used for building energy simulations, the simulation program must calculate the solar radiation based on the cloud cover and cloud type information available in the TRY data. The representative year is obtained by eliminating years that contained months having high and low temperature means. This process continues until a single reference year remains. The elimination of extremes results in datasets, which are significantly more moderate than other contiguous years for the period of record. The TRY data therefore represent a poor choice when evaluating atypical or extreme conditions **(Fagbenle, 1995)**.

- **EWY – Example Weather Years**

Example Weather Year datasets in the United Kingdom were also developed in the 1970s using methodologies similar to those used for TRY-US. These data were compiled using a representative contiguous year from a 20-year period of record.

- **TRY (TRY-ROW) – Test Reference Years**

TRY datasets created in Europe and other parts of the world employed methods and data elements similar to those used in TMY datasets. Therefore, TRY-US and TRY-ROW are not interchangeable **(Rahman, 2007 ; De Miguel, 2005)**.

- **TMY – Typical Meteorological Year**

A typical meteorological year (TMY) is a collation of selected weather data for a specific location, generated from a data bank much longer than a year in duration. It is specially selected so that it presents the range of weather phenomena for the location in question, while still giving annual averages that are consistent with the long-term averages for the location in question **(Hall,1978)**.

TMY data is frequently used in building simulation, in order to assess the expected heating and cooling costs for the design of the building. It is also used by designers of solar energy systems including solar domestic hot water systems and large scale solar thermal power plants.

To construct a TMY, we have to choose the main characteristics that can be followed through hour values at least for 10 years (temperature, humidity, solar radiation, pressure, wind speed etc) **(Argiriou, 1999; Skeiker, 2004)**. The TMY files do a good job capturing typical conditions but (by design) do not show the extremes, which becomes increasingly important as the movement toward energy efficient design **(Hisaya ISHINO, 2005; Ohunakim, 2013).**

The construction is done in two stages **(IOLANDA , 2008)**:

A. In the first stage, a typical month is chosen based on meteorological data, recorded in several real years. For example, a typical January will be a real January from the observation years taken into account.

B. In the second stage, the data between two typical months (which can be from two different years) are adjusted, in order to do a smooth transition between months. There are a lot of smoothing variants, like, for an example, a local mediation with Gaussian variables or interpolation with cubic spline functions.

Two primary types of TMY files subsequently replaced the initial TMY file:

- ✓ TMY2 files that use 30 years of data replaced the initial TMY file in about 1990, with an enhanced weighted average selection method. The TMY2 data sets were updated by NREL to represent the most recent period of record available for work that requires insolation data. TMY2 should be used in building energy simulations where insolation is critical to the results, since it provides insolation that is closer to the long-term average than the other available data sets (Drury , 1998).
- ✓ TMY3 files that use 15 years of data were introduced in 2005 with a higher emphasis on solar radiation variables and also included precipitation as a variable. While statistically stable files require 30 years of data, the TMY3 utilized only 15 because that is the period where adequate satellite input was available.

Different approaches were used for generating TMY files. Skeiker have developed six methods to generate TMY dataset for Damascus (Skeiker, 2004). TMY weather file capture only typical conditions but do not show the extremes, which is progressively important as the movement toward energy efficient design drives heating and cooling systems to be only as big as they have to be and then being overtaxed with extreme conditions they were not designed to handle. This type of weather data is only created from where the measurements were (airports) and they do not necessarily represent the climate at any site unless the site is near an airport.

- **WYEC – Weather Year for Energy Calculations**

In 1983, ASHRAE created WYEC datasets as another means for simulating 'typical' weather patterns. This database was built on the TRY format utilizing solar data that was either measured or estimated from cloud cover and type. ASHRAE designed the WYEC2 data set to represent typical weather patterns (Drury, 1998).

- **CWEC – Canadian Weather for Energy Calculations**

The CWEC datasets represent typical year data based on the WYEC2/TMY methodologies. They were created by WATSUN Simulation Laboratory for use by the National Research Council Canada in developing and complying with their new National Energy Code for Buildings.

- **IWEC – International Weather Year for Energy Calculation**

ASHRAE released IWEC weather files in 2000. These datasets contain 'typical' weather data based on the TMY format intended for use with building energy simulation programs. The IWEC format utilizes 18 years of hourly data.

- **AMY – Actual Meteorological Year**

As the title implies, AMY files represent actual hourly contiguous datasets for a given location and time, where energy use data is available. It is used to manage and confirm the actual performance of a building **(Y. Cui et al., 2017)**.The advantage of AMY datasets is their flexibility and customization; however, when creating customized datasets. AMY files are the way to go when seeking customized datasets that account for actual observed conditions and climate extremes. AMY files can be created from a local airport station **(Tianzhen, 1999)**. They are used to assess the impact of weather on long-term building performance and evaluate the energy saving.

- **MDRY – Moisture Design Reference Years**

In 2011, ASHRAE 1325-RP developed Environmental Weather Loads for Hygrothermal Analysis and Design of Buildings with the purpose of developing representative weather year data for moisture design calculations. This undertaking created a methodology to determine Moisture Design Reference Years (MDRY) from hourly climate records for 100 locations in the United States and 7 locations in Canada.

There are two primary sources for climate data:

- Direct Observations: we can have those files from Weather Stations (ground, buoys, and balloons). Generally accurate but measure a limited number of variables (5 – 10).

- Modeled data: Reanalysis data, through full or partial atmospheric models run for individual sites.

The use of inappropriate weather data can result in large discrepancies between predicted and measured performance of buildings.

4- METHODOLOGY : DESIGN DAY SELECTION USING THE NONDOMINATED SORTING GENETIC ALGORITHM II "NSGA-II"

According to our objective, the design day is selected from the 365 days in 2015 where the selection is based only on daily averages of temperature and wind speed parameters, thus the selected day is the day having the maximum temperature (*t*) and the maximum wind speed (*ws*). In this context, the problem is defined as research, from a set of possible year days, the day (d^*) that makes these two criteria in their maximum values. To optimize (maximize) simultaneously these criteria, the multiobjective optimization (MO) techniques are used in the problem of the design day selection. Users of simulation programs and designers have to make serious decisions based on multiple criteria involving more than one objective function to be optimized simultaneously. Often such problems are subject to Multi-Objective Optimization, where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives.

In multiobjective optimization problems (MOP), we have two or more objective functions to be optimized at the same time, instead of having only one. As a consequence, there is no unique solution to multiobjective optimization problems, but instead, we are aiming to find all of the good trade-off solutions available (the so-called Pareto optimal set). A solution xp is a Pareto optimal solution if no objective function can be improved without worsening at least one other objective function. Such solution is not unique, and the set of the Pareto optimal solutions are known as the Pareto front.

Several bio-inspired optimization techniques have been developed for MO problems, the most known are genetic algorithms (AGs). The nondominated sorting genetic algorithm II "NSGA-II" [5] is the most popular genetic algorithm for solving MOP. This algorithm can find multiple Pareto-optimal solutions in a multi-objective optimization problem and has the following three features: It uses an elitist principle, it uses an explicit diversity preserving mechanism, and it emphasizes non-dominated solutions.

In the table Table.1, we present two daily weather parameters, temperature and wind speed, from the 2015 AMY weather file, such as for each parameter, the annual maximum, minimum and average are described. These weather parameters have an influence on the energy and ventilation performance of a building [4]. Besides acting as control criteria in the selection of a design day, these criteria offer clues for interventions to reduce discomfort in occupied zones.

Weather parameter	Annual maximum	Annual minimum	Annual average
Temperature T [°c]	44,9	-2,1	19,87
Wind speed V[m/s]	10,6	0,1	1,87

Table .1. Annual statistics of the Biskra 2015 AMY

The design day is selected from the 365 days in 2015. The selected design day weather file consists of detailed data of 24 hourly values of climatic criteria parameters: temperature, wind velocity. The figure Fig. 1 illustrates, in two dimensions, the Pareto fronts in the case of the design day selection. The design day is one of the days presented in the table Table .2.

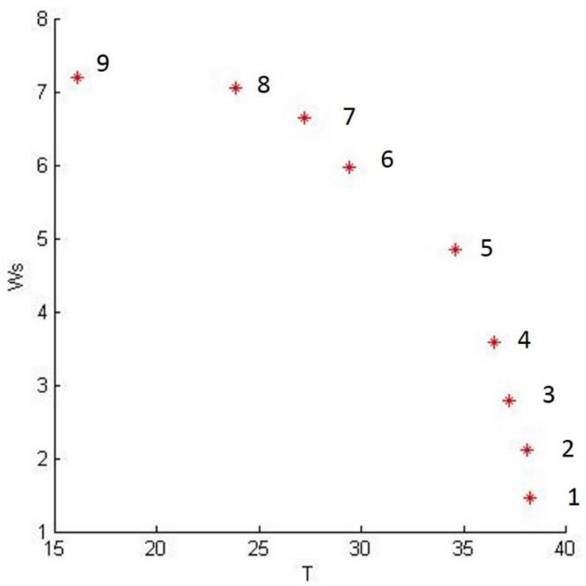

Fig .1. Pareto front found by NSGA-II, in the case of the maximization of two criteria: temperature (*t*) wind speed (*ws*).

The day (*d**)	1	2	3	4	5	6	7	8	9
	13 July	19 July	1 August	21 July	4 July	31 May	4 November	15 March	22 April
Temperature (daily average)	38.21	38.1	37.24	36.49	34.59	29.38	27.19	23.81	16.1
Wind speed (daily average)	1.47	2.12	2.8	3.58	4.85	5.99	6.65	7.07	7.22

Table .2. Set of the Pareto optimal solutions

CONCLUSION

Designers, energy efficiency planners are interested in weather data files, in order to estimate the buildings energy use because the climate factors have a big influence on the Building's energy use in order to realize a comparison in economic and environment protection terms, between different energy systems. This paper reviews a new method to select design days for using them to study the energetic behavior simulations to understand and optimize building's challenges. This proposed approach is based on multi-objective optimization using the nondominated sorting genetic algorithm II "NSGA-II". It represents a significant enhancement in the world of building's behavior simulation; because it facilitate and accelerate the energy performance studies and in the other hand to facilitate designers tasks that's confronts them with annual weather data which are not easily available and building designers involved in performance simulations are not the ones responsible for weather information gathering and recording. This proposed method provides very reasonable results.

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