# Intelligent Control for Sustainable Energy Management in Underground Stations

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Abstract: We present the scientific approach of the EU-FP7 SEAM4US project to the problem of sustainable energy management of underground systems, in particular the optimal and scalable control of single metro stations and their surroundings that will yield at least a 5% saving in non-traction electricity consumption, equivalent to that consumed by more than 175 households. To this end we first formulate the sustainable energy management problem as a constrained optimization problem and then present a modified Newton's method as solution. Preliminary simulation results of the model-in-the-loop are delivered and promising.



## 1 INTRODUCTION

Underground transportation systems are big energy consumers (e.g. 631 million kWh / year), and have significant impacts on energy consumptions at a regional scale (Anderson et al., 2009). Approximately one third of the metro networks' energy is required for operating the subsystems of metro stations and surroundings, such as ventilators, lifts, escalators, and lighting (Oscar, 2011).

Although a relatively small percentage of energy can be saved with the optimal management of these subsystems, a large energy saving in absolute terms can be obtained on a regional scale. The EU-FP7 project, SEAM4US (Sustainable Energy mAnageMent 4(for) Underground Systems) is to develop advanced technologies for optimal and scalable energy consumption control of metro stations that will yield a 5% saving in non-traction electricity consumption, equivalent to that consumed by more than 175 households.

The objective of the SEAM4US project is to develop an intelligent control system for metro stations, which is adaptive on the basis of environmental factor forecasts and occupancy flow patterns. Most of the works are ongoing; related hardware and software deployment in the pilot station are supposed to be implemented before October 2014.

A metro station is a very complex system. It involves, among others, multi-storey underground spaces with multi-faceted thermal behaviours, e.g., intricate air exchange dynamics with the outside, heat conduction with the surrounding soil and high variable internal gains due to travelling passengers and trains. Processes that occur in metro stations, such as the arrival and departure of trains, passenger transit, commercial activities, surface traffic and weather take place on different spatio-temporal and dynamic scales (Ansuini et al., 2012). Furthermore, a typical metro station is a very large environment. The modelling of the environmental conditions requires analysis at the urban block scale, which means a size up to thousands of meters. It is well known that at, this dimensional scale, fluid dynamics finite element models (FEM) are pushed to their limits (Franke et al., 2004).

Thus the overall modelling task of SEAM4US project is very complex; it involves user behaviour modelling, environmental factor modelling, and optimal controller design. We will present the scientific position of the project in particular on the controller design.

The structure of the paper is organized as follows. We first introduce related work in Section 2, followed by a mathematical problem formulation for sustainable energy management of a metro station in Section 3. Section 4 proposes our model-in-the-loop framework as solution. Simulation results are presented in Section 5, followed by discussions and future works in Section 6.


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## 2 RELATED WORK IN ENERGY CONTROL

Energy efficiency has been gaining increasing research interest in the past two decades. As economic crisis continues, people are keen to design energy efficient systems and apply them to various application areas.

Energy efficiency is a traversal problem across numerous application domains such as sensor networks (Cui et al., 2004), building management (Lamoudi et al., 2011), (Samuel, et al., 2011), and data centre management (Lakshmi, 2012) requiring sophisticated approaches. Cui (Cui et al., 2004) showed, for instance, that cooperative multi-input-multi-output (MIMO) transmission and reception simultaneously achieve both energy savings and delay reduction in radio application of sensor networks.

Buildings account for 40% of worldwide energy use (US department of energy, 2008). Many EU projects focus on the energy performance of buildings, like Adapt4EE (SEC-288150). Model predictive control (MPC) methods have been applied to minimize the energy consumption in buildings (Lamoudi et al., 2011).

## 3 SCIENTIFIC PROBLEM FORMULATION

The SEAM4US project is about (1) acquiring optimized energy consumption minimizing strategies (2) given a certain context determined by outside temperature, airflow status, passenger density, train schedule, etc., (3) while satisfying various constraints, such as comfort-levels and operational constraints.

Consequently, SEAM4US defines the control task as a constrained optimization problem, i.e., find a distributed, but coordinated, control strategy $w_i$, which minimize the total energy consumption across the target metro station.

$$\int_t \sum_i e(w_i) dt \tag{1}$$

Subject to comfort level constraints:

$$\begin{gathered} \text{Temp\_L} \le \text{Temp}\,(x, t) \le \text{Temp\_H} \\ Airflow\text{\_L} \le Airflow\,(x, t) \le Airflow\text{\_H} \\ \text{Temp\_L} \le \text{Temp}\,(x, t) \le \text{Temp\_H} \\ \text{Hum\_L} \le \text{H}um\,(x, t) \le \text{H}um\text{\_H} \\ \text{Co2\_L} \le \text{Co2}(x, t) \le \text{Co2\_H} \\ \text{Lum\_L} \le \text{L}um(x, t) \le \text{L}um\text{\_H} \end{gathered} \tag{2}$$

and operational constraints:

$$\| w_i(t+1) - w_i(t) \| < C \tag{3}$$

Where $w_i$ is the frequency of fan or any other subsystem i, $e(w_i)$ is the energy consumption rate of fan , lighting or any other subsystems given input frequency or lighting luminance level, and where $xx\_L$ and $xx\_H$ refer to the lower bound and upper bound of the referred context variable, respectively. For instance, $Temp\_L$ refers to minimal requirement of temperature.

Note that passenger density (user modelling) will influence the Temp, Airflow, humidity, CO2, etc. Furthermore, all context variables (temperature, humidity, level of pollutants, airflow rate) are functions of passenger density (spatial-temporal) distribution, train effects, and other context variables such as outside wind, outside temperature, etc. Therefore, the modelling task is trying to establish and quantify the relationships between the fan frequency, lighting luminance level and the environmental and thermal factors and the passenger behavioural patterns as part of the contexts such as temperature, humidity, CO2 concentration, etc.

For constrained optimization the interior point method (Alizadeh, 1991) is usually used to unify the inequality constraints into the objective function. There are two types of interior functions that we can use, barrier interior function (Gill et al., 1986) and primal-dual interior function (Alizadeh et al., 1998). When the constraints are box-like constraints, meaning that we want to bound the constraints within a range, barrier interior functions are typically used. When the constraints are single sided constraints or change as time goes on, the primal-dual interior method is often used.

After unifying the constraints into the objective function, we reach an unconstrained optimization problem.

If the objective function is twice differentiable, then Newton's method is a good candidate to learn the optimal point. When the objective function is differentiable, but not twice differentiable, we can use gradient-based methods (Boyd and Vandenberghe , 2004), such as steepest gradient method. When the objective function is not differentiable, we can use the sub-gradient method (Boyd and Vandenberghe, 2004) for optimization.

In the following section, we will elaborate our modified Newton's method to solve the sustainable energy management problem.

# 4 MODEL-IN-THE-LOOP SOLUTION

The modified Newton's learning method is used to reach the optimized solution (minimized fan energy consumption) of the problem. The modified method is divided into three steps, namely, (1) unifying objectives with the constraints, (2) determining the Newton step for next-time-step fan frequency, (3) backtrack line search to determine the actual update step.

## 4.1 Unifying Objectives with Constraints

Since all of the constraints are box constraints, which means that we are interested in keeping the target variable $x$ within a range . We use logarithmic-barrier function to transform the constraints into objectives. Logarithmic-barrier function (Den Hertog et al., 1990) is defined as follows:

$$\Phi(x)=\begin{cases}-\log(x_1-x)-\log(-x_0+x) & x_0\le x\le x_1\\ +\infty & else\end{cases} \quad (4)$$

The unified objective function for the preliminary problem becomes

$$obj = e(t+1)+\frac{1}{\lambda}(\Phi(Temp(x,t+1)) \\ +\Phi(Airflow(x,t+1))) \quad (5)$$

Where $\lambda$ is a meta-parameter that gauges the preference weight between the main objective (energy minimization) and the associated objectives (keeping context variables within a target range), as $\lambda$ increases to $+\infty$ , the transformed problem becomes the same as the constrained problem.

## 4.2 Newton's Method

After unifying the constraints into the minimization objectives, we successfully transformed the constrained optimization problem into an unconstrained optimization problem. We use Newton's method (Boyd and Vandenberghe , 2004) to learn the direction and step size. Before introducing Newton's method, we would like to display the general objective of unconstrained optimization. In order to optimize a function $f(x)$, we are in fact searching for a $x_*$ which makes the first order derivative $f^{'}(x_*)=0$. In case that there are multiple $x_*$ that makes $f^{'}(x_*)=0$ , we select the minimal $f(x_*)$ as the solution.

Newton's method attempts to construct a sequence $x_n$ from an initial guess $x_0$ that converges towards $x_*$ such that $f^{'}(x_*)=0$. This $x_*$ is called a stationary point of $f(.)$. The second order Taylor expansion $f(x)$ of function $f(.)$ around $x_n$ (where $\Delta x = x - x_n$ ) is:

$$f(x_n+\Delta x)=f(x_n)+f^{'}(x_n)\Delta x+\frac{1}{2}f^{''}(x_n)\Delta x^2 \quad (6)$$

attains its extremism when its derivative with respect to $\Delta x$ is equal to zero, i.e. when $\Delta x$ solves the linear equation:

$$f^{'}(x_n)+f^{''}(x_n)\Delta x=0 \quad (7)$$

(Considering the right-hand side of the above equation as a quadratic in $\Delta x$ , with constant coefficients.)

Thus, provided that $f(x)$ is a twice-differentiable function well approximated by its second order Taylor expansion and the initial guess $x_0$ is chosen close enough to $x_*$, the sequence $(x_n)$ defined by:

$$\Delta x = x - x_n = -\frac{f^{'}(x_n)}{f^{''}(x_n)} \\ x_{n+1}=x_n-\frac{f^{'}(x_n)}{f^{''}(x_n)} \quad n=0,1,... \quad (8)$$

will converge towards a root of $f^{'}$, i.e. $x_*$ for which $f^{'}(x_*)=0$.

Back to our optimization problem, the definition of f is the objective function that we are trying to minimize:

$$f(w(t+1))=e(t+1)+\frac{1}{\lambda}(\Phi(Temp(x,t+1)) \\ +\Phi(Airflow(x,t+1))) \quad (9)$$

## 4.3 Backtrack Line Search

Although Newton learning guarantees that we can find a $x_*$ that makes $f^{'}(x_*)=0$, the Newton step might be really large in reality. However, in real world application, the fan frequency has a limited range; it cannot go to infinity. Therefore, we use backtrack line search (Boyd and Vandenberghe, 2004) algorithm to find the optimal step for learning.

Suppose that we have an initial guess of displacement obtained from Newton's method $\Delta x$. We evaluate $f(x+\Delta x)$ to see if it satisfies all the operational constraints and if it did minimize the energy consumption, if so, we let $\Delta x$ as it is. If not, we update $\Delta x$ according the following rule $\Delta x := \alpha \cdot \Delta x$, where $\alpha$ is a pre-specified learning rate. We evaluate the new $f(x+\Delta x)$. We stop updating $\Delta x$ until we have a feasible and improved $f(x+\Delta x)$ or $\Delta x$ is smaller than a certain threshold $\xi$.

## 5 SIMULATION RESULTS

The final goal of the SEAM4US project is to develop an advanced control system and run it on an actual metro station. However, in the design phase, we should better only simulate the behaviour of metro stations and test the algorithm on the virtual station.

We have developed a simulator for the metro station in dymola, and the modified Newton's method is tested in the simulated virtual station environment. In the dymola model, we currently only simulate one controllable entity, the fan. Other facilities such as lighting and escalators will be added in the later stage. Environmental models and user models are used to predict the future context variable changes such as future temperature, airflow rate, and occupancy density level. However, we do not concentrate on how those models are developed in this position paper. We focus on the effectiveness of the controller.

Fig. 4.1 shows the Model-In-The-Loop framework, and how we do energy minimization while considering comfort level and operational constraints.

We first start with a fan frequency $w_0$, and through unifying objectives and constraints, we are able to represent the constrained optimization problem as an unconstrained optimization problem. From Newton's method, we are able calculate out a displacement ( $\Delta x$ ), going into the backtrack line search box, we are able to search out the 'best' fan frequency. The best fan frequency will go into the virtual station; the executed results together with new predictions from Bayesian Networks, and user models will trigger another round of Newton learning and backtracking line search. Thus, the modified Newton's method, when including the virtual station in the loop, is an online learning scheme, which is able to adapt its policies in real time.

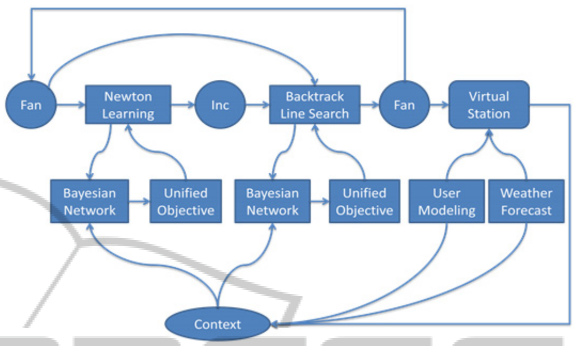


Figure 4.1: Model-In-The-Loop Scheme.

In the simulation, we specify $\lambda$ in Eq. (1) as 10 (theoretically, we should specify $\lambda$ as large as possible, however, that would make the qualified fan frequency range very short, and it would therefore be hard for the fan control agent to reach an optimal fan frequency). The learning rate $\alpha$ is set to be 0.9, threshold $\xi$ is set to be 0.2 ( $\xi$ corresponds to the granularity of the fan frequency control, $\xi$ =0.2 means that we can increase/decrease the fan frequency by a minimum of 0.2). The upper and lower bound of the target temperature range is 25 and 35 respectively, and the upper and lower bound of the target airflow rate is 40 and 80 respectively. The starting fan frequency is 35, and the fan frequency feasible range is from 0 to 50. We used the model-in-the-loop framework for simulation, and we simulated the behaviour of the controller in a single day from 5am to 11pm.

Fig. 5.1 shows the fan frequency update over the day. From Fig. 5.1 we can see that when adopting our modified Newton learning strategy, we can always have a lower fan frequency output than the normal fan policy. Fig. 5.2, Fig. 5.3 and Fig. 5.4 show the expected energy consumption, expected airflow rate and expected temperature at different hours of the day. In the figure, we can see that, after several steps of Newton Learning, we can decrease the energy consumption of the subsystems, while maintaining the environment factors such as temperature, airflow rate within the pre-specified range.

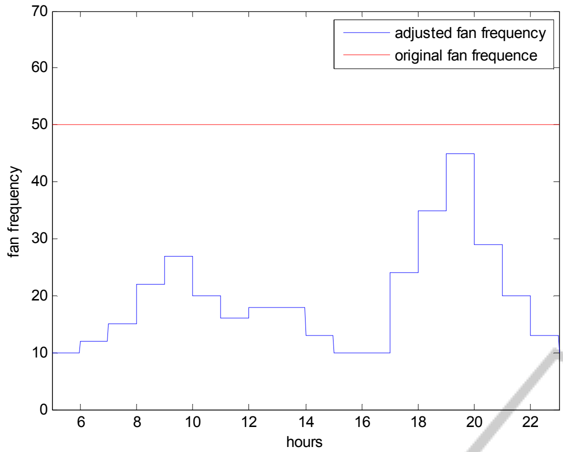


Figure 5.1: Fan frequency at different hours.

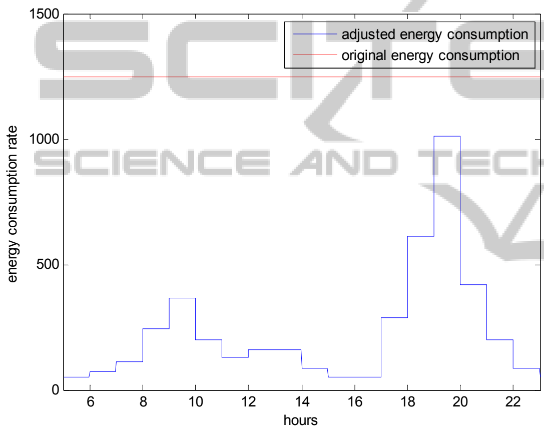


Figure 5.2: Expected energy consumption rate at different hours.

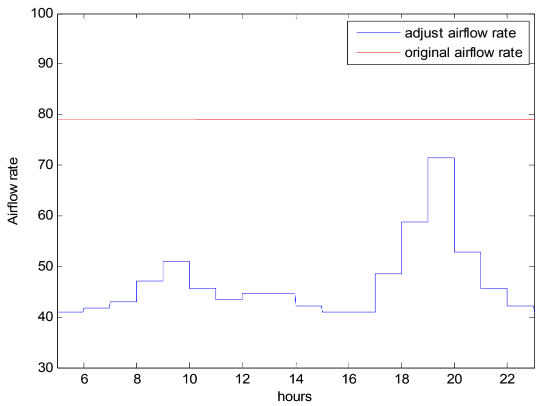


Figure 5.3: Airflow rate at different hours.

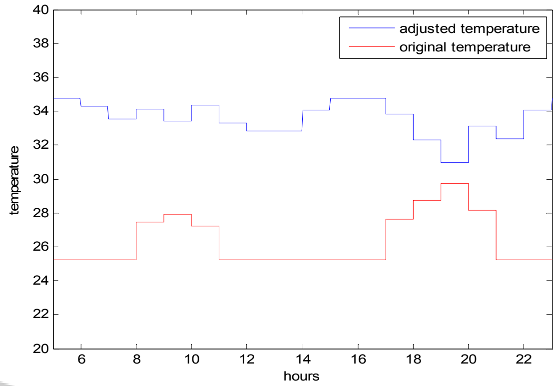


Figure 5.4: Platform temperature at different hours.

# 6 CONCLUSIONS AND FUTURE WORKS

In this position paper, we have presented a mathematic problem formulation and tentatively solved the scientific problem through modified Newton's method. Preliminary and promising results within the model-in-the-loop framework are presented but need further experimental verification.

Therefore, we are currently deploying sensor networks in the pilot station to gather metro system, passenger density and environmental data. After the data collection, we will first validate and improve the virtual station control model in dymola.

An alternative approach to the control problem based on fuzzy control is currently investigated for subsystem control. Furthermore, we are up to develop distributed but coordinated control solutions at multiple scales to tackle robustness and computational issues. By the end of 2014, we will have implemented algorithm and deployed the SEAM4US system to the pilot station in Barcelona.

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# REFERENCES

Anderson, R. J., Maxwell, R., Harris, N. 2009. Maximizing the potential for metros to reduce energy consumption and deliver low-carbon transportation in cities. Working paper for *the CoMET and Nova Metro Benchmarking Groups*.

Franke, J., Hirsch, C. Jensen, A. G., Krüs, H. W., Schatzmann, M., Westbury, P. S., Miles, S. D., Wisse, J. A., Wright, N.G., 2004. Recommendations on the use of CFD in wind engineering. In: van Beeck, J.P.A.J. (Ed.), *Proc.of the International Conference on Urban Wind Engineering and Building Aerodynamics*. COST Action C14. Von Karman Institute, Sint-Genesius-Rode, Belgium.

Ansuini R., Larghetti R., Vaccarini M., Carbonari A., Giretti A., Ruffini S., Guo H., Lau S. L. (2012). Hybrid Modeling for Energy Saving in Subway Stations. In: *Jonathan Wright and Malcolm Cook, (Editors); 2012, "Proceedings of the 2012 Building Simulation and Optimization Conference";* 10-11 September 2012, Loughborough, Leicestershire, UK; ISBN 978-1-897911-42-6. Published by Loughborough University.

Cui S.; Goldsmith, A. J.; Bahai, A., "Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks," *Selected Areas in Communications, IEEE Journal on* , vol.22, no.6, pp.1089,1098, Aug. 2004 doi: 10.1109/JSAC.2004.830916

Den Hertog D., Roos C. and Terlaky T., (1990) On the Classical Logarithmic Barrier Function Method for a Class of Smooth Convex Programming Problems, In *Journal of Optimization Theory and Applications*, volume 73, Issue 1, pp 1-25.

Boyd S.and Vandenberghe L., Convex Optimization (2004), Cambridge University Press.

Alizadeh F., Haeberly J.-P. A., and Overton M. L., Primal-dual interiorpoint methods for semidefinite programming: Convergence rates, stability and numerical results. *SIAM Journal on Optimization,* 8(3):746–768, 1998.

Alizadeh F.. *Combinatorial Optimization with Interior-Point Methods and Semi-Definite Matrices*. PhD thesis, University of Minnesota, 1991.

Gill P. G., Murray W., Saunders M. A., Tomlin J. A., and M. H. Wright. On projected newton barrier methods for linear programming and an equivalence to Karmarkar's projective method. *Mathematical Programming*, 36:183–209,1986.

US Department of Energy, Energy Efficiency Trends in Residential and Commercial Buildings (2008), in *Energy Efficiency and Renewable Energy.*

Lamoudi M. Y, Alamir M. and Béguery P., "Distributed constrained Model Predictive Control based on bundle method for building energy management,". 2011 *50th IEEE Conference on Decision and Control and European Control Conference* (CDC-ECC) Orlando, FL, USA, pp. 8118-8124, Dec 2011.

Samuel P., Jan S., Lukas F., Jiri C., Model predictive control of a building heating system, The first experience, in *Journal of Energy and Buildings*, 2011, volume 43, issue 2-3, pp 564-572.

Lakshmi G., Data Center Energy Management, PhD dissertation, Cornell University, 2012.

Oscar P., private communication, TMB, Barcelona, October, 2011.

SEAM4US consortium. (2013, 04 01). *SEAM4US website*. Available: http://www.seam4us.eu.