Optimizing Distributed Energy Resources, Passive Measures, and the daily Operation at Campus Pinkafeld

M. Groissböck[1,a], M. Stadler[1,2,b], A. Siddiqui[3,4,c], S. Heydari[3,d], M. Henkel[4,e], J. Stirna[4,f], E. Lopez[5,g], J. Moguerza[5,h], E. Perea[6,i]

[1] Center for Energy and innovative Technologies, Hofamt Priel, Austria
[2] Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, United States of America
[3] University College London, London, United Kingdom
[4] Stockholm University, Stockholm, Sweden
[5] Universidad Rey Juan Carlos, Madrid, Spain
[6] Tecnalia Research and Innovation, Donostia - San Sebastián, Spain
[a] MGroissboeck@cet.or.at, [b] MStadler@cet.or.at, [c] Afzal.Siddiqui@ucl.ac.uk, [d] B.Heydari@ucl.ac.uk, [e] MartinH@dsv.su.se, [f] JS@dsv.su.se, [g] Emilio.Lopez@urjc.es, [h] Javier.Moguerza@urjc.es, [i] Eugenio.Perea@tecnalia.com

ABSTRACT: Building managers and operators as at Campus Pinkafeld are interested in a cost optimal fulfilment of their energy needs. From a strategic point of view they are interested in optimal investments and upgrades. From an operative point of view they are interested in an optimal use of all available resources. This paper shows how the decision support system (DSS) of the project Energy Efficiency and Risk Management in Public Buildings (EnRiMa) will help with this challenges and the integration of the DSS with the existing energy management system (EMS) is one of the key issues for a successful project. The strategic DSS will inform the building owner about possible new technologies that might reduce the total building energy costs or environmental impact. The benefit of an operational DSS is to enable the building operator to use already adopted energy efficiency improving technologies as pre-cooling, pre-heating or any other demand response related tasks to decrease costs and emissions caused by the heating and cooling system of the building. Assuming an upper and lower limit for the room temperature, we model the effect of active equipment control (via changes to either the set point or the valve flow) on the zone temperature taking into account the external temperature, solar gains, the building shell, and internal loads. The energy required to change the zone temperature in each time period is then used to calculate the energy cost or efficiency in the objective function of an optimization problem. This paper reports on example results for Campus Pinkafeld, shows the technical approach, and that such a flexible approach can save 10% costs only on an operational level.

1. INTRODUCTION

In October 2010 the EU research program Energy Efficiency and Risk Management in Public Buildings (EnRiMa) started with nine research institutions and commercial companies. The goal of this project is a web-based decision support system (DSS) to support operators of public buildings with energy efficiency, cost reductions and carbon dioxide (CO_2) emission reductions. Therefore, an integration of EnRiMa's DSS with the existing information technology (IT) and building management system (BMS) as e.g. DESIGO™ is required. One test site in Austria and one in Spain are available for EnRiMa. The integration of existing BMSs is done in a transparent way to enable further extension to other systems (e.g. Sauter) and standards (e.g. SCADA, Beckhoff).

The overall goal of EnRiMa is to create a multi-objective DSS to improve the energy efficiency by lowering costs and given comfort and financial risks. Therefore, sometimes contradictory goals as minimize cost, cover the energy requirements, minimize emissions, or reduce financial risks are considered. Also, long term planning to increase the energy efficiency within the building is possible. Especially, an analysis of retrofit and/or extension of the available energy systems is done. The following technologies are considered within

EnRiMa: passive building improvements as e.g. replacement of windows and adding insulation, photovoltaic (PV), solar thermal systems, electrical and thermal storages, fuel cell and other distributed combined heat and power (CHP) or combined cooling, heating and power (CCHP) systems are considered. It is possible to extend the considered technologies and to change their parameters at any time.

2. APPROACH

Currently, after an extensive inventory and modelling of the energy flows the user friendly EnRiMa-DSS graphical user interface (GUI) is been developed. The laboratory building KUBIK in Bizkaia, Spain, will be used to check the operability and correctness of the DSS. In a community centre (Siero, Spain) and at Campus Pinkafeld (Pinkafeld, Austria) the DSS will be tested in real operation condition. Due to high-class equipment at ENERGYbase (Vienna, Austria) it will be used to calibrate the EnRiMa-DSS.

Within the project EnRiMa an operative and a strategic DSS has been created. The overall interaction is shown in Figure 2-1. The operative DSS performs the operational optimization for the next day(s). The strategic DSS will determine feasible investment decisions for a given building. Within the operative DSS the user comfort is the main criterion, which has to be guaranteed. By comparison the strategic DSS is a pure cost and/or emission minimization algorithm for the next years. In both cases, a stochastic optimization, which considers uncertainty as e.g. energy prices or weather, will be available.

Figure 2-1 shows the interaction between the modules within the EnRiMa project. The objective of the strategic module is to optimize the investments in new technologies, financial hedging and/or passive building improvements (e.g. replace windows or buy CHP technologies). Modelling of the upper-level area is considered in an easy and rough way without too much details of daily operation. Strategic decision variables are variables in the optimization model, which are required to decide if a device should be installed or should be decommissioned. Limitations on budget, emissions, need of services (e.g. thermal heat) are strategic constraints within the strategic DSS, which are either historical values or are predefined by the user. The operative DSS, which plans the usage of all available technologies, considers the thermodynamic processes in much more detail and is aligned with the optimal usage of available devices. The lower-level energy balance constraints considers thermodynamic relations as e.g. solar gain and heat transfer on an hourly base to calculate the required user comfort in the building.

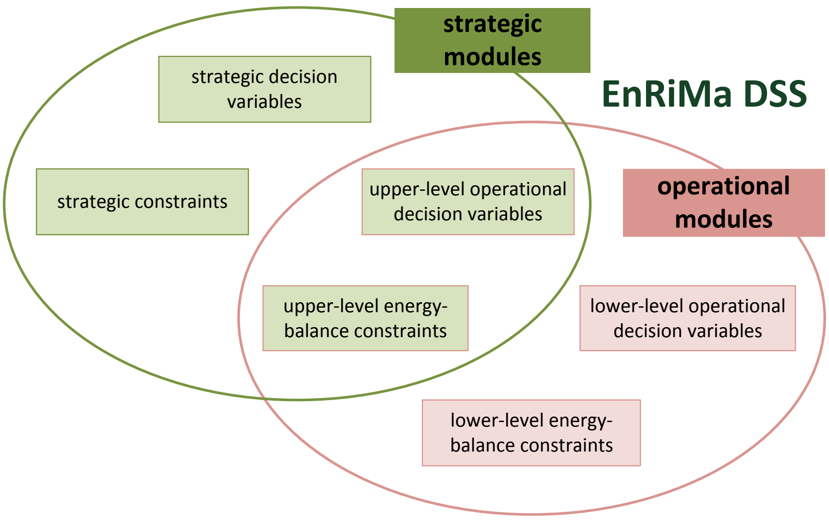


Figure 2-1: Modular approach of the EnRima-DSS [1]

The high-level optimization formulation used in EnRiMa follows the standard linear programming approach [2]:

$$\min\ f = \mathbf{c}^T \cdot \mathbf{x} = \begin{pmatrix} c_1 \\ \dots \\ c_n \end{pmatrix}^T \cdot \begin{pmatrix} x_1 \\ \dots \\ x_n \end{pmatrix} = c_1 \cdot x_1 + \dots + c_n \cdot x_n \qquad (1)$$

s.t.

$$A_n \cdot x_n \le b_n$$

$$L_n \le x_n \le U_n$$

With

c: cost coefficient vector; ***x***: decision variable vector; ***A***: constraint coefficient matrix; ***b***: constraint coefficient vector; ***L***: decision variable lower boundary vector; ***U***: decision variable upper boundary vector;

The objective function *f*, which can be either a cost or CO_2 emission function, will be minimized by varying the decision variables x_n. Currently, Matlab [3] and GAMS [4] are used to solve this complex problem consisting of several hundred equations. EnRiMa also allows multi-objective optimization, with weighted cost and CO_2 functions.

First, to visualize and analyse the status-quo of the energy flows within the test buildings Sankey diagrams are used. Sankey diagrams are commonly used to show material flows. By using this graphical representation of material flows or energy flows an overview about the main energy flows in a building are given. By visual review of the conversion processes first weak points are visible and first improvements can be proposed. Figure 2-2 shows the energy flow of ENERGYbase on January 10th 2012. Yellow lines represent electricity, red lines heat, and blue lines cooling demand (e.g. cold water). Orange lines are energy losses by the conversion processes. Due to limited capabilities of DESIGO™ at Pinkafeld no detailed Sankey diagram could be designed at the time of writing this paper. However, currently an upgrade is under way at Campus Pinkafeld and this will also enable similar Sankey diagrams for Pinkafeld.

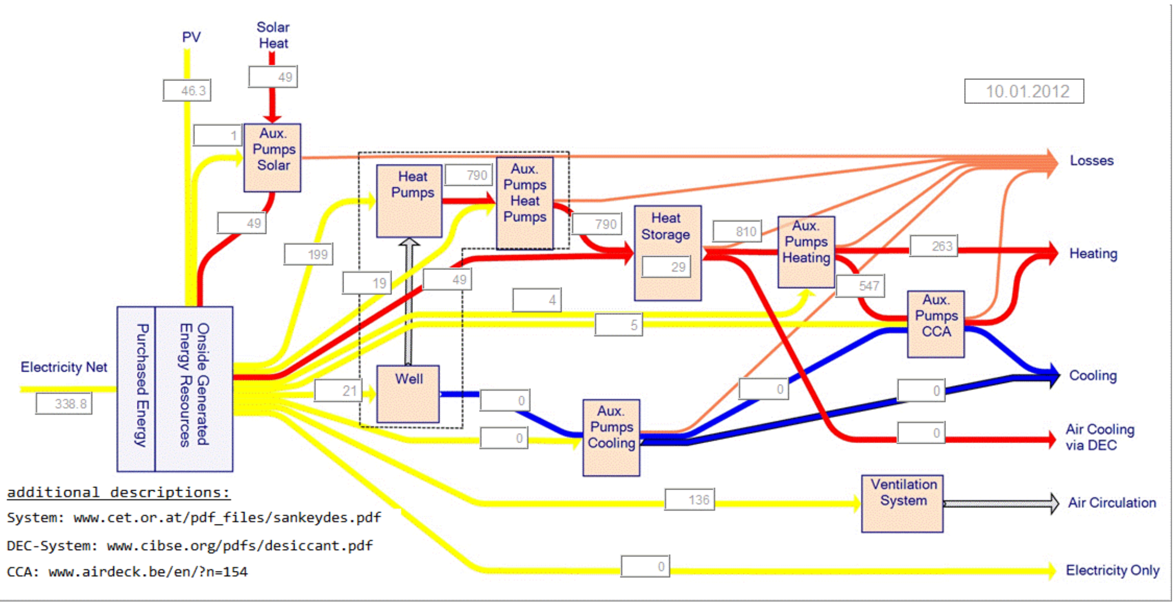


Figure 2-2: Automated Sankey diagram for ENERGYbase, http://www.cet.or.at/enrima/sankey_de.php

The innovation of this project is the combination of a multi-objective optimization and the existing BMSs or energy management systems (EMS) as e.g. DESIGO^{TM} to collect (for e.g. Sankey diagrams) and exchange data. These data are evaluated over a secured internet connection on EnRiMa's optimization platform.

In a next step the weather forecast from service providers will be included in EnRiMa's optimization platform to optimize the operation at the customer site and the result will be delivered to the building operator or the BMS. With this approach it is possible to perform such optimization without huge local installation expenditures on a variety of sites.

The collection process at the back-up test site building ENERGYbase in Vienna is done as follows:

- The onsite sensors are continuously read out by the building management software and stored within a database.
- The required data for the Sankey diagram are validated and collected on a daily base from the building management software. These values are stored in a tabular format within an MS Excel^{TM} file, which also creates the Sankey diagram itself.
- The Sankey diagram is transferred to CET's web-server and is available for further processing. ENERGYbase Sankey diagrams are available at the following web-address: http://www.cet.or.at/enrima/sankey_de.php.

3. FIRST OPERATIONAL RESULTS WITH EXISTING EQUIPMENT

Onsite tests will be done together with a cost-benefit-analysis to derive proposals for the energy policy as well as for the users of the EnRiMa-DSS to enable them to reduce the energy consumption and the CO_2 emissions by about 10%. First test runs with a deterministic prototype of the operational DSS (done with MatLab, [3]) show, that a reduction by 10% on costs respectively energy consumption could be reached in the test cases.

Unlike most work on the economics of DER, the approach within EnRiMa assume that certain types of end-use energy demands, e.g., for space heat and cooling, are not exogenously given. Rather, the building operator provides acceptable temperature ranges based on user preferences for comfort or based on national standards. For example, the end-use demand, $D_{t,space\_heat}$, may not be fixed and would be determined endogenously. The operational module of the DSS determines the required heating and cooling load to achieve the target temperature within the building. For convenience, we assume that the interior of the building consists of a single zone.

The modelling of the energy flows is primary based on DIN V 18599 [5] and DIN EN ISO 13790 [6] where the following issues are considered:

- weather (temperature, wind speed, solar gains)
- building physics (heat transfer, thermal conduction)
- conventional heating systems
- heating, ventilation, and air conditioning (HVAC) systems
- internal loads (people, machines)
- user preferences regulated by the building operator.

Next, we describe some of the equations that reflect the main energy flows and building physics the EnRiMa modules. For the sake of space, we only provide the most important of them. The complete formulation can be consulted in [7].

3.1 LOWER LEVEL MATHEMATICAL FORMULATION

Eq. 2 updates the zone temperature based on the current zone temperature, the external temperature, internal load, and both conventional and HVAC systems with air-handling unit (AHU) while accounting for the building shell's characteristics. It is derived from [8] by adding solar gains and the conventional heating sources. In particular, the terms inside the parentheses reflect the temperature change within the building zone, the heat added by the radiator, the energy lost or gained due to the external temperature, the effect of solar gains through windows, any internal loads, and heating or cooling via the HVAC system. Eq. 3 defines the lower and upper level limits for the zone temperature (optimization constraints). Other constraints in the model (see [1] for details) deal with equipment characteristics and energy flow calculations.

$$T_{\text{int},t} = \frac{1}{\frac{c_a \cdot \rho_a \cdot V_z}{\Delta t} + U_{avg} \cdot A_{total} + f_{vent} \cdot \rho_a \cdot c_a} \cdot \left(\begin{array}{l} \frac{c_a \cdot \rho_a \cdot V_z}{\Delta t} \cdot T_{\text{int},t-1} + Q_{rad,t} + U_{avg} \cdot A_{total} \cdot T_{ext,t-1} + Q_{solar,t-1} \cdot g \cdot F_c \cdot A_g \\ + Q_{\text{int},t-1} + f_{vent} \cdot \rho_a \cdot c_a \cdot T_{vent,t} \end{array} \right) \quad (2)$$

$$\underline{T}_t \le T_{\text{int},t} \le \overline{T}_t \quad (3)$$

With

Physical Constants and Parameters

Δt: time step of optimization (s), e.g. 1 hour; t: time period index; c_a: specific heat capacity of air (kJ/kg·K); ρ_a: density of air (kg/m³);

Environmental Parameters

$T_{int,0}$: internal temperature at t=0 (°C); $T_{ext,t}$: external temperature during period t (°C); $Q_{solar,t}$: solar gain (weighted average over different directions) during short-term period t (kW/m²); T_{vent}: HVAC inlet air temperature (depends on external temperature) (°C);

Building Parameters

V_z: volume of the zone (m³); U_{avg}: weighted average of the heat transition coefficient of the building envelope against the air (W/m²·K); A_{total}, A_g: total area, area of glass (m²); g: mean energy transmission coefficient of glass (-); F_c: mean sun protection factor (-); $Q_{int,t}$: internal load (people, lighting, machines) (W/m²); $\underline{T}_t$, $\overline{T}_t$ t: lower, upper limit of the zone during period t (°C);

Decision Variables

$T_{int,t}$: internal temperature during short-term period t (°C); Q_{rad}: heat from the radiator system (kW f_{vent}: flow rate of air of HVAC system during short-term time period t (m^3/s);

3.2 UPPER LEVEL MATHEMATICAL FORMULATION

Figure 3-1 shows how Eq. 4 is used to meet the energy load at each time period (e.g. year, day, hour or year, month, hour). Note that the energy demand is a parameter within the upper level formulation (strategic model) while it is a decision variable within the operational model.

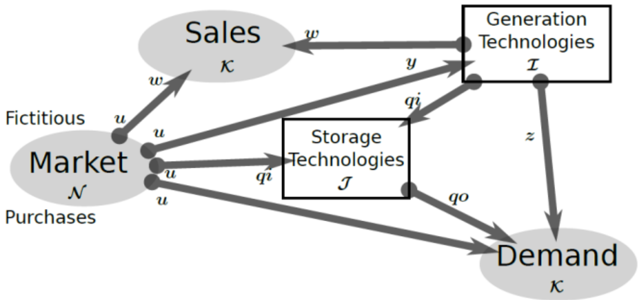


Figure 3-1: Energy flow within the EnRiMa models [7]

The energy supplied must meet the energy demand minus the energy reduced due to absorbing technologies (e.g. batteries). Eq. 4 is the result of the energy produced with energy-generation technologies plus the energy purchased in the market minus the energy for sale, energy for storage and primary energy for generation (e.g. natural gas). On the demand side, the energy released from storage and the energy reduced with passive technologies diminish the original total demand. The passive technologies are modelled in two ways: the building parameter dependent energy savings as heating demand reductions and the usage dependent ones that increase efficiency (e.g. lighting). Regarding the building parameter depending passive technologies, ϕ is a function used to calculate the energy savings obtained by the inclusion of passive technologies such as room-enclosing opaque surfaces, energy efficient windows, etc. (see examples in [7]).

$$\begin{aligned}&EnergyPurchase + DistGen - EnergyIn - EnergySale - ToStorage\\&\geq Demand - FromStorage - EnergySavings - Efficiency\ Increase\\&\sum_{N_{B(k)}} \cdot \sum_{M_A} u_{k,n}^{p,m,t,mm} + \sum_{I} z_{i,k}^{p,m,t} - \sum_{I} y_{i,k}^{p,m,t} - \sum_{M_S} \cdot \sum_{N_{S(k)}} w_{k,n}^{p,m,t,mm} - \sum_{J_S} qi_{k,j}^{p,m,t}\\&\geq D_k^{p,m,t} - \sum_{J_S} qo_{k,j}^{p,m,t} - \sum_{J_{PS}} \phi_j^{p,m,t} - \sum_{J_{PU}} OD_{k,j} \cdot x_j^p \cdot D_k^{p,m,t}\end{aligned} \tag{4}$$

With

Sets

I: Energy-supplying technologies (supply side);J: Energy-absorbing technologies (demand side) (J_S: storage technologies, J_{PS}: building dependent passive technologies; J_{PU}: usage dependent passive technologies); K: Energy type; M: Mid-term representation period (profile, e.g. day) (M_A: energy is purchased in forward markets; M_S: energy is sold in forward market); N: Markets for energy products and primary fuels ($N_{B(k)}$: markets where type of energy can be bought; $N_{S(k)}$: markets where type of energy can be sold); P: Long-term time period for strategic decisions (e.g. year); t: Short-term decision period (e.g. hour);

Input Parameter

$D_k^{p,m,t}$: energy demand in long-term period p, mid-term period m, short-term period t, energy type k (kWh);

Decision Variables

$z_{i,k}^{p,m,t}$: output of energy of supplying technology i and energy type k (kWh) (e.g. NG-fired boiler, PV); $u_{k,n}^{p,m,t,mm}$: purchase of energy in market n, (kWh) (e.g. electricity from spot market); mm: auxiliary index for mid-term periods to enable forward contract; $y_{i,k}^{p,m,t}$: input of energy (kWh) (e.g. NG or solar radiation); $w_{k,n}^{p,m,t,mm}$: sale of energy (kWh); $qi_{k,j}^{p,m,t}$: energy added to storage (kWh); $qo_{k,j}^{p,m,t}$: energy released from storage (kWh); $\phi_j^{p,m,t}$: energy savings by use of passive technologies j (kWh); $OD_{k,j}$: proportion of savings in energy demand type k per unit of passive technology j available compared to a configuration of the building without passive technology (-); x_j^p : available capacity in long-term period p, energy-absorbing technology j (kWh);

3.3 RESULTS FOR A REFERENCE WINTER DAY AT CAMPUS PINKAFELD

For a reference winter day at Campus Pinkafeld three different test cases are performed: fixed mean-temperature requirements (FMT, the mean of the lower and upper desired room temperature limits), fixed lower temperature requirements (FLT), and a temperature range over which the EnRiMa optimisation of the heating and the natural ventilation systems can occur (OFP), respectively. The reference winter day is built on the average of all available valid weather data.

The deterministic optimisation problem is implemented in MatLab 2012a and solved for the reference winter day using hourly decision-making steps within 33 seconds on a computer with Windows XP, Intel Core2 Quad with 3.00 GHz and 3.25 GB memory. In the long run the optimization will be performed on an EnRiMa Webserver.

The optimal daily energy consumption as well as the daily costs are shown in Figure 3-2 and summarized in Table 3-1.

Table 3-1: Preliminary optimization results of the operative EnRiMa-DSS for Campus Pinkafeld, reference winter day

test cases	heat demand (kWh_t / day)		heat demand $kW_{t,peak}$	cooling demand (HVAC system) (kWh_e / day)		objective function total costs (€ /day)	
FMT	696.11	100%	94.7	5.77	100%	56.74	100%
FLT	631.01	91%	74.0	7.77	135%	51.83	91%
OFP	629.15	90%	65.2	3.64	63%	51.05	90%

FMT: fixed mean-temperature requirements (the mean of the lower and upper desired room temperature limits); FLT: fixed lower temperature requirements; OFP: temperature range (lower and upper desired limits)

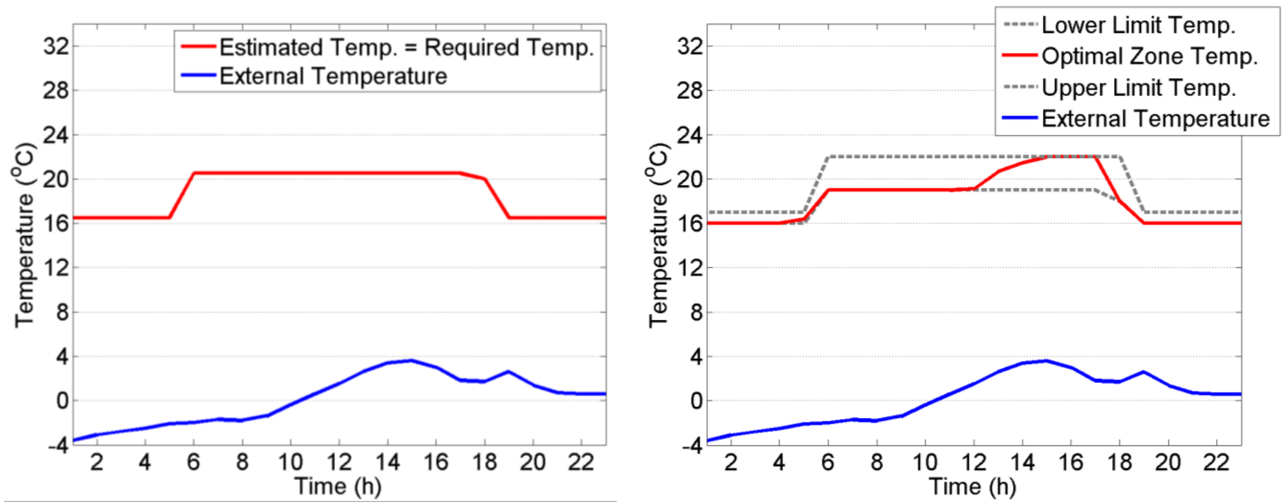


Figure 3-2: Optimization results (left: FMT, right: OFP)

The OFP case results in daily energy consumption of 629.15 kWh_t, which is a 10% reduction from the level of 696.11 in the FMT case. When the rigid temperature requirement is set to the lower limit, the total energy consumption is 631.01 kWh_t, which is 1% higher than in the optimised case but with less user comfort. Also the peak demand for heating can be reduced by this procedure. The OFP peak demand is given by 65.2 kW_t and is about 31% lower than peak demand within the FMT case (94.7 kW_t). Hence, the optimisation approach proposed here may support building operators in reducing energy costs with user comfort consideration.

The OFP optimisation case is able to use the temperature bandwidth to reduce the heating and cooling needs. Surprisingly, even with a lower fixed temperature setting (case FLT) the energy and cost savings are not as high as with an optimisation within a temperature range. In effect, the flexibility of the building's heating and cooling systems to respond to environmental and market conditions is valuable from both economic and energy-efficiency perspectives. The result between FLT and OFP varies in about 1% so no significant difference is available. OFP is able to deal with (future) time-of-use tariffs and considers user comfort as well, and therefore, shows most flexibility

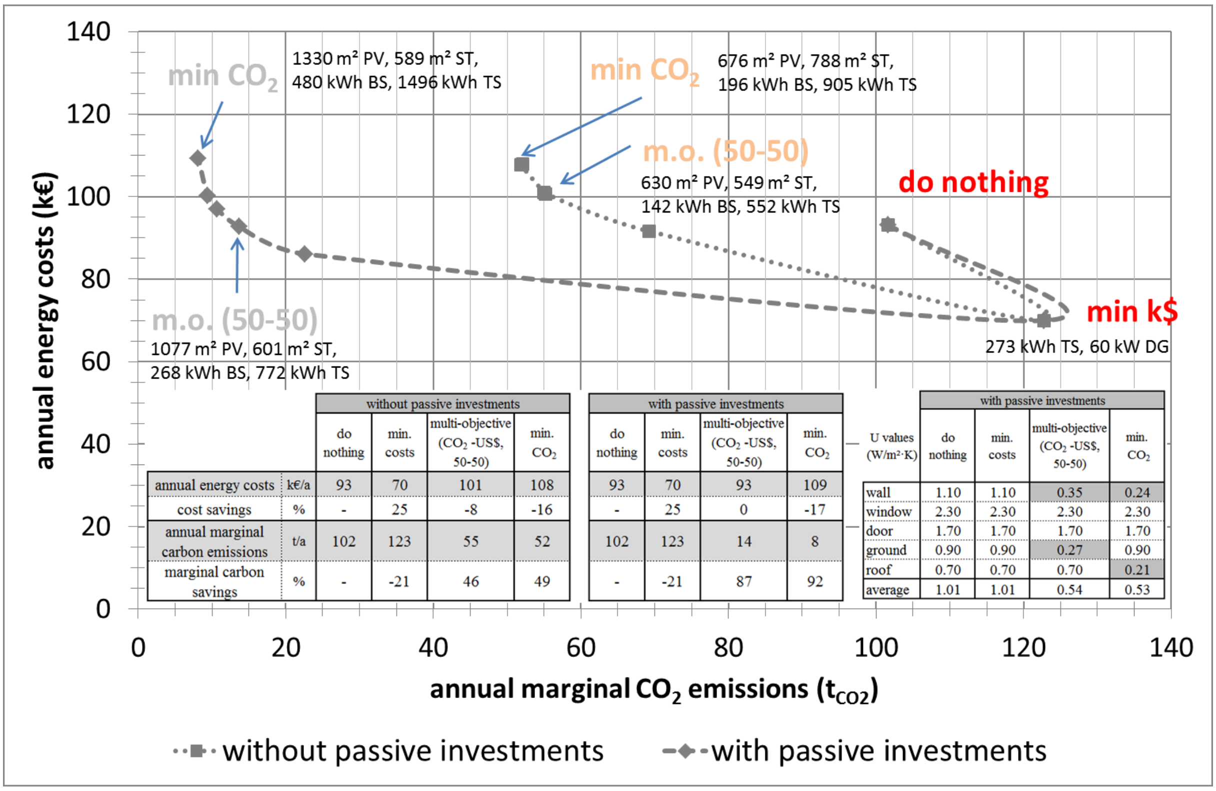
4. FIRST STRATEGIC RESULTS

Within the EnRiMa project the strategic optimization equations are not fully implemented at this moment. Therefore, we use another optimization tool for this paper to get first strategic results for the Campus Pinkafeld. In this paper the *deterministic* Distributed Energy Resources Customer Adoption Model (DER-CAM) optimization tool is used. DER-CAM has been created by Ernest Orlando Lawrence Berkeley National Laboratory (LBNL), California, U.S.A. ([9], [10], [11]). The latest version of DER-CAM considers basic passive measures, which can emulate possible outcomes for a finished EnRiMa-DSS.

Figure 4-1 shows first multi-objective results. The dotted line represents the multi-objective results for several optimizations without the option of passive improvements and only DER is allowed. The dashed line are the results with the option of DER and passive improvements (U-value changes) and shows the trade-off between energy costs and CO_2 emissions by varying the weight factor for cost and CO_2 emission reduction in the optimization.

The basis for all optimizations is the assumption that the buildings at Campus Pinkafeld haven't been refurbished in 2002. We assume that the buildings are unchanged since their creation in the 1970's. Therefore, we assume U values given in Figure 4-1 within the column "do nothing". This approach allows us to compare the optimal technology portfolio with the current implemented technologies and building upgrades.

An interesting result is that the minimization of both options (with and without passive measures) results in the same point: with costs of about 70 k€/a and carbon emissions of about 123 t/a. The optimization case "minimize CO_2" was limited with maximum cost of 150% of the base case costs to limit the financial impact on the building owner. In both cases, the costs for the "minimize CO_2" case is about 16 respectively 17% above the "do nothing" case. For the given energy prices and building improvement costs the best average U-value within the optimization results is about 0.53 W/m²K. Today's real average U-value of around 0.39 W/m²K and is about 25% lower as the optimal solution, which also considers the interaction with distributed energy resources as PV or solar thermal. As a consequence Campus Pinkafeld is well-placed even for times when the energy costs will increase and can almost reach zero CO_2 emissions as shown by Figure 4-1 and the dashed line.



		without passive investments				with passive investments			
		do nothing	min. costs	multi-objective (CO_2 -US$, 50-50)	min. CO_2	do nothing	min. costs	multi-objective (CO_2 -US$, 50-50)	min. CO_2
annual energy costs	k€/a	93	70	101	108	93	70	93	109
cost savings	%	-	25	-8	-16	-	25	0	-17
annual marginal carbon emissions	t/a	102	123	55	52	102	123	14	8
marginal carbon savings	%	-	-21	46	49	-	-21	87	92

	with passive investments			
U values (W/m²·K)	do nothing	min. costs	multi-objective (CO_2 -US$, 50-50)	min. CO_2
wall	1.10	1.10	0.35	0.24
window	2.30	2.30	2.30	2.30
door	1.70	1.70	1.70	1.70
ground	0.90	0.90	0.27	0.90
roof	0.70	0.70	0.70	0.21
average	1.01	1.01	0.54	0.53

Figure 4-1: Preliminary comparison of strategic optimization runs for Campus Pinkafeld (DER-CAM, CET, based on [12])
Notes on abbreviations: m.o.: multi-objective; w/o: without, w: with; PV: photovoltaic; ST: solar thermal; BS: battery storage; TS: thermal storage; DG: distributed generation; a multi-objective point of 50-50 means that the optimization focuses equally on cost and CO_2 minimisation.

5. PROJECT STATUS

At the moment the graphical user interface (GUI) for the operative DSS is being developed. After that the strategic DSS and all other required components (scenario generation, solver) will be considered within the development process.

After the end of the project in March 2014 it is conceivable that the EnRiMa-DSS will be available for non-public building operators as well. As part of the public relation work the EnRiMa team will get in contact with e.g. energy consultants, technology companies and building management software developer to use the results of the project. More details on the dissemination process and other publications are available on the projects homepage [13].

Figure 5-1 shows a first screenshot of the operative EnRiMa-DSS. It will be a browser-based application which can be used without any local installation. To be independent of any operating system the project EnRiMa realizes the GUI with Vaadin [14], a Java™ framework for building modern web applications.

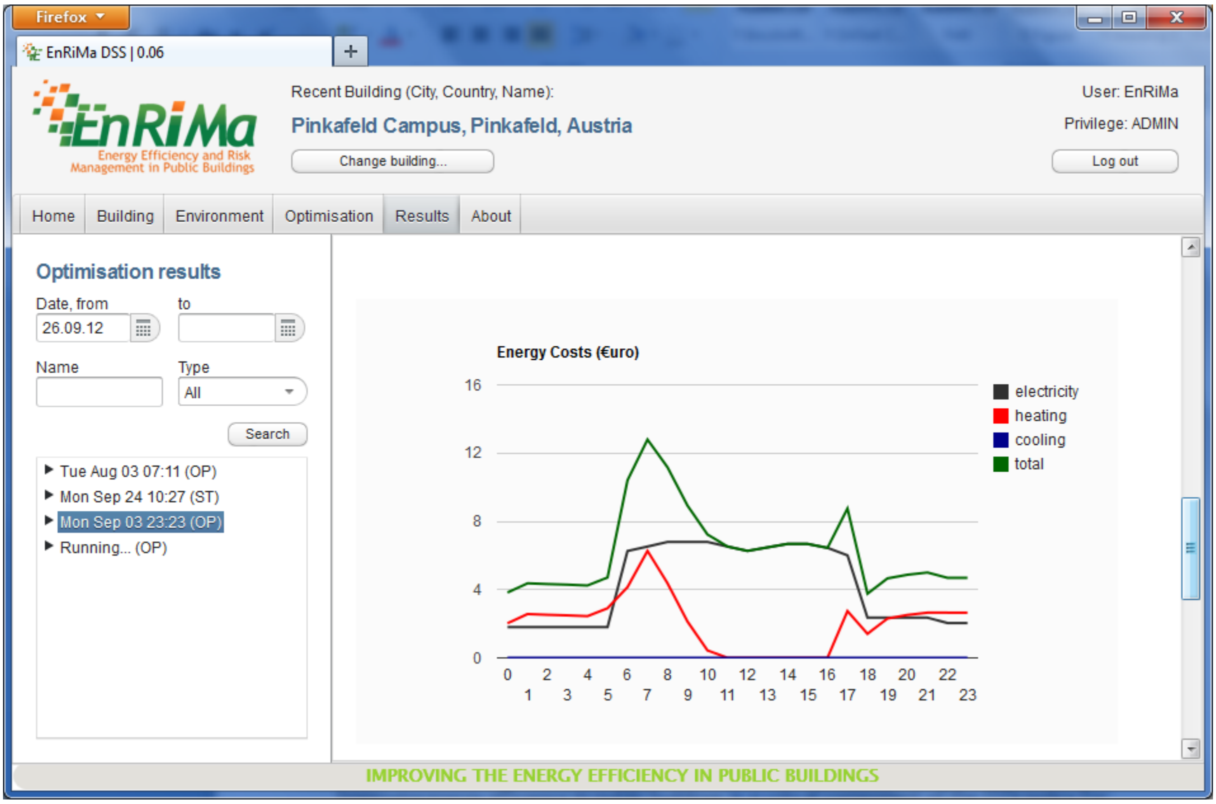


Figure 5-1: First prototype of the operational DSS, result of an optimization run

6. CONCLUSIONS

Improving energy efficiency in public buildings is a critical component of the EU's policy for reaching its climate target goals for 2020, i.e., total energy reduction by 20%, 20% contribution of renewable energies to total energy generation, and 20% reduction of greenhouse gases such as CO_2 below 1990 levels. The EnRiMa project seeks to develop an ICT-based DSS with enhancements to the existing state-of-the-art research in terms of modelling energy flows, generating scenarios for dealing with uncertainties, and handling multi-criteria stochastic optimisation at the building level. This paper focus on the first feature and developed an approach for incorporating building physics into lower-level energy-balance constraints, i.e., abstracting from strategic decisions and focusing on the operation of conventional heating and HVAC systems. Using the data from Campus Pinkafeld an operational optimisation was done. With the help of DER-CAM a first test regarding the passive improvements was done. The first results are encouraging because they imply that energy consumption and cost may be reduced by 10% from simply deploying the existing energy resources in a way that accounts for system thermodynamics, building characteristics, and external attributes. Indeed, this lower-level operational optimisation will be merged with upper-level operational constraints, i.e., treating energy purchases and on-site generation to meet all energy requirements at a site, in order to provide an operational DSS for public buildings.

At this stage, the model needs to be validated using additional data from the test sites. In addition, we plan to use a laboratory facility in order to calibrate the model better. Indeed, since EnRiMa is supposed to deliver operational and strategic DSS modules that could provide tangible benefits to not only the test sites but also EU public buildings in general, an extensive validation phase is necessary. Further directions for enhancements include stochastic optimisation, multi-criteria objectives, and risk management capabilities.

7. ACKNOWLEDGMENT

The work described in this paper has been performed in course of the European project EnRiMa "Energy Efficiency and Risk Management in Public Buildings" and is supported by the European Commission, within the 7th Framework Programme (FP7).

The "Austrian Federal Ministry for Transport, Innovation and Technology" also supports the Center for Energy and innovative Technologies (CET) through the „Building of Tomorrow" program.

Additionally, the Theodor Kery Foundation of the province of Burgenland also supports the Center for Energy and innovative Technologies (CET) in course of EnRiMa.

We also want to thank the University of Applied Science at Pinkafeld and University of Applied Science at Vienna (ENERGYbase) for their great support. The authors also thank all other EnRiMa partners: Stockholm University, University College London, International Institute for Applied Systems Analysis (IIASA), Universidad Rey Juan Carlos, Minerva Consulting and Communication, SINTEF Group, Tecnalia, and Hidrocantábrico Energía for their valuable input and support.

The Distributed Energy Resources Customer Adoption Model (DER-CAM) has been designed at Lawrence Berkeley National Laboratory (LBNL) and is owned by the U.S. department of Energy. In course of this work the free available web-version of DER-CAM was used.

LITERATURE

[1] Deliverable D2.2, A Mathematical Formulation of Energy Balance and Flow Constraints, Internal Report, European Commission FP7 Project Number 260041, 2012.

[2] Du, D.-Z., Ko K.-I, Hu,X. Design and Analysis of Approximation Algorithms, Springer Optimization and Its Applications 62. DOI 10.1007/978-1-4614-1701-9_7, Springer Science+Business Media.

[3] MatLab, http://www.mathworks.co.uk/products/matlab/, accessed on 26.07.2012.

[4] GAMS, http://www.gams.com/, accessed on 25.09.2012.

[5] DIN V 18599 (draft), Energy efficiency of buildings – Calculation of the net, final and primary energy demand for heating, cooling, ventilation, domestic hot water and lighting, German Standard, 2007.

[6] EN ISO 13790, Energy performance of buildings – Calculation of energy use for space heating and cooling (ISO 13790:2008), European Standard, 2008.

[7] Deliverable D4.2, Symbolic Model Specification, Public Report, European Commission FP7 Project Number 260041, 2012.

[8] G. Platt, J. Li, R. Li, G. Poulton, G. James, and J. Wall, Adaptive HVAC Zone Modeling for Sustainable Buildings, Energy and Buildings, vol. 42, pp. 412–421, 2010.

[9] Siddiqui, A., Marnay, C., Edwards, J., Firestone, R., Ghosh, S., Stadler, M.: Effects of a CarbonTax on Microgrid Combined Heat and Power Adoption, Journal of Energy Engineering, American Society of Civil Engineers (ASCE), Special Issue: Quantitative Model for Energy Systems, April 2005, Volume 131, Number 1, page 2 – 25, ISSN 0733-9402.

[10] Stadler, M., Donadee, J., Marnay, C., Mendes, G., Appen, J. von, Mégel, O., Bhattacharya, P., Lai, J: Application of the Software as a Service Model to the Control of Complex Building Systems. ECEEE 2011 Summer Study, 6–11 June 2011, Belambra Presqu'ile de Giens, France, ISBN 978-91-633-4455-8, LBNL-4860E.

[11] DER-CAM: DER-CAM Web-Tool. Remote Desktop Application: http://der.lbl.gov/, accessed on 15.09.2012.

[12] Groissböck, M., Stadler, M., Edlinger, T., Siddiqui, A., Heydari, S., and Perea, E. The first step for implementing a stochastic based energy management system at campus Pinkafeld, e-nova international congress 2011, University of Applied Science Campus Pinkafeld, Nov. 24-25 2011, Pinkafeld, Austria.

[13] Project home page, Energy Efficiency and Risk Management in Public Buildings, http://www.enrima-project.eu/, accessed 26.07.2012.

[14] Vaadin – thinking of U and I. https://vaadin.com/, accessed on 13.09.2012.