Continuous Simulation for Urban Energy Planning Based on a Non-Linear Data-Driven Modelling Approach

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Ernst Andreas Koch

Hauptreferent: Prof. Andreas Wagner

Korreferent: Prof. Markus Neppl

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Ernst Andreas Koch

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Prof. Markus Neppl

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Abstract

Cities play an important role in the global debate on climate protection, resource efficiency and the economy. In order to pursue a more sustainable development path urban energy planning is identified as an important task. This thesis develops the argument for scale sensitive local energy planning in order to combine energy demand simulation and the development of continuous benchmarks. The current state of urban energy simulation is described and a structure is proposed for classifying existing energy system models suitable for describing energy needs for urban neighbourhoods. Typical local energy planning tasks are described and linked to assessment methods and simulation models.

Based on this discussion a non-linear data driven modelling approach is selected to represent daily and hourly space heating needs for existing and new built urban areas. The model is applied to the scale of buildings, building clusters and neighbourhoods in order to test the application's robustness and its scalability. The single variant model, initially designed for a large application scale, is for the first time successfully applied at the scale of building clusters and urban neighbourhoods.

Comparison with measured energy needs from six case studies containing residential and non-residential users showed the applicability of the data-driven approach to the scale of neighbourhoods or building clusters. Based on selected statistic tests, aggregation effects of heating energy needs are discussed that occur at the scale of building clusters and equalize individual user's specific thermal load profiles. To improve the simulation results a new set of parameters is proposed for the application in periods of very low temperatures for which the model in its current state shows distinct weaknesses. In addition, a modified simulation approach is developed adapted to the intermediate scale of neighbourhoods.

In the application, the model allows for an easy application yet delivers robust simulation results for daily and hourly heating needs in early stages of urban development projects. It is judged suitable to follow up performance in the form of continuous benchmarks with high temporal resolution.

Zusammenfassung

In der aktuellen Debatte über Maßnahmen zum Klimaschutz, Ressourceneffizienz und der wirtschaftlichen Entwicklung spielen Städte eine wichtige Rolle. Städtische Energieplanung ist ein wichtiges Instrument zur Verfolgung nachhaltiger Entwicklungsziele. Um die lokale Energieplanung zu unterstützen schlägt diese Arbeit einen Ansatz vor, der Energiesimulation und fortlaufend gebildete Kennwerte verbindet. Hierzu wird zunächst der Stand der Entwicklung städtischer Energieplanungs-Werkzeuge diskutiert und Kategorien werden vorgeschlagen, um existierende Energiesystemmodelle zu klassifizieren. Zusätzlich werden typische Planungsaufgaben beschrieben und den Planungswerkzeugen bzw. den zugrundeliegenden Modellen zugeordnet.

Auf dieser Grundlage wurde ein nicht-linearer datenbasierter Modellansatz gewählt, um tägliche und stündliche Heizenergiebedarfe für bestehende und neue Stadtquartiere zu simulieren. Das Modell wurde auf den Maßstabsebenen von Gebäuden, Gebäudegruppen und Quartieren angewandt, um die Aussagekraft und die Skalierbarkeit des Ansatzes zu testen. Das ursprünglich für den Maßstab von Regelzonen entwickelte Energiesignaturmodell wurde zum ersten Mal erfolgreich auf den Maßstab von Quartieren und Gebäuden angewandt.

Der Vergleich mit Messdaten aus sechs Fallstudien, die Wohn- und verschiedene Nichtwohngebäude beinhalten, bestätigt die Anwendbarkeit des datenbasierten Modells für den Maßstab von Stadtquartieren und Gebäudegruppen. Basierend auf den Fallstudien wird eine Methode zur Anwendung für bestehende und neue Stadtquartiere vorgeschlagen. Zur Verbesserung der Vorhersagegenauigkeit bei der Anwendung für tiefe Temperaturen wurde weiterhin ein neuer Satz Modellparameter vorgeschlagen, der die Simulationsergebnisse für Temperaturen unter -5 °C verbessern konnte.

Das gewählte Modell erlaubt eine unkomplizierte Anwendung und liefert verlässliche Ergebnisse für den täglichen und stündlichen Heizenergiebedarf. Das Modell kann als geeignet angesehen werden, fortlaufende Kennwerte mit hoher zeitlicher Auflösung zum Vergleich mit Messdaten zu erstellen, die eine bessere Kontrolle in der Betriebsphase von Stadtquartieren erlauben.

Acknowledgement

The work presented in this thesis was supported by a large number of colleagues in multiple projects and benefited from discussions with colleagues from a wide range of backgrounds too numerous to be named here. Specifically my thanks are due to Dr. Reinhard Jank as coordinator of the IEA Annex 51: Energy Efficient Communities and for the ongoing support throughout the work on this thesis. The French national contribution was cofounded by the ADEME and EDF.

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My family.

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Abbreviations

ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BDEW	German Association of Energy and Water Industries
BAU	Business as Usual
BMWi	German Federal Ministry for Economic Affairs and Energy
BREEAM	Building Research Establishment Environmental Assessment Method
CASBEE	Comprehensive Assessment System for Built Environment Efficiency
CHP	Combined Heat and Power
DSM	Demand Side Management
CVRMSE	Coefficient of Variation of Root Mean Square Error
DGNB	German Green Building Council
DH	District Heating
DIN	German Institute for Standardization
DWD	Deutscher Wetterdienst
EBC	Energy in Buildings and Communities Programme (IEA implementing agreement)
ECBCS	Energy Conservation in Building and Community Systems
EnEV	German Energy Saving Ordinance
EnOB	Energy Optimized Building
ETI	Energy Technologies Institute
FEMP	Federal Energy Management Program
GHG	Green House Gases
GIS	Geographic Information System
GML	Geography Markup Language
GRG	Generalized Reduced Gradient
HDD	Heating Degree Days
IEA	International Energy Agency
IPMVP	International Performance Measurement and Verification Protocol
ISO	International Organization for Standardization
LEED	Leadership in Energy and Environmental Design
LEP	Local Energy Planning
MBE	Mean Biased Error
OLAP	Online Analytical Processing
OGC	Open Geospatial Consortium
PV	Photovoltaic
RMSE	Root Mean Square Error
TRNSYS	Transient System Simulation Tool
TRY	Test Reference Year
UNEP	United Nations Environment Programme
VDI	Association of German Engineers
VKU	Association of Communal Enterprises

Symbols

A_t	[-]	Realised change of variable x at time t
d_x	[d]	Length of measurement period
$H_{\mathrm{tr,adj}}$	[W/(m^{2}K)]	Transmission heat transfer coefficient
h	[kWh]	Normalised daily energy use
$\bar{h}_a$	[kWh]	Mean daily energy use in the calculation year
h_i	[kWh]	Calculated daily energy use based on the sigmoid function
$\bar{h}_x$	[kWh]	Mean daily energy use in the measurement period
$h_{\vartheta\mathrm{a}}$	[kWh]	De-normalised daily energy use
N_p	[-]	Number of values in the interval p
P_t	[-]	Predicted variable x at time t
$Q_{H,nd}$	[kWh]	Total heat demand
Q_{int}	[kWh]	Internal heat gains
Q_{sol}	[kWh]	Solar gains
Q_{tr}	[kWh]	Transmission losses
Q_{ve}	[kWh]	Ventilation losses
s	[-]	Standard Deviation
s^2_n	[-]	Variance
s_{xy}	[-]	Covariance
t	[h]	Time
U	[-]	Theil’s coefficient of inequality
U_c	[-]	Component of Theil’s U for correlation
U_m	[-]	Component of Theil’s U for mean value
U_v	[-]	Component of Theil’s U for variance
W_a	[kWh]	total energy use in the calculation year
W_x	[kWh]	total energy use in a measurement period
$W_{\vartheta\mathrm{a}}$	[kWh]	de-normalised daily energy use
$\eta_{H,gn}$	[-]	Utilization factor of solar gains
ϑ_a	[°C]	Calculated equivalent temperature for the day
ϑ_e	[°C]	outdoor temperature
ϑ_0	[°C]	Model specific point of discontinuity (40°C)
$\vartheta_{\mathrm{int,set,H}}$	[°C]	set temperature for the zone
ϑ_t	[°C]	Measured mean temperature for the day
$\vartheta_{\mathrm{t-n}}$	[°C]	Measured mean temperature for n days before
ρ	[-]	Bravais-Pearson correlation coefficient

1 Introduction

Cities have reached a high level of importance in the global debate on climate protection, resource efficiency and the economy (European Union 2007, IPCC 2007, UNEP 2011). As centres of activities they are often identified as the places and drivers for change (IEA 2009). In order to live up to the role they have been assigned in the current discourse, cities need new planning processes, policies and tools. Urban emission inventories (Webster, Baier et al. 2013), as part of local climate protection strategies, link the environmental impact of the city's technical infrastructure and systems to the larger political context. Planning of the spatial and technical system can provide a leverage for decision makers to improve the performance of the urban infrastructure (Dotzauer 2002, Woods, Riley et al. 2005, Nielsen and Madsen 2006). The objectives of such interventions are the reduction of greenhouse gas emissions inscribed in strategies to promote resource efficiency and the integration of renewable energy sources into the energy system (pro:21 GmbH and Projektträger Jülich 2013). Both strategies are usually linked to facilitate economic growth (Wang, Peng et al. 2010, UNEP 2011).

In addition to energy networks and the connected conversion systems on the demand side, multiple opportunities for urban areas emerge at the scale of buildings, building clusters and neighbourhoods (Erhorn-Kluttig, Jank et al. 2011, Strzalka, Bogdahn et al. 2011, Bahu, Koch et al. 2013). Such measures tackle parts of, or the whole, building stock in order to improve the energy performance of buildings at different scales. In order to understand the above mentioned developments, energy system simulation is often applied for diagnosis as well as predicting and assessing the performance of different systems and for the development and evaluation of alternative solutions (Coakley, Raftery et al. 2014). However, as the issues and planning tasks are diverse there is no silver bullet among the available solutions to support local energy planning (LEP).

Based on the discussion of urban energy planning, this thesis will assess and classify current model-supported approaches to local energy planning. The work will investigate the scale of urban neighbourhoods, an important but usually ill-defined, target scale for urban development projects. It will provide a review and analysis of different models to simulate the heating energy needs for buildings on this intermediate urban scale. Based on the work in the IEA EBC Annex51 (Koch and Kersting 2011) a focus was put on the identified need to combine simulation and data collection in the early planning stages and monitoring and concomitant simulation after construction when urban projects often lack the resources to continuously support complex simulation or optimisation models. In this way a continuous benchmarking of energy use in neighbourhoods throughout the planning, implementation and operation phase is proposed (Figure 1).

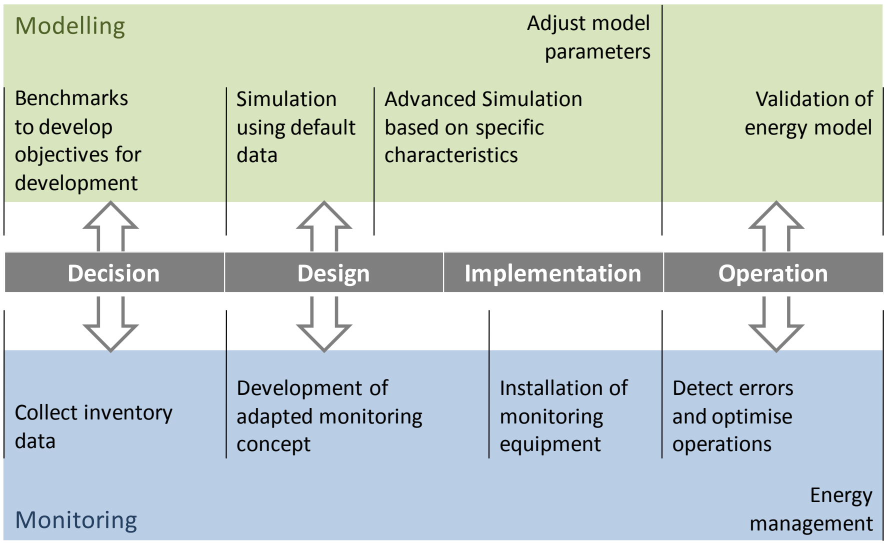

Figure 1: Modelling and monitoring steps aligned with project phases (Koch and Kersting 2011)

As a result of the analysis, this thesis will specify a model suitable for modelling building energy performance for urban development planning tasks at the neighbourhood scale (micro), for modelling technical infrastructure, such as district heating networks (meso) and supporting local GHG inventories by building stock modelling for cities (macro). It will propose a robust energy model for early design stages, which can also be used for continuous commissioning by providing a means of accurately predicting realistic benchmarks for space heating needs. The basic model described in Chapter 3.2.3 was initially developed for gas load predictions at the macro scale of gas distribution networks (Regelzone). The application of the data driven model for neighbourhood scale simulation is for the first time successfully tested. A set of statistic tests will be described to validate the simulation results against measured data from a number of measurement campaigns representing building clusters from single apartments to the scale of a neighbourhood. Different temporal, as well as spatial scales, for data aggregation will be tested to deliver a solution that addresses the specific scale of urban neighbourhoods.

The combination of simulation and data base solution was prototyped in the form of an OnLine Analytical Processing solution (OLAP) for one case study. While the underlying concept was developed in the course of this thesis, the IT-solution was developed by Jose Juan Hernandez, José Evora and Octavio Roncal of the University of Las Palmas (SIANI) in a cooperative programme with the European Institute for Energy Research (EIFER).

1.1 Why cities act – the environmental challenge

The environmental impact of human activity poses one of the great challenges of our time. With rapidly increasing rates of urbanisation, today more than half the world's population lives in cities (OECD 2010). In Germany, an industrialised country, this figure reached nearly 74% in 2011 (United Nations 2012). Globally this trend is expected to continue and will become a major challenge to new and existing urban areas (Figure 2). As a focal point for human activity, cities are attributed with creating 60-80 % of all CO_2 emissions (OECD 2010). It follows that cities and communities have to take on an active role in the efforts to reduce greenhouse gas emissions (GHG). More importantly, developing countries identify urbanisation as a means for providing better services to citizens and thus increasing the quality of life and also increasing intrinsic economic growth by stimulating private consumption (Wang, Peng et al. 2010). As pointed out in the World Urbanisation Prospects (United Nations 2015) "owing in part to their higher incomes, urban dwellers tend to consume more per capita than rural dwellers". The predicted growth of the world's cities along with an increased consumption of goods and energy (Wang, Peng et al. 2010) leads to the conclusion that such growth can only be sustained through a fundamental change of our economy. Suitable measures in moving towards a green economy were outlined in the United Nation Environment Programme's Green Economy Report (UNEP 2011), the importance of cities and buildings were discussed in more detail by Rode, Burdett et al. (2011).

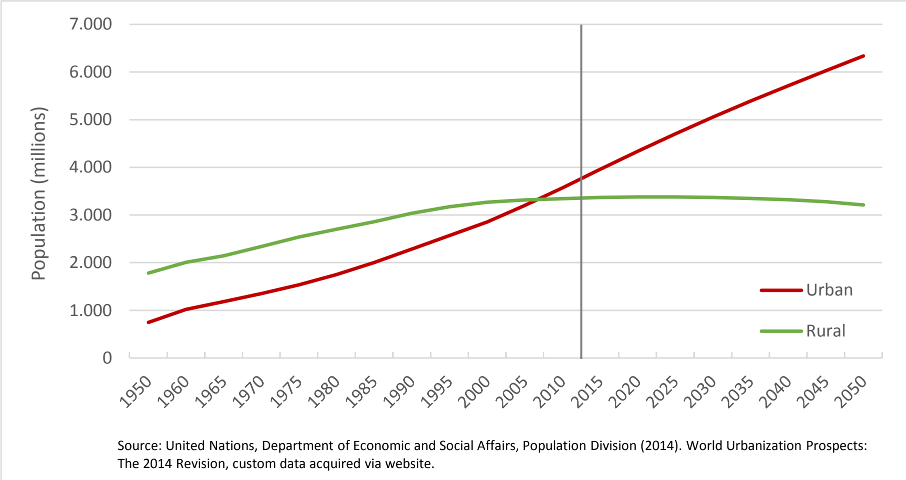

Figure 2: World Urbanisation Prospects, own illustration based on (United Nations 2015), http://esa.un.org accessed 3.8.2015

It follows that, "[a]s the world continues to urbanize, sustainable development challenges will be increasingly concentrated in cities" (United Nations 2014). The specific role of communities in the implementation of climate protection measures can be traced back to the Brundtland Report from the World Commission for the Environment (Brundtland, Khalid et al. 1987) and the Agenda 21 process, initiated at the Rio climate summit in 1992. The European Commission also acknowledges the role of communities in the 2007 Green Book (European Commission 2007). Kern and Alber (2009) point out, "local governments have become major players in the area of climate change policy over the past 20 years". The argument, which is further supported by Betsill and Bulkeley (2006), highlights three key issues: access to local information, the potential to react to local needs, and control of local policy instruments. The role of cities is summarized by Toly (2008) as follows:

> "Like other governmental, but non-state actors, cities have jurisdiction, govern with a flexibility not enjoyed by nation-states, and typically do not face conflicts with strategic interests. Unlike non-governmental actors, cities have large populations and much more direct influence on emissions." (Toly 2008)

The main fields of action in climate change policies for local governments are: energy supply, transport planning, urban planning and development, waste and waste water management and public procurement (Kern, Niederhafner et al. 2005). In connection with energy supply, local forestry and agriculture can play a key role if bioenergy solutions are part of local strategies to reduce the non-renewable part of the primary energy use. These sectors are also addressed by the Covenant of Mayors, founded in 2008 as a network of communities committed to reaching European Energy and Climate protection targets. In return, the communities are provided with political and financial support by various EU authorities through specific programmes. In 2015 the Covenant counted more than 6,400 signatories (Covenant of Mayors 2013, http://www.covenantofmayors.eu/ seen 11.8.2015). Upon joining the Covenant, each community agrees to issue a Sustainable Energy Action Plan (SEAP). Starting from a baseline emission inventory, the SEAP describes the most suitable measures for a given community to reach CO_2 emission reduction targets by 2020. “It defines concrete reduction measures, together with time frames and assigned responsibilities, which translate the long-term strategy into action.” (Bertoldi, Cayuela et al. 2010).

Building a Greenhouse Gas (GHG) emission inventory, as described for example in the SEAPs, is the initial step for a community or city in order to determine the primary action items and measures to successfully reducing the city’s environmental impact. Jank, Church et al. (2013) propose a five step approach for managing the local energy transition process (Figure 3). As a first step, an energy and emission Inventory is created for the whole city or metropolitan area. The inventory also serves to track future emissions. Second, a stakeholder analysis is proposed to identify a common vision and to establish joint long-term quantitative targets. Based on this inventory, different scenarios are developed in a third step. This typically includes a business as usual (BAU) scenario against which all other possible future developments can be assessed.

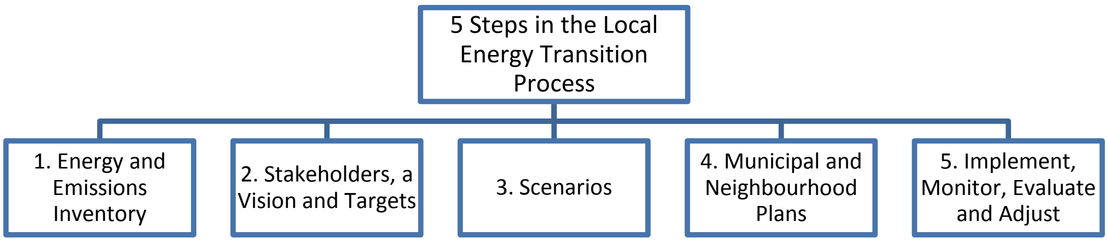

Figure 3: Overview of local energy planning transition process, adapted from (Jank, Church et al. 2013)

A municipal energy master plan is developed from the information gathered in the first steps (4.), which is in line with the established vision and scenarios and is based on the inventory. The municipal energy master plan addresses the different fields of action and includes the different targets as well as key indicators. In addition, neighbourhood energy plans are developed providing detailed technical information on demand characteristics, available supply solutions and cost structures. Information should be exchanged between the two planning scales in an iterative process. In a last step, the defined measures are implemented and monitored over time. Depending on the evaluation of the measures' adjustments might be needed or revision of one of the earlier steps. Finally, it is important to note that all five steps are "interconnected parts of a whole comprehensive process with iterations and feedback loops" (Jank, Church et al. 2013). As explained local energy transition processes are driven mostly by national and international environmental policy and translate the high-level objectives into local targets. This is typically supported by energy system models that allow the quantification of individual measures. Figure 4 illustrates this iterative process and some exemplary tasks. As depicted, different layers in the process from strategic planning to implementation can be identified. Chapter 2 will introduce the different scales at which local energy planning takes place, based on the aforementioned municipal and neighbourhood plans. Planning, and parts of the other process steps, rely heavily on different representations (i.e. models) of resource flows in urban systems. Local energy planning and its links to citywide strategic planning will be discussed in the next chapter.

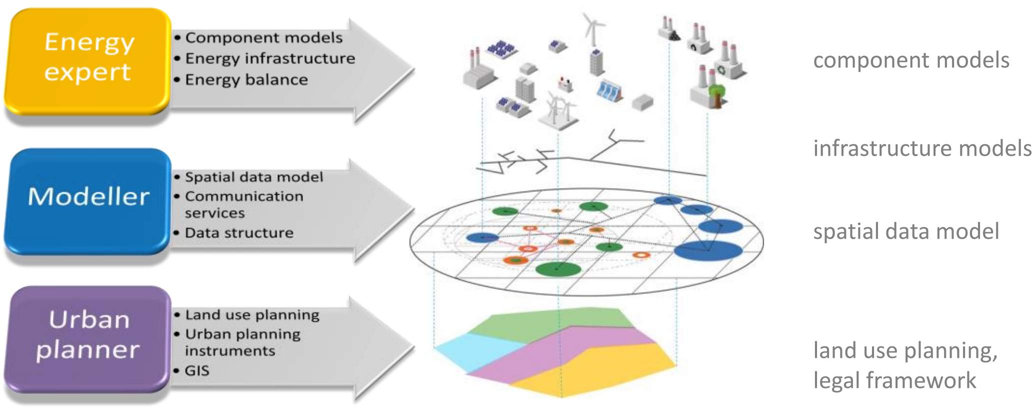

Figure 4: Supporting Urban Planning through Multi-Scale Energy System Models

Supporting urban energy planning in order to arrive at well-adapted solutions, a number of applied methods are provided by the scientific community as well as by practitioners. Many of them represent partial urban energy system models that can be used to simulate the performance of the system or apply an optimisation to search for optimal solutions within a given solution space (Mendes, Ioakimidis et al. 2011). A number of these tools or models are described in chapter 3. The section discusses different approaches within a more general methodological framework and classifies the different tools and methods.

Integrating energy planning into the urban planning process will become more common with the emergence of more refined planning tools. However, energy concepts are becoming ever more complex as they involve different actors from different disciplines and often combine a number of technical solutions. A clear need for suitable benchmarks and a continuous performance monitoring can be identified (Erhorn, Erhorn-Kluttig et al. 2012) in order to deliver the energy or carbon emission savings predicted in the planning process. Yet, even among widely discussed demonstration projects of the past years, a distinct lack of a continuous monitoring exists as Zinko and Moshfegh (2012) point out. This research gap was part of the main conclusions from the first phase of the IEA ECBCS Annex 51 (Koch and Kersting 2011). Related to the data analysis and discussion of the different modelling approaches, the question of neighbourhood scale monitoring will be discussed based on the outcome of the case study results.

The research objectives can be summarised as follows:

1. Provide structured descriptions of tasks and related energy simulation models for local energy planning.
2. Develop a suitable approach for the assessment of heating energy needs for early planning stages for the specific scale of urban neighbourhoods.
3. Support continuous commissioning in the operation phase by providing a suitable heating energy needs model to deliver daily and hourly benchmarks.

2 Local energy planning (LEP) - from strategic planning to local action

Model-based integrated local energy planning (LEP) has been discussed since the early nineties (Barton 2005). Since then a number of successful projects have been implemented and a multitude of technical support tools have been developed (German Association of Cities 2013). This chapter will identify the most relevant objectives of local energy planning and define typical applications for model based planning support. LEP tools, methods, and their databases can be seen as ways to structure and integrate expert and stakeholder knowledge in the planning process. Planning of interrelated measures encompassing the whole urban or metropolitan area is often referred to comprehensive or integrated planning (UN-HABITAT 2009). The development of such overall plans captured in the city model (Figure 5) is especially necessary as “decisions are (1) interdependent, (2) indivisible, (3) irreversible, and (4) face imperfect foresight” (Hopkins 2001). The planning scheme shown in Figure 5 describes the workflow for continuous local energy modelling and corresponds to the planning steps outlined in Figure 3. The process is designed to support choices between concurrent decisions.

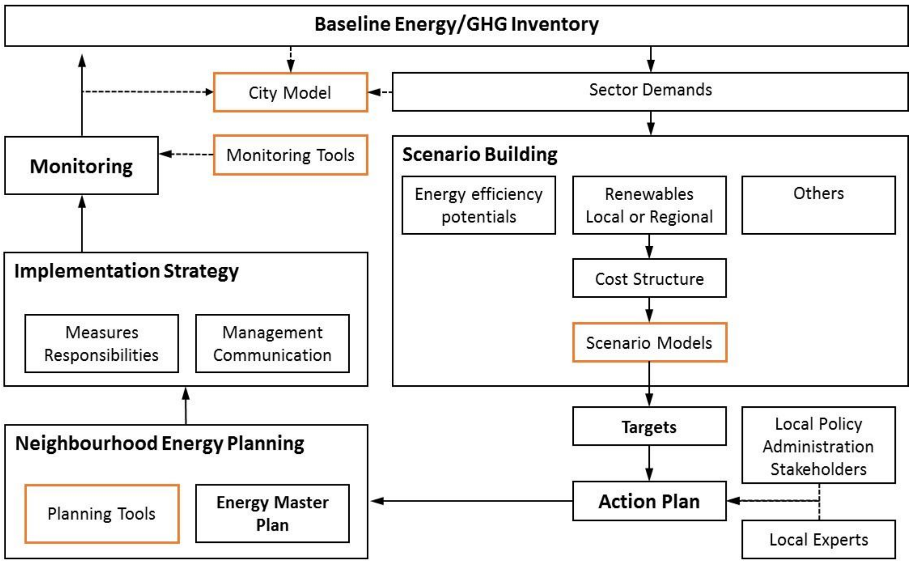

Figure 5: Model supported planning steps in local energy planning; adapted from (Jank 2012)

As a first step, the GHG inventory is established for the community to provide strategic orientations. There are a number of methods and tools to develop GHG emission inventory on the city scale such as EnergyBalance in Denmark and Bilan

Carbone in France. In the German city of Freiburg a solution referred to as “Scenario Model” was developed by the Öko-Institut (Timpe, Seebach et al. 2007). The tool was developed further by the Institut für Energie- und Umweltforschung Heidelberg GmbH (ifeu) to monitor CO_2-emissions in other municipalities. Today, ifeu uses this tool in about ten German cities. A recent overview of existing Greenhouse Gas (GHG) inventories is provided by (Bertoldi, Cayuela et al. 2010). Recently, the methodology for accounting GHG emissions in cities has been addressed more specifically (Bader and Bleischwitz 2009, Kennedy, Steinberger et al. 2010). One of the main problems identified was that “inventories compiled with different tools are hardly comparable” (Bader and Bleischwitz 2009) which can be explained through different scopes, methodologies or even underlying indicators. This greatly limits the comparison of the different cities’ efforts. Once strategic (political) targets are defined, the sectors represented in the GHG inventory can be further divided by individual sources of emissions, according to their contribution to the overall balance. In the context of the SEAPs the European Commission (2010) points out that “Buildings are responsible for 40 % of total EU energy consumption and are often the largest energy consumer and CO2 emitter in urban areas.” The resulting actions (policies or planning documents) of the individual sectors are then organised in a comprehensive or city-wide energy master plan. Master plans “depict on a map the state and form of an urban area at a future point in time when the plan is ‘realized’” (UN-HABITAT 2009). This provides a complete view of the sum of all measures related to strategic targets and allows the assessment of individual measures’ impacts on the whole system. Typically, the relevant sectors include residential users, services, industry and transport. In many cases, public buildings are regarded separately as they provide an opportunity for highlighting projects to which the municipality has direct access. Ideally, the municipal energy master plan is established as central document and is then further divided into sectorial planning policies, which describe concrete measures at a smaller scale or with a narrower scope, such as residential building stock strategies or neighbourhood development plans. Thus, the results of individual measures targeting single sectors can be evaluated in a common master plan. This approach further allows the identification of synergies or opposing objectives at city level. Section 2.1 describes energy related objectives at the city scale, corresponding to the urban development plan. Here objectives are understood as the translation of urban needs and problems into strategic planning. Based on the objectives, concrete targets and measureable results can be set which will be described in section 2.2.

2.1 Objectives in urban development projects

The following discussion of objectives for urban development projects is based on the analysis of international case studies in the context of IEA Annex 51 as well as a review of recent guidelines on the topic (Egger 2011, Rösler 2011, Malottki, Koch et al. 2013, Müller and Koch 2014). In the framework of Annex 51 Subtask A, the analysis was structured and conducted by the author. The international case studies were described by the national participants. The submitted case studies targeted completed or nearly completed development projects at the scale of urban neighbourhoods; full case study descriptions and assessments can be found in Koch and Kersting (2011). For this thesis, part of the material was reassessed to describe local energy planning tasks, which relate to the different environmental objectives and the defined targets in the projects. In most of the cases, it is important to note that the main objectives were not necessarily connected to the environmental impacts of the development (Table 1). A main driver for new developments was urban growth and the need for new housing development (Table 1, rows 1, 2, 5, 8, 11, 14). An often-cited objective for existing neighbourhoods is improved quality of urban space or residential areas, sometimes expressed in a desire to develop a more sustainable neighbourhood (Table 1, rows 3, 4, 15, 16). While the selection of case studies is not representative it indicates that even in urban development projects identified as national demonstration cases, the objectives relate to societal questions and in second instance connect to environmental targets. It follows that in order to judge the success of urban development projects energy performance ratings alone are clearly insufficient. The energy assessment should always be seen in the context of additional objectives of the projects.

Table 1: Assessment of the main objectives in urban demonstration projects based on the case studies provided by national participants in Annex 51; based on (Koch and Kersting 2011)

	Project	Major Objective	Environmental & Energy Objectives	Monitoring
1	solarCity Pichling (AU)	Housing development, sustainability	Low-energy standard, promote walking, participation of tenants	Municipality
2	Obertrum (AU)	Housing development, low cost, promote energy optimisation	Low-energy standard, district heating system	DH operator
3	Dockside Green (CA)	Sustainability showcase	GHG neutral, closed loop system, water, transportation, waste	Developer and city audit
4	Regent Park (CA)	Revitalisation	High standards of energy efficiency mixed community	Independent consultant
5	Stuttgart-Burgholzhof (DE)	Housing development, solar showcase	Low energy level, solar energy	Energy bills, heat meters
6	Samsø Island (DK)	Use of renewable resources	100% renewable (self-sufficiency) with exist. Technologies	Collection of energy data
7	Stenløse Syd (DK)	Housing development, high energy performance	Danish low-energy standard, use of solar energy	-
8	ZAC de Bonne (FR)	Rehabilitation & high energy efficiency	Increased energy performance, use of solar energy, recycled materials	-
9	Grand Lyon (FR)	Quality of life, environmental protection, economic dev.	-20% CO_2, - 20% energy use, +20% renewable energy supply (2020), - 75% CO_2 (2050)	-
10	Andromède Toulouse (FR)	Housing development, sustainability	- 10 % (regulation)	-
11	Nagoya-city (JP)	Energy saving	7% energy-saving efficiency (compared to BAU)	DH Operator
12	Shin-Yokohama (JP)	Replace energy systems of public buildings	-18% energy use, -30% CO_2 emissions, -31% costs (compared to BAU)	-
13	Stad van de Zon (NL)	Housing development, CO_2 neutral showcase CO_2	CO2 neutral area, sustainable energy	-
14	Västra Hamnen (SE)	Revitalisation, sustainability showcase	100% renewable energy supply, district heating	University, DH operator
15	Hammarby Sjöstad (SE)	Revitalisation, sustainability showcase	Reduced emission from energy and waste, local renewables	-

However, related to the major objective, "[u]rban planning can help mainstream climate change considerations into urban development processes" (UN-HABITAT 2009). The following main needs for planning sustainable cities are identified by UN-HABITAT (2009):

1. developing renewable energy;
2. striving for carbon-neutral cities;
3. developing distributed power and water systems;
4. increasing photosynthetic spaces as part of green infrastructure;
5. improving eco-efficiency;
6. increasing a sense of place;
7. developing sustainable transport; and

8. developing 'cities without slums'

Here the focus is put on the objectives related to LEP, which are the increased use of renewable energy (1.), moving towards carbon neutral cities (2.), distributed power systems (3.) and eco-efficiency (5.). This is consistent with the environmental objectives for the urban development projects discussed above that relate to citywide GHG emission reduction or specific energy efficiency targets (Table 1). The three main strategies to reduce GHG emissions in cities can be summarised as:

1. Increased energy efficiency related to energy performance of buildings and building clusters
2. Efficient local energy supply systems including district scale distribution and distributed combined heat and power (CHP) systems
3. Increased share of energy from renewable sources including waste heat from nearby processes

These strategies correspond to sustainable development goals by addressing efficiency and consistency strategies. As Malottki, Koch et al. (2013) point out sufficiency as a third strategy is rarely addressed in urban development projects. The three above mentioned fields of action and their combination form the key strategies to reach environmental targets in urban development.

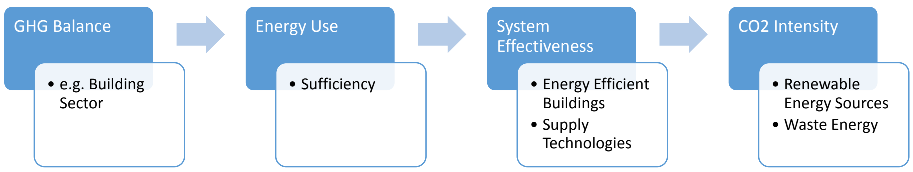

Figure 6: GHG balance and influencing factors for the building sector adapted from (Malottki, Koch et al. 2013)

They are ideally integrated as subsequent steps in a local climate protection strategy, putting efficiency first and satisfying the remaining energy needs with energy from renewable sources (Figure 6).

2.2 Targets and planning tasks in local energy planning

Linked to the identified strategies, specific tasks in urban energy planning can be identified that define targets linked to the three strategies to reduce GHG emissions: energy efficient buildings, supply technologies and renewable resources.

Table 2: Summary of the technical measures proposed in national demonstration projects

	Project	Energy Efficient Buildings	Supply Technologies	Renewable Resources
1	*solarCity Pichling (AT)*	-	District Heating	Solar Thermal, PV
2	*Obertrum (AT)*	Low Energy Buildings	District Heating	Biomass
3	*Dockside Green (CA)*	Low Energy Buildings, LEED	District Heating	Biomass
4	*Regent Park (CA)*	Low Energy Buildings	District Heating, Cogeneration	-
5	Samsø Island *(DK)*	Low Energy Buildings	District Heating	Wind, Biomass, Solar Thermal
6	Stenløse Syd *(DK)*	Low Energy Buildings	District Heating	Biomass, Solar Thermal
7	*Stuttgart-Burgholzhof (DE)*	Low Energy Buildings	District Heating	Solar Thermal
8	*ZAC de Bonne (FR)*	Low Energy Buildings	MicroCHP	PV
9	*Nagoya-city (JP)*	-	District Heating	-
10	*Shin-Yokohama (JP)*	-	District Heating & Cooling, Waste Heat	-
11	*Stad van de Zon (NL)*	Low Energy Buildings	-	PV, Wind
12	*Västra Hamnen (SE)*	-	District Heating	PV, Wind, Sea Water Heat Pump

While these targets are typically pursued in combination, individual projects will result in distinct choices of technologies, which are strongly influenced by national boundary conditions. Table 2 provides examples of targets and technology choices described in the international demonstration projects (Koch and Kersting 2011). In the following sections, the three fields of actions will be described. However, it should be kept in mind, that in most of the planning tasks listed, municipal planning has little direct power to impose measures that go beyond current regulation (Erhorn-Kluttig, Jank et al. 2011). Opportunities for energy efficient buildings and the use of renewable energies can be created based on zoning and suitable land-use plans

(Bebauungspläne). Further targets can be integrated in informal planning instruments such as private contracts between the municipality and the developer (städtebaulicher Vertrag) (Bayrische Baubehörde 2010). This clearly points out a limitation of strategic action in the existing building stock. Not surprisingly, many of the case studies discussed here are urban revitalisation projects targeting brownfield sites (e.g. case study "Bad Aibling") or refer to housing estates owned by a private or municipal housing agency (e.g. case study "Rintheimer Feld"). This issue is discussed in more detail by Libbe, Köhler et al. (2010).

Recent projects show, that in order to develop comprehensive local energy actions a larger scope is required targeting the whole system and enlarging the action to the neighbourhood scale. The neighbourhood scale seems preferable to the administrative boundaries (i.e. district). While the district describes an administrative boundary, a neighbourhood suggests a degree of homogeneity as it is often used to describe groups of relatively similar buildings emerging from previous urban development projects. Renovation measures of larger settlements provide opportunities to increase the overall efficiency of the buildings and the technical infrastructure (Jank, Church et al. 2013). In addition, the concept of neighbourhood is also used in the social sciences to describe an urban area. In this sense, a group of citizens can form a neighbourhood as a focus of social connections (Schnur and Gebhardt 2008). This latter aspect can help to facilitate participatory processes. Galster (2001) integrates both points of view and describes the neighbourhood as a bundle of spatially referenced attributes. These include the structural characteristics of buildings and infrastructure as well as the demographic characteristics of the area (Galster 2001). The twofold character of neighbourhoods as a social and spatial delimitation offers opportunities to target not only technical systems connected to buildings or urban infrastructure within the perimeter of a neighbourhood due to a homogeneous building structure. In addition, it holds the potential to identify local initiatives or tackle issues relevant to a larger part of the population of a neighbourhood due to similar interests, shared values or comparable living situations. The former characteristic is mostly stressed in technical assessments while the latter point of view is usually found in sustainability assessments as well as in social science based approaches to local energy transformation processes (Heyder, Huber et al. 2012). International sustainability labels such as LEED Neighbourhood, BREAM Community, CASBEE Urban Development and DGNB Stadtquartiere have consequently targeted the urban neighbourhood as assessment scale in recent years (Koch and Neumann 2011).

The following sub-chapters will discuss specific planning tasks relevant to the neighbourhood scale. The planning tasks and the needs for the technical assessments are summarised at the end of each chapter. Based on the discussion of energy system models in chapter 3, the developed structure will be used to propose suitable modelling approaches for each task (section 3.2.3).

2.2.1 Energy performance of building clusters

Within many cities, energy use in buildings is one of the biggest single uses of energy. In 2011, space heating accounted for 26% of the total use of final energy in Germany (Arbeitsgemeinschaft Energiebilanzen 2013). In the residential sector, space heating (66%) and domestic hot water provision (16%) were the two largest uses for final energy. In the tertiary sector, they accounted for 44% and 5% of the total final energy use (Arbeitsgemeinschaft Energiebilanzen 2013) (Figure 7). Consequently the energy performance of buildings plays a key role in defining local climate protection concepts (Umweltamt Düsseldorf 2005, Heidelberg 2006).

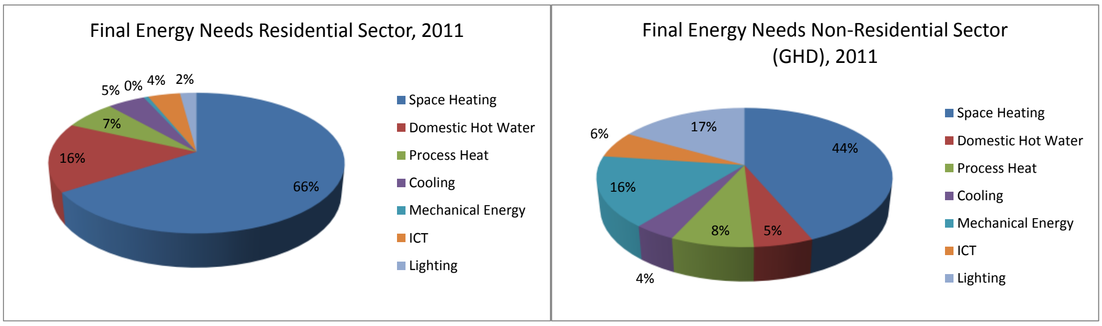

Figure 7: Structure of the German final energy balance by use for the residential and tertiary sector, own illustration based on (Arbeitsgemeinschaft Energiebilanzen 2013)

Performance regulations like the German Energy Saving Ordinance (EnEV) mainly target the energy performance of new buildings. Often, existing building stock is highlighted as the most important field for action (Friedrich, Becker et al. 2007), yet ambitious targets are only pursued on a voluntary basis. Energy efficiency targets are most commonly translated into performance classes for individual building usually corresponding to the national legislation such as the Energy Saving Ordinance (EnEV) in Germany. In current practice, the implementation is often left to the market or individual investment decisions, which is usually not sufficient to reach the community's climate protection targets (Erhorn-Kluttig, Jank et al. 2011).

Table 3: Energy Performance of Buildings - Planning Tasks and Technical Assessment

Energy Performance of Building		
Action	**Planning Task**	**Technical Assessment**
Refurbishment	Refurbishment of the existing building stock by improving the performance of the building envelope	Annual indicators for specific heating needs, monthly energy balance for legal compliance, detailed simulation for complex technical solutions, measurements to assess energy savings
New Construction	High performance buildings in new districts, influence on density, compactness and orientation	See above
Re-densification	Increase of the urban density by combined refurbishment and insertion of new buildings or building parts	See above

The related actions are summarised in Table 3. In refurbishment projects, the building related measures are applied to the existing urban form. In contrast, new developments or re-densification projects (i.e. adding new construction to existing neighbourhoods) have the potential to increase the density and in the case of new buildings influence the compactness and orientation of the project. The technical assessment ranges from annual indicators to monthly energy balances, which are calculated for legal compliance. Projects, which involve advanced measures in renovation or new construction, are typically assessed based on detailed dynamic simulations.

2.2.2 Efficient local generation and distribution systems

In addition to the building envelope, efficient supply technologies form an important part of the overall system efficiency. Urban neighbourhoods are an important scale to enlarge the outreach of energy efficient supply solutions (Erhorn-Kluttig, Jank et al. 2011, Rapp, Vautz et al. 2012, pro:21 GmbH and Projektträger Jülich 2013) and to compare individual heating solutions with district heating systems. This is also reflected in the Energy Performance of Buildings Directive (European Commission 2010) where common supply systems such as district heating and cooling are considered. The directive states that the "analysis of alternative systems may be carried out for individual buildings or for groups of similar buildings or for common typologies of buildings in the same area" (European Commission 2010). Such measures often benefit from economies of scale as discussed in (Boutaud, Koch et al. 2011) for the case of Quartier Franklin in Mulhouse. They can also help to avoid redundancies in energy infrastructure (e.g. parallel gas and district heating networks). In local energy planning, urban demonstration projects in the European CONCERTO initiative (Pol 2011) or in the German Eneff:Stadt research program (Erhorn-Kluttig, Jank et al. 2011) show a wide range of examples. The IEA EBC Annex 51 project identified international case studies including a number of projects from the aforementioned programs. Demonstration projects often were based on district heating schemes (Table 2) connected to a central biomass plant, local waste heat sources or cogeneration. The latter two can be seen as key strategies in the urban context as biomass supply often poses logistic problems and induces additional transport related emissions in dense urban areas. Table 4 describes the requirement of the demand assessment for different non-renewable supply solutions. When comparing cogeneration systems with pure heating solutions, first layout planning is typically done based on an hourly description of the load profile often in the form of an annual load duration curve to allow the assessment of CHP running hours. The use of waste heat also requires a more detailed demand assessment in order to judge the match of supply and demand in a given area.

Table 4: Efficient Supply Technologies - Planning Tasks and Technical Assessment

Efficient Supply Technologies		
Action	**Planning Task**	**Technical Assessment**
Fossil fuels	Exchange of existing heating systems with new and more efficient technologies, often reduced temperatures in the internal distribution system	Calculation of the heating loads, annual or monthly energy balance based on simulation of measurements to determine savings in the use of non-renewable primary energy and associated GHG emissions
Cogeneration (CHP)	Combined Heat and Power systems for individual buildings or building clusters connected by a distribution systems, mostly driven by heat demand, often self-consumption or direct marketing of produced electricity are investigated	Annual duration curve to estimate operating hours, hourly heat and electricity demand based on measurement, simulation or standard load profiles
Waste Heat	When available in close proximity waste heat is often considered as heat source for district heating systems to render the overall system more efficient by integrating cascading energy use	Waste heat potential based on measurements or comparable processes, hourly heat demand based on measurement, simulation or standard load profiles

2.2.3 Integration of Renewable Energy Sources

After the improvement of the systems' efficiency, the remaining energy needs should be satisfied based on renewable sources in order to meet local climate protection targets. At the enlarged scale of a neighbourhood, technical measures for efficient low carbon supply solutions and optimized urban planning for the use of renewable energies should be included at the design stage. Especially for the use of solar energy the urban form determined in the zoning plan can play an important role (Everding 2007).

Most of the renewable solutions for on-site generation of electricity use intermittent energy sources such as solar energy or wind power. Therefore, systems that balance energy needs over the course of a year (net-zero energy buildings) require a detailed assessment depending on their energy management strategy (Koch, Girard et al. 2012). Across scales the concept is sometimes expressed as "self-sufficiency" (Table

2, Samso Island) or “positive-energy buildings” (Table 2, Grenoble). The latter is referring to the same assessment as “net-zero-energy” buildings (Voss, Sartori et al. 2010). The annual balance is used as a target for dimensioning on-site generation to satisfy annual energy needs or to produce additional energy. At first sight, this seems to be merely continued evolution from low energy houses to passive houses. Conversely, it can be argued that the switch from passive to positive energy resembles a change of paradigm in the role within the larger energy system played by the building sector (Koch, Girard et al. 2012). According to the definition proposed by Voss, Sartori et al. (2010) net zero energy concepts require on-site generation technologies to balance the buildings’ energy needs. Seen from the larger scale of energy infrastructure, fluctuating production from wind or photovoltaic systems and the objective of matching production and demand at any time, makes a case for new approaches to energy management. While electricity management today is mostly carried out at national level with the corresponding regulatory zones or regional scale in smart grid demonstration projects, matching local power production with electric or thermal demand patterns will require local management. In the urban context, the neighbourhood scale could provide an opportunity to guarantee a certain level of diversity of demand through both mixed use and the number of connected users. In addition, it offers the opportunity to distribute thermal energy via district heating systems. With a view to model based planning support, net-zero concepts are typically designed as hybrid systems in which thermal needs are balanced by electricity generation. Therefore evaluation of energy from fluctuating renewable sources should not only be made on a monthly basis but the temporal resolution should be increased to hourly or sub-hourly time steps to better reflect the simultaneity of local electricity production and energy needs in the system (Table 5). This further allows assessing the load match, i.e. whether the electricity can be used on-site or in connected systems.

Table 5: Integration of Renewable Energy Sources - Planning Tasks and Technical Assessment

Integration of Renewable Energy Sources		
Action	**Planning Task**	**Technical Assessment**
Biomass	In cities biomass systems are mostly based on woody biomass such as pellets for individual buildings and wood chips for district heating systems, solid bio waste can be considered for large systems	Calculation of the heating loads, annual or monthly energy balance based on simulation of measurements to determine savings in the use of non-renewable primary energy and associated GHG emissions
Solar thermal	Solar thermal systems connected directly to individual user or as support for local district heating system	Assessment of solar irradiation on based on meteorological data and the urban form, monthly balance for legal compliance, hourly heat demand based on measurement, simulation or standard load profiles
Heat Pump	Heat Pump systems based on geothermal, ground water or air as renewable heat source, sometimes considered for cooling purposes	Calculation of the heating loads, Availability of renewable heat source based on measurement and environmental data, hourly heating needs to determine electric load profile
Photovoltaic (PV)	PV systems for on-site generation of electricity, as for CHP systems often self-consumption strategies or direct marketing of produced electricity are investigated	Assessment of solar irradiation on horizontal and vertical surfaces based on meteorological data and the urban form, monthly balance for legal compliance, hourly or sub-hourly electricity demand based on measurement or standard load profiles
Wind turbines	Wind power potential in urban spaces is often limited to micro wind installations due to the available wind speeds and impacts of large turbines on neighbouring uses	Wind potential assessment based on meteorological data or on site measurement for larger installations

2.3 Actors in urban energy planning

The discussion of the objectives and targets in urban energy planning showed a diverse range of strategies and tasks, which results in a number of actors both private and public, involved in urban development projects making cooperation a necessity. C40 and ARUP (2015) go as far as stating, “there is no solution without collaboration”.

The German Association of Cities (Deutscher Städtetag) sees a tradition of integrated urban planning since the 1960s with the distinction that the integrated schemes in the 60s and 70s remained theoretical studies and have only more recently become concrete implementation projects (German Association of Cities 2013). This view is shared by Castán Broto and Bulkeley (2013) who show the relation of the occurrence of climate change actions being more frequent after ratification of the Kyoto protocol in 2005. While a direct correlation with the Kyoto protocol is disputable, their analysis supports the tendency of a rising number of implemented projects. In their assessment of 627 urban climate change projects in 100 cities Castán Broto and Bulkeley (2013) structure the actors according to the main groups of local government, other governmental actors such as national government, private actors as well as civil society. A similar classification is described by C40 and ARUP (2015). While the relations and possible cooperation are manifold, common structures can be identified between specific actors.

National government can facilitate local actions by shaping the framework in which local governments act (Bailey and Kirk 2015). The German Association of Cities (Städtetag 2011) consequently describes facilitating structures such as rehabilitation areas (Sanierungsgebiete) in the German building law (BauGB) but equally highlights the need for further legislating support as for example changes in the zoning law (BauNVO) to allow for more flexible densities in local development projects. A similar solution was applied in North American cases in the form of density bonuses. In Annex 51 density bonus was provided in the Dockside Green development project in Toronto, Canada. A higher density was accepted in exchange for compliance with LEED platinum Standard. On the other hand, in the cooperation with private actors local governments take on a facilitating role. Joint financial concepts are among the most important objectives for such cooperation (Bailey and Kirk 2015). Private commercial actors are distinguished from public participation. As a result “negotiate rather than command” (German Association of Cities 2013) can be seen as a more adopted strategy for urban energy planning. In order to integrate the different actors the German Association of Cities (2013) proposes integrated urban planning as the interface between different groups and actors (Figure 8).

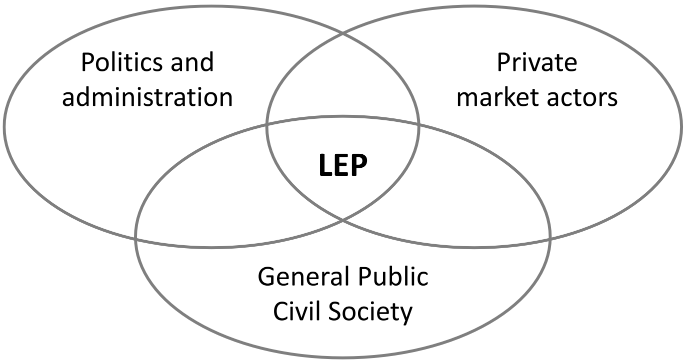

Figure 8: Local Energy Planning as interface between different actors, adapted from (German Association of Cities 2013)

Despite the multitude of actors, local governments and subsequent departments remain dominant and most important actors, yet local energy planning cannot successfully attained without further actors. In the majority of the cases investigated worldwide by (Castán Broto and Bulkeley 2013), local governments take on a leading role. Based on a survey in the year 2009 the German Association of Cities states that in most cases climate mitigation measures are promoted by specific departmental planning in the fields of green space, environment and energy (Städtetag 2011). While the importance of cooperation is highlighted in all of the regarded studies Castán Broto and Bulkeley (2013) point out that cooperation does not always overcome sectorial barriers, especially regarding energy efficiency and the energy infrastructure. According to their assessment "there is still a separation between interventions seeking to reconfigure consumption patterns, mostly in the built environment, and interventions seeking to transform the systems of energy production." This conclusion is supported by the Association of German Cities which identified a dominance of sectorial action and individual projects in urban planning (Städtetag 2011). Therefore integration has to be applied to actors as well as sectors to unlock the potential identified in cities (C40 and ARUP 2015).

So far, the different objectives, targets and actors were described as necessary elements to develop local energy strategies. As discussed in the introduction the most important aspect for any climate protection measure remains the degree to which the targets are realised. Chapter 2.4 will discuss the question how the realisation of objectives and targets can be assessed in urban energy planning projects.

2.4 Measuring success

Once the objectives are translated into targets and specific actions, the question of monitoring has to be addressed. This step is crucial to realise the planned gains in energy efficiency and reduction of non-renewable primary energy use. Here the focus is put on the system's effectiveness. In other words, the objectives of a given project are compared to the outcome (Figure 9). In the context of an urban energy transition the overall success of urban energy planning projects, must be measured by comparing societal problems or issues and the final impacts of an intervention (Vreuls 2005), as discussed in the previous chapter. Once the objectives are agreed, they should be connected to useful indicators in combination with realistic target values, or benchmarks, against which the project outcomes can be compared to assess the intervention's effectiveness (Figure 9).

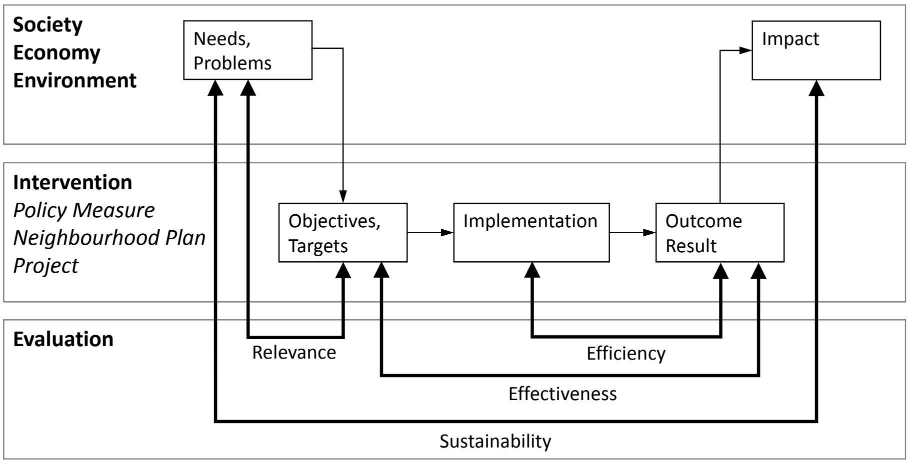

Figure 9: Policy Evaluation framework, adapted from (Vreuls 2005)

These objectives are defined as the outcomes of a structured planning process, which usually includes documentation of a number of quantitative and qualitative requirements. Typical targets in urban development projects include specific energy needs, as targets of building energy performance or the share of energy from renewable sources for supply solutions, the latter is often expressed in the non-renewable part of primary energy use. While the comparison of the objectives with the outcomes indicates the effectiveness of the project, its efficiency is measured as comparison of the inputs and outputs. In the following, a focus will be put on the technical efficiency assessment and the effectiveness. Even though it is acknowledged that in order to evaluate the success of urban development projects, a wider range of impacts has to be considered and compared to the initial needs and objectives.

While in planning practice, the translation of needs and issues seems to be well understood, as it is a main requirement for traditional urban development planning, the measurement of outputs of specific efficiency or consistency was rarely rigorously implemented even in European lighthouse projects (Koch and Kersting 2011). Little can be said about the success of a given urban development project, in terms of the project's sustainability, policy effectiveness, and efficiency unless all development steps are continuously tracked. This is not a recent issue as Fels (1986) points out:

> "In the past, programs designed to induce energy conservation in housing have nearly all been casual about their measurement of energy savings. […] This is particularly distressing given that the single most important objective of these programs, the saving of energy, is intrinsically quantifiable and relatively accessible by means of data recorded systematically for another purpose – billing." (Fels 1986)

The international case studies discussed in the Annex 51 project provided a large variety of innovative and highly efficient supply technologies as well as efficiency measures. In addition to the state of the art in energy planning, a large number of case studies were identified as demonstration projects. In both categories, a wide range of expertise and the assessment of alternative methodologies were provided throughout the planning process. Even though detailed planning and often assessment of the specific costs of efficiency measures was an integral part of the projects less than half of the identified national case studies that had national or greater visibility provided measured evidence for envisioned savings, due to a lack of subsequent monitoring (Koch, Jank et al. 2011). In the assessment of more recent case studies, Zinko and Moshfegh (2012) found that a larger number of the projects implemented monitoring to up to a certain degree. An important conclusion from their work is that "monitoring and subsequent evaluation of the anticipated energy goals and cost structures should be an essential component of energy conservation projects" (Zinko and Moshfegh 2013). Lack of monitoring can be attributed to resource constraints or a lack of political interest (Vreuls 2005). In the case of neighbourhoods, a lack of resources does not necessarily refer to the investment costs of the monitoring equipment but rather to shortcomings in providing a continuous measurement and evaluation of the projects. These projects are typically of much longer duration that building projects, often taking up to ten years from planning to the completion of the final phases. In addition, only measuring energy use after project completion is not enough, as evidenced by the case studies. A longer period of adjustment is often needed to provide “verified qualified monitoring” (Jank 2013, Zinko and Moshfegh 2013).

In recent research projects funded by the German program Eneff:Stadt monitoring is a mandatory requirement. Research projects such as “Rintheimer Feld” in Karlsruhe or “Nullenergiestadt Bad Aibling”, that serve as case studies for this work, use automated remote meter readings for monitoring energy use or communicating information on building performance to tenants. To make full use of the potential of automated data assessment, common definitions of the data structure and proposed metering points are necessary. In the context of energy efficient buildings, notably the program Research for Energy Optimized Building (EnOB) in the German context, structured guidelines have been developed (Neumann, Herkel et al. 2006) and, more recently, transferred to neighbourhood development schemes (Erhorn, Erhorn-Kluttig et al. 2012). The guidelines provide a first step on how to monitor the technical performance of neighbourhood systems. So far, they have not addressed the lack of responsibility in ensuring long-term monitoring and data assessment in urban development projects. With project durations of around ten years from early planning to the start of operations, it seems necessary to “start processing data as soon as the data is provided [and] not wait before all data is available because it might be too late to do sufficient analysis or make any corrections.” (pro:21 GmbH and Projektträger Jülich 2013). This again points out the necessity to make suitable results from simulation available in all project phases as benchmarks for the ongoing development (Figure 1).

Different analytical steps in planning are typically supported by energy system models. Chapter 3 will provide an overview on different modelling approaches, describe the current practice of energy system modelling at the urban scale and conclude by linking the identified planning tasks to suitable modelling approaches.

3 Modelling urban energy needs

In the urban context, energy system models are used at different scales to support the various disciplines involved in urban development projects. Modelling can help to understand possible impacts of LEP better and to communicate results to a wide group of stakeholders. In this process, the range of tasks and modelling applications is huge and covers multiple spatial and temporal scales, from buildings to cities, from yearly to hourly demand patterns. According to Keirstead, Jennings et al. (2012) an urban energy system model can be understood as a formalised mathematical representation of the "combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area" (Keirstead, Jennings et al. 2012).

Defining the needs of a project within its resource and time constraints is a key task before choosing a modelling approach or a dedicated planning tool. From the assessment of international case studies Webster, Baier et al. (2013) provide five categories and requirements for the selection criteria to choose the right modelling solution for the task at hand.

Table 6: Criteria for the selection of an energy system model qtd. in (Webster, Baier et al. 2013)

Model applicability	- Model flexibility and robustness - Study framework definition - Ease of use
Approach selection	- Purpose of study and design criteria […] - Model flexibility and adaptability
Quality and accuracy	- Modelling assumptions and methodology - Design stages and quality of data - Validation of results and simulation procedures
Data availability	- Access to relevant sources of information - Appropriate and high-quality input data - Climate data, internal heat gains, material and construction
Desired outcomes	- Parameter sensitivity - Key design messages - Transparency for communication

In the following section, solutions supporting urban or local energy planning are discussed, with a focus on their representation of thermal energy needs for buildings, building clusters or neighbourhoods. The comparison includes a number of approaches identified by Erhorn-Kluttig, Jank et al. (2011), Rapp, Vautz et al. (2012) and pro:21 GmbH and Projektträger Jülich (2013). Furthermore, modelling approaches were included, which are developed by associations or academic institutions. A number of these are discussed in (Zhao and Magoulès 2012), (Mendes, Ioakimidis et al. 2011) and (Keirstead, Jennings et al. 2012). A more general review of energy system modelling is provided by Koch, Harnisch et al. (2003).

3.1 Energy system models

Several approaches have been traditionally pursued to simulate urban energy needs. They range from bottom-up representations that include statistical and physical methods to top-down approaches that treat urban area as an energy sink and do not detail individual end-uses. Each method shows strengths and limitations, relying on various levels of inputs, different modelling approaches, and leading to a large range of applicable results, suitable for different phases of development projects.

3.1.1 Top-down and Bottom-up – a question of perspective

The classification of top-down and bottom-up approaches (Kavgic, Mavrogianni et al. 2010) reflects the model's capability to represent detailed descriptions of individual entities in the system (bottom-up) or the description of the overall system (Mendes, Ioakimidis et al. 2011). Top-down approaches typically treat individual sectors as energy sinks or sources without a detailed distinction of the structure of the energy needs (Swan and Ugursal 2009). The variables of such approaches are commonly based on, or include, the gross domestic product, employment rates, price indices, etc. Top-down approaches are also used for long-term energy scenarios and are based on historic data. Here only conclusions concerning the central system can be drawn (Heller 2000). Bottom-up models are employed for detailed demand predictions for different sectors based for example on energy bill data. Such detailed description can either be expressed based on physical representations of the system or statistical methods (Kavgic, Mavrogianni et al. 2010).

3.1.2 Process representation

In their review of quantitative building performance assessment methods Wang, Yan et al. (2012) distinguish forward and inverse models. Forward models are based on the knowledge of the system's physical processes, while inverse or data-driven models are based on results of past experiments. The same categories of modelling approaches are proposed by ASHRAE (2005) where the former are also referred to as white-box and the latter are referred to as black-box models. Finally Grey-box models are described by Coakley, Raftery et al. (2014) as an intermediate category containing "certain key (or aggregated) system parameters". In their application forward approaches seek to represent the individual building's performance as well as individual technologies (Yamaguchi, Shimoda et al. 2013). In contrast, data-driven approaches can often be found when infrastructure systems are assessed as described for example by Nielsen and Madsen (2006). These latter models typically consider the aggregated demand of e.g. a number of buildings. An overview on a number of tools discussed in this chapter can be found in Annex E: Urban energy planning tools.

3.1.2.1 Forward or deterministic models

The forward modelling approach uses input variables and applies the representation of physical processes to predict outputs. With readily available computing power, complex models have been designed to include natural phenomena and physics based interactions within the system. The forward approach delivers a more or less complete representation of the physical world. Heller (2000) classifies this category as deterministic modelling. It is the most common approach used to describe and predict energy use at the building scale. This category of models includes dynamic building simulations such as EnergyPlus, DOE-2 and TRNSYS (Coakley, Raftery et al. 2014) as well as steady state or quasi steady-state models, as for example specified by EN 832, DIN 18599 and EN ISO 13790. At the building scale, these models can address detailed comparisons of planning alternatives by simulating the buildings' energy needs (i.e. micro-simulation). They are based on a representation of physical properties of buildings as well as the supply and distribution systems used to satisfy the energy needs. For the building scale a recent overview is provided by Wang, Yan et al. (2012). At the scale of neighbourhoods, however, these forward modelling approaches require an intensive data collection phase as specific parameterisation is essential to ensure the results' reliability (Coakley, Raftery et al. 2014). Following an object oriented micro-simulation approach, the modelling language MODELICA (Modelica Association 2011) - with different frontends such as Dymola or Open Modelica - gained support for detailed modelling of buildings and HVAC equipment beyond the single building scale (Huber and Nytsch-Geusen 2011). Other examples of specific languages are INSEL (Schumacher 1991) as well as TRNSYS a modelling framework using Fortran for programming model components. All three solutions are typically employed to support detailed forward modelling. While the level of detail for the studies varies, all of the micro simulation approaches have the benefit of providing a high level of flexibility in representing changes in individual energy efficiency measures or technologies. Another example of a citywide application of such a micro model was conducted for the city of Osaka by Shimoda, Asahi et al. (2007). In their study, the heating and cooling needs of 20 building categories were simulated with five different insulation levels. In connection with forward building models also sub models representing user behaviour can be included which is the case for SunTool (Starkovic, Campell et al. 2006). SunTool and its successor CitySim (Robinson, Haldi et al. 2009) are based on archetype buildings providing default parameters for the forward demand model.

In order to provide a tool for the development of local energy concepts, the District Energy Concept Advisor (D-ECA) (Erhorn-Kluttig, Erhorn et al. 2013) was developed by Fraunhofer IBP and represents a further simplification of the simulation. Buildings are represented by archetypes so that the user is provided with initial default values. The calculation of thermal needs is done according to DIN 18599 as a steady state monthly energy balance. In comparison to a pure building archetype approach (IWU 2003, Klauß 2010) the D-ECA's adaptation adds flexibility in the definition of building properties as well as supply technologies. Instead of using the geometry of archetype buildings, energy balance models such as ISO 13790 are recently also coupled with spatial urban data models (Bahu, Koch et al. 2013). The 3D city models are structured according to the CityGML (Geography Markup Language) standard developed by the

Open Geospatial Consortium (OGC). The approach was applied by Strzalka, Bogdahn et al. (2011) to the area of the Scharnhauser Park and tested against measured data. Bahu (2012) calculated the heating energy needs for the City of Lyon and used the city's 3D model to classify the building stock.

Figure 10: Results from building classification and steady-state heat demand calculation (Bahu, Koch et al. 2013)

In their application, forward models require detailed knowledge of the phenomena affecting system behaviour as well as the various interactions to ensure accurate and meaningful results. As scale increases, the parameterisation of forward models becomes increasingly challenging. When moving towards city scale, the amount of involved parameters, operation schedules and data dramatically increases and induces a large number of potential sources for uncertainties and propagating errors in physical models (Coakley, Raftery et al. 2014). Therefore, in addition to the correct representation of the individual processes, the quality of the input data becomes a critical feature for white box models in their application to cities and neighbourhoods.

3.1.2.2 Data driven modelling

The data-driven approach uses input and output variables that are known and measured to determine a mathematical description of the system. This obviously requires the system to have already been built and for measurements to have been taken. Data-driven approaches are often not only simpler to use but also more robust predictors of performance than deterministic models (ASHRAE 2005). A pure black box model defines the input output relation without describing the physical properties of the modelled process. Black box models are performant but sometimes inflexible in their application. By its empirical nature, this approach does not require an understanding of the underlying physical processes. This leads to a simplified model structure but a loss of flexibility as parameters cannot always be traced back to the physical behaviours. In addition, the transferability of the data sets used to develop the model to the application case must be tested.

Statistic load profiles for district scale supply systems

A well-known approach to represent aggregated thermal needs is based on specific load curves described per building use. The data is typically based on real cases. Schulz (2007) used this approach to assess different strategies of integrating combined heat and power systems into the electricity grid. A similar approach based on measured data was proposed for URBS (Richter 2003). While the benefit is obviously a realistic load profile, this pure black box approach requires a thorough investigation of the existing energy users or significant engineering knowledge to overcome the limited inherent transferability. The Distributed Energy Resource Customer Adoption Model (DER-CAM) is an optimisation approach developed by LBNL, which follows the same concept and, based on custom profiles, focuses on identifying the best combinations of DG technologies to meet thermal and electric demand.

Typical days

Another widely used approach consists in the application of typical days, which are connected to form an annual profile for daily energy use. This method is used in TIMES HEAT (Merkel 2012) and GOMBIS (Saadat 2003) and was also applied by Woldt (2007) for the integration of local CHP systems into the electricity market. The VDI 4655 (VDI 2008) describes reference profiles for thermal and electric energy use in single and multifamily buildings. It is specifically targeting the design of combined heat and power (CHP) systems. The annual distribution of the heat demand is based on either the calculated annual heat demand or the measured demand of the previous period.

The climatic conditions are identified using 15 climatic zones defined by DIN 4710:2003-1, which are also used by the German Meteorological Service (DWD). The data basis is provided by the test reference years (TRY), as published by the DWD. Test reference years are “data records of selected meteorological measurements […] for each hour of one year.” (VDI 2008). The number of typical days in one year is determined from the zone’s TRY. The categories applied are summarised in Table 7.

Table 7: Typical-day categories after VDI 4655 (VDI 2008)

Season	Workday W		Sunday S	
	Fine H	Cloudy B	Fine H	Cloudy B
Transition - Ü	ÜWH	ÜWB	ÜSH	ÜSB
Summer - S	SWX		SSX	
Winter - W	WWH	WWB	WSH	WSB

For the distribution of energy demand per day the VDI 4655 provides factors on a resolution per minute basis resulting in the daily demand curve. For the planning of cogeneration systems COPRA (9.2.4) uses a similar method, which is based on nine different type days (i.e. (Transition, Summer, Winter) x (Workday, Saturday, Sunday)) (Dr. Valentin Energie Software GmbH 2002) for the distribution of monthly heating needs. A similar solution, based on the use of typical days, is applied to represent thermal needs in the Hybrid Optimization Model for Electric Renewables (HOMER), which was developed in 1993 by the North-American National Renewable Energy Laboratory (NREL). HOMER is mainly used to evaluate grid connected or off-grid concepts for micro grids. To represent thermal loads, it uses typical daily load profiles; the user can then adjust the minimum, maximum and average values for the monthly variation. Alternatively, HOMER reads external profiles for thermal loads (NREL 2005). The use of TRY allows the model to be adjusted to specific climate conditions. A drawback with this method is that the limited number of differentiated time intervals results in abrupt changes in the transition periods, which are visible as steps in the annual load duration curve.

Archetype buildings and urban forms

In Germany settlement typologies were developed for the residential sector as early as 1980 (Roth, Häubi et al. 1980). The approach has continuously been developed (Jenssen and Karakoyun 2005, Maïzia, Sèze et al. 2009, Koch 2010) and was also applied to the potential for renewable energy sources (Hegger and Dettmar 2014). Yet their application for heat demand estimation beyond large scale assessment for regions and early concept phases is critically discussed (Jentsch, Pohlig et al. 2008) as some urban archetypes display large variations.

The added value of archetypes of buildings and urban form can be seen in the possibility to link benchmark values to urban patterns and thus make it available for urban planning at a larger scale (Webster 2007). At the smaller scale, building archetypes are a common way to describe the properties of specific building classes, which are typically defined by age and use. Typologies exist for residential buildings (IWU 2003, Diefenbach and Born 2007) as well as for non-residential buildings (Klauß 2010). Archetypes are often used in the development of strategic energy planning (Heidelberg 1996, Umweltamt Düsseldorf 2005). As such archetypes offer an easy to use classification of different buildings, they are also used as reference values in a number of energy planning tools such as the District Energy Concept Advisor (Erhorn-Kluttig, Erhorn et al. 2013). The tool was originally developed in the German context but includes international building archetypes in the international version. Archetypes are mainly used to define annual benchmarks for larger urban areas or as input to deterministic models, describing building properties for a given class of buildings.

3.1.3 Grey-Box Approach

The grey-box approach combines both data-driven and forward methods. In a grey box model, the main physical dependencies describing the system are identified, yet these do not fully depict the physical reality as certain elements are approximated by general rules. Due to this, grey box models are expected to provide a higher degree of flexibility as physical representations can be altered according to the modelled system. They are faster in the application yet more restricted in the freedom of technology choices as a limited number of parameters are modelled compared to forward modelling approaches. Déqué, Ollivier et al. (2000), Nielsen and Madsen (2006) and Hellwig (2003) provide examples of grey-box models.

3.1.3.1 Heating degree days

Heating and cooling degree days are a further method that reduces the information required on the physical properties of buildings. Heating degree days (HDD) are defined by the number of days during which the average temperature is lower than a given limit temperature. Below this temperature the heat losses by transmission and ventilation induce a heat input to maintain an inside temperature.

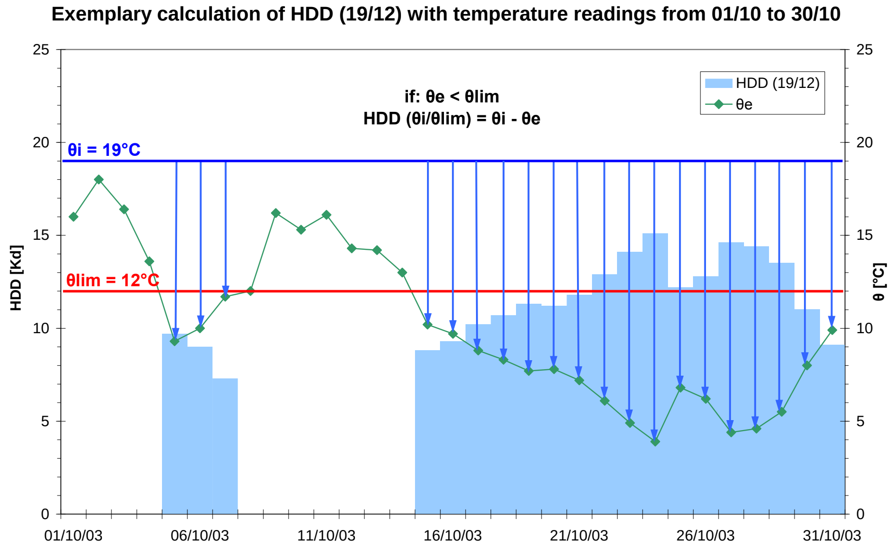

Figure 11: Exemplary calculation of the number of heating days and the heating degree days HDD (19/12), (Koch and Girard 2009)

Figure 11 illustrates the calculation of daily heating degree-days during a month with an inside nominal temperature (θ_i) and limit temperatures (θ_{lim}) of 19°C and 12°C respectively. In this example, the heating period is 20 days long and accounts for 229 Kd. Once the number of HDD is calculated, they are multiplied by the overall heat loss coefficient representing the building's performance and divided by the seasonal equipment efficiency. A multitude of variations of the basic method exist for different applications, discussed in detail by Day (2006), the objective of the approach is to determine weather related energy use in buildings.

In the Clean Energy Project Analysis toolkit RETScreen, Natural Resources Canada (2005) proposes an approach based on heating degree days to calculate monthly energy needs. In order to calculate an hourly annual load duration curve for the layout planning of combined heat and power systems a peak and base load factor are added.

3.1.3.2 Energy signatures

The above-discussed approaches represent forward models of decreasing physical representation. In addition, data-driven models are used at the scale of buildings. In the assessment of the energy performance of HVAC equipment, energy signatures are commonly used (Bauer and Scartezzini 1998) (Rabl and Rialhe 1992). According to Day (2006) energy signature models were first described by Jacobsen (1985) in order to assess building performance data. A more recent application of energy signature models for the purpose of the assessment of energy performance of large samples of buildings is described by Raffio, Isambert et al. (2007) and Mazzarella, Liziero et al. (2009). A good overview is presented in the form of ASHRAE's inverse modelling toolkit (Kissock, Haberl et al. 2003).

The simplest form of an energy signature describing space-heating needs is a linear regression model matching heating energy use and mean outdoor temperature. Such a model can be referred to as a linear single-variant data driven approach. The VDI standard 3807 (VDI 2007) describes regressions for different temporal resolutions. The 2005 ASHRAE Handbook (ASHRAE 2005) provides further examples of this class of models. The following section will focus on methods to determine the daily energy use. The regression model's inherent logic can be explained by the buildings' thermal balance. This becomes obvious when compared to the basic principles for the calculation of the heat demand for a given zone. Here the equations described relate to DIN EN ISO 13790:2008-09. The space heating needs ($Q_{H,nd}$) described in Equation 3-1 is composed of the heat transfer through transmission (Q_{tr}) and ventilation losses (Q_{ve}), the internal (Q_{int}) and usable solar gains ($\eta_{H,gn}\ Q_{sol}$) as well as the heat demand for domestic hot water preparation (Q_W).

$$Q_{H,nd} = Q_{tr} + Q_{ve} - Q_{int} - \eta_{H,gn}\ Q_{sol} + Q_W \qquad \text{Equation 3-1}$$

Equation 3-2 and Equation 3-3 (DIN EN ISO 13790:2008-09 equations 16 and 20) establish the approximately linear dependency of energy losses through transmission and ventilation on the outdoor temperature, which is also reflected in energy signature models.

$$Q_{tr} = H_{tr,adj}\,(\theta_{int,set,H} - \theta_e)\,t$$ **Equation 3-2**

$H_{tr,adj}$	total transmission heat transfer coefficient of the zone
$\theta_{int,set,H}$	set temperature for the zone
θ_e	outdoor temperature
t	time

$$Q_{ve} = H_{ve,adj}\,(\theta_{int,set,H,z} - \theta_e)\,t$$ **Equation 3-3**

$H_{ve,adj}$	total ventilation transfer coefficient
$\theta_{int,set,H}$	set temperature for the zone
θ_e	outdoor temperature
t	time

Often the temperature independent share of energy used (e.g. domestic hot water) is represented by a base load (Figure 12, Q_B) as a horizontal line. The interception between the heating curve (regression line) and this base load is the heating limit temperature (Figure 12, θ_{lim}). For domestic use, the change point is between 12°C and 18°C outdoor temperature (Mazzarella, Liziero et al. 2009) depending on the building's performance and set indoor temperature. In urban energy modelling a linear energy signature is used, for example in the tool EnerGIS (Girardin, Marechal et al. 2010) to represent the thermal needs of urban districts. Ali, Mokhtar et al. (2011) used a linear regression model for the prediction of the electricity demand for cooling and (electric) heating at community scale.

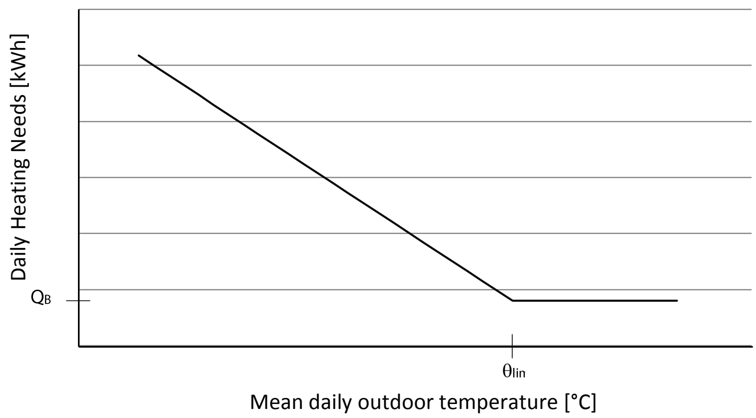

Figure 12: Dependency of daily heating energy needs on average daily temperature

The model depicted in Figure 12 can be referred to as a three parameter (3P) single change point model, as it contains two linear sections. In addition, linear models have been developed with multiple change points to reflect other effects such as limited heating capacity in winter (Mazzarella, Liziero et al. 2009). Based on the assessment of measured data Dotzauer (2002) proposed a segmented linear model for the prediction of thermal loads in district heating systems with four change points which resembles the selected non-linear energy signature model described in section 4.1. These grey-box models constructed along the logic of the energy balance thus represent a link between the forward and data-driven calibrated approaches (Kissock, Haberl et al. 2003). To assess cooling loads Masuda and Claridge (2014) compared the 4P-CP to multiple linear regression models and found the former easier to calibrate via iterative calculations of the least square regression analysis proposed by Kissock, Haberl et al. (2003). The segmented linear model with four change points approximates the non-linear models that are discussed in detail below. These sigmoid energy signature models were developed for the gas load predictions (Geiger and Hellwig 2002, Eichlseder 2008, BDEW, VKU et al. 2014). This model category was applied by the author at the scale of district heating systems (Woods 2012), which will be described in more detail in Chapter 5.1.

3.1.4 Description of state transitions – steady-state and dynamic models

Steady-state models are based on a simplified thermodynamic description of the energy system. In contrast to prescriptive regulations defining maximum values for individual building parts, performance based building codes often rely on reference values from steady-state physical models. This is due to the decreased level of complexity but also the fact that compliance is usually proven based on the monthly energy balance. Dynamic models tend to include a higher temporal resolution compared to steady-state models and typically require a larger number of inputs. Usually dynamic models are used for tasks requiring hourly or sub-hourly data, which is for example the case for applications where the effects of the building's thermal mass play a significant role (ASHRAE 2005). As Wang, Yan et al. (2012) point out, the description of state transitions is not bound to the general type of modelling approach (i.e. forward or data-driven).

3.1.5 Optimisation of energy system models

Optimisation methods can also be applied to models of the energy system, usually integrating its technical, economic and environmental aspects, including both demand and supply side descriptions in the models. The resulting equilibrium system is then optimised towards a target function using mathematical approaches such as linear programming (Koch, Harnisch et al. 2003). Often the total costs of the system are used as target functions. In order to obtain a realistic representation of the energy system, optimisation models include a number of additional conditions also referred to as bounds such as the availability of technologies. Bounds provide the limiting conditions under which a decision in the optimisation process is taken. Therefore defining of the bounds is vitally important to ensure the relevance of the modelling results. Just as their documentation is vital to the transparency to the overall modelling process. TIMES HEAT (Fichtner, Genoese et al. 2013) is an example of an optimisation approach. In contrast to the first category, simulation models describe the energy system by adding single processes to process chains or networks. While optimisation models tend to focus on cost functions, simulation models are usually applied to quantify the technical or techno-economic potential for energy savings or emission reductions (Koch, Harnisch et al. 2003). Expert knowledge, used in the detailed description of simulation models, replaces the solemnly mechanistic approach in optimisation models and technical measures can be discussed on a detailed level. As noted in the case of optimisation models, the quality and transparent documentation of expert knowledge as the equivalent of the bounds can prove as a main factor determining the model's quality. Even though the approaches follow clearly different paths, Koch, Harnisch et al. (2003) suggest that through increasing the number of bounds, the optimisation eventually transforms into a simulation approach.

3.2 Applications of energy system models for neighbourhoods

3.2.1 Intermediate Summary

The discussion of different methods delivers categories to classify the different models applied for the representation of heating needs at the scale of urban areas. Table 8 provides an overview on the discussed tools, models or research projects. The differentiation between deterministic and data-driven models is a principal criteria to differentiate the approaches. When reading the table from left to right the level of flexibility in the models decrease. At the same time the dependency on detailed input data increases when read from right to left. Based on the introduced methods the next section will explore the temporal resolution of the different models as a second criteria for the choice of models for different planning tasks, which will be discussed at the end of this chapter.

Table 8: Overview on the representation of heating needs at neighbourhood or city scale by current energy demand models

Deterministic Models		Data-Driven Models			
Dynamic	Steady-State	Energy Signatures		Typical Days	Load Profiles
		Non-Linear	Linear		
SunTool (Starkovic, Campell et al. 2006) **CitySim** (Robinson, Haldi et al. 2009) **INSEL** (Eicker 2006) **MODELCA** (Huber and Nytsch-Geusen 2011)	**3D-GIS** (Strzalka, Bogdahn et al. 2011) (Bahu, Koch et al. 2013) **District-ECA** (Erhorn-Kluttig, Erhorn et al. 2013) (Shimoda, Asahi et al. 2007) (Yamaguchi and Shimoda 2010)	(Nielsen and Madsen 2006) **MacroDE** (Woods 2012) (Hellwig 2003)	**ENERGIS** (Girardin, Marechal et al. 2010) **Inverse Modelling Toolkit** (Kissock, Haberl et al. 2003) (Rabl and Rialhe 1992)	**COPRA** (Dr. Valentin Energie Software GmbH 2002) **GOMBIS** (Saadat 2003) **TIMES HEAT** (McKenna 2013) **VPP** (Brauner, Pöppl et al. 2006) **HOMER** (NREL 2005)	**POLIS** (Richter 2004) **URBS** (Richter 2003) **BHKW Plan** **DER-CAM**

3.2.2 Temporal resolution of existing modelling approaches

Based on the previously described categories, the calculation of heating needs at different time scales is a key characteristic of the approaches. Figure 13 illustrates the different methods and their general approach to aggregate or disaggregate thermal needs from hourly to annual time steps.

For many of the identified planning tasks, heating needs are represented at the hourly scale. Forward approaches achieve this by detailed building descriptions and simulation of the physical behaviour at hourly or sub-hourly scale. This approach is for example used by Shimoda, Asahi et al. (2007) or Robinson, Haldi et al. (2009). The methodologies include many examples of R-C models with different numbers of nodes. Energy balance calculations described by DIN 18599, DIN 4108, EN 832 or ISO 13790 are used to calculate monthly energy balances (Nouvel, Schulte et al. 2013). ISO 13790 links the micro-simulation and an energy balance approach as it provides a simplified dynamic model. A recent example of a monthly energy balance is used by the Energy Concept Advisor (D-ECA) (http://www.district-eca.de) developed by Fraunhofer Institute for Building Physics (pro:21 GmbH and Projektträger Jülich 2013). Further discussions of different approaches are provided by Swan and Ugursal (2009) and Zhao and Magoulès (2012). A requirement for micro-simulation models is a detailed description of building characteristics and in cases where simulation is on an hourly or sub-hourly scale, information on technical installation as well as building operation schedules. This often proves as a major obstacle to the application in early planning stages. Figure 13 shows a number of applied methods or models with their respective time scale. In their study on virtual power plants Brauner, Pöppl et al. (2006) refer to an R-C model according to VDI 2067 (VDI 1998) to calculate daily energy needs. These were then transformed into hourly profiles, based on standardised profiles from a comparison of calculated profiles with measurement data. The calculation described by the VDI 2067 is also used in the COPRA tool developed by Valentin Energie Software GmbH (Dr. Valentin Energie Software GmbH 2002) in addition to the application of typical days.

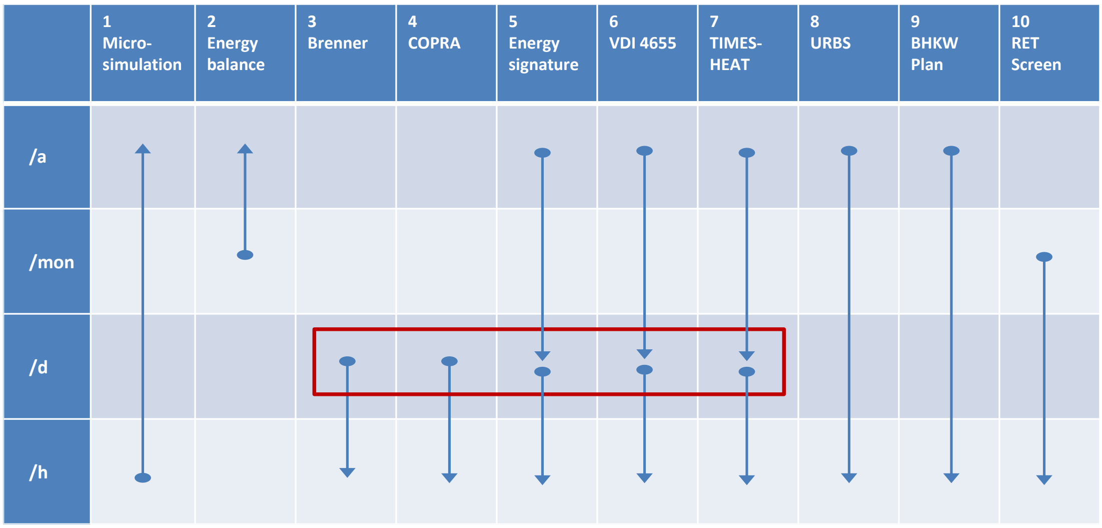

Figure 13: Bottom-Up and Top-Down approaches according to their temporal resolution (/a = annual, /mon = monthly, /d = daily, /h = hourly demand)

In the group of data-driven models, a number of approaches can be found that use the annual energy needs and disaggregate them to daily energy needs (Figure 13, column 5, 6, 7). These are then further disaggregated by using statistic load profiles for hourly energy use. The models introduced by Brauner, Pöppl et al. (2006), Girardin, Marechal et al. (2010), Hellwig (2003), Sawillion (2002) and in the VDI 4655 (VDI 2008) fall into this category. While temporal aggregation scales are similar, they vary in the form of the calculation. As an example of a non-linear energy signature model Hellwig (2003) used a single variant regression to determine daily heating needs from annual energy needs. The latter were based on the energy use from previous years. For the disaggregation to an hourly demand curve, temperature dependant hourly load profiles were extracted from measured data and applied to daily energy use. Many larger geographic scale applications use a distribution of an annual heat demand based on typical days. In the German context, the typical days are often based on VDI 4655 (VDI 2008). For the application of the method, annual heating needs are calculated, for example, based on a steady-state energy balance applied to archetype buildings (IWU 2003, McKenna 2013). The year is then classified according to the different seasons (winter, summer & transition), weekdays, weekends or holidays and the cloudiness of the day, resulting in 10 typical profiles. The same approach can be found in COPRA with different predefined typical days that also represent different seasons (winter, summer, transition) and define weekdays, Saturdays and Sundays for each season. In the TIMES model different time slices from typical days are also used to represent an hourly load profile for different building categories (Fichtner, Genoese et al. 2013). Richter (2003) used calculated reference load curves for the complete year to distribute annual energy needs in the URBS model.

A number of models use a two-step disaggregation of annual heating needs because the temporal scale of days shows a strong correlation with the mean outdoor temperature (Heller 2002). The hourly distribution over the course of the days depends more on individual factors, such as the operating schedule for the heating system, as well as the presence and activity of inhabitants. The models (Figure 13, rows 3,4,5,6 & 7) therefore show compatibility at the scale of daily energy needs.

Using the daily energy needs as common denominator, hourly profiles could be exchanged because all of the listed models refer to statistic profiles for aggregated users.

3.2.3 Modelling Requirements for Local Energy Planning

It has been pointed out that the three steps to reduce GHG emissions in the building stock relate to different assessment methods. Looking at the thermal energy needs a higher temporal resolution is required going from energy performance targets for buildings to integrated systems using intermittent (e.g. PV, wind) or time dependant (waste heat) energy sources. Table 9 provides an overview on the different planning tasks as well as the connected methods to assess energy needs and exemplary solutions. It lies in the logic of the increasing requirements from urban energy master planning to detailed assessment of renewable that the requirements on temporal resolution and flexibility decrease from top to the bottom of Table 9.

Table 9: Energy Needs Assessment Methods for different Local Energy Planning Tasks

Planning Task	Energy Needs Calculation	Exemplary Approaches
Energy Efficient Buildings		
Urban Energy Master Plan	Annual Indicator [kWh/(m²a)]	Building Archetypes, Settlement Typologies
Construction Permit, Energy Efficient Buildings	Monthly Energy Balance	DIN 18599, D-ECA, RETScreen
Efficient Supply Solutions		
Potential for CHP (Feed-In) & District Heating	Annual load duration curve	COPRA, Energy Signature, ISO 13790, POLIS
Use of Waste Heat	Hourly Demand Curve	COPRA, Energy Signature, ISO 13790, POLIS
Renewable Energy Sources		
Biomass, Heat Pump	Hourly Demand Curve	COPRA, Energy Signature, ISO 13790, POLIS
CHP, PV, Wind (on site use)	¼ Hourly Demand Curve	EnergyPlus, TRNSYS

Even though simpler planning tasks could be solved using a more complex solution, it is common sense to apply the simplest method possible as they involve fewer hypothesis and thus sources of uncertainty. This principle is also known as Occam's razor (Young, Parkinson et al. 1996). The sum of the planning tasks should be executed as consecutive steps in any urban energy-planning project. In this way, Table 9 can also be read as process steps to move from a municipal GHG emission inventory to local energy master plans as described in Figure 5. Malottki, Koch et al. (2013) propose to first develop an overview model ("Grobmodell") and then link detailed models for specific purposes.

4 Methodology and Data

Based on the description of urban planning tasks and the different approaches in urban energy modelling, an energy signature model was selected for modelling energy needs at the scale of neighbourhoods. The following sections provide the underlying rational that led to the choice of the non-linear data driven model as well as the statistic tests applied to assess the fitness of the approach in comparison with a number of case studies. Tests were applied at different scales from individual apartments to district heating systems of approximately 7.2 MW_{th} installed capacity and at temporal resolutions from monthly to hourly time series.

4.1 Modelling approach

To provide guidance in the early stages of planning processes of energy efficient urban redevelopment projects, the objective of the thesis is to test a methodology, which is fast in its application yet robust when transferred to new development projects. During implementation and operation, continuous benchmarks are required suitable to assess monitored data on a daily or hourly basis. This second objective follows the logic of a continuous modellingto detect inefficient operations within short time delays and is linked to the operation of building clusters. While advanced building simulations can deliver accurate and reliable results for a small number of buildings, the use of expert modelling languages or frameworks such as Modelica or TRNSYS is limited to the later planning phases because of the high resource needs. In addition, the quality of the results is highly dependent on a detailed knowledge on the building properties and for large areas “require[s] more input than the available data can support” (Coakley, Raftery et al. 2014) which is often the case in existing urban areas. In such cases, the use of statistical models is proposed to replace detailed forward modelling approaches as they can easily be used for the continuation of initial planning phases throughout the building operation. At the building scale, data-driven models are often used to monitor individual objects (Kissock, Haberl et al. 2003, Raffio, Isambert et al. 2007). The difficulty of model parameterisation due to lack of structured data (Mendes, Ioakimidis et al. 2011) in urban energy planning provides for an argument in favour of a data-driven approach. Among the reviewed solutions the sigmoid model developed by Geiger and Hellwig (2002) was deemed to be the most promising solution. The model was originally developed for application in gas distribution grids. Similar data-driven models are commonly used at the urban or regional scale to estimate day-ahead gas consumption (BDEW 2010, BDEW, VKU et al. 2014). Here, the applicability of a single-variant, data-driven model will be tested on the scale of neighbourhoods. In the urban planning context, the neighbourhood level is an important implementation scale for direct planning actions. Data-driven models inherently perform better at a large scale, to assess the limits of the approach case validation considers the neighbourhood scale and performs tests down to the scale of individual buildings. The selected modelling approach will be discussed in more detail after a general introduction to the family of single variant, data driven models, (also referred to as energy signature or regression models, (section 4.1.1). This will be followed by the identification of meaningful statistic tests (section 4.2) in order to make a judgement of the fitness of the model for the application to the case studies and for comparison to measured data (section 4.3).

Single variant data driven models have been applied by Kissock, Haberl et al. (2003) in the development of an inverse modelling toolkit for building stocks, and by Girardin, Marechal et al. (2010) for urban districts. While such models have been found to successfully predict demand patterns at the large scale, the obvious short-comings are the “insensitivity to dynamic effects (e.g., thermal mass) and to variables other than temperature (e.g., humidity and solar gain)” (ASHRAE 2005).

The representation of thermal capacity in the selected sigmoid model will be discussed in the model description. The significance of the solar gains will be investigated based on one of the case studies. Heller (2002) estimates the significance of solar radiation as 7.7% compared to a significance on 83% of the ambient temperature, however, this literature based assessment does not discuss the cross correlation of the two. The correlation also can be expected to depend on the building standard, which also greatly influences the heating limit temperature as the latter decreases with higher building standard. This question will be investigated based on the case study data that includes buildings from various performance standards.

4.1.1 Selected non-linear single variant inverse modelling approach

In the German gas market the volume of gas to be delivered daily to bulk customers is estimated a day in advance. Gas suppliers base their load prediction on a standardised assessment defined by the BDEW, VKU et al. (2014). The gas vendor estimates the next day's gas consumption and notifies the organisation responsible of the specific market area. On the following day, the actual amount of gas delivered is measured, and the difference is cleared by the market area responsible (BDEW, VKU et al. 2014). A sigmoid regression model is used to estimate daily gas consumption using a set of parameter to describe different customers' profiles. In addition, a second, purely statistical, model is applied to distribute daily energy use to hourly values. Due to the distinct modelling steps and underlying methods, the model validation will be conducted using different temporal scales. While the model was developed for the application at the macro scale, of thousands of households or other gas customers, the main interest of this thesis is to test the application on the scale of the neighbourhood. According to Breuer (Breuer and Schmell 2007) a neighbourhood can be estimated to encompass around 500 residential units, or a spatial scale of 10 ha. The question of scalability in terms of both space and time will be revisited in the discussion (Chapter 6).

4.1.1.1 Mathematical description of the model

The described sigmoid regression model was initially developed at the TU Munich by (Geiger and Hellwig 2002), (Hellwig 2003) and was adapted by (Eichlseder 2008) for the Austrian context. The single variant model is mainly based on outdoor temperature and is parameterised by a set of four variables, according to the building use and an additional factor describing different weekdays. The latter is applied only for non-residential uses. The original set of parameters developed at the TU Munich considered the use (i.e. residential and several non-residential uses) as well as the performance of the building envelope. Eichlseder (2008) used only one value per building type (see Table 10). Equation 4-1 provides the basic formula for the sigmoid function. The parameters A, B and C modify the slope and the change point of the function and therefore correspond to the building type and performance while D shifts the curve vertically and thus represents the part of energy use that is independent of the outside temperature (e.g. domestic hot water; see Figure 14). The temperature ϑ_0 describes the point of discontinuity with T equals 40°C.

$$h = \frac{A}{1 + \left(\frac{B}{\vartheta_a - \vartheta_0}\right)^C} + D \qquad \text{Equation 4-1}$$

h: normalised daily energy use
ϑ_a: equivalent temperature for the day
ϑ_0: 40°C (point of discontinuity)

A main advantage of the sigmoid function in comparison to polynomial regression functions is that it allows for asymmetric transformation. Figure 16 shows variations of each individual factor for the purpose of illustration.

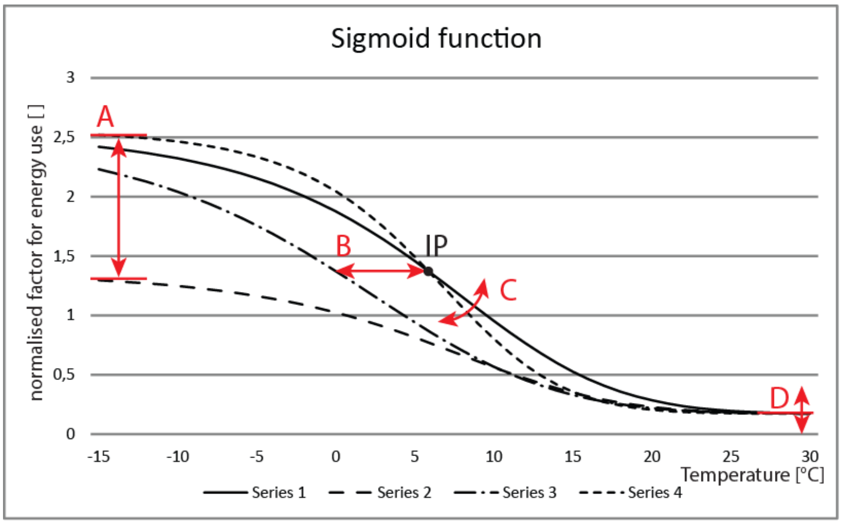

Figure 14: Sigmoid function with parameter set for different building types and variations shown in Table 10

The basic function (Series 1) uses the values proposed by Eichlseder (2008) for multiple dwelling units as a reference. Series 2 uses a lower value for parameter A, resulting in a lower maximum energy need for colder days and a flatter slope of the function. Thus, the new curve would be more representative for buildings with a higher energy performance. Decreasing the negative factor B shifts the inflection point (IP) of the function parallel to the abscissae towards the origin (Series 3). Increasing factor C maintains the inflection point but increases the slope of the curve (Series 4). Finally, modifications of D shift the curve vertically.

Table 10: Parameter sets (A, B, C, D) see (Eichlseder 2008) and variations (HEF: single dwelling unit, HMF: multiple dwelling unit, HG: tertiary units)

Type	A	B	C	D
HEF	2.8423	-36.8892	6.5692	0.1225
HMF (Series 1)	2.3994	-35.6696	5.6347	0.1728
Series 2	1.2000	-35.6696	5.6347	0.1728
Series 3	2.3994	-40.000	5.6347	0.1728
Series 4	2.3994	-35.6696	8.000	0.1728

For comparison, Table 11 provides the set of parameters of residential buildings of different age classes. Geiger and Hellwig (2002) referred to new buildings for constructions between 1979 and 2002. As described above, the depicted modification of the parameters A and C results in a lower daily demand, as well as a shallower function representing uses with less temperature dependant energy use patterns such.

Table 11: Parameters for the variables A, B, C and D for old and new buildings after (Geiger and Hellwig 2002) and (BDEW, VKU et al. 2014), (HEF: single dwelling unit, HMF: multi dwelling unit)

	Single dwelling			Multiple dwelling		
	old	*new*	*HEF*	*old*	*new*	*HMF*
A	3.130	2.794	3.1850	2.496	2.059	2.5187
B	-37.19	-37.28	-37.4124	-34.74	-34.74	-35.0333
C	5.752	5.403	6.1723	5.661	6.427	6.2240
D	0.0983	0.1714	0.0761	0.1021	0.2807	0.1010

While these factor modifications can be explained by the mathematical function, the increase of the temperature independent share of the daily energy needs is the result of the statistic samples used for the model synthetisation. The values reflect a relatively higher share of DHW needs for better performing buildings (i.e. new construction). In the basic application to simulate daily energy use for a given location, the temperature is smoothened as will be explained in section 4.1.1.2. The sigmoid function then delivers the normalised daily energy use h, which together with the average energy use per day, results in the predicted daily load curve. The annual energy use is typically estimated based on the climate corrected past annual energy use.

4.1.1.2 Representation of dynamic effects

In order to represent latent effects in the heating needs, which can be explained, for example by the thermal inertia of buildings, Geiger and Hellwig (2002) introduced a calculated temperature value (ϑ_a) that is used in the sigmoid function (Equation 4-1). The temperature value is calculated based on a geometric sequence with four elements. Thus, the calculation takes into account the weighted measured temperature of the day for which the energy needs are calculated, as well as for the three days before, with a weighting factor decreasing by 0.5 per day (Equation 4-2).

$$\vartheta_a = \frac{\vartheta_t + 0.5 \times \vartheta_{t-1} + 0.25 \times \vartheta_{t-2} + 0.125 \times \vartheta_{t-3}}{1 + 0.5 + 0.25 + 0.125} \qquad \text{Equation 4-2}$$

ϑ_a: calculated temperature for the day
ϑ_t: measured temperature for the day
ϑ_{t-1}: measured temperature for the day before
ϑ_{t-2}: measured temperature for the two days before
ϑ_{t-3}: measured temperature for the three days before

In the application of the model this leads to a smoothing of isolated peaks in the outdoor temperature and resembles a latent reaction of the building system.

4.1.1.3 Representation of different week days

For energy use in buildings, different patterns can be observed depending on the temporal scale. While so far the model has been described in relation to the mean daily outdoor temperature, other cyclic factors can be observed that affect the use of energy. For non-residential buildings, Geiger and Hellwig (2002) proposed to introduce week-day factors to provide a weighting based on the specific day. Depending on the sector, these factors show a distinct pattern with the highest modifications on weekends. For residential use, no modification is foreseen.

Table 12: Weekday factors for exemplary uses after (Hellwig 2003)

	F_{Mon}	F_{Tue}	F_{Wed}	F_{Thu}	F_{Fri}	F_{Sat}	F_{Sun}
Retail	1.0692	1.07	1.0589	1.0478	1.0449	0.9123	0.7982
Hotels	0.9767	1.0389	1.0028	1.0162	1.0024	1.0043	0.9584
Residential	1.0	1.0	1.0	1.0	1.0	1.0	1.0

4.1.1.4 Temporal correction

For use as predictive model, the application requires the recalculation of measured total energy use W_x to the period of a year. The length of the measurement expressed in the number of days (d_x) should ideally include a full heating period. The type of use must be specified so that the variables for the calculation of the normalised daily energy use for the measurement period can be calculated according to Equation 4-1, based on the smoothened outdoor temperature for the period. The temperature series can consist in measured or predicted data for a given period.

The annual energy use W_a is calculated using Equation 4-3

$$W_a = \frac{\bar{h}_a}{\bar{h}_x} \times \frac{365}{d_x} \times W_x \qquad \text{Equation 4-3}$$

with

$$\bar{h}_a = \frac{\sum_{i=1}^{365} h_i}{365} \qquad \text{Equation 4-4}$$

and

$$\bar{h}_x = \frac{\sum_{i=1}^{x} h_i}{d_x} \qquad \text{Equation 4-5}$$

W_a total energy use in the calculation year
W_x total energy use in the measurement period
$\bar{h}_a$ mean daily energy use in the calculation year
$\bar{h}_x$ mean daily energy use in the measurement period
h_i calculated daily energy use based on the sigmoid function
d_x length of measurement period in days

4.1.1.5 De-normalisation

The daily energy use $W(\vartheta_a)$ is then calculated using Equation 4-6 based on the average daily energy use $\overline{W}_a$.

$$W(\vartheta_a) = h(\vartheta_a) \times \frac{\overline{W}_a}{\overline{h}_a} \qquad \text{Equation 4-6}$$

with

$$\overline{W}_a = \frac{W_a}{365} \qquad \text{Equation 4-7}$$

ϑ_a predicted mean daily temperature
$h(\vartheta_a)$ normalised daily energy use
$W(\vartheta_a)$ de-normalised daily energy use
$\overline{W}_a$ mean daily energy use

Continuous daily reference values can be calculated for measured sites based on the smoothening of the daily mean outdoor temperature values using the geometric series (Equation 4-2). In a second step, the normalised daily energy use $\overline{h}_a$ is calculated by applying Equation 4-1 for a given building type.

4.1.1.6 Hourly application

After the daily heating needs are calculated, statistic hourly load profiles are applied to distribute the daily demand or the mean power requirements over the course of a day. The hourly profiles cover specific temperature bands (Figure 15).

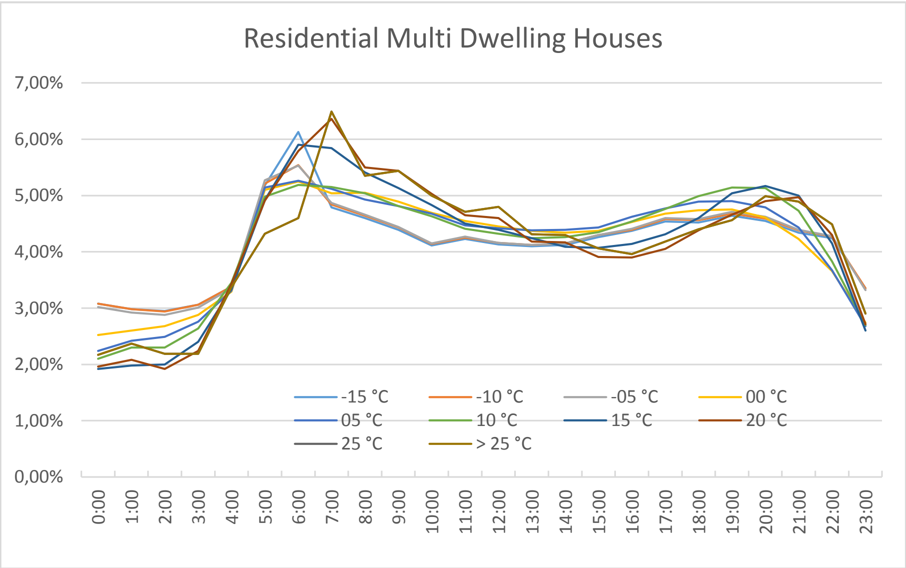

Figure 15: Hourly Load Profiles for Different Outdoor Temperatures for Residential Multi Dwelling Houses, own illustration adapted from (Geiger and Hellwig 2002)

Due to the two-step modelling approach, the statistic profiles could be replaced by site-specific load profiles for small building clusters. A suitable method for the load profile synthetisation is described by (Grohmann 2000). At the scale of neighbourhoods, the extraction of specific profiles has limited relevance as different use profiles seem difficult to extract. Instead aggregated load profiles could be extracted.

4.1.1.7 Model to model comparison

In addition to case studies based on measured energy use data, described in chapter 4.3 the data driven model was compared to results of a deterministic model. In (Koch 2010) a simplified steady state energy balance model is compared to the energy signature model representing a non-linear, data-driven approach. For the reference case daily energy needs for a virtual test case of a cluster of single family buildings were calculated, using a simplified deterministic simulation model based on DIN EN ISO 13790 (DIN 2008). Building archetypes (IWU 2003) were used to determine the specific geometry and main properties for the theoretic case study. For the comparison, heating needs of a number of buildings were calculated without consideration of distribution losses in a local district heating system. This inter-model comparison is not suitable for assessing the quality of results, but is included here to describe the inherent logic of the energy signature.

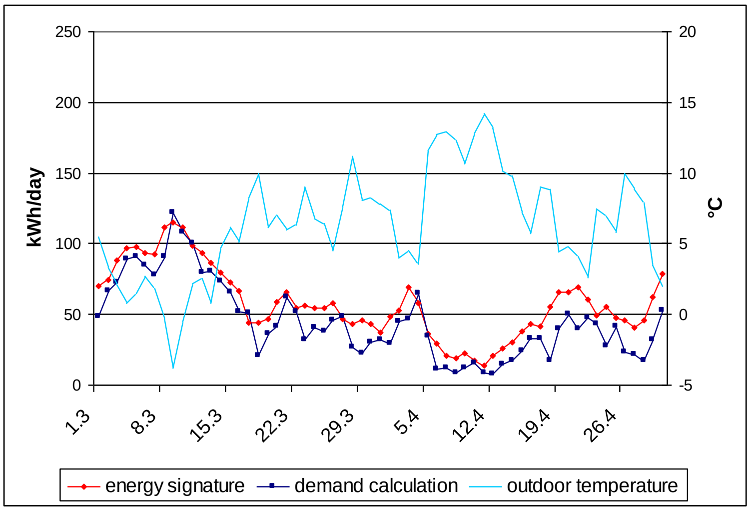

Figure 16: Comparison of Simulations based on a Forward and Data-Driven Approach (Koch 2010)

The data driven model follows the same tendency described by the forward approach. The subdued reactivity of the energy signature (Figure 16) can be attributed to the geometric sequence of past days' outdoor temperature used to determine the calculated temperature for the day (Equation 4-2). In the data-driven model, this aspect represents the building inertia, which is not represented in the steady state calculation model.

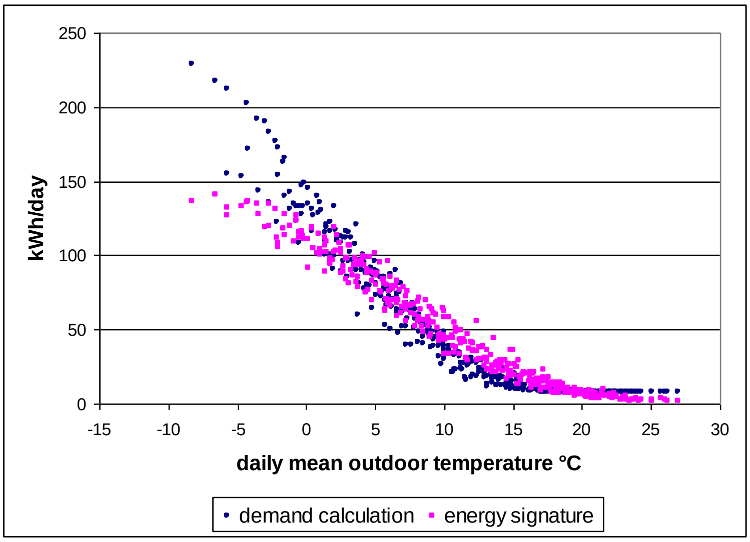

Figure 17: Comparison of the daily energy needs calculated with a steady state energy balance and an energy signature model assuming the same annual heat demand (Koch 2010)

While the general relationship between energy use and mean daily outdoor temperature is an inherent feature of both models, it can be seen that the linear increase of heating needs at low temperatures (<0°C) is not followed by the sigmoid function, which assumes a decline in the slope of energy needs (Figure 17). With reference to (BMFT 1977) Verbruggen (1982) described the "decreasing marginal heat consumption with decreasing outside temperature" as a "generally identified property". The same characteristic is described by (Sawillion 2002).

Mazzarella, Liziero et al. (2009) argued that the non-linear increase of thermal daily energy use with decreasing outdoor temperatures in energy signatures could be explained by the installed power, which is limited to a design point. In the German context where usually rather over-dimensioned heating systems can be found (Diefenbach, Loga et al. 2002) this argument seems hardly convincing. A more plausible explanation for this phenomenon could be a decreasing ventilation rate with decreasing outdoor temperatures. In the assessment of the passive house settlement “Gartenhofsiedlung Lummerlund” Ebel, Großklos et al. (2003) found that the average window opening hours varied greatly between summer (average of 10,6 h/d) and the heating period (average of 0,88 h/d). The correlation between window opening hours and the mean daily outdoor temperature was found to be relatively stable between 5°C and 18°C; below 5°C the opening was largely reduced. In the sigmoid function, this phenomenon is depicted based on the statistical evidence. The effect could be described in an energy balance by a variation of the air exchange rate depending on the mean outdoor temperatures for temperatures below zero degrees. However, as Eichlseder (2008) points out, for the German or Austrian context, it is particularly difficult to provide sufficient proof for the argument as few measured data sets exists for low temperatures, due to the absence of days with mean temperatures below -5 °C.

The model-to-model comparison indicated that the energy signature provided plausible results for an aggregated scale with little input data. For a more reliable validation, the model designed for the scale of regulatory zones of the gas grid was tested against measurements of mixed-use case studies at the scale of single buildings up to district heating systems.

4.1.2 Proposed parameter set for low temperatures

A distinct weakness in the prediction of peak loads at very low temperatures was identified in first applications of the model. This finding is consistent with the assessment of gas load predictions for the cold year 2012 conducted by Roon, Gobmaier et al. (2014). To overcome this issue, new parameter sets were calculated based on data from the year 2012 of the case study “Rintheimer Feld” using a non-linear curve fitting based on a Generalized Reduced Gradient solver to identify an optimal parameter set for the case study data. Figure 18 shows the measured data and simulation results of the existing parameter set (sim HMF) and the new parameter set (sim HMFx) as well as the fitted curve based on the GRG algorithm. The corresponding parameter sets are provided in Table 13.

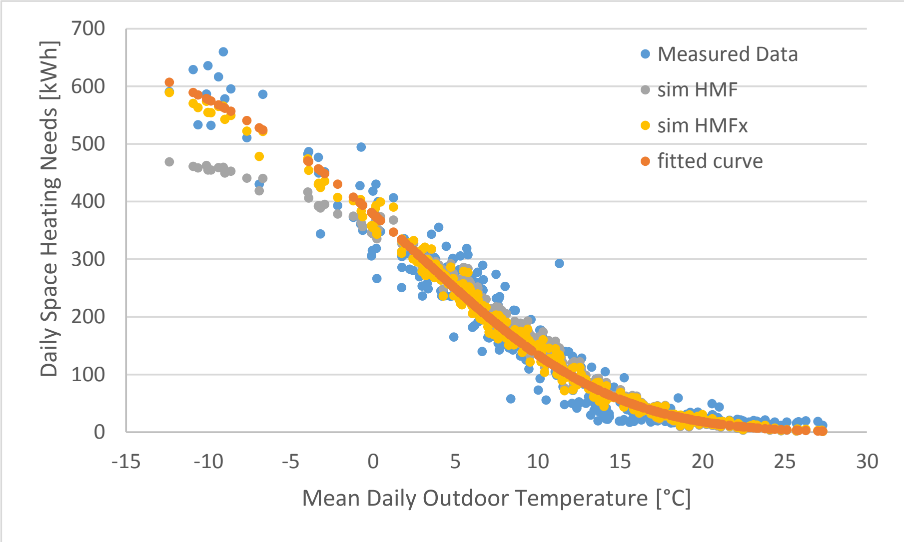

Figure 18: Measured data for the year 2012 (Rintheim case study) and fitted sigmoid curve

Non-linear curve fitting was applied by minimising the root mean square error of the sigmoid function compared to the measured data. The curve fitting was restricted to the temperature dependant part of the heating energy needs (i.e. parameters A, B & C). The solver used was the Generalized Reduced Gradient (GRG2) Algorithm developed by Leon Lasdon and Allan Waren (Lasdon, Waren et al. 1978). Within the given constraints for the parameter variation, the solver iteratively tests solutions for multiple variables and optimizes the calculation for a given objective. In this case, the selected objective is to minimize the root mean square error of the simulation results compared to the measured values. The optimum is a function of the adjustable model parameters A, B and C. As the function includes multiple values for which the rate of change must be measured, the function has multiple partial derivatives, forming a vector, which is referred to as a gradient of the function.

Table 13: Exemplary Parameter Sets for Single (HEF) and Multiple (HMF) Dwelling Buildings (BDEW, VKU et al. 2014) and Proposed Parameter Set (HMFx)

Parameter	***Single Dwelling***	***Multiple Dwelling***	
	HEF04	HMF04	HMFx
A	3,1850	2,5187	2,059
B	-37,4124	-35,0333	-39,7624
C	6,1723	6,2240	5,3844

By applying the finite difference estimate of the derivative, each adjustable cell is modified and the impact on the optimum cell is observed. This process is repeated in multiple iterations to identify optimality conditions. Optimality conditions are reached when the gradient of the optimum cell is zero, as it reflects the rate of change with regard to the adjustable cells. Thereby the parameters resulting in the maximum or in this case minimum value of the optimum cell (CVRSME) are identified.

Before comparing the results to further case study data their plausibility in relation to the physical properties of a heating load curve is discussed. In comparison to the function calculated with the existing parameter set (i.e. HMF04), the new curve has a higher peak value at low temperatures along with an increase in the steepness of the sigmoid curve (Figure 19). This was the main weakness of the existing profile "HMF 04" in the application to residential buildings in the very cold year 2012. As further parameters were modified, the difference was regarded as a relative indicator in the form of the difference between the peak power at a given temperature below the change point and the value delivered by the derivation of the curve (ΔP). Figure 19 shows the two parameter sets "HMF04" and "HMFx" instantiated for annual space heating needs with ΔP_{HMF} and ΔP_{HMFx} respectively.

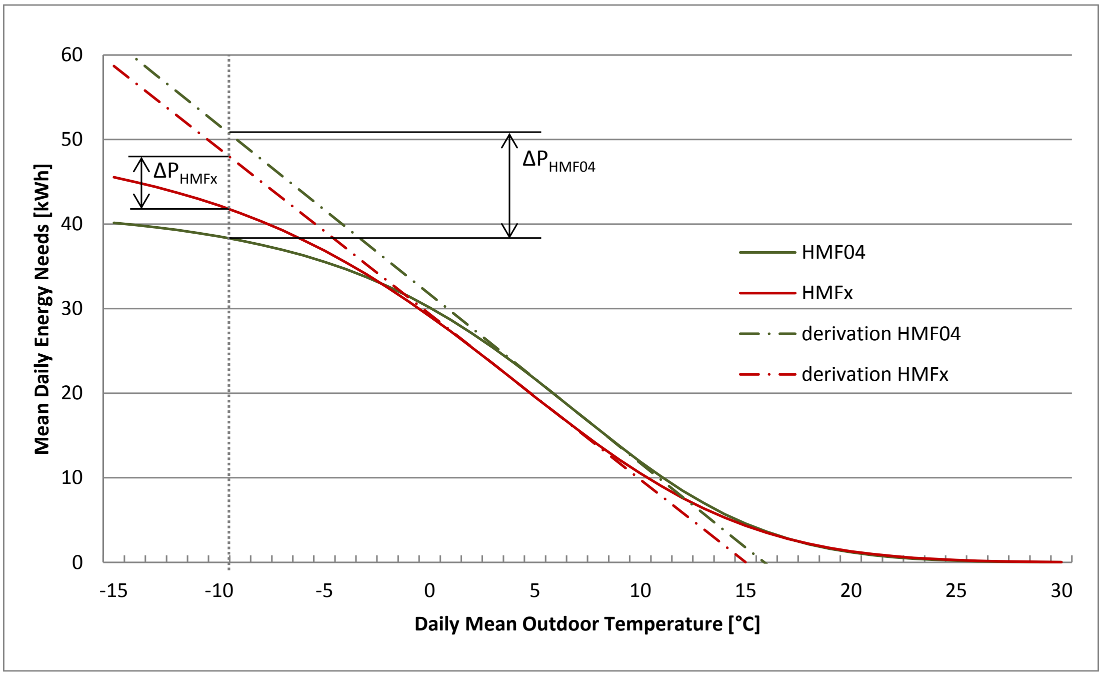

Figure 19: Comparison of the energy signature based on the existing parameter set "HMF04" and the proposed set "HMFx"

As discussed in section 4.1.1.7, ΔP can be explained by a lower ventilation rate and thus lower ventilation losses in the building's energy balance. At -10°C the existing profile for multi dwelling units HMF04 has a ΔP of 32%, the new parameter set

(HMFx) results in a value of 17%. Compared to an actual heating load curve the derivation of the sigmoid describing the inclination at the change point can be used as an approximation to identify the heating limit temperature. For the new parameter set the deviation results in a heating limit temperature of 15 °C. This is comparable to the value for the HMF04 profile (16°C) and corresponds to target values of low energy buildings (Figure 19). The modification of parameter “C” results in a reduction of the heating limit temperature and increases the inverted “S” shape. Finally, a modification of parameter “B” in the regression reduces the heating limit temperature by shifting the curve towards the origin (see Figure 14).

The new parameter set referred to as HMFx was applied without further calibration to other case studies in order to assess its fitness. Especially for low temperatures in 2012, the new parameter set well depicted the thermal behaviour of groups of buildings especially regarding peak loads of heating needs. The detailed discussion is provided in the result section.

4.2 Statistic tests

In order to test the quality of the results, a number of statistical indicators will be introduced to determine a suitable measure of quality. In order to test the fitness of the model, the simulated results for a given sample are compared to the measured data based on different spatial and temporal aggregations (i.e. size of samples).

An important criterion often used in building simulation is the mean biased error (MBE) that delivers a non-dimensional description of the bias of the model (Coakley, Raftery et al. 2014). In addition, the coefficient of variation of the root mean square error (CV RMSE) is proposed as a common indicator for the fitness of a model. Table 14 provides acceptance criteria for the different indicators based on a monthly and hourly building performance simulation developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) (ASHRAE 2002), the International Performance Measurement and Verification Protocol (IPMVP) (EVO 2007), and the American Federal Energy Management Program (FEMP) (US DOE and Nexant 2008).

Table 14: Acceptance criteria for building energy performance simulation models (ASHRAE 2002, EVO 2007, US DOE and Nexant 2008), qtd. in (Coakley, Raftery et al. 2014)

Standard/guideline	Monthly criteria (%)		Hourly criteria (%)	
	MBE	CVRMSE	MBE	CVRMSE
ASHRAE Guideline 14	5	15	10	30
IPMVP	20	–	5	20
FEMP	5	15	10	30

Hellwig (2003) proposed the standard deviation as a description of the sigmoid function. In order to relate the test to the non-linear function, the standard deviation was calculated for segments of 1 °C. In the samples used in the original study, as in the case study data examined here, the very low temperature segments suffer from an absence of sample data, which renders the calculation of the standard deviation difficult. Consequently, the confidence interval decreased substantially with decreasing temperatures.

As further test the least squares regression with the resulting coefficient of determination and the Bravais-Pearson correlation coefficient will be calculated (Kühlmeyer 2001). The combination with further statistical tests seems necessary because the correlation, even though it is often used as main indicator in model validation, does not deliver sufficient evidence to determine the fitness of the model (Bland and Altman 1986) (Figure 20). Along the same line of thought Grohmann (2000) proposed to assess load curves by combining the correlation in combination with the variance and the mean value for a given timescale. As the selected model uses the annual energy use as basis and therefore implicitly shows the same mean value as the measured data. The standard deviation of the simulated as well as the measured data will be compared as a measure for a similar variance.

Figure 20 illustrates different combinations and the limited validity that could arise from using only one or two of the described indicators. Series A and Series B show the same variance and mean value, but a negative correlation. Series A and C have a perfect positive correlation and the same mean value, but a different variance.

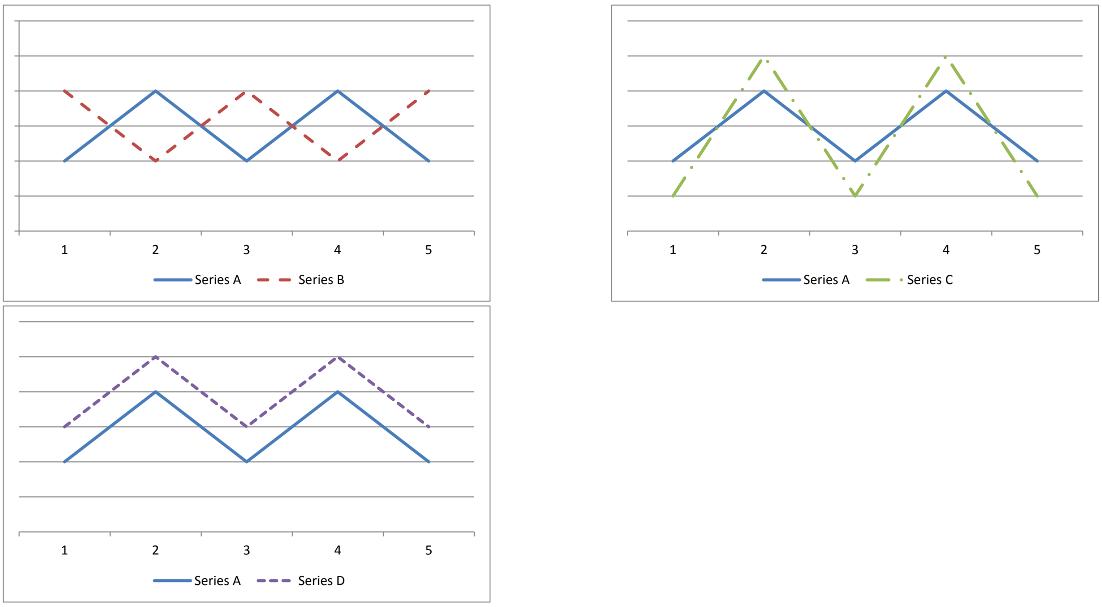

Figure 20a-c: Illustration of the different criteria to compare individual profiles adapted from (Grohmann 2000)

Series A and Series D are strongly correlated and have the same variance, but differ in their mean value. Figure 20 b and c also illustrates Bland and Altman's criticism (Bland and Altman 1986) that the correlation coefficient alone must not be used to determine the fitness of a model. For both cases the correlation coefficient is 1, however it is apparent that Series A and Series C have a different spread and Series A and D a different mean value. Consequently the results will be discussed based on a set of statistic tests for correlation, mean value and variance. Theil's coefficient of inequality (Theil's U) is applied as itcombines the three criteria of mean value, variance and correlation (Sterman 2000). In the interpretation of the results, these indicators will be used in parallel to the Bravais-Pearson correlation coefficient as well as the CV RMSE in order to compare the results to common criteria of acceptance.

4.2.1 Mean bias error (MBE) =MRGP

The MBE is often used to compare simulation results with real measurements. The limitation of this indicator is that positive and negative errors will compensate each other.

$$\mathrm{MBE} = \frac{\sum_{i=1}^{N_p}(x_i - y_i)}{\sum_{i=1}^{N_p}(x_i)} \qquad \textbf{Equation 4-8}$$

The MBE captures the mean difference between each instance (i) of a series of measured (x) and simulated (y) values. N provides the number of values in the interval p. However, positive and negative errors will compensate each other which limits the interpretation of the MBE (Coakley, Raftery et al. 2014). As the errors are normalised, larger values are not overweighed in the assessment (Andres and Spiwoks 2000), the MBE is sometimes also referred to as mean relative weighted error. In this application the MBE has a limited explanatory power as the simulation model is fed with the annual energy heating needs of the given case. The mean value will coincide and thus the value of MBE will implicitly be very small.

4.2.2 Coefficient of variation of root mean square error (CV RMSE)

In the assessment of simulation results, the Root Mean Square Error (RMSE) is often used to describe the differences between measurement and prediction. The RMSE represents the sum of these differences, which are also referred to as residuals. The RMSE is a scale dependant measure. Here it is used in relation to the mean observation ($\bar{x}$) as the coefficient of variation of the root mean square error (CV RMSE).

$$\text{CV RMSE} = \frac{\sqrt{\sum_{i=1}^{N_p} \frac{(x_i - y_i)^2}{N_p}}}{\bar{x}} \qquad \text{Equation 4-9}$$

Due to the normalisation, the CV RMSE is scale independent and can be compared to general compliance criteria described in Table 14 (Coakley, Raftery et al. 2014).

4.2.3 Variance

The variance s^2_n is a measure for the spread of a sample and thus describes the density of n samples of the variable x. The variance is defined as the average of the squared differences from the mean (Kühlmeyer 2001).

$$s_n{}^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad \text{Equation 4-10}$$

The standard deviation s is defined as the square root of the variance.

$$\mathrm{s} = \sqrt{s^2} \qquad \text{Equation 4-11}$$

4.2.4 Covariance

The covariance s_{xy} describes the interdependency of two data sets. For $s_{xy} = 0$ the two variables can be regarded as independent; the inverse conclusion cannot be drawn (Kühlmeyer 2001).

$$s_{xy} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x}) * (y_i - \bar{y}) \qquad \text{Equation 4-12}$$

with $-\infty \leq s_{xy} \leq +\infty$

While the covariance displays a unidirectional linear relation as a positive and the inverse as a negative value, the strength of the correlation cannot be concluded from the covariance.

4.2.5 Bravais-Pearson correlation coefficient

In order to measure the strength and direction of a linear relationship between two metric variables the Bravais-Pearson correlation coefficient ρ is calculated. The correlation coefficient is calculated on the basis of the covariance of two variables x and y divided by the product of their standard deviations (Duller 2006).

$$\rho = \frac{s_{xy}}{s_x * s_y} \qquad \text{Equation 4-13}$$

with $-1 \leq \rho \leq +1$

From $\rho < 0$ it can be concluded that the values are inversely linear related, for $\rho = 0$ no linear relation is existing and $\rho > 0$ proves a unidirectional linear relation. For two samples x and y that fall on one a straight line $|\rho| = 1$.

The correlation coefficient used here is only measuring the linear correlation of two sets of data. Therefore, to test the fitness of the model, the simulated values will be related to the measured values in a regression analysis instead of comparing the two nonlinear functions. According to (Duller 2006) $0.7 < \rho < 1$ indicates a strong correlation and thus indicate a close match between simulation and reality.

4.2.6 Coefficient of Determination R^2

The coefficient of determination is the relation of the variance explained by the regression of x and y (Andres and Spiwoks 2000). The value of one indicates a perfect prediction. For R^2= 0.9, ninety percent of the variation in the response variable can be explained by the explanatory variables. The remaining ten percent can be attributed to unknown, lurking variables or inherent variability. The depiction of measured space heating needs, compared to calculated aggregated needs, is an often-used depiction of the fitness of the model, see for example Yamaguchi, Shimoda et al. (2013). Especially for non-linear models, the discussion of the deviation in this form is comparatively easy to assess.

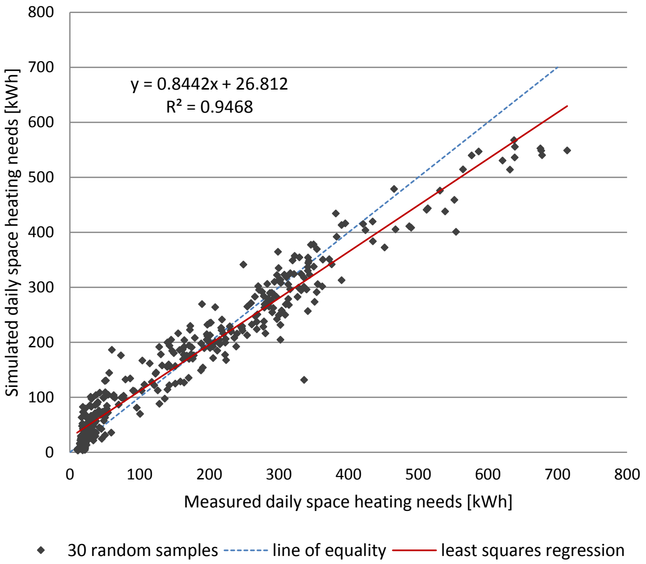

Figure 21: Regression of measured and simulated values with the trendline (red) as well as the line of equality (dotted blue line)

When comparing simulation and measurement, R^2 provides a good impression of the relation of the two variables. R^2 alone can be misleading as it shows the consistency of the variation but not the agreement in absolute values. As Bland and Altman (1986) point out, the correlation, as sole indicator is insufficient. For analysis, the line of equality (in this case a line plot with y=x) and the distribution of residuals should be taken into account (see Figure 21).

4.2.7 Theil's coefficient of inequality (Theil's U)

Finally, a statistical measure combining the above-described requirements of comparing the mean and the variance, as well as the covariance of two time series, is a derivation of Theil's coefficient of inequality (Theil's U). The objective of the original test was to assess the quality of a prediction and to compare it to the naïve prognosis represented by the prior value of the time series (Andres and Spiwoks 2000).

$$\mathrm{U} = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{N}(P_t - A_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{N}(A_t)^2}}$$ Equation 4-14

With P being the predicted change at time t,

$$\mathrm{P}_t = \frac{y_t - x_{t-h}}{x_{t-h}}$$ Equation 4-15

and A being the measured change at time t.

$$\mathrm{A}_t = \frac{x_t - x_{t-h}}{x_{t-h}}$$ Equation 4-16

As described in more detail in Andres and Spiwoks (2000), Theil's U can be dismantled in three components to test the mean value (U_m, Equation 4-17), the variance (U_v, Equation 4-18) and the correlation (U_c, Equation 4-19) as individual error components. Here, the variation proposed by Sterman (2000), also referred to in Schmidt, Jäger et al. (2013) is used that applies Theil's U to the measured and simulated values.

$$\mathrm{U}_m = \frac{(\bar{y}_t - \bar{x}_t)^2}{\frac{1}{n}\sum_{t=1}^{N}(y_t - x_t)^2}$$ Equation 4-17

$$\mathrm{U}_v = \frac{(s_y - s_x)^2}{\frac{1}{n}\sum_{t=1}^{N}(y_t - x_t)^2}$$ Equation 4-18

$$\mathrm{U}_c = \frac{2\left(1 - r_{xy}\right) * s_y * s_x}{\frac{1}{n}\sum_{t=1}^{N}(y_t - x_t)^2}$$ Equation 4-19

With s being the standard deviation and r the correlation coefficient for the variables x and y. The combined indicators provide the ratio of errors that can be attributed to the different sources with $U_m + U_v + U_c = 1$.

As explained for the MBE, U_m has a limited significance regarding the fitness of the model. In this case it still proves useful to detect deviations from the mean value, which in this case rather point out difficulties in the application of the model where $U_m \neq 0$. The individual indicators are expressed as percentage values. Two time series have the same mean value with $U_m = 0$ and the same variance with $U_v = 0$. A perfect correlation of two time series would result in $U_c = 1$.

4.3 Case study description

In the course of the research work, different data sets were made available for developing and testing the modelling approach, which are described in detail in Annex C. In all case studies, data was anonymised and treated without reference to individual users or units. Table 15 summarises the case studies used for the model validation. In all cases, data was used at the lowest scale of measurement and further used for aggregated buildings or building clusters up to a complete neighbourhood or zones.

Table 15: Case studies used for the model validation

	Case Study	Building Use	Size	Scale
1	Rintheimer Feld	Residential	3,900 m²	Apartment, Buildings, Building Cluster
2	Single family buildings	Residential	600 m²	Buildings
3	Blaue Heimat	Residential	4,700 m2	Buildings, Building Cluster
4	Bad Aibling	Residential, Hotel, School, Office	26,800 m²	Building Cluster, Neighbourhood, DH
5	CHP Ops	Residential, School, Recreational facility	2.8 MW_{th}	Building cluster, Neighbourhood, DH
6	Commercial Zone	Office, Light Industrial	n.a.	Building Cluster, Commercial Zone

4.3.1 Rintheimer Feld

Measurement of two low energy buildings was accessible for testing the fitness of the energy signature model. The demonstration buildings in the Rintheimer Feld project were assessed in comparison to a reference building renovated to meet the standard measures applied in other renovations conducted by VOLKSWOHNUNG GmbH. Monitoring was installed for one staircase in the reference building (10 units) and in all 60 units of the two demonstration buildings. Each building contains three staircases (entrances) with ten residential units each with a cellar in which the central space heating and domestic hot water provision is located. Data was received and treated in an anonymised form, so that no reference is made to individual apartments or users. As the selected simulation approach does not consider specific physical properties of individual apartments, the single objects are not referenced to their specific location. Reliable measurements on the installed sensors was obtained from September 2011 onwards (Jank 2013). For the model validation, measurements were available for a period of twelve months between January 2012 and December 2012.

The temporal resolution is, depending on the sensor, provided in one minute time intervals. For synchronisation, measurements were aggregated to hourly and daily time series. In total nine measurement failures longer than four hours were identified as missing days each affecting ten apartments each (90 missing values). The days were substituted by the maximum value of the continuous measurement for that day and checked against the following day's value. From the sixty samples, two apartments were excluded from further work as the time series delivered implausible patterns. To test the proposed approach combining simulation and monitoring, a data warehouse solution was implemented. Data analysis and queries were conducted based on an online analytical processing (OLAP) solution, described in section 5.2.

4.3.2 Single building systems

For the individual building case study, monitoring data from eight individual buildings in South West Germany was used. The data was recorded between the 1st of August 2008 and the 31st of July 2010. For privacy reasons no address specific information is correlated to the datasets and the individual buildings are referred to "building A" up to "building H". All buildings are situated within a 20 km radius in a village context so that similar weather conditions are assumed for the analysis. All buildings were recently modernised and each was equipped with a new individual heating system for provision of space heating and domestic hot water.

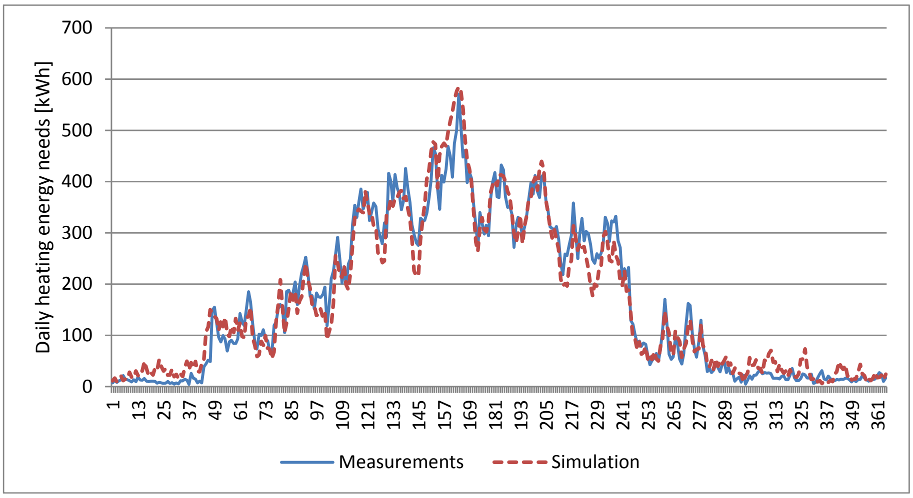

Figure 22: Measurements and simulation of the aggregated daily heating needs of all single-family buildings

The data was available in hourly time steps. Due to long consecutive periods of missing values and implausible values, two buildings were excluded from the case study. Data from the space heating needs of six buildings were selected for comparison with simulated demand in different levels of aggregation. In order to do so, a randomly chosen building was added to the cumulated load for each simulation run. The last case therefore corresponded to the aggregated demand of all buildings.

4.3.3 Blaue Heimat

The building cluster “Blaue Heimat” originally built 1951 was renovated in 2005 with the target of a net-zero energy building. After renovation, the low energy building contained 40 residential units. The concept includes two adjacent buildings supplied by the same energy system, which were not renovated to the same standard. Data was provided for all three buildings at a 15-minute resolution. Data was made available for the period between 14.7.2009 until 1.1.2011 and thus contained data for 536 days. In total six measurement failures with 41.6 days were reported as missing values. Data for 365 days was used for the model validation. As a number of consecutive missing values fell in the month of December 2010, the 1st of September 2009 was selected as starting point. The selected year contained 8.2 days as missing values.

The case study consists of three data sets for two existing buildings as well as the central low energy building. Figure 55 shows the measured data for space heating and domestic hot water use mapped to the ambient temperature. The energy signatures of the three buildings show typical curves for a well-operated system with clear dependency on the outdoor temperature. Due to its higher performance and lower peak demand the low energy buildings are typically represented by the shallower curve (MFH A).

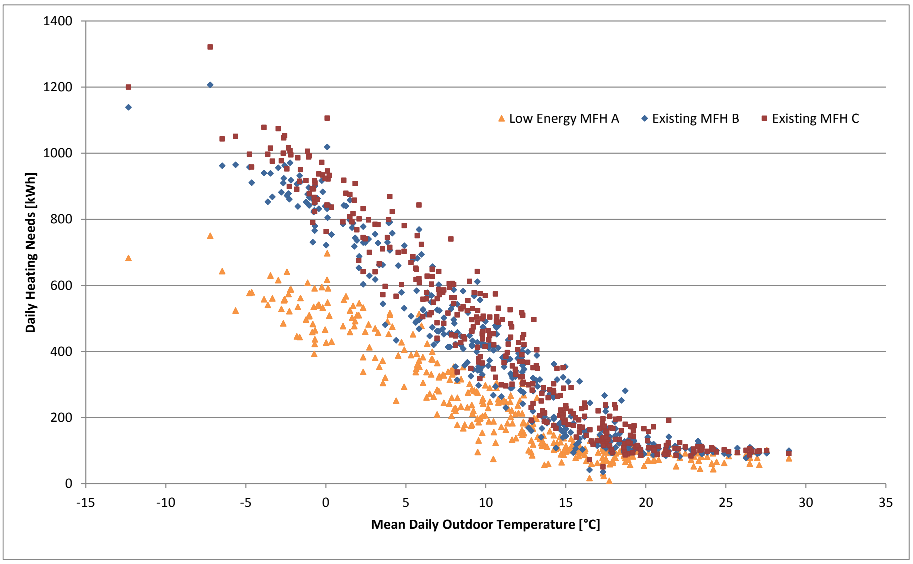

Figure 23: Energy signatures of the three building parts in the "Blaue Heimat" case study

4.3.4 Bad Aibling

For the Bad Aibling case study, data for the zero energy development project in Bad Aibling was kindly made available. The B&O Park Area in Bad Aibling is a conversion of a former military site. The target was defined as zero energy development for the brown field project (Böhm, Schroeder et al. 2010). The redevelopment project and accompanied research activities were funded through the EnEff:Stadt research program by the German Ministry for Economics (BMWi). For the purpose of this thesis, hourly data was provided aggregated at building level and specified per use. It was further assigned to the branches of the local district heating network. For the tests, data was anonymised and treated without reference to specific buildings or users. Data was provided for the years 2012 and 2013 for different uses. Hotels represented an especially large share of the available data. In total, measurements for 2012 and 2013 contained five missing days. Furthermore, a residential cluster along with office and school buildings were also used. Over the course of the two years 15 days were reported as missing data. As the hourly temperature data contained a number of missing values, it was compared to the hourly and mean daily temperature measured at the DWD station 1262 located at Munich airport (Figure 57).

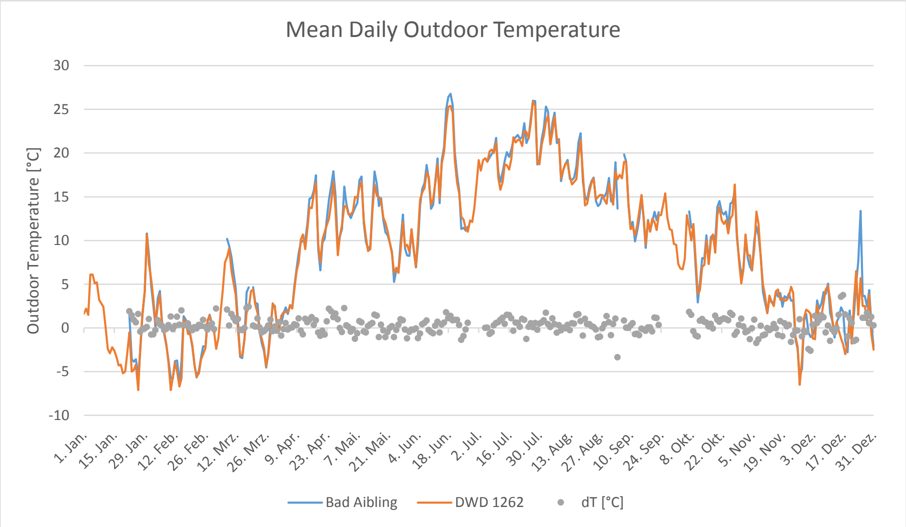

Figure 24: Comparison of the site-specific mean daily outdoor temperature measured in Bad Aibling and Munich (DWD station 1262) for the year 2013

This comparison was done to complete missing values in the temperature data and to test the sensitivity of the simulation results to site-specific temperature data. The comparison showed good agreement between the two temperature measurements. Figure 57 shows the comparison of data from 2013.

4.3.5 CHP Ops

Data was provided for five individual building clusters of different use types connected to the district heating system here referred to as “CHP Ops”. The data contains the delivered energy at each building cluster and therefore does not contain losses in the distribution system outside the buildings. The mean power output of a district was made available in 10-minute time steps for two measurement periods between 1.2.2008 until 27.1.2009 and 5.7.2009 until 1.7.2010.

Seventy-six percent of total demand refers to residential uses. About a third of the apartments were built in 2005. The rest of the residential building stock consisted of buildings from the last century, which, however, were well maintained, and a small number of small multifamily apartments built in the 1970s. The non-residential uses include a recreation centre including a swimming pool, a school building as well as a nursery. For one of the five building clusters, 34 daily measurements were missing. These were added by linear interpolation and compared to the same weekdays of the week before and after.

4.3.6 Commercial Zone District Heating System

At a high aggregation level, the total load of a district heating system supplying heat for a commercial zone was used as a case study. For confidentiality reasons no reference to the exact location or the specific user or processes was provided. The site located in the south of Germany consisted of two-third light industrial use and one-third office spaces. The absolute energy use in 2013 was 291 MWh and 222 MWh in 2014. Based on annual benchmark values (BMVBS 2009) it can be estimated that the site hosts approximately 1000 m^2 of office buildings and 1500 m^2 of light industrial use. Data was provided as complete time series of hourly energy use for the years 2013 and 2014.

5 Results

5.1 Model validation

The model validation presented in this chapter is based on the case studies described in chapter 4.3. Due to the limited number of cases, the results cannot provide proof of a method. Yet, as all case studies across different use categories, scales and geographical locations point to similar conclusions, the presented results are interpreted as robust trends. It can be stated as a common result that the quality of simulation results, or the fitness of the model, increases with larger sample size. The case study “CHP Ops”, which delivered the best results in terms of CV RMSE comes closest to the scale of a neighbourhood. The case studies “Blaue Heimat” and “Bad Aibling” resemble small neighbourhoods while the assessment of single apartments in the case study “Rintheimer Feld” and the single-family buildings, represent extreme application cases for a data driven model. Yet, even the latter produced very good results at a daily resolution. These results confirm the basic research hypothesis that the data driven approach is applicable at the scale of a neighbourhood and even at the scale of building clusters.

For low temperatures, a new set of parameters is proposed which delivered better results than the original parameters for multifamily buildings for the cold year 2012. This is especially true for the representation of peak loads and is indicated by the improved value when comparing the variance of measured and simulated time series.

In the case of "Blaue Heimat" the measured data for heating energy needs was available including domestic hot water needs. Here, the simulation was calibrated to correspond to actual mean daily domestic hot water consumption. The calibration, which was done analogous to the proceeding proposed by Richter (2004), proved to be an effective and easy way to improve simulation results. For a useful application in the urban context, few modifications should be necessary, as an automated application is essential. The adjustment of the parameter (D) for the domestic hot water demand was judged an effective calibration measure with reasonable effort.

For non-domestic uses, the use-specific correction of the weekday factors proved an additional way to improve the model for the use as a continuous benchmark.

The detailed results of the simulations and the application of the chosen statistic indicators are provided in the following sections for each individual case study.

5.1.1 CHP Ops

For the case study "CHP Ops" the mean daily thermal power, as well as the hourly power demand, was simulated based on the described set of model parameters, as well as the total heating energy needs over the year. The headline results of the comparison of measurements and simulation are published in (Woods 2012).

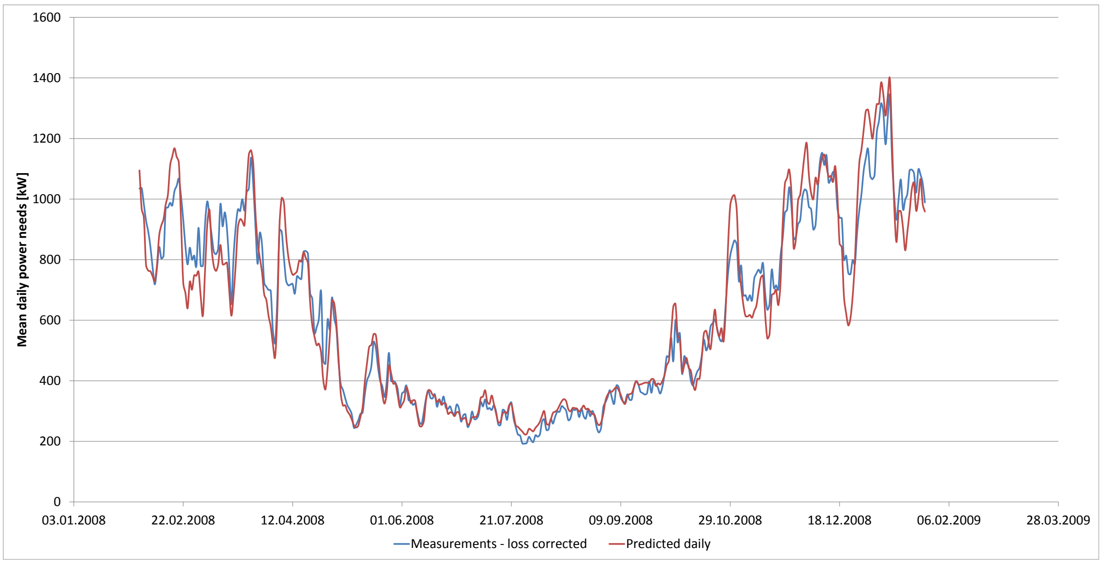

Figure 25: Comparison of the aggregated measurements and simulations for mean daily power from the CHP Ops case study (Woods 2012)

As the target scale for the model was rather large, no calibration was foreseen for the test, but rather, an application without modification of the model in order to maintain a realistic application scenario. The simulation was run for six different measurement points in the district heating system, three residential and three non-residential. Losses of the distribution system were not included in the data as the delivered energy use was considered. Table 16 shows the individual results for each building cluster, as well as an aggregation of all residential users (Table 16, row 7) and the non-residential users (Table 16, row 8). Finally, the total energy needs were simulated, based on the annual power demand of all uses.

Table 16: Selected results from the model validation for the case study „CHP Ops“

	Daily Series	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Residential building cluster 1	13.53%	0.94	0.96	0.94	0.06%	6.41%	93.81%
2	Residential building cluster 2	17.26%	0.88	0.94	1.13	0.00%	10.45%	89.83%
3	Residential building cluster 3	23.88%	0.95	0.97	1.55	0.00%	78.72%	21.56%
4	Tertiary buildings GBH	19.57%	0.81	0.96	1.03	0.00%	0.49%	99.79%
5	Tertiary building cluster 1	50.54%	0.70	0.83	0.76	0.00%	18.49%	81.78%
6	Tertiary building cluster 2	63.95%	0.61	0.78	0.68	0.00%	25.11%	75.17%
7	Aggregated residential buildings	12.33%	0.94	0.97	1.01	0.06%	0.06%	100.16%
8	Aggregated tertiary buildings	19,72%	0.84	0.91	1.00	0.00%	0.00%	100,28%
9	All buildings	11.18%	0.95	0.97	1.02	0.04%	1.15%	99.09%

The simulation for residential building clusters delivers good results regarding the CV RMSE between 13.53% and 23.88%. The aggregated value is even lower, at 12.33% for all residential buildings. The majority of the tertiary buildings perform less well, with CV RMSE values up to nearly 64%. This can be explained mainly by the lack of calibration of the model taking into account the weekday factors. The tertiary time series shows regular weekly patterns, which were not adopted in order to remain comparable to a large-scale application. Still, for aggregated non-domestic uses, the CV RMSE reaches a good value of 21.38%. When considering all uses of the system the error is even further reduced to a value of 11.18%. Here, the large share of residential users helps to improve the result in comparison to non-domestic users. The share of the heating energy needs for residential users was 76% of the total demand.

Out of the residential buildings, the variance is well depicted for clusters one and two while the third cluster showed a much lower standard deviation for the measurements in comparison with the simulations. The third residential cluster (Table 16, row 3) also has a low value of U_c as this indicator combines the correlation with the standard deviations of both measured and simulated values. Even though the spread of the sample cannot be explained by the model, the correlation still delivers a very good result at over 95% for all residential uses. The model performed poorly on this individual building cluster.

Even though non-domestic uses are typically less temperature dependant and depend more on the operation schedule and day of the week, the model shows good correlation between 78% and 96% for different uses.

In the aggregation, the model depicts both the domestic and non-domestic uses extremely well. The model regards the variance of measurements with only one percent deviation for the residential building clusters and a perfect fit for the non-residential aggregated heating energy needs. A very high level of fitness is finally reached when aggregating the whole mean daily power demand of the system (Table 16, row 9) with a correlation coefficient of 97% and U_c = 99,09%, The variance is also very well matched with a Theil's coefficient for the variance (U_v) of only 1,15%. The aggregated results show that by the increase of scale, some of the limitations to the predictions of individual uses, such as building cluster 3, are overcome. Profiles largely deviating from normal – in this case residential – use are compensated by the averaging effect with increasing size.

The objective of the Macro DE project was not only to deliver daily power demand but, more so, the hourly power demand suitable to generate an annual load duration curve for the potential sites for district heating systems across the UK. Hence, the hourly simulation results were evaluated for the case study. The model shows good results for the aggregation of all buildings, as well as for the residential buildings remaining in the boundaries set for the expected accurateness of an hourly building energy performance simulation by (ASHRAE 2002).

Table 17: Selected results from the model validation for the case study "CHP Ops" (hourly simulation)

	Hourly Series	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Residential Buildings	29.71%	0.76	0.87	0.94	0.00%	1.43%	98.58%
2	Non-Domestic Buildings	37.25%	0.62	0.79	0.87	0.00%	4.11%	95.90%
3	All Buildings	24.13%	0.82	0.91	0.98	0.00%	0.18%	99.83%
4	All Buildings, annual load duration curve	2.00%	1.00	1.00	0.98	0.09%	26.42%	73.51%

As could be expected, non-domestic uses perform less well with a value of 37.25% for the CV RMSE (Table 17). Again, it should be mentioned that no detailed analysis was conducted on, for example, working hours and daily schedules. For the complete hourly power demand simulation of the system, the coefficient of determination indicates that 82% of the measurements can be explained by the model. For the whole site, variation as well as correlation, reach very good levels of 0.18% and 99.83% respectively.

Row four of Table 17 provides assessment of the annual load duration curve comparing measured and simulated data. Hourly simulation delivers excellent results as the variance is well represented with a value of 98%. The correlation coefficient, as well as the coefficient of determination, implicitly show complete agreement, as the annual load duration curve is a sorted data series (Figure 26).

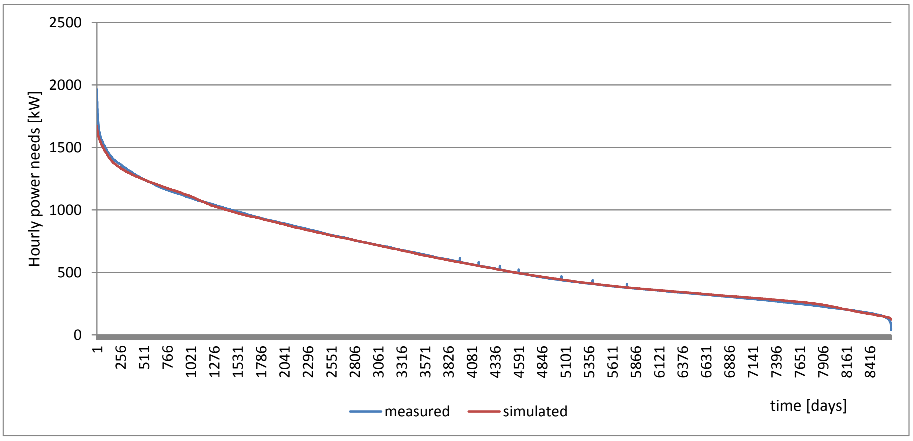

Figure 26: Annual load duration curve for the "CHP Ops" case study

As Figure 27 and Figure 28 illustrate, hourly simulation at a larger scale depicts the variance quite precisely both in summer (Figure 27) and in winter (Figure 28). While this individual application does not prove the fitness of the model in general, it does provide supporting arguments for the use of temperature dependant hourly load profiles. The profile is dominated by domestic hot water use during summer and has less significant peaks in winter.

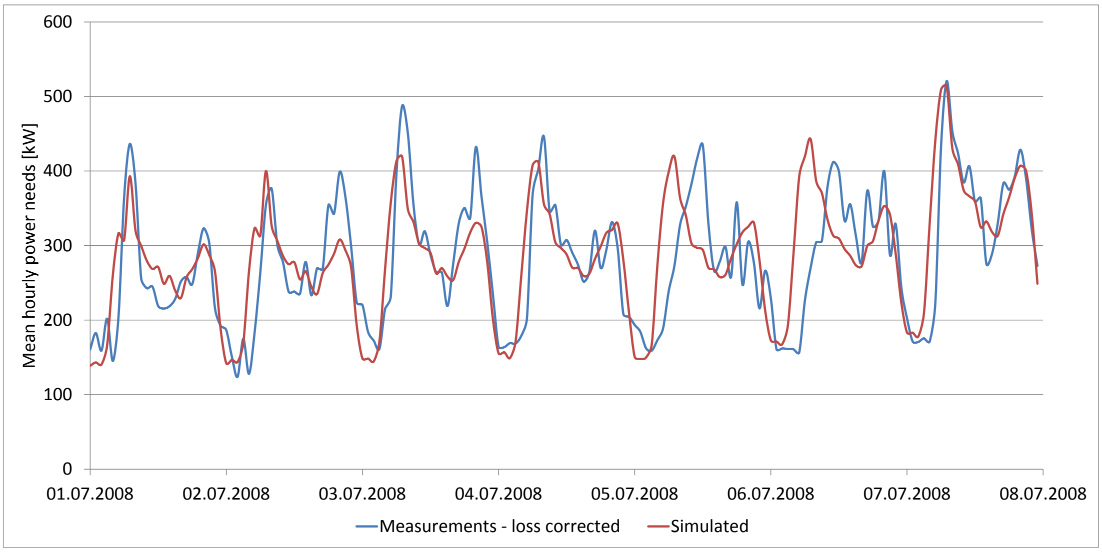

Figure 27: Measured and simulated hourly energy needs for a summer week for the "CHP Ops" case study

Both exemplary weeks also show a limitation of the unbiased application, as the simulation does not correctly represent the differences between weekdays and weekends. The weekend in the shown sample fell on the fifth and sixth of July (Figure 27), in the winter sample it was the seventh and eighth of December (Figure 28). Also in winter, the sharp drop around noon was not correctly predicted.

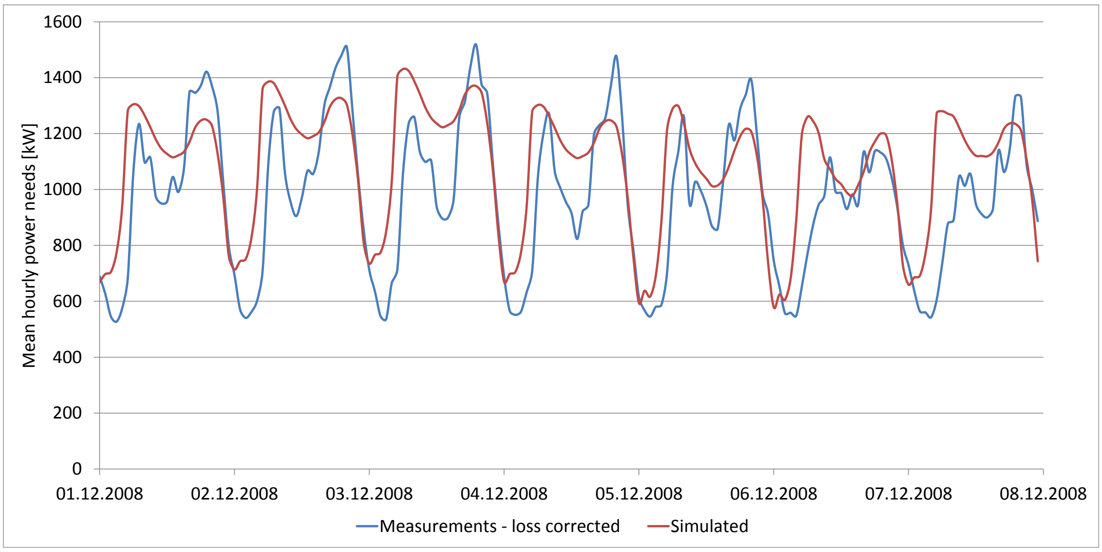

Figure 28: Measured and simulated hourly energy needs for a winter week for the "CHP Ops" case study

Table 18 summarises the results of the model validation in different temporal scales. The error (CV RMSE) increases but for the aggregated site remains within the bounds of 30% defined by (ASHRAE 2002), even for hourly resolution over the whole district heating system. Non-domestic uses show the highest CV RMSE at hourly resolution with 37.25%, which is not surprising given the specific uses in the non-domestic sector to which as previously mentioned the load profiles were not adapted. At the hourly scale, the simulation of the non-domestic uses shows a decreasing correlation and variance which points to a weakness in the hourly load profile. Yet even for the non-domestic users, the results indicate a high robustness up to a daily time scale.

Table 18: Selected results from the model validation for the case study „CHP Ops", comparing indicators at monthly, daily and hourly time scale

	Series	CV RMSE			ρ			σ_s / σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Residential buildings	5.98%	12.33%	29.71%	0.91	0.97	0.87	0.95	1.01	0.94
2	Non-Domestic buildings	6.65%	19.72%	37.25%	0.90	0.91	0.79	1.00	1.00	0.87
3	All buildings	3.62%	11.18%	24.13%	0.91	0.97	0.91	0.97	1.03	0.98

For the whole site, the correlation and the variance are very well represented, even at hourly resolution, with a value of 91% for the correlation coefficient and 98% for the variance. For the scale of the "CHP Ops" district heating system, both indicators deliver good results independent of temporal resolution.

5.1.2 Blaue Heimat

For the "Blaue Heimat" case study, simulations of daily heating energy needs were carried out for two existing apartment buildings, as well as for the renovated apartment building reaching low energy standard. For the two existing buildings, hourly simulations of the heating energy needs were also conducted. The corresponding measurements include space heating needs, as well as domestic hot water needs. Finally, daily and hourly simulations were taken for the aggregation of the largest possible number of users. To test the low energy buildings simulation, the newly refurbished building was simulated using the set of model parameters for multi-family buildings (HMF), as well as the newly proposed parameter set (HMFx). The selected results of the model application (Table 19) show a good agreement between simulated and measured data for both parameter sets.

As mentioned in the case study description in section 10.3.2, the base load, or the energy needs in summer, included domestic hot water needs as well as distribution losses. This base load is represented in the energy signature by the factor “D”. In order to represent the summer months correctly, the factor was recalculated based on the mean monthly domestic hot water demand, which was distributed to daily needs. As a result, the model reflects the average daily needs during the months of June, July and August. The corresponding factor was set as D = 0.19.

Table 19: Selected results from the model validation for the case study “Blaue Heimat” (daily simulation)

	Daily Series	CV RMSE	R^2	ρ	σ_s/ σ_m	U_m	U_v	U_c
1	Multifamily Building A (HMF)	20.74%	0.93	0.96	0.83	0.00%	34.28%	66.00%
2	Multifamily Building A (HMFx)	18.30%	0.93	0.96	0.93	0.00%	6.32%	93.96%
3	Multifamily Building B (existing)	13.65%	0.97	0.98	0.92	5.13%	17.36%	77.77%
4	Multifamily Building C (existing)	20.74%	0.97	0.98	0.94	6.45%	10.78%	83.03%
5	All buildings A-C	11.59%	0.98	0.99	0.91	4.08%	25.77%	70.42%
6	All buildings A-C (HMFx)	11.05%	0.98	0.99	0.94	4.48%	14.27%	81.51%

The simulation with the existing parameter set for new apartment buildings (Table 19, row 1) underestimates peak demand on cold days as can be seen in Figure 29 expressed in a low value of U_v of 34.28%. This difference in the variance can also be seen by the ratio of the standard deviations of the two data sets (σ_s / σ_m), which is significantly lower than the value of the simulation using the new parameters. The value of CV RMSE shows an acceptable agreement with the result just within the limits of the criteria range for building energy performance models (ASHRAE 2002). In comparison, the simulation with the new parameter set (Table 19, row 2) decreases the value of CV RMSE to 18.3%. More importantly, peak demand during colder periods is well described (Figure 29) and is reflected in an increase in the ratio of the standard deviations by 10% as well as a good measure of Theil’s U for the variance of 6.32% and the correlation (93.96%).

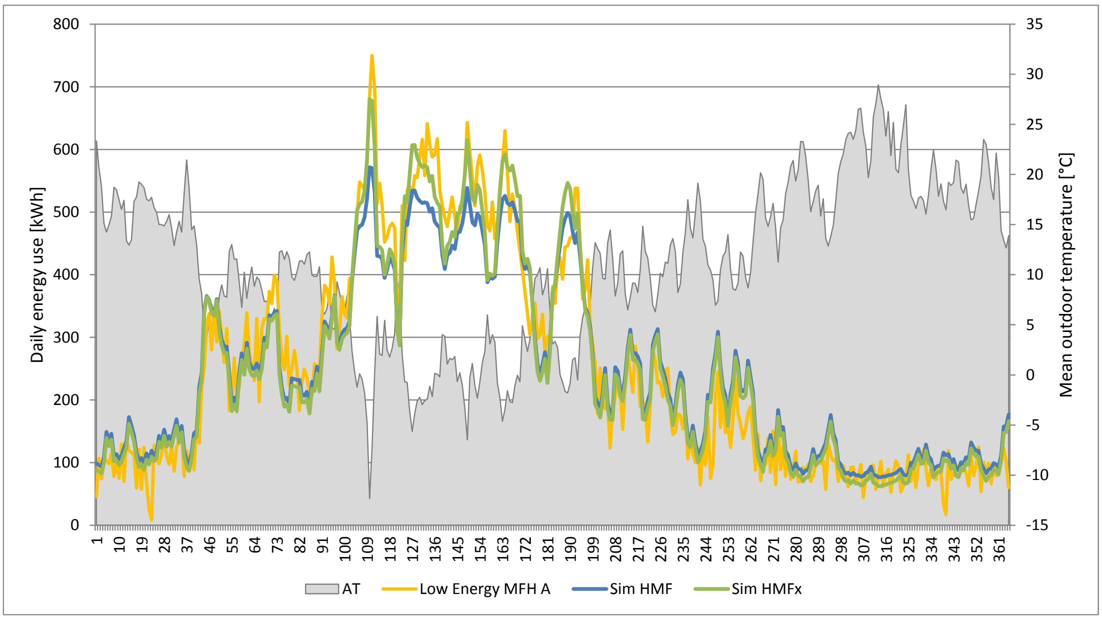

Figure 29: Time series plot of simulation for building A with T_a, Measured, HMF (CV RMSE 20.74%, σs/ σm = 0.83, HMFx (CV RMSE 18.3%, σ_s/ σ_m = 0.93)

Both simulation runs result in the same coefficient of determination (R^2). Yet, as discussed for the selection of the statistic indicators, R^2 should be regarded in connection with other indicators such as the line of equality (Bland and Altman 1986). Figure 30 shows that the trend line (red) fits the line of equality (black) better for the proposed parameter set HMFx (Figure 30a).

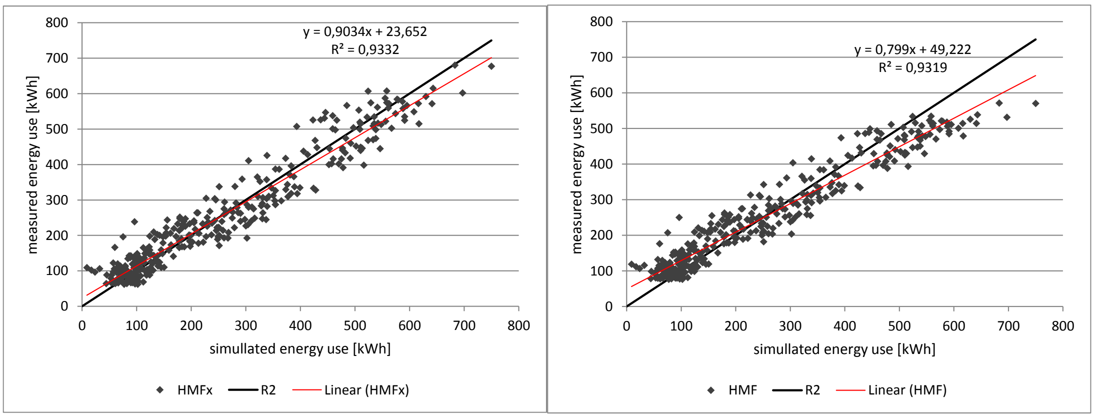

Figure 30a, b: Regression plot of the measured and simulated daily energy use based on the HMFx profile (left) as well as the HMF profile (right)

The simulations of the two existing buildings deliver good results for the variance expressed by the ratio between the two standard deviations (σ_s/σ_m). In the application to the two existing apartment buildings, CV RMSE also delivers a very good result of 13.65% for building B and a good value of 20.74% for building C. For the two cases, Theil's U for the mean value delivers a value 5.13% and 6.45% respectively. Due to the simulation design, these values indicate a slight deviation of the mean values of the measured values and the simulated results. This can be explained by missing values for a total of 8.2 days over the year. The variation of the mean value can be explained by the temperature data, which was maintained for the replaced values but which does not correspond to the relationship on which the model is based. The sum of all buildings (Table 19, row 5 & 6) delivers the best value for CV RMSE (11.59%). The result is only slightly improved by the profile applied for the low energy building. With the newly proposed profile, CV RMSE decreases to 11.05%. Even though the demand of the low energy buildings represents only 22.7% of the total demand, the improvement of the model parameter shows an increase of accuracy for the variance with a level of agreement of 94% for the two standard deviations.

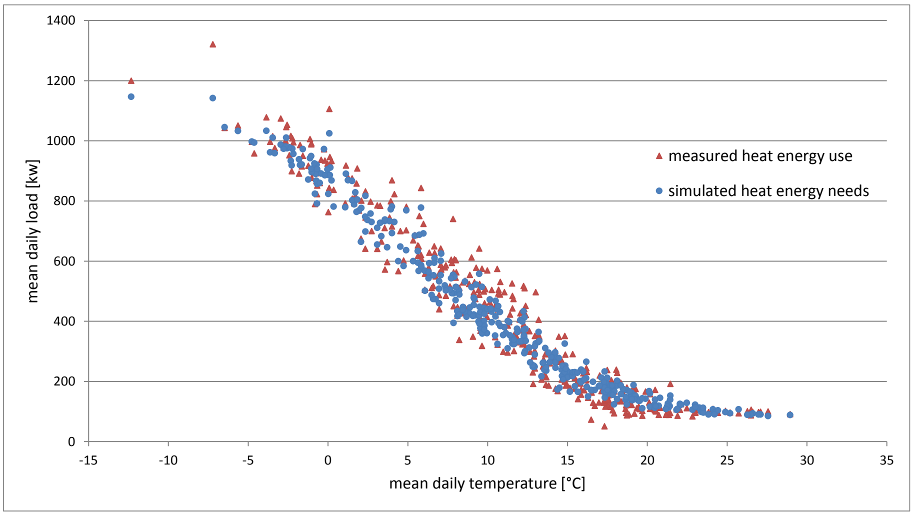

Figure 31: Measured and simulated daily energy use for building C

Based on the data provided for the "Blaue Heimat" case study, the hourly distribution was simulated and compared with the hourly measured values for the two existing residential buildings. Even though the data included a number of storage units attached to the CHP system with a value of 36.27%, the CV RMSE just slightly exceeds the threshold of 30% for the aggregated hourly demand (Table 20). The Bravais-Pearson coefficient shows a high correlation of measured and simulated hourly values. In addition, the variance can be explained well by the model with a low value of 1.28% for U_V. This shows very high suitability for assessing the annual load duration curve, which fundamentally requires a good prediction of the variance to predict peak loads correctly and thus the maximum power requirement.

Table 20: Selected results from the model validation for the case study "Blaue Heimat" (hourly simulation)

	Hourly Series	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Residential building B	41.61%	0.72	0.85	0.89	0.00%	4.10%	95.91%
2	Residential building C	46.67%	0.65	0.81	0.89	0.00%	3.22%	96.79%
3	Aggregated buildings	36.27%	0.76	0.87	0.94	0.00%	1.28%	98.73%
4	Annual load duration curve	7.72%	0.99	1.00	0.00	0.00%	28.37%	71.65%

In this case study, the annual load duration curve is represented with a CV RMSE of 7.72% and shows a perfect correlation between simulated and measured values. While the hourly application for individual buildings shows substantial errors (CV RSME). As in all applications discussed here, the model was not adjusted except for the adaptation of the total amount of domestic hot water.

Table 21: Selected results from the model validation for the case study „Blaue Heimat", comparing indicators at monthly, daily and hourly time scale

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Multifamily Building A	9.35%	18.30%	-	0.91	0.96	-	0.91	0.95	-
2	Multifamily Building B	8.88%	13.65%	41.61%	0.91	0.98	0.85	0.90	0.92	0.89
3	Multifamily Building C	14.09%	20.74%	46.67%	0.91	0.98	0.81	0.93	0.94	0.89
4	All buildings A-C	7.36%	11.05%	36.27%	0.91	0.99	0.87	0.92	0.94	0.94

To investigate dependency on the temporal resolution in connection to the already discussed spatial resolution, the simulation results and measured values were aggregated at monthly resolution. Table 21 shows the results of the model validation for CV RMSE, the Bravais-Pearson coefficient (ρ) as well as the variance expressed by the ratio of the standard deviation of the simulated and measured time series (σ_s/σ_m). The value of CV RMSE increases notably with the passage from daily to hourly resolution. A possible reason might be seen in the inclusion of three 1000 l storage tanks of the central CHP system as well as smaller storage (375 l) between the two connected non-renovated buildings and each heat meter. Despite this specific layout and the relatively small size, the hourly value is close to an acceptable error with 36.27% for the aggregation of buildings B and C. The daily and monthly simulation shows a very good fit with a low error of 7.37% at monthly scale. On the other hand, the correlation coefficient and the variance deliver robust results with no change of the variance between hourly and daily simulations and a slight decrease for the correlation, which remains on a high level of 87%. The case study further provided data for low energy buildings and existing buildings in the same location with the same monitoring period. Figure 32 shows the correlation of the space heating energy needs with ambient temperature in the upper row and the correlation with solar radiation in the lower row. The left hand sample refers to the building section constructed in low energy standard. The column on the right side refer to one of the existing buildings. As the scale of the axis was maintained Figure 32 also depicts the much better energy performance of the refurbishment resulting in a shallower energy signature (left column).

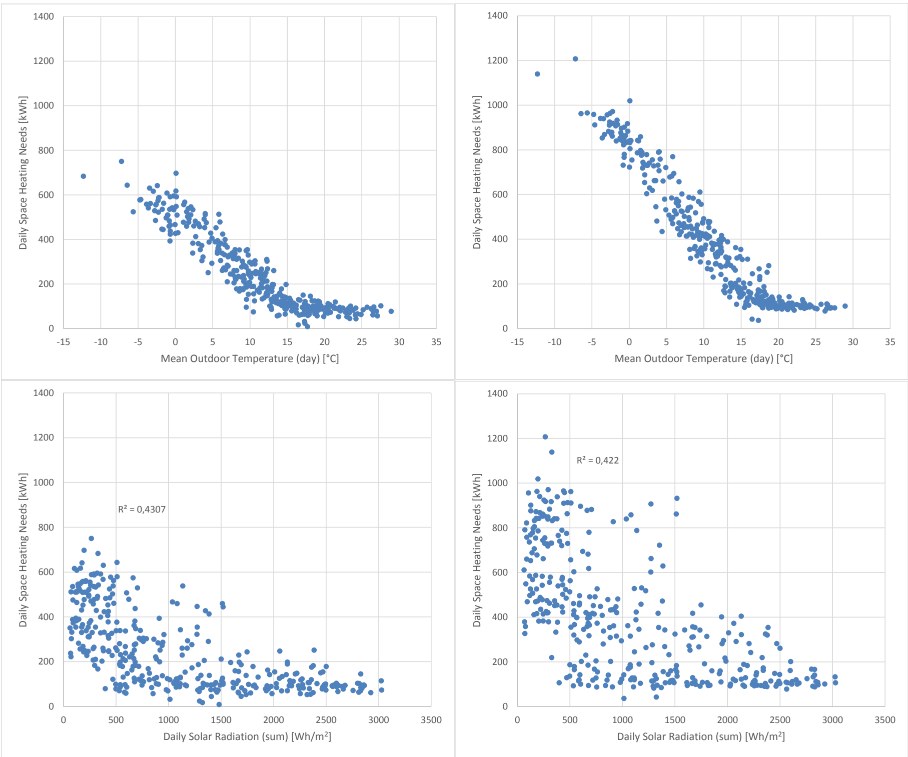

Figure 32: Correlation of space heating energy needs with ambient temperature (top row) and solar radiation (bottom row) for a low energy and an existing building, "Blaue Heimat" case study

For all cases, the scatter plot shows a high coefficient of determination (R^2) for the ambient temperature with a distinct nearly linear form in the heating period. For solar radiation, a relatively weak link is shown by a coefficient of determination below 0.5. The correlation between heating needs and solar radiation does not significantly increase for the low energy building.

5.1.3 Rintheimer Feld

In the "Rintheimer Feld" case study individual apartments were monitored with heat meters. This case study, therefore, lends itself to investigating the effect of aggregation and testing the limiting scale for the application of an energy signature approach. This is of particular interest as the model was initially intended for large scale building stock, of hundreds or thousands of users.

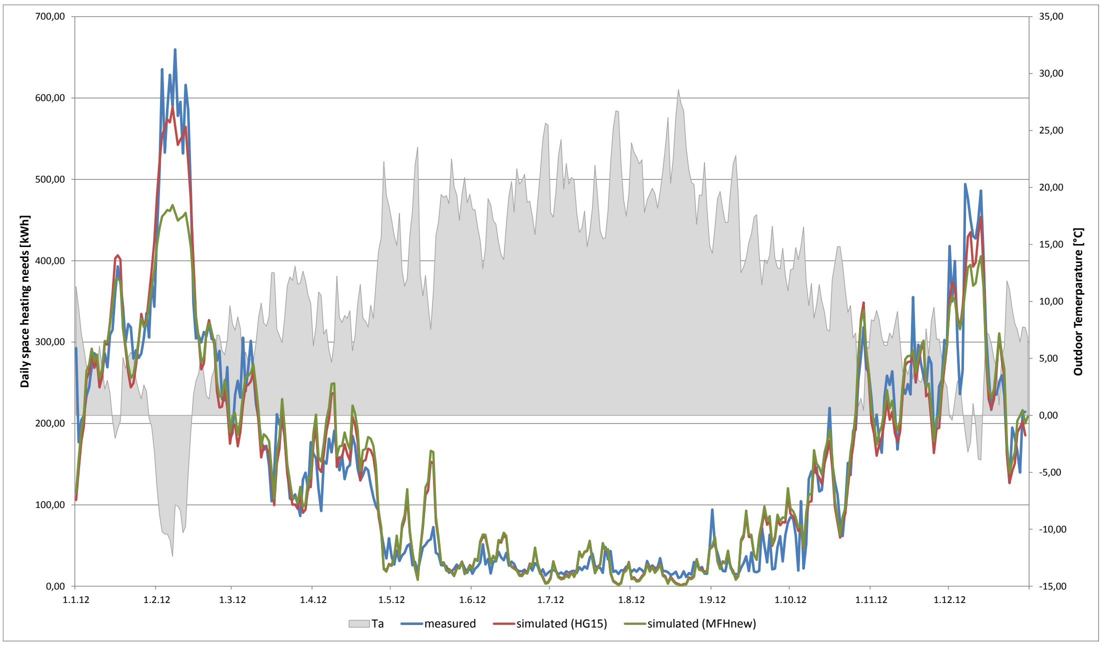

Figure 33: Measured and simulated daily space heating needs with existing ("HMF") and proposed parameter set ("HMFx"), building 2

The main results of the model application to simulate the heating energy needs for the demonstration buildings are summarised in Table 22 and Table 23, the time series is displayed in Figure 33. For the total demand, the individual residential units were aggregated. The demand curve, therefore, provides heating needs without internal distribution losses.

Table 22: Selected results from the model validation for the case study "Rintheimer Feld" for a complete apartment building (daily resolution)

	Daily Series	CV RMSE	R^2	ρ	σ_s/ σ_m	U_m	U_v	U_c
1	Multifamily Building (complete)	26.11%	0.93	0.96	0.88	0.00%	18.16%	82.12%
2	Multifamily Building (complete, NEH)	20.27%	0.95	0.97	0.96	0.00%	4.17%	96.10%

The simulation of all buildings shows a good match of simulated and measured values. This is especially the case when the model is applied with the newly proposed parameter set HMFx (Table 22, row 2). The variance is well represented with a result of U_v, slightly above four percent. In addition, the correlation shows a very good result of U_c = 96.1%. The error CV RMSE shows a good value of 20.27%. For the existing parameter set the error is 6.5% higher, the old parameter set fails to represent the peak load. U_v reaches a value of 18.16%, the ratio of the two standard deviations is 0.88 compared to 0.96 for the HMFx parameter set. The difference in the standard deviations with the existing parameters results from an underestimation of the peak for very cold days, which occur mainly in February as shown in Figure 33. While both model runs deliver an acceptable error, the results of the old parameter set would not be suitable to estimate the heating power in, for example, district heating systems, for mean daily temperatures below -5°C (Figure 34). In its original design, the model does not predict the peak correctly. While the new parameter set can predict energy use at low temperatures, it should be noted that such low mean daily temperatures were a rare occurrence in the near past.

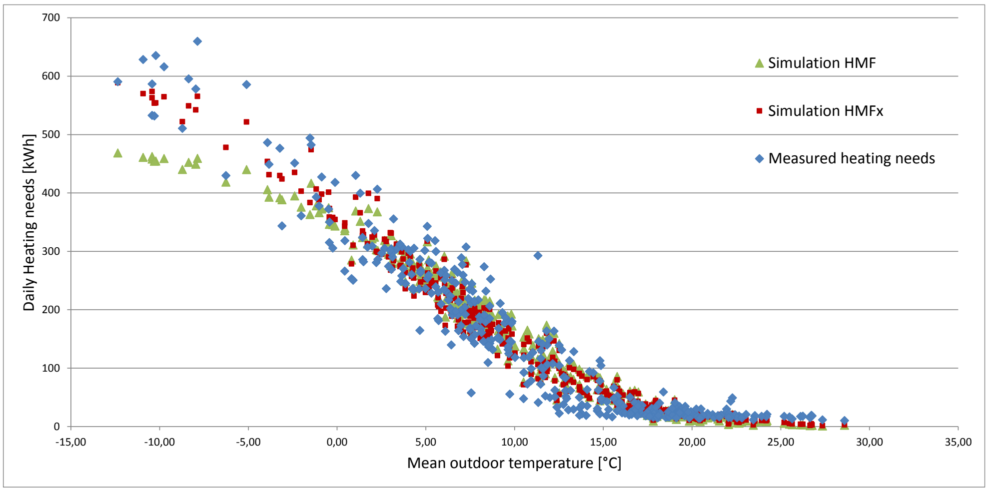

Figure 34: Energy signature for the daily heating needs of all apartments in the "Rintheimer Feld", measured values (blue) are compared to simulation (HMF, green triangles; HMFx, red squares)

In order to investigate the relevance of scale in the data-driven energy performance simulation, the individual units' space heating needs were simulated. The units were aggregated in a random order without reference to the position within the building (i.e. storey or staircase). Table 23 shows the simulation for one, five, ten, fifteen, twenty and thirty units. As could be expected, the simulation of an individual unit involves a high relative error of 143.08% and shows a low coefficient of determination of 54%. The standard deviation of the simulated sample is less than half the value of the measurement. Theil's U again shows the limits of correctly predicting the variance and correlation for a single unit.

Table 23: Selected results from the model validation for the case study „Rintheimer Feld", random aggregation of individual apartments (daily resolution)

	Daily Series	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Multifamily Building 1 unit	143.08%	0.54	0.73	0.42	0.00%	59.90%	40.38%
2	Multifamily Building 5 units	44.56%	0.73	0.85	0.98	0.00%	0.16%	100.12%
3	Multifamily Building 10 units	39.37%	0.86	0.92	0.81	0.00%	23.71%	76.57%
4	Multifamily Building 15 units	27.39%	0.93	0.96	0.85	0.00%	25.90%	74.37%
5	Multifamily Building 20 units	23.66%	0.94	0.97	0.87	0.00%	24.97%	75.31%
6	Multifamily Building 30 units	23.60%	0.95	0.97	0.87	0.00%	27.32%	72.96%

The results for the aggregated simulation in Table 23 show, however, that the error is decreasing with each increase in the scale until the heating needs of the complete building with 30 units are simulated with an error of 23.6%. The same effect can be seen for the other indicators as the correlation increases as well as the coefficient of determination. In the applied tests, a less stringent development of the indicators for the variance can be seen. This, again, highlights the need to use a set of indicators to validate the modelling results in comparison to the measurements. For example, for the five units (Table 23, row 2) Theil's U delivers very good results, yet the relative error (CV RMSE) and the coefficient of determination clearly show the limits of the simulation at such a low scale. Figure 35 shows the measured and simulated values for randomly selected apartments. First a single apartment (top left) is selected which shows a low level of correlation. Samples of five, ten and thirty apartments show increasing correlations. As discussed in section 4.2 in addition to the regression function the line of equality (i.e. x = y) is provided to put the correlation into context. An improvement of the results with increasing scale can also be seen for the coefficient of determination, which increases with each additional unit.

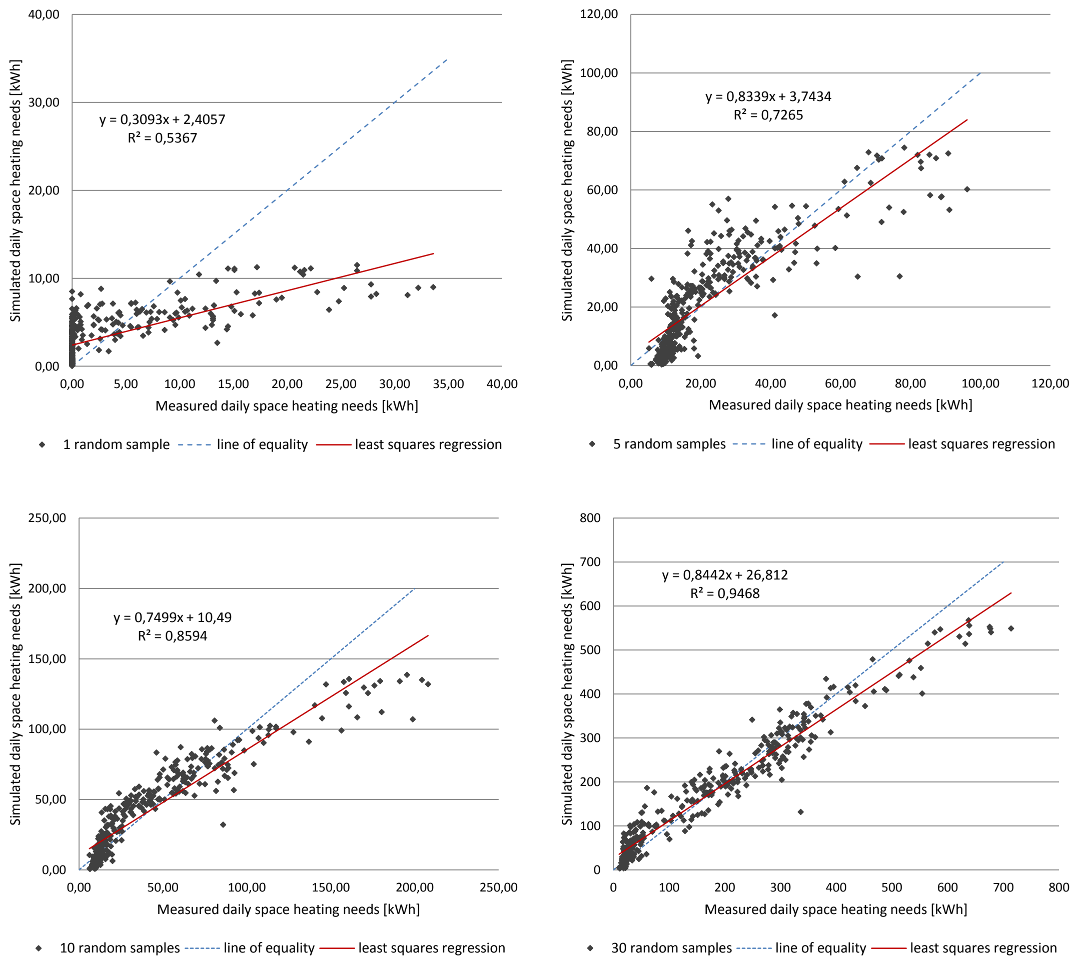

Figure 35: Regression analysis of simulated against measured daily space heating needs for random samples of one, five, ten and thirty apartments (top left to bottom right) with least square regression function and line of equality

When applied to the case study, this shows that from a random sample of fifteen apartments, the coefficient of determination (R^2) starts to stabilise above 90% (Figure 36). Below ten units the results become more volatile, as some units are better represented than others are.

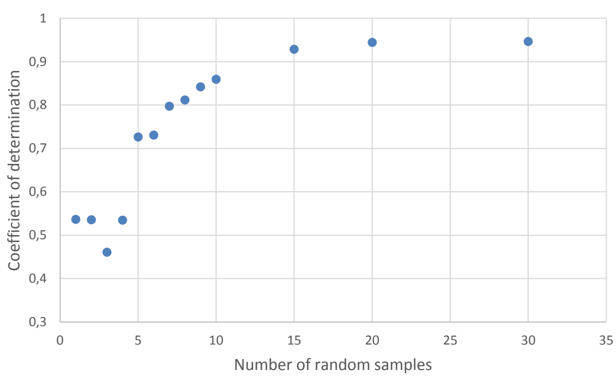

Figure 36: Coefficient of determination (R^2) in dependence of the size of a random sample

Table 24 provides the complete set of values for the coefficient of determination in addition to the Bravais-Pearson Correlation coefficient at the different aggregation levels.

Table 24: Coefficient of determination (R^2) and Bravais-Pearson Correlation Coefficient (ρ) in dependence on the sample size (random sample) for the simulation

sample size	1	2	3	4	5	6	7	8	9	10	15	20	30
R^2	0.54	0.54	0.46	0.53	0.73	0.73	0.80	0.81	0.84	0.86	0.93	0.94	0.95
Ρ	0.73	0.73	0.68	0.73	0.85	0.86	0.89	0.90	0.92	0.93	0.96	0.97	0.97

For the "Rintheimer Feld" case study, the residuals were also considered which are summed up in the Root Mean Square Error (RMSE). The distribution of the residuals (Figure 37) shows an increasing RMSE for temperatures above 15°C. This is both plausible and expected as the single variant model is mainly suited to predict the temperature dependant part of the load even though the heating limit temperature was observed to be higher than 15°C (Jank 2013). Prediction errors are largely reduced with decreasing temperatures.

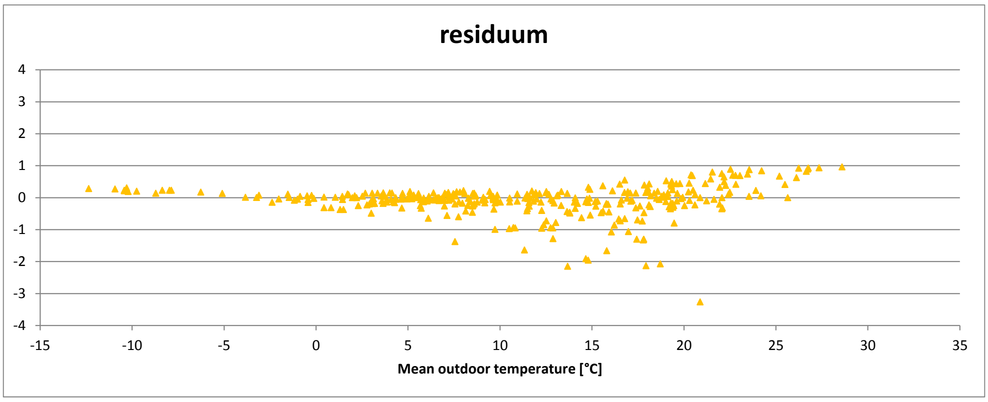

Figure 37: Residuum values for the simulation of two complete buildings for the case study of "Rintheimer Feld"

The comparison to the daily solar radiation showed no correlation to the residuum i.e. the error of the simulated values. Again, the correlation of the daily energy needs with the solar radiation was tested (Figure 38). As in the case study "Blaue Heimat" no distinct correlation could be found. The measured solar radiation has little explanatory power for the daily space heating needs compared to the ambient temperature for the case study data.

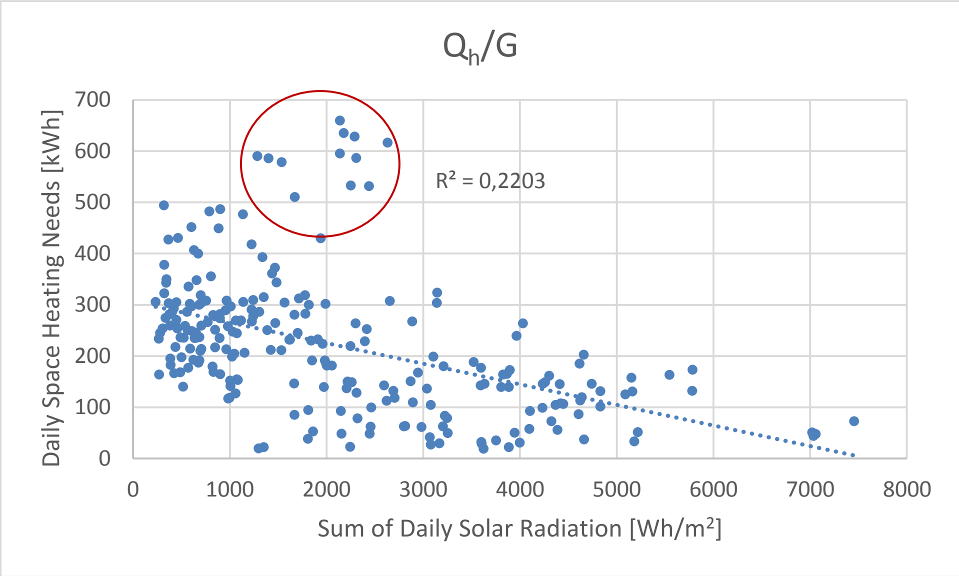

Figure 38: Test for correlation between daily heating needs and the sum of daily solar radiation, "Rintheimer Feld"

For the year 2012 depicted in Figure 38 a small cluster of values can be identified around a value of 2000 Wh/m^2 and day correlated to high energy needs (red circle). This group of values relates to the very cold days in February 2012, which had temperatures around -10 °C but due to clear sky a relatively high solar radiation.

5.1.4 Single-dwelling residential buildings

On the one hand, the case study of single-dwelling residential units enabled the investigation of a new set of parameters for individual buildings. On the other hand, it provided a test case to aggregate individual users to a larger sample, as was done in the "Rintheimer Feld" case study. This latter aspect specifically aims at investigating the limits of significance for the chosen modelling approach. The single dwelling residential buildings were simulated individually (Table 25). In addition, a random aggregation of the buildings was done adding an additional building to the sample in each consequent step (Table 26). Overall, the model predicted heating needs relatively well given that, for this case study, the scale was decreased to individual buildings. The errors moved in a span between 24.10% up to 44.12% for individual buildings. However, even at a small scale, the aggregation of five buildings resulted in a good value for the CV RSME of 19.14% for all buildings. In three of five cases, the variance was well described and the prediction for the whole sample showed a very good result of less than one percent for U_v. For all buildings, the correlation coefficient delivered high values. This, in combination with the high coefficient of determination, underlines that the model is capable of explaining and correctly predicting the trend between 83% and 96% of the measurements for single buildings and 95% of the aggregated buildings.

Table 25: Selected results from the model validation for the single-family buildings

	Daily Series	CV RMSE	R^2	ρ	σ_s / σ_m	U_m	U_v	U_c
1	SFH A	34.81%	0.87	0.93	1.10	0.00%	6.73%	93.54%
2	SFH B	25.22%	0.92	0.96	1.02	0.00%	0.61%	99.67%
3	SFH C	24.10%	0.96	0.98	0.85	0.00%	37.98%	62.29%
4	SFH D	30.22%	0.88	0.94	1.00	0.00%	0.00%	100.27%
5	SFH G	44.12%	0.83	0.91	0.78	0.00%	25.04%	75.24%
6	SFH A. C. G. D. B	19.14%	0.95	0.97	0.98	0.00%	0.83%	99.44%

In the comparison of individual buildings, the simulation of building G delivered the least convincing results for an individual building, with a CV RMSE of 44.12% and an agreement of 78% for the standard deviation of the measured and simulated time series. This can be seen by the large spread of measured data in the energy signature when compared to the slender curve of simulated data (Figure 39a). On the other hand, the overall variance of total energy use for all five buildings is well represented by the model (Figure 39b) with a nearly similar standard deviation for measured and simulated heating needs (U_v = 0,83%).

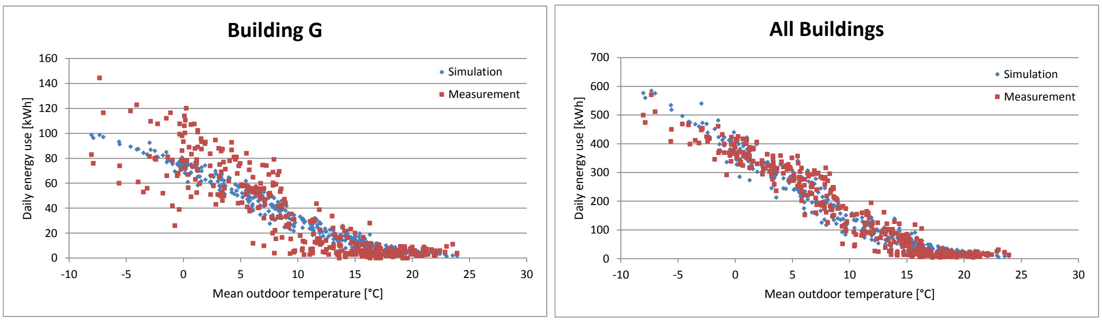

Figure 39a, b: Energy signature of building G and the total energy for all buildings (depicted with different scale)

Table 26: Selected results from the model validation for the random aggregation of individual single family buildings

	Daily Series	CV RMSE	R^2	ρ	σ_s / σ_m	U_m	U_v	U_c
1	SFH A	34.81%	0.87	0.93	1.10	0.00%	6.73%	93.54%
2	SFH A. C	22.67%	0.94	0.93	1.01	0.00%	0.09%	100.18%
3	SFH A. C. G	21.77%	0.95	0.97	0.95	0.00%	4.06%	96.22%
4	SFH A. C. G. D	34.81%	0.95	0.97	0.97	0.00%	2.37%	97.91%
5	SFH A. C. G. D. B	19.14%	0.95	0.97	0.98	0.00%	0.83%	99.44%

The individual residential buildings were included here to test the aggregation of similar individual uses of the same kind. Even though the number of units is too small to see a saturation effect, which in the "Rintheimer Feld" case study, could be observed in samples larger than 20 units, the small sample already shows increasing accuracy with an increasing number of users. As a random order was chosen, the trend is not linear: this was also true for the "Rintheimer Feld" case when using samples smaller than five units. As shown by the results in Table 26 aggregated results for buildings A and C as well as A, C and G perform better than the individual buildings' results (Table 25). This supports the argument that the individual operation schedules and usage of the buildings evens out when aggregated.

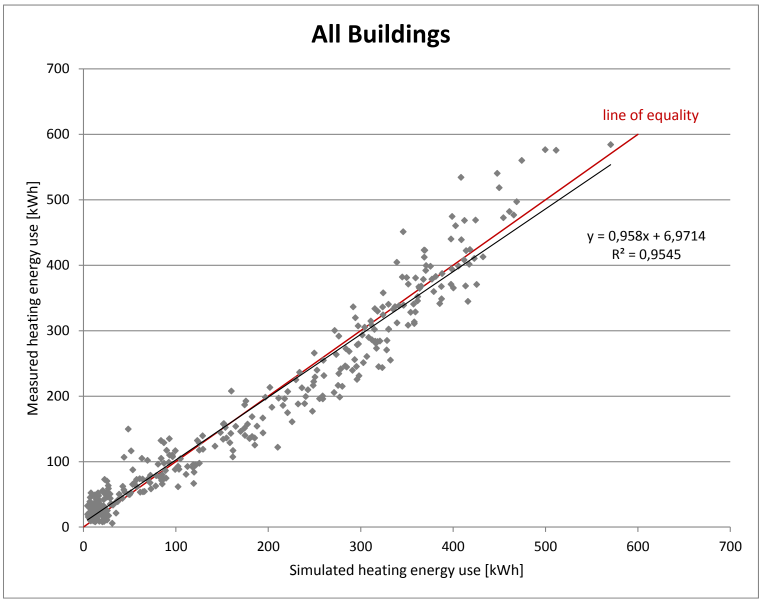

Figure 40: Scatter plot oft eh measured and simulated daily energy needs for all single family buildings with the trend line (black) and the line of equality (x = y; red)

Consequently, the aggregation of all buildings performs best when compared to all other combinations of smaller sample sizes (Figure 40). For single-dwelling buildings, the monthly and daily temporal resolutions are compared in Table 27. Nearly all errors remain in the established limits, except for building A with 26%. For the aggregated five buildings, the monthly error is again substantially smaller, at 12%. As seen in the other case studies, variance and correlation are less sensitive to the temporal scale and deliver comparable results for both simulations. A decrease for the Bravais-Pearson coefficient can be seen which can be explained by the much smaller sample size of the monthly simulations.

Table 27: Selected results from the model validation for the random aggregation of individual single family buildings comparing indicators at monthly and daily time scale

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	SFH A	26.40%	34.81%	-	0.88	0.93	-	1.09	1.10	-
2	SFH B	11.74%	25.22%	-	0.91	0.96	-	1.02	1.02	-
3	SFH C	15.30%	24.10%	-	0.91	0.98	-	0.86	0.85	-
4	SFH D	13.82%	30.22%	-	0.90	0.94	-	1.00	1.00	-
5	SFH G	20.55%	44.12%	-	0.91	0.91	-	0.81	0.78	-
6	SFH A. C. G. D. B	11.98%	19.14%	-	0.91	0.97	-	0.96	0.98	-

5.1.5 Bad Aibling

In the case study of Bad Aibling especially the non-residential uses were of interest for the model evaluation. The provided data allowed for tests based on hotels, offices as well as school buildings and included some residential buildings located in the north loop of the district heating network. In order to investigate aggregating effects the analysis was conducted based on data of the years 2012 and 2013, which included the most complete data sets. The simulation was carried out for individual uses aggregated by floor space and is discussed individually. Finally the western and eastern part of the network were aggregated which each included different uses.

In the western part of the north loop, the dominant user is the hotel with more than 3000 square meter of net surface. While this surface also includes the restaurant and other specific uses of the hotel the space heating needs were simulated using a profile specified for hotels (GBH) (BDEW, VKU et al. 2014). The selected profile includes specific weekday factors, which distinguish between the individual weekdays. However, the results for the simulation (Table 28, row 5) show little improvement when compared to the simulation based on the profile used for residential buildings (Table 28, row 6 and 7). The latter do not use weekday factors. The Bravais-Pearson Correlation Coefficient is identical for all cases as is the coefficient of determination (R^2) and the ratio between the variance of the simulated and measured values (Table 28). Only a slight difference is shown for the CV RMSE, which especially for the Hotel (GBH) and the residential (HMF) profile is marginal with a value of 0.01%, the new profile tested (HMFx) shows a slightly higher error 0.45% above that of the hotel profile.

Table 28: Selected results from the model validation for the North-West loop of the network in Bad Aibling

	Daily Series	Profile	CV RMSE	R^2	ρ	σ_s / σ_m	U_m	U_v	U_c
1	Office Buildings	Kat 7	44.75%	0.69	0.83	0.89	0.00%	4.07%	96.21%
2	Hotels (580 sqm)	GBH	49.14%	0.76	0.87	0.74	0.00%	26.44%	73.84%
3	Hotels (1160 sqm)	GBH	27.44%	0.87	0.93	0.93	0.00%	4.03%	96.25%
4	Hotels (2030 sqm)	GBH	22.42%	0.91	0.95	0.95	0.00%	2.31%	97.96%
5	All Hotels (3230 sqm)	GBH	19.98%	0.92	0.96	0.99	0.00%	0.13%	100.14%
6	All Hotels	HMFx	20.45%	0.92	0.96	0.99	0.00%	0.08%	100.19%
7	All Hotels	HMF	20.01%	0.92	0.96	0.99	0.00%	0.09%	100.18%
8	All buildings. North West Loop	mixed	22.73%	0.90	0.95	0.99	0.00%	0.16%	100.11%

As the results indicate the daily energy use of all hotels has a firm correlation to the mean daily outdoor temperature with little significance of weekdays (Figure 41).

In contrast to the aggregated space heating needs for the hotels, the single office building shows a distinct error (CV RMSE) of 44.75%. Also the correlation delivers poor results of 69% with relatively well depiction of the spread.

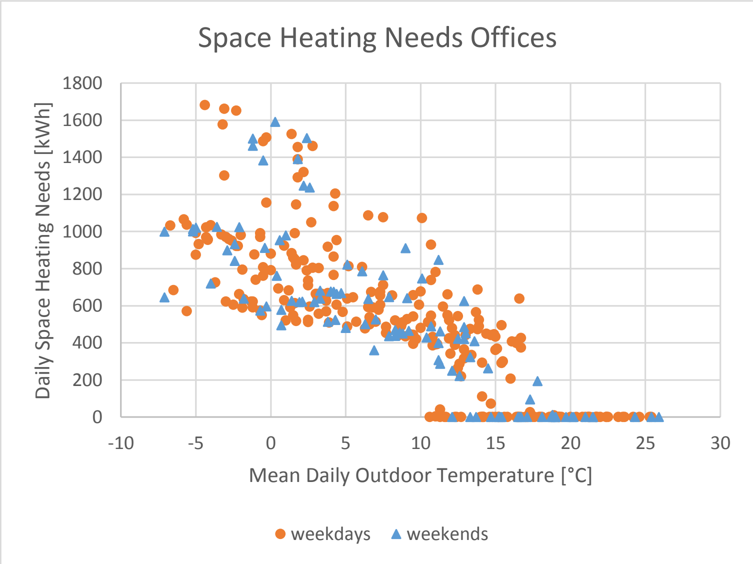

Figure 41: Correlation between daily space heating needs and mean daily outdoor temperature for the office building for weekdays (orange circles) and weekends (blue triangle)

The significant error in the simulation of the space heating needs for the single office building can also be shown in the correlation between mean outdoor temperature and the daily heating needs. Here a distinct cluster of measurements above a mean daily energy need of 1200 kWh lies outside the cloud of points which is relatively well predicted. For specific uses such patterns can indicate specific days e.g. weekdays that show a higher or lower value and must thus be assessed separately or represented by weekday factors (Mazzarella, Liziero et al. 2009). Here all measurements above the value fall in the period between 14th Mars and 8th April with no significant correlation to weekdays (Figure 41) and the mean outdoor temperature which varies between -4 °C and +4 °C and is +0.6 °C on average. In this case the only possible explanation is to a specific user behavior or malfunction of the operation schedule. On the other hand the remaining values show a relatively compact point cloud with again little relevance of the day of the week.

The aggregation across different uses in the western part of the north loop shows an equalizing effect with increasing numbers of users. Here the relatively large error from office buildings is merged with the good prediction for hotel buildings. The simulation for all buildings results in a good value of 22.73% (CV RMSE) with a very good depiction of the variation and the correlation. The trend line for the comparison between simulated and measured values (Figure 42) lies close to the line of equality.

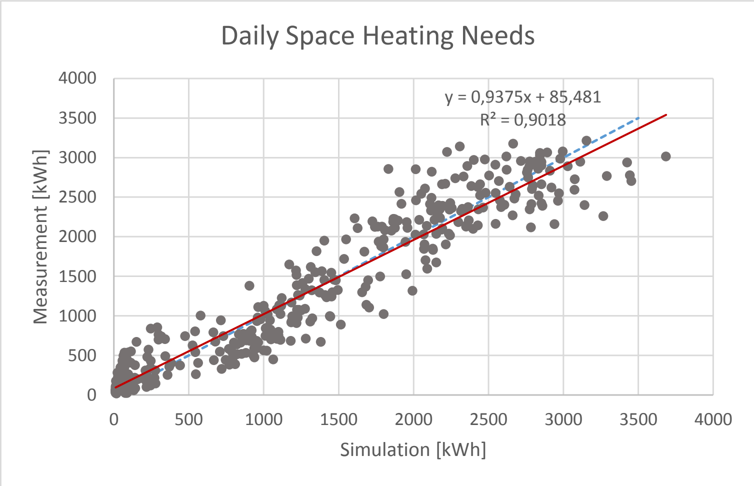

Figure 42: Correlation of the measured and simulated daily space heating needs for the all buildings in the western section of the district heating loop with trend line (red) and line of equality (dotted blue)

In the North Eastern part of the low temperature network the space heating demand is dominated by the school buildings, in addition the residential block was included in the simulation. Table 29 shows the main results from the statistical analysis of the simulation. The residential building cluster was simulated using the existing parameter set as well as the proposed parameters for multifamily buildings. In this case both deliver comparable results with a CV RMSE of 24% and 27% respectively.

Table 29: Selected results from the model validation for the Northeast loop of the network in Bad Aibling

	Daily Series	Profil	CV RMSE	R^2	P	σ_s / σ_m	U_m	U_v	U_c
1	Residential (2250 sqm)	HMF	24.34%	0.90	0.94	0.97	0.45%	1.07%	98.75%
2	Residential (2250 sqm)	NEH	26.87%	0.88	0.94	1.04	0.38%	1.10%	98.79%
3	School & Boarding (2150 sqm)	NEH	31.03%	0.86	0.93	0.92	0.01%	4.27%	96.00%
4	School (8090 sqm /partial)	NEH	29.41%	0.91	0.95	0.85	0.06%	22.62%	77.59%
5	All School buildings	NEH	26.08%	0.91	0.95	0.91	0.00%	9.46%	90.81%
6	All buildings. North East Loop	NEH	20.01%	0.92	0.96	0.99	0.00%	0.09%	100.18%

The daily space heating needs are generally well represented by both simulations, an important factor not represented in the simulation is the apparent shut down of the heating system until early September in the residential building, which might be due to a planned scheduling of the heating system to avoid unnecessary heating needs during colder summer nights. This goes hand in hand with a local peak at the days in which the heating system is started which might be correlated to heating up the building as before no space heating was supplied. Both effects can be seen in the comparison of the load curves in Figure 43 and contribute a substantial part of the total CV RMSE.

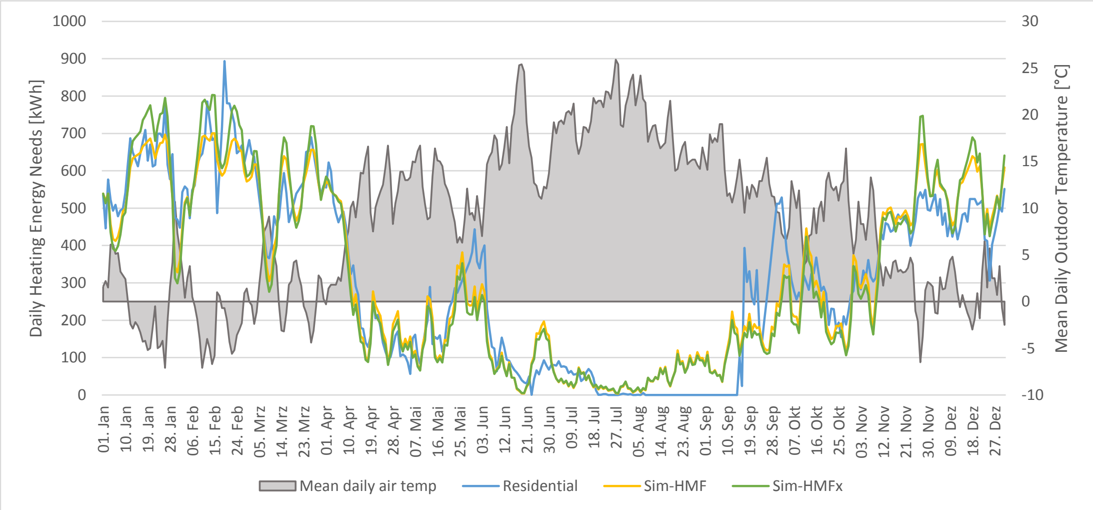

Figure 43: Daily space heating needs in one residential building compared to simulated values using different parameter sets

The two school buildings were simulated using the residential parameter set (Table 29, rows 3 to 5). Even though they represent a specific use the simulation represents the correlation well with values for the Bravais Pearson coefficient of 93% and 95%, the total results in a value of 95%. The variance is well depicted for the total floor space with a value of 91%. The school buildings' energy needs were predicted with an error of 31% and 29% respectively. As for the hotels no correlation to specific weekdays was identified in the correlation analysis. The larger scale of all aggregated buildings delivered good results of an error of 20% for the daily space heating needs. The model can be said to explain 92% of the measurements (R^2), finally also the variance of simulation and measurement coincides resulting in a ratio of 99%.

For the case study furthermore data for the year 2012 was provided which also in Bavaria included a series of very cold days. The proposed profile to better represent the peak loads during cold periods was applied to the case study as well. Results of both years are compared in Table 30 for residential uses and in Table 31 for the hotels.

Table 30: Comparison of Simulation results for residential uses for the years 2012 and 2013

	Daily Series	Profile	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Residential (2250 sqm) 2012	HMF	24.36%	0.92	0.96	0.89	0.00%	14.68%	85.81%
2	Residential (2250 sqm) 2012	HMFx	27.31%	0.89	0.94	0.98	0.00%	0.26%	100.29%
3	Residential (2250 sqm) 2013	HMF	24.34%	0.90	0.94	0.97	0.45%	1.07%	98.75%
4	Residential (2250 sqm) 2013	HMFx	26.87%	0.88	0.94	1.04	0.38%	1.10%	98.79%

While the variance is in all cases better represented by the newly proposed profile only the simulation for non-domestic uses delivers better results in both years. For residential uses, the simulation results indicate an increase of the CV RSME of 3% for 2012 and 2.5% for 2013, the deviation of the variance is improved by 8% in 2012 but delivers comparable deviations for simulations in 2013.

Table 31: Comparison of simulation results for non-residential uses for the years 2012 and 2013

	Daily Series	Profile	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	Hotels 2012	HMF	30.41%	0.91	0.95	0.81	0.00%	32.09%	67.85%
2	Hotels 2012	HMFx	26.67%	0.92	0.95	0.90	0.00%	12.11%	87.68%
3	Hotels 2012	GBH	30.61%	0.91	0.95	0.81	0.00%	30.81%	69.28%
4	Hotels 2013	HMF	24.10%	0.91	0.95	0.92	0.00%	6.96%	93.31%
5	Hotels 2013	HMFx	23.66%	0.91	0.95	0.99	0.00%	0.21%	100.06%
6	Hotels 2013	GBH	24.45%	0.90	0.95	0.92	0.00%	6.46%	93.81%

The good representation of the peak demand in the year 2012 by the HMFx profile is shown in Figure 44. The variance for the aggregated hotel use is improved by 9% in 2012 and by 7% in 2013. In the former, a good value of 90% is reached for the ratio between the two standard deviations, for the latter an excellent value of 99% of agreement for the variation is reached.

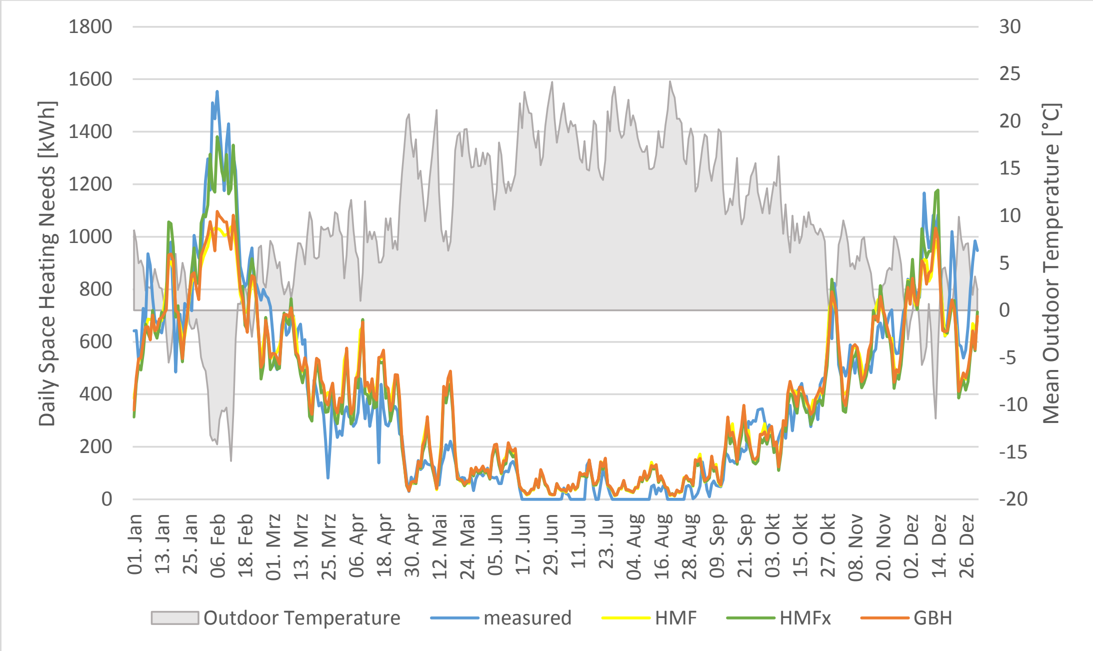

Figure 44: Measured and simulated daily heating needs for aggregated hotel use for the year 2012, "Bad Aibling"

Finally, the simulation was applied to an hourly time resolution for the aggregated hotel buildings as well as the residential building cluster. Especially the hotels were relatively well depicted as shown in Table 32. The parameter sets HMF and HMFx only slightly surpass the threshold of 30% for the hourly simulation. With a relation of the standard deviations of 97%, the HMF profile shows good representation of the spread of the sample.

Table 32: Selected results from the model validation for the case study "Bad Aibling" (hourly simulation)

	Hourly Series	Profil	CV RMSE	R^2	ρ	σ_s/ σ_m	U_m	U_v	U_c
1	All Hotels	HMF	32.32%	0.84	0.91	0.97	0.00%	0.63%	99.38%
2	All Hotels	GBH	37.86%	0.78	0.88	0.95	0.00%	1.25%	98.76%
3	All Hotels	HMFx	34.07%	0.82	0.90	0.94	0.00%	2.20%	97.80%
4	Residential	HMF	42.54%	0.77	0.88	0.89	0.00%	5.42%	94.65%
5	Residential	HMFx	47.36%	0.73	0.86	0.99	0.00%	0.01%	100.04%
4	Annual load duration curve (hotel)	HMF	8.24%	0.99	0.99	0.97	0.01%	9.63%	90.37%

The relatively large error for the residential simulations was carried through to the hourly simulation resulting in a CV RMSE of 43% (HMF) and 47% (HMFx). As in the other applications, the latter depicts the variation extremely well with a value of

0.01% for U_v. Sorting into an annual load duration curve delivers small errors of 8.24% and nearly full compliance for the correlation and the variation.

5.1.6 Commercial Zone District Heating System

Simulations were carried out for both years using the share of light industrial (GKO) and office use (GMK) that referred to the total energy use (Table 33, rows 1 & 3). The daily error showed good results of 19% for 2013 and 22.25% for 2014 at a daily resolution. Based on the default values the coefficient of determination delivers good results of 0.94 for 2013 and 0.92 for the year 2014. With values above 97%, the Bravais-Pearson coefficient of determination shows a close correlation of measurement and simulation. The good results are also reflected in the results of Theil's U.

Table 33: Selected results from the application case to a mixed use district heating system for daily energy use

	Daily Series	Profile	CV RMSE	R^2	ρ	σ_s / σ_m	U_m	U_v	U_c
1	2013	GKO	19.02%	0.94	0.97	0.98	0.00%	0.68%	99.59%
2	2013 MOD	GKO	14.97%	0.97	0.98	0.97	0.16%	2.30%	97.81%
3	2014	GKO	22.25%	0.92	0.97	1.01	0.00%	0.06%	100.21%
4	2014 MOD	GKO	19.24%	0.94	0.97	0.97	0.19%	1.12%	98.97%

To test the application, a first adjustment was made to the weekday factors. The distribution of daily energy use per day of the week was calculated and compared to the default weekday factors based on the energy signature model (Table 34). The comparison showed that the original simulation overestimated energy use on the weekends. According to the measured data of the year 2013, the weekday factors of the simulation were adjusted. In this case, the calculated weekday factors for the specific site were used. The simulation results at a daily resolution were improved by 4% for 2013 and 3% for 2014 (Table 33, rows 2 & 4). The coefficient of determination slightly increased for both years by 3% and 3% respectively.

Table 34: Weekday factors calculated for the measured daily energy use 2013 and 2014 and profile values

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
2013	1,128	1,093	1,062	1,067	0,998	0,772	0,881
2014	1,108	1,082	1,126	1,020	0,946	0,786	0,931
Simulation	1,061	1,070	0,986	1,005	1,036	0,925	0,917

In a second step, the hourly distribution of the heating needs was simulated using the default hourly load curves to distribute the daily energy use. For the hourly resolution, the application of the default parameter resulted in high relative root mean square errors around 50% (Table 35, rows 1 & 3). The results for the coefficient of determination drop below 0.7 for the year 2014. Still a distinct correlation is indicated by the correlation coefficient as well as a good match of the variance. The latter is confirmed by looking at the annual load duration curve (Table 35, rows 5 & 6). The sorted energy use simulation closely matches the measured data.

Table 35: Selected results from the application case to a mixed use district heating system for hourly energy use

	Hourly Series	Profile	CV RMSE	R^2	ρ	σ_s/σ_m	U_m	U_v	U_c
1	2013 - 1/3 Office. 2/3 Prod	GKO	47.74%	0.71	0.84	0.94	0.00%	1.16%	98.85%
2	2013 MOD f.h - 1/3 Office. 2/3 Prod	GKO	29.33%	0.89	0.94	0.94	0.04%	3.42%	96.55%
3	2014 - 1/3 Office. 2/3 Prod	GBH	53.92%	0.63	0.79	0.96	0.00%	0.49%	99.52%
4	2014 MOD f.h - 1/3 Office. 2/3 Prod	GBH	36.20%	0.82	0.91	0.93	0.05%	2.60%	97.36%
5	JDL 2013 - 1/3 Office. 2/3 Prod	GBH	14.00%	0.98	0.99	0.94	0.00%	13.53%	86.48%
6	JDL 2014 - 1/3 Office. 2/3 Prod	GBH	9.29%	0.99	0.99	0.96	0.00%	16.41%	83.60%

Figure 45 shows the systematic error between measured (blue line) and simulated values (dotted line). Over the course of the year, a relatively constant time delay between measured and simulated peak values of approximately eight hours can be identified. The parameters of the hourly load distribution over the course of a day was modified and the simulation was repeated (orange line).

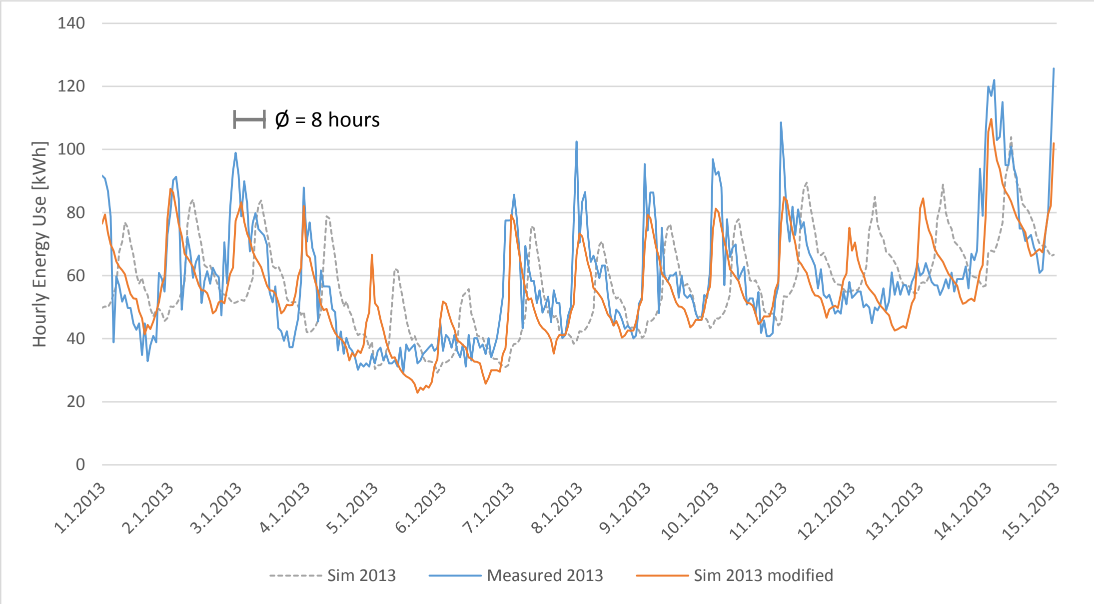

Figure 45: Measured and simulated hourly load curve for the first two weeks of the year 2013, Commercial Zone

By detecting the two described systematic errors in the simulation results for the year 2013 the parameters were changed and the simulation was carried out for 2014 (Table 35, row 3, 4). The CV RMSE for the hourly simulation for the year 2013 improved by 18.4% to 29.33%. The same indicator improved by 17.7% to 36.2% for the year 2014. Even the latter therefore is close to the quality criteria defined for the hourly simulation. The coefficient of determination was improved by 18% and 19% respectively to 89% and 82%. This shows that the simple adaptation largely improved the explanatory power of the model. The variance remained constant for 2013 and decreased slightly by 2% for 2014. With regard to the hourly load profiles two further phenomena, which are not well depicted by the model are secondary peaks on weekdays and flat load profiles on the weekends that typically fall between Friday 17:00 and Sunday 22:00. To improve the model further would require an in-depth load analysis, which would require detailed information on the involved processes and operation schedules, vacation periods, local weather conditions as well as a better understanding of the measurement points on site (Grohmann 2000). Such a proceeding would be a possible application for a given site but is beyond the scope of this thesis as it was judged difficult for the application to urban neighbourhoods.

5.2 Tool specification for combined simulation and monitoring for neighbourhoods

In parallel to the validation of the model results, case studies were used as a basis to discuss a framework to implement data analysis functions for monitoring, as well as simulation. The concept was implemented in a first prototype. Work in this thesis covered the concept definition, simulations for the case study as well as the specification of the OLAP queries. The implementation was done in cooperation with the institute SIANI of the University of Las Palmas.

The application to the case study data showed the robustness of the selected model. A second commonly highlighted feature of data driven models is that, in the application, relatively little expertise is required to run the models. The single variant model thus lends itself to being implemented in a data base system to supply continuous daily or hourly benchmarks after completion of a given urban development project. In this section, a software solution for combined simulation and building monitoring at the scale of urban neighbourhoods is proposed and presented as a prototype. The objective of this application case is to deliver benchmarks with a short delay, so that the results can immediately be compared to information on actual energy use per day. The benchmark consists of the simulated daily energy use based on the described regression model for load prediction. The final objective is to detect malfunctions or ineffective/unnecessary energy use in the building more quickly for the system operator and provide the possibility of a direct feedback for the user. By connecting the simulation with online weather forecasts, the simulation of benchmark values could be effectively transformed into a thermal load prediction for a number of residential units. Here, however, the approach was tested with ex-post monitoring data.

While the concept and functionality of the proposed solution is based on analysis of the monitoring data presented here, the implementation was realised by Octavio Roncal, a student under the supervision of Jose Juan Hernandez and Jose Evora. The OLAP solution is based on the Monet framework developed at the University of Las Palmas (SIANI). An application for the assessment of smart grid simulation data is described in (Evora, Hernandez et al. 2013).

In order to access the data via a graphical analytical interface, the data was transformed into a data warehouse solution and prepared for access via an online analytical processing (OLAP) approach. The OLAP interface will display monitoring data of buildings' thermal needs and, at the same time, provide daily benchmark values.

5.2.1.1 Online Analytical Processing OLAP – general approach

In the family of data warehouse applications for decision support, "OLAP applications are based on multidimensional modelling that intuitively represents data under the metaphor of a cube whose cells correspond to events that occurred in the business domain". (Wrembel and Koncilia 2007).

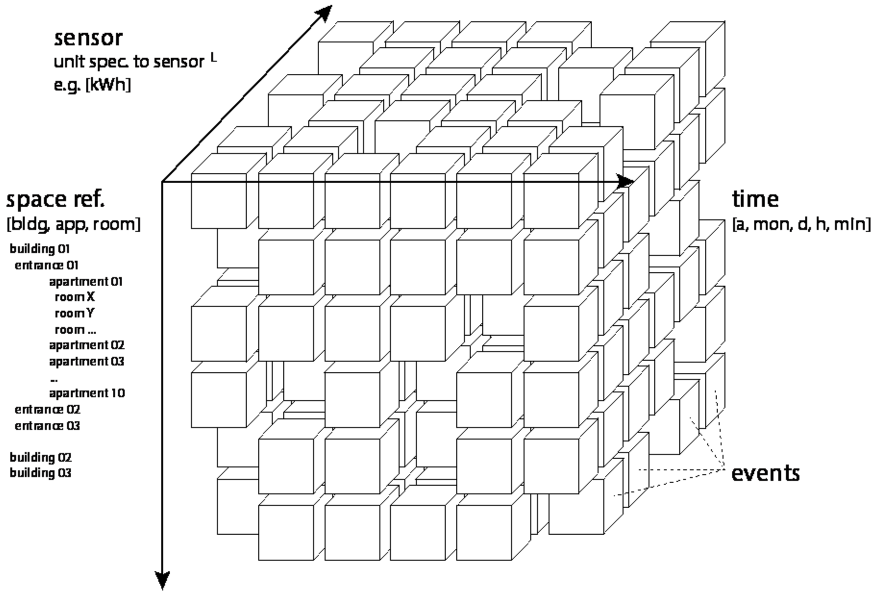

Figure 46: The data cube concept with measurements, dimensions and their hierarchy, own illustration adapted from (Wrembel and Koncilia 2007)

Continuing this metaphor, the edges of the cube represent the dimensions that usually contain further hierarchies. In the case of monitoring data from the Rintheim project, the hierarchy of the spatial dimension can be deduced from the data structured by, for example, building, staircase, apartment and room (see Figure 47). For the OLAP analysis, solutions combine the flexibility of spread sheets for data analysis with robust data storage and fast access for large data sets (Farkisch 2011). The interface allows maintaining a hierarchical structure in the analysis. In addition, OLAP allows for the aggregation, or disaggregation, of different attributes as well as the temporal dimension or linking sensors across the spatial reference. While a tree structure in different relational database formats is easy to navigate (e.g. building or staircase), OLAP can, for example, be used to compare measurements of specific sensors in specific room types across all monitored buildings at different temporal scales. As will be discussed in section 6.3 this is a key requirement for monitoring at the scale of urban neighbourhoods.

5.2.1.2 Implementation of a prototype

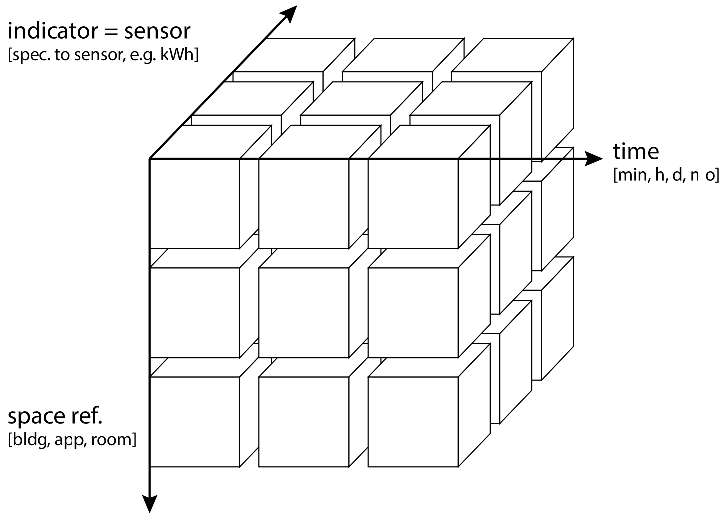

Figure 47 a), b): Dimensions used in the data cubes available for analysis, own illustration

The cubes represent the logic order of quantitative data aligned with descriptive object layers (Gabriel, Gluchowski et al. 2009). The monitoring data (e.g. heat meter in kWh) can thus be analysed according to spatial reference (i.e. building, apartment, room, zone, etc.). It is displayed according to different temporal scales (minutes, hours, days or month). The complete hierarchy of the spatial reference can be adjusted to the monitoring infrastructure of a given installation. The Rintheim case study data for 2012 was integrated into the OLAP solution.

Different concepts are available for displaying a section of the data cube for navigating through the data structure. The operation used for selecting and displaying a certain fraction of the data related to one or two dimensions is referred to as "slicing"; a "slice is a subset of a multi-dimensional array corresponding to a single value for one or more members of the dimensions not in the subset" (OLAP Council 2014). Based on the simplified cube metaphor, Figure 48 a) shows a slice for the collective sensors of a spatial reference. This could for example be the total annual data collected from one apartment. This data slice would then include diverse sensors such as heat meters, temperature and CO_2 sensors etc. and their specific time stamps; the slice could be viewed in different temporal aggregations. In Figure 48 b), a different slice is shown, which in this case refers to time series from the same sensors in different locations. Such a slice could deliver all DHW meters in each of the bathrooms in all three buildings.

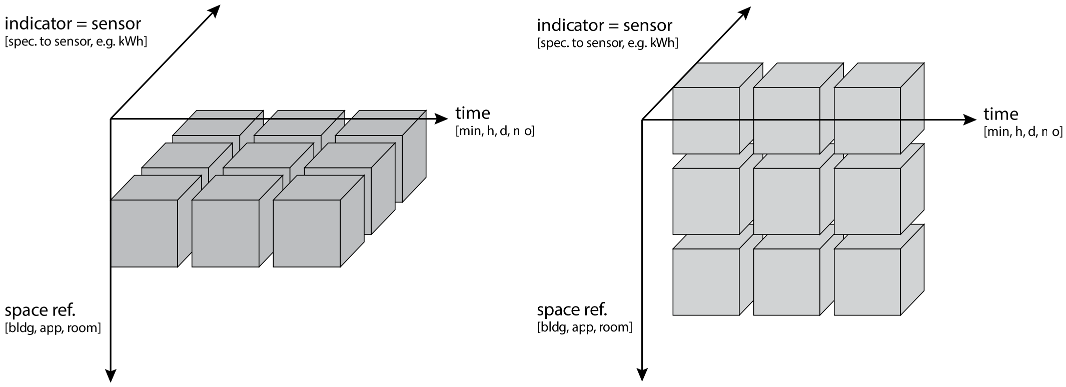

Figure 48 a), b): Illustration of slicing operation for e.g. all sensors of one apartment (left) or one sensor for all apartments (right), own illustration

While the concept of slicing shows the overview and limit one dimension to a single value, the extraction of a smaller share of the data is also possible. This concept is referred to as “dicing”. Figure 49 shows the representation of a time series for a single measurement in one location (e.g. internal temperature in the one room over time, Figure 49 a). In this, the operation can be seen as an overlay of multiple slices. The second example is of an individual measurement of one data object related to one spatial scale and a time span (Figure 49 b). Both could be either more, or less, aggregated within the represented hierarchy.

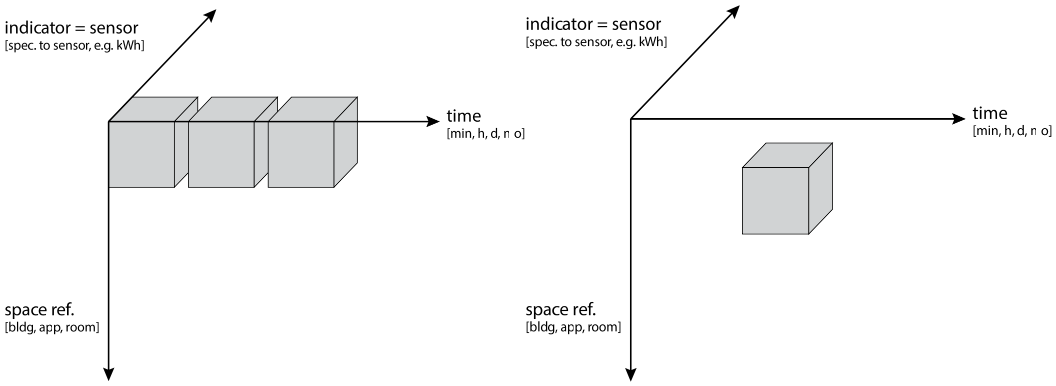

Figure 49 a), b): Illustration of dicing operation for e.g. a time series of heat meter data for one apartment (left) and an individual data point (right), own illustration

The concepts for changing the scale within the hierarchy of the dimensions is referred to as "drill-down", to deepen the level of analysis, and "roll-up", to go back to see the larger aggregated picture. Especially the different aggregations for the spatial reference were used in the discussion of the robustness of the statistic approach at small scales (i.e. a small number of users). When the highest level of detail is reached the query (i.e. the original measurement data) is referred to as "drill-through". Specific data views that deliver the neighbouring elements on the same hierarchical level are called "drill-across".

Figure 50: Screenshot of OLAP based on Monet framework

6 Discussion

The presented work contributes to connecting urban planning and local energy planning. Even though the focus is put on the latter aspect, both fields should be addressed in common when assessing the results in terms of quality and usefulness. In the following discussion, the main findings as well as the positioning of the thesis in the context of current applied research are reflected.

6.1 Applied energy system models for local energy planning

The area of application investigated in the framework of this thesis exemplifies two main strands of urban energy modelling, which are the development of forward and data-driven approaches. The intermediate neighbourhood scale has yet to be claimed by either side. It is argued here that there is no silver bullet to solve all questions in energy planning at this scale. Therefore, key tasks for the application of simulation models were identified from which propositions can be deducted to apply either one or the other solution. In future a more differentiated discourse seems necessary in order to address the different tasks which are clearly identified at building scale (Wang, Yan et al. 2012, Zhao and Magoulès 2012) and are currently discussed as part of the standardisation for city wide urban energy planning (IEC/SEG 1-WG2 2015). At the macro scale GHG inventories have been developed and applied by many cities (Bader and Bleischwitz 2009). The intermediate scale ranging from building clusters to urban neighbourhoods falls in the middle of the two. The current discussion shows a clear need for clarifying sector specific modelling connected to local energy planning tasks and eventually their relation to urban planning tasks (Cajot, Koch et al. 2015). A number of urban energy planning tasks have been identified (Table 9) and linked to the requirements for energy system models.

New construction, and possibly building stock with well-known and well-documented properties, can benefit from detailed, forward models that can be parametrised based on data bases or three dimensional geometry models in combination with steady state or dynamic physical building model approaches (Bahu, Koch et al. 2013). This allows for a large flexibility in simulating different technical solutions in detail and simulate system operation schedules. The case study of Rintheim can be seen as an example for such a well-known and monitored building stock. Often this will go hand in hand with a single ownership and management by a single housing association.

For most of the building stock in our cities, such detailed descriptions of the building properties are not available or are difficult to obtain due to diverse ownership, privacy restrictions or simply lack of documentation. In such cases, data-driven models can play an important role, as deterministic models are over-parameterised for this purpose (Coakley, Raftery et al. 2014). Such applications include the estimation of heating needs for district heating systems, where data-driven models are already widely used (Dotzauer 2002, Nielsen and Madsen 2006). As was shown, data driven models are well suited to support local energy planning, for example, by determining energy efficiency targets through the aggregated assessment of block structures based on energy use. Finally, due to their scalability they can be applied to the development of citywide energy master plans. This latter application was demonstrated by Hellwig (2003) in the original validation case for the energy signature model, which was compared to gas consumption data for the city of Berlin.

Early planning phases, where little information is available, lend themselves to this kind of modelling approach. To assess different planning alternatives, data-driven models, such as the energy signature approach discussed here, can be coupled with forward models to represent technologies and calculate annual heating energy needs. These needs can be used as input to deliver realistic hourly load profiles by applying a data-driven model.

Today, however, the discussion on data-driven and deterministic models seems to have developed into two competing strands of research rather than a joint discussion. The cause can possibly be found in a lack of structure in the target domain (i.e. which solution for which problem) and the desire and ambition to identify a solution that fits all needs. This discourse holds in its core the questions about the degree of uncertainty in natural and man-made systems:

> "While large models based on a deterministic-reductionist philosophy have an important part to play in environmental research, it is advantageous to consider alternative modelling methodologies which overtly acknowledge the poorly defined and uncertain nature of most environmental systems." (Young, Parkinson et al. 1996)

By testing the limits of scale this thesis contributes to the current discussion on urban application cases and their scale. With regard to the distinction of forward and data-driven models, the choice of a specific model is essentially a choice between statistical significance versus the availability of structured data for parametrising the model (Figure 51).

Figure 51: Deterministic and data-driven models with the corresponding scale

From a methodological point, the presented work connects to previous modelling approaches conducted at different spatial scales. The core model concept is directly derived from work by Hellwig (2003) which is still used in the gas load prediction (BDEW, VKU et al. 2014). The general approach of energy signatures and so-called grey box models is also widely used in the simulation of heat demand for district heating systems (Heller 2000). For the latter, mostly linear signature models are used. Energy signatures with various numbers of change points have long been used in building performance assessment (Kissock, Haberl et al. 2003). The thesis applied for the first time the selected single variant data driven model at different scales and tested the lower spatial and temporal limits of the sigmoid energy signature model in predicting heating energy needs for residential and a number non-domestic use types.

In the current mostly academic discussion, a number of new simulation approaches at city scale were proposed that are predominantly based on a physical simulation i.e. deterministic models (see chapter 3). An exception seem to be tools for planning district heating systems. Here a number of data-driven approaches can be found (Nielsen and Madsen 2006, Zhivov, Liesen et al. 2010). Both simulation approaches were discussed with their strength and weaknesses. While a decision for either approach depends on the specific case, a preference for physical modelling for new construction can be seen when parameters are known or defined. The data driven approach can generally be expected to be better suited in cases where little information is available, as is most often the case in existing neighbourhoods. In such cases, data-driven models can help to avoid errors resulting from inaccurate parametrisation that are inherent to deterministic approaches at large scales. In addition, data driven simulation has a clear advantage when simulation models are passed on to users inexperienced in building simulation, when monitoring is to be continued beyond the duration of a scientific research project.

6.1.1 Scaling down black box models

The investigation of energy use in individual buildings and residential units in the case study Rintheim showed that already at the relatively small scale of buildings and building clusters, different use patterns are compensated by the number of users. The result is a more homogeneous demand curve at hourly and daily time resolution that is well represented by the energy signature model. Based on the investigated case studies it proved robust and applicable for a small number of users. This was further supported by the case study data from Bad Aibling in which meaningful results with a CV RMSE around 20% were reached for daily energy use in residential or hotel building clusters above 2000 square meter conditioned surface. This size corresponds well with the size 20 to 30 residential units, which lead to equally good results.

The CHP Ops case study provided a good example for a larger area including non-residential buildings that thus showed more diverse heat demand patterns, especially over different weekdays. Here, however, the total needs were dominated by residential demand, therefore in total an accurate simulated load profile was provided for the site.

Both the temporal and the spatial scale were tested in different case studies. As can be expected when applying data driven models, errors increase when the temporal or spatial scale is decreased. Results for the daily energy use remain robust at the larger scale of the CHP Ops case study. At this scale, even hourly predictions were possible for the residential and aggregated district heating system within the limits of acceptable errors according to ASHRAE (ASHRAE 2002).

It was shown that the quality of results is a function of spatial scale and temporal resolution. This means that the model can be used with a high amount of confidence for small scales when the temporal resolution remains at the daily scale. In an extreme case, even single residential units' monthly demand curve was well predicted. When the scale increases to that of a typical urban neighbourhood, higher temporal resolution can be simulated up to hourly demand curves.

The robustness regarding variance and correlation that was shown for residential buildings, and building clusters in the non-domestic sector, indicate that the method is highly suitable for the generation of annual load duration curves, which are often used, for layout planning of cogeneration systems.

6.1.2 Scaling up deterministic models

As noted before, the main challenge of using deterministic models at a large scale lies in their parametrisation. Typically, the key parameters when assessing heating needs of buildings relate to the building geometry, the characteristics of the building parts and the technical equipment as well as the operational schedule and the operation by the user.

6.1.2.1 Building parameter

With the rapid development of open standards for the description of building geometry at the urban scale, the application of automated parametrisation for forward models has become less resource intensive. Amongst other solutions CityGML is one of the solutions that offers an accessible way to provide input data for deterministic models, which can be executed as batch simulation based on 3D data (Bahu, Koch et al. 2013, Nouvel, Schulte et al. 2013). A main advantage lies in the automatised data import, which typically includes information on surfaces and volumes of building parts as well as their orientation. In addition, solar irradiation on specific surfaces can be calculated. Today, many cities and federal states such as Berlin and Bavaria, are engaged in providing information on the level of detail 2 (LOD 2), corresponding to the volumetric depiction of buildings including roof geometry. Dedicated internal zones of buildings and locations of windows in the façade surfaces (LOD 3) are less common in large-scale CityGML models. As discussed above such applications facilitate the calculation of heating needs when other building parameters such as the thermal transmittance (U-value) of individual building parts and the supply system layout are known (Strzalka, Bogdahn et al. 2011). While these developments solve part of the important technical questions of data handling and a homogeneous data model, existing urban areas with a diverse ownership still prove difficult to be assessed with forward models. Such neighbourhoods do not undergo homogeneous maintenance cycles and therefore show a large diversity of performance classes. In addition, access to building information is limited and the structure of available data inconsistent. Even at the scale of individual buildings Karlsson, Rohdin et al. (2007) found differences up to 50% of which a large part was attributed to the technology representation but also the operation schedule. At the scale of neighbourhoods "lack of precise inputs will lead to low accurate simulation" (Zhao and Magoulès 2012). In such situations deterministic models are often over too detailed (Coakley, Raftery et al. 2014), as errors from poor input data result in larger errors throughout the calculation process. Moreover, in the existing building stock, measurements are usually easier to obtain than parametrising detailed models (Wang, Yan et al. 2012).

6.1.2.2 Operation schedule

Increased computing power has facilitated the standardised calculation of heat demand for larger areas. Even though calculation can be executed, the modelling approach is not per se prepared to accommodate non-standard operation schedules. Comparison with measured data can lead to derivations by the factor of three once buildings are inhabited (Strzalka, Bogdahn et al. 2011). Schnieders, Feist et al. (2001) showed this effect when comparing four passive house settlements with identical construction. These showed a spread of +/- 100% in a nearly normal distribution pattern in energy use for space heating. Such a normal distribution pattern was also reported by Ebel, Großklos et al. (2003) as well as by Eikmeier, Pfaffenberger et al. (2004) where the frequency distribution was differentiated according to building type (i.e. multi-dwelling units, semi-detached and detached houses). An alternative to representing the operation schedule for a large number of buildings is the data driven modelling of individual parameters such as window opening hours, indoor temperature, shading devices, etc. as part of the parametrisation of deterministic models, resulting in a grey-box approach. It can be concluded that, at the scale of urban areas and based on the methodological improvement in building simulation, deterministic models are today mainly suitable for calculating energy needs in newly constructed and homogenously managed neighbourhoods where characteristics of the buildings are known and well documented. The better predictability of future strategies in the redevelopment might eventually stimulate increased efficiency in housing estates managed by public or private associations despite the critique such areas received in the past. The emerging discussion on stochastic models for modelling user behaviour (Haldi and Robinson 2011) might eventually enrich deterministic models by stochastic information.

6.1.3 Lack of accepted tools and methods

While the discussion on urban energy modelling has gained structuring inputs regarding planning tasks and suitable energy system models by Coakley, Raftery et al. (2014), Yamaguchi and Shimoda (2010) and others it remains a predominantly academic discussion. The reality of urban planning is often much less ambitious. Depending on the project stage and the project's objectives, sometimes simple models or rules of thumb are used to take far reaching decisions. Developing detailed simulation solutions that aim to cover the full range of possible applications does not always seem to be the right solution. Moreover, it is of utmost importance to ask the right questions at the appropriate stage of the project. Future work should consider the integration of urban planner and local decision maker in the development of solutions. In the assessment of current practices in energy simulation for urban planning, the investigated tools point to the conclusion that "current energy-environmental modelling packages are rarely used at the community level" (Mendes, Ioakimidis et al. 2011). This is consistent with the findings from IEA Annex 51 (pro:21 GmbH and Projektträger Jülich 2013). Possible reasons for the disconnect between urban planning and the local energy planning discourse are discussed by Cajot, Koch et al. (2015). Essentially, urban planning tasks are generally characterised "by the involvement of many actors with different interests, the difficulty to state the problem explicitly, and the lack of immediate or ultimate solutions". Therefore linking specific energy planning tasks to the larger process of urban planning can be seen as a key requirement to integrate the explanatory power of energy system models into urban development planning.

6.1.4 Urban energy modelling

It is commonly agreed that a main challenge in successful urban energy planning is to develop comprehensive energy concepts in early planning stages (Erhorn-Kluttig, Jank et al. 2011). As urban planning processes have become “more participatory, flexible, strategic and action oriented” (UN-HABITAT 2009), the action oriented approach proposed by Jank, Church et al. (2013) seems a possible way to link objectives to concrete measures. Therefore, access to results from energy system models is required at a point in time when little information is available. The planning tasks described in chapter 2 allow for the consecutive application of models from simple benchmarks to complex simulation tools. A stepwise approach seems a suitable method to ensure consistent assumptions throughout the planning development phases. The selection of the models should predominantly be made based on the planning task. Reflecting the discussion of international case studies and the specific planning tasks for local energy planning the following successive steps are proposed which are consistent with the general concept described in Figure 1. In a first step, a baseline model is developed using annual benchmarks based on measured annual energy needs or archetype buildings. The annual benchmarks can be transformed into hourly load profiles for specific uses on site or an annual load duration curve by applying the discussed energy signature model as one suitable solution.

Energy efficiency measures and use of energy from renewable sources in the design stage can be discussed using forward models, archetype buildings or a combination of both as proposed in the District Energy Concept Advisor. Again, the energy signature can be used to calculate hourly values from monthly energy needs. Forward models should be employed for the assessment of detailed load matching, dynamic effects within the local energy system or specific operational strategies.

In the implementation phase, changes in the selected measures should be reflected in the model. Where projects are executed in a series of construction stages, monitoring results from first stages should be used for comparison against the modelling results. During operation, annual and monthly benchmarks should be continuously updated. The described energy signature model provides the opportunity to derive daily and hourly benchmarks that can help to detect unforeseen energy use with a minor time lag. Especially in the implementation and operation phase, the proceeding can benefit from the use of data driven models as these allow the application by the developer or operator of the site to deliver continuous benchmarks at the scale of the urban neighbourhood. In order to develop the described approach, site-specific measurements can be used to calibrate the energy signature for a given project. In addition, standard parameter sets can be developed from the assessment of measurements to complement existing energy signatures.

6.2 Application of the energy signature model at neighbourhood scale

Conducted research work (pro:21 GmbH and Projektträger Jülich 2013, Cajot, Koch et al. 2015) has clearly shown the relevance of an intermediate scale for urban (re-) development projects. Even though no harmonised vocabulary is used, the different definitions are all targeting an operational scale within cities. The planning has been referred to as local energy planning (LEP). This intermediate scale lies in between building and city-wide energy assessment.

6.2.1 Relevance of the approach

It was shown that based on annual energy-use data and limited information on the built structure, the tested energy signature model delivered reliable results with a limited amount of effort. This is especially important, as consistent data is usually not available for the largest part of our cities. In comparison to the available case study data, the selected energy signature model delivered very good results that have been discussed in detail in Chapter 5.

A clear benefit for the application in the existing urban fabric is the limited amount of input data needed. Also for the application case with no contextual information for a commercial zone the model delivered results with good resemblance of the actual load curve in terms of correlation and variance and acceptable values for CV RMSE. The hourly time scale of the simulation is relevant for most urban energy planning tasks from the assessment of energy efficiency measures to hourly use of distributed generation from fossil or renewable energy sources. For an early stage layout planning for district heating connected to CHP systems the model delivers realistic predictions for a site specific annual load duration curve.

While the quality of the results is the key criteria to judge a simulation approach in the urban planning context an easy applicability can be judged equally important. Energy signature models are easy to use and can be applied in the context of continuous commissioning by users who are not specifically experts in energy simulation. This application scenario corresponds well to the different applications of energy signature models, often used for assessing large amounts of data (Stram and Fels 1986, Rabl and Rialhe 1992, Masuda and Claridge 2014) and continuous monitoring (Mazzarella, Liziero et al. 2009). For the latter task, the concept of an online analytical processing solution was developed based on the data analysis of the different case studies.

6.2.2 New parameter set for low outdoor temperatures

Based on the assessment of simulation results, a new set of parameters was proposed for the energy signature model developed by (Hellwig 2003). At the time the model was developed, the “new buildings” category referred to buildings built before 2002 and equipped with monitoring equipment. In 2002, a more rigid regulation was introduced with the Energy Savings Ordinance 2002 (BMVBW 2002). The application of the model with the existing parameter set for residential and non-residential uses (Hellwig 2003, BGW 2006, BDEW, VKU et al. 2014) showed limitations in predicting peak demand for periods of extremely cold temperature. A new set of parameters was deduced from the analysis to improve the prediction of heating needs. The need to improve the model for periods of very cold temperatures was pointed out by Roon, Gobmaier et al. (2014) in the context of gas load predictions. The new parameter set for the model delivered improved results, based on 2012 data from the Rintheim and Bad Aibling case studies.

6.2.3 Potential for future improvement

The sigmoid model, in its original context of gas load prediction, is designed for use without reference to buildings or operation schedules. When applied to urban areas and building clusters, the approach lends itself to be improved by integrating easily accessible information. This holds the potential to improve the modelling results in future application cases. For application in neighbourhoods, it seems both promising and feasible to analyse the demand curve in more detail by using existing measurements or by including a short-term measurement campaign, before conducting simulations. The model proved robust for daily simulations at neighbourhood scale. Especially for hourly simulations for non-domestic users, data analysis of past measurement periods holds the potential to further improve the simulation model for a given neighbourhood, by improving weekday factors and site-specific patterns of use. The application for the commercial zone clearly showed this potential.

6.2.3.1 Non temperature dependant needs

When modelling smaller urban areas (e.g. building blocks), it is proposed to individually determine the factor for summer needs, mainly corresponding to domestic hot water needs in residential buildings. This can be done either by daily or monthly measurements of domestic hot water needs for the summer months or by a standard assessment based on the household size for residential buildings, as for example provided by a number of standards (VDI 2007). In the “Blaue Heimat” case study instead of using statistical values for domestic hot water use, the model was calibrated using the mean daily value for the months of June, July and August. This is consistent with the approach proposed by (Richter 2004) for POLIS and is based on information which generally should be available to local energy planners. At the scale of building clusters, or neighbourhoods, it seems feasible either to use measured data or to estimate daily energy use for domestic hot water by the number of households or the residential surface. As domestic hot water use is not explained by a temperature dependant model, it is recommended to substitute the purely statistical values for the parameter “D” by a factor adjusted to a more detailed assessment when working at the neighbourhood scale. The profiles developed by Grießbaum (2012), as well as stochastic domestic hot water profiles developed by Jordan and Vajen (2000), could provide further means to better adapt hourly simulation. The former profiles were developed in the course of a master thesis supervised by the author. Finally, for a detailed application, on site measurements could be taken to provide coherence with residents’ schedules

While domestic hot water needs are relatively easy to estimate for a larger sample, schedules for non-domestic users are less evident. In the CHP Ops case study, a swimming pool was included in the load and showed distinct patterns that obviously cannot be explained by a temperature dependant energy model. As in the Macro DE project, aimed at an automatic application for England, Scotland and Wales, no calibration was made. Yet on the scale of the district heating system, these heating energy needs could be determined in the same way as a base load over the course of the year (parameter “D”). In such cases, future applications should consider on-site measurements outside the heating period to improve modelling results.

6.2.3.2 Weekdays

As was shown in the CHP Ops case study, non-domestic uses often have a dedicated use pattern specific to weekdays. This fact is incorporated in the energy signature approach, yet in the selected model, the relation is not very expressive i.e. different weekdays vary only slightly. In a real application, such patterns should, as domestic hot water needs, be part of a pre investigation of a given site. Even though in most cases, the weekday differentiation was overruled by the number of users who were insensitive to the day of the week, simulation results especially for non-residential use could be further improved by site-specific values. In the Bad Aibling case study a school building, offices and hotels were included in the data used for testing the energy signature. No significant sensitivity to the days of the week could be found for the office and school uses. While this mainly depends on the operational schedule of the facility itself, the low energy standard can be seen as a reason for continuous heating rather than a low setback temperature. The application case for a commercial zone showed the relevance of weekday factors at daily and hourly resolution. For the case study, both daily as well as hourly simulation results were improved by including site-specific values. For detailed applications for building clusters also weekday specific hourly load profiles can improve simulation results.

6.2.3.3 Solar radiation

The energy signature model uses the ambient temperature as a single regressor variable, therefore, solar radiation is not directly used to explain heating demand patterns. As solar energy plays a significant role in today's building concepts, solar radiation was tested as potential factor in improving modelling results. The regression analysis on solar radiation returned poor results compared to the significance of ambient temperature, as shown for the example of Blaue Heimat in Figure 32. This is consistent with the assessment made by Heller (2002) who attributed only 7.7% of the explanatory power to the solar radiation, compared with 83% for ambient temperature. While the estimation of solar radiation is an important step in deterministic modelling, especially for non-domestic buildings, their relevance in the data-driven heating needs assessment was found secondary to the ambient temperature. As the two factors are cross-correlated, it is difficult to determine the specific explanatory power. Future work could be useful targeting buildings with high efficiency standard such as passive house constructions.

6.3 Simulation and Monitoring

The depiction of realistic demand profiles is an important task in the early planning stages of urban development. It is essential to improve and update simulation results throughout the implementation and operation process in order to deliver the desired positive effects. Therefore, as proposed in this thesis, monitoring and simulation tasks should go hand in hand (Figure 1). In each step, both monitoring of the projects and energy simulation with a relevant level of precision are necessary to evaluate the potential, and later the success, of urban policies and energy efficient development projects. As discussed in the Annex 51 project "consistent monitoring remains one of the most important aspects that should be carried out throughout the project phases" (Koch, Kersting, 2011). In the described iterative process, monitoring can deliver the necessary inputs for running energy simulations. The results of the latter can be compared to measurements in the form of continuously updated benchmarks.

While such target values are important in early planning stages in order to compare different solutions, they are even more necessary when the development project starts operation. Typically, targets for the buildings' performance are rarely achieved in the first years of operation. Hence, a continuous monitoring is indispensable for measuring the success of the development. Without a suitable monitoring concept, or at least measurement of key performance data, there is little value in detailed energy simulations as the target values will remain good intentions and describe a theoretical potential.

On the other hand, reliable simulation results can help to identify malfunctioning equipment and put monitoring results into perspective of clear target values. For such tasks, energy signature models have been successfully applied in the past at the building scale (Mazzarella, Liziero et al. 2009, Masuda and Claridge 2014). Once validated for a specific site, simulation results can also serve to evaluate the data reliability. Kohlhepp and Buchgeister (2013) propose the continuous updating of simulation models through the planning, implementation and operation cycle of buildings. While for individual buildings, this task can be carried out based on deterministic simulation models as shown for example by Eicker (2006), it seems unrealistic to maintain the support for a detailed simulation model during the urban planning cycle which can easily span a decade from early concepts to implementation (Koch and Kersting 2011). In urban projects, also the lack of responsibilities for continuous monitoring and the development of benchmarks can be seen as a main obstacle to efficient project delivery.

6.3.1 Scalability

As an indirect result, the work conducted leads to the conclusion that the solution for data assessment in monitoring must be scalable. The aggregation of measurement data is equalising to a large part of the variation of individual users due to system operation, user behaviour, etc. While this effect enables the application of the energy signature model, it can also overshadow malfunctions or poorly operated individual systems. This indicates that the energy signature analysis proposed by Neumann and Jacob (2008) at building scale should be restricted to smaller systems, as effects of scale can overshadow malfunctioning in individual systems. In order to allow for specific investigation of a system's performance, overall modelling is not sufficient. From this arises the dilemma that reliable load prediction is feasible at a larger scale with a limited possibility of detecting individual malfunctions. At a smaller scale, non-intended use of energy or malfunctioning can be detected but the prediction of energy needs becomes less robust due to the reduced scale. IT solutions to store monitoring data at the district scale must thus be flexible enough to allow for a scalable investigation in terms of time and space (i.e. building, residential unit, and technical component). With the concept of slicing, the proposed OLAP solution ensures the temporal and spatial scalability, which is a general quality of data warehouse solutions. Monitoring at the scale of urban neighbourhoods can, for the reasons described, not replace the optimisation of individual systems at building level. Once correct operation can be ensured, the data-driven model can carry forward realistic benchmarks.

In the course of the work conducted for this thesis a number of data sources were analysed for which little knowledge on the specific measurements was available except for technical reports, as for example in the "Rintheimer Feld" case study. This reflects the conditions for which the approach was developed; moreover, it showed that statistical results of the model pointed towards particularities or unplausible values in the data. Therefore, modelling can be understood, not only as a means to predict but also to analyse (Figure 52).

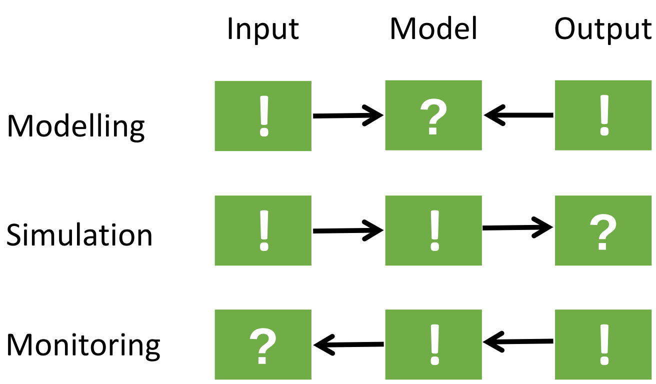

Figure 52: Schematic comparison between modelling, simulation and monitoring

Figure 52 shows the idealised information flow between known (!) and unknown (?) values for modelling, simulation and monitoring. Once applicability is ensured in the modelling process, the tested model can be used either to predict outputs in the form of a simulation or to assess operation via measured outputs and a known model in which the operational parameters have been correctly assigned.

6.3.2 Data availability

The simulation in the framework of this thesis was carried out with generally limited access to information on the projects. This highlights one advantage of a data-driven approach, as it can be conducted with little information on the building properties. While most of the case studies provided information on the installed systems and the buildings' characteristics, in a realistic urban planning scenario only a fraction of this information would be available. The three main case studies from Manheim, Karlsruhe and Bad Aibling delivered a high level of detail and a high quality of data for the statistic tests. However, such diligent monitoring of urban development projects is far from the current standard. As the case studies in EBC Annex 51 showed, even international lighthouse projects do not always apply a high quality of energy monitoring (Zinko and Moshfegh 2012).

6.3.2.1 Weather data

The approach proofed to be robust and not dependant on on-site measurements. Ambient temperature data provided by the German Meteorological Service (Deutscher Wetterdienst -DWD) was used for the Blaue Heimat and Bad Aibling case studies. In both cases, weather station data delivered good results. In Karlsruhe (Rheinhafen) and Bad Aibling (Munich) measured data corresponded well to DWD station data. Specific urban temperature phenomena such as urban heat islands might, in some dense areas, render the simulation more difficult. Based on the case studies for the heating period no adverse effect was identified.

6.3.3 Missing values

Resulting from discussions with Rafael Botsch on the case study of Bad Aibling it was tested to use the data driven model in order to substitute missing values for larger periods. Here only a random case was calculated to test the application for missing values. In Figure 53 a period of eight days was randomly deleted from the measured data resulting in a time series of 358 days. In order to apply the energy signature model the missing values, a linear interpolation was applied. The energy use estimated for the missing period was added to the rest of the year to receive an approximation of the total annual energy use. With the annual energy use, the simulation was carried out. The process was iterated with the sum over the missing days that resulted from the simulation.

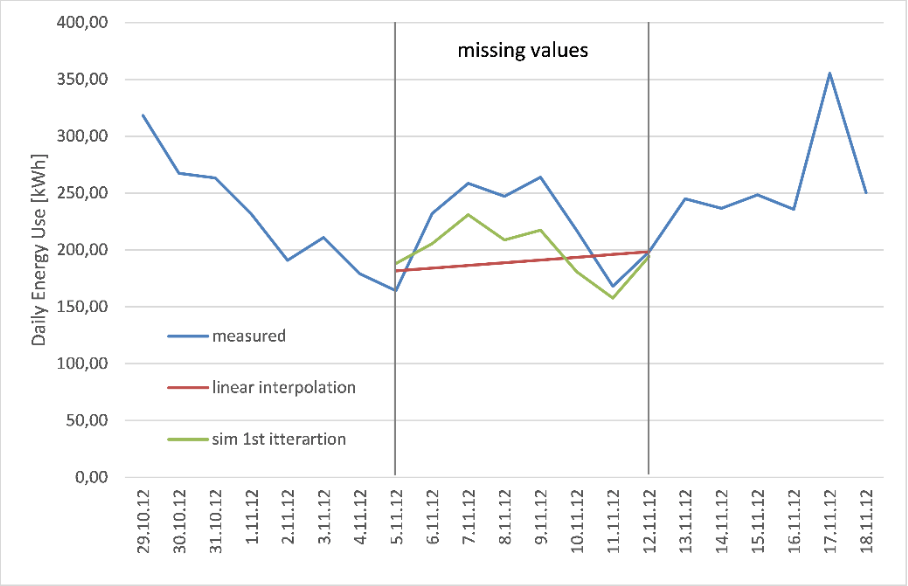

Figure 53: Application of the Energy Signature Model to Substitute Missing Values

The variation between the linear approximation and the first simulation was 4.9% over eight days. The second iteration did not result in a significant increase of the simulated energy needs for the period (<0.2%). Here only a first test could be provided. The correct application would need more exhaustive testing as it obviously depends on the length of the period as well as the variance of the load in that time.

7 Conclusions

7.1 Application of the energy signature model

The selected energy signature model was, for the first time, applied to a small number of users representing scales from building clusters up to urban neighbourhoods. In addition, the model was successfully tested at different temporal resolutions from months to hours. The scales corresponded to the different case studies and the monitoring resolution. Simulations were carried out for monthly and daily energy needs and, where sufficient measurements were available, at hourly time scales. The small number of users was considered a proper test for the fitness of the model in testing its limits of scale or the temporal resolutions. For aggregated buildings, the coefficient of variation of the root mean square error (CV RSME) lay between 20% and 30% for daily simulations and 30% to 40% for hourly simulation. At the large scale of a district heating system (CHP Ops case study), the results lay well within the range proposed by ASHRAE (Table 14) for hourly simulation. For daily simulation, the correlation measured with the Bravais-Pearson correlation coefficient lay above 90% for all aggregated uses and above 96% for aggregated residential uses. For hourly simulations, the coefficient ranged from 79% for non-residential uses to 87%, and up to 91% for residential uses. The relation of the standard deviation of measured and simulated samples was used to test the similarity of the variance. The ratio of the standard deviations for daily simulations reached values between 91% and 99% for non-residential uses and 95% to 100% for residential uses. The hourly simulation resulted in 87% for tertiary buildings and 94% to 97% for aggregated residential buildings. These results confirm the usability of the selected energy signature model for urban neighbourhoods and building clusters. The practical value also lies in the fact that little input data is required to run such models. The difficulties in the parametrisation of deterministic models can be seen as the main obstacle to base the assessment on the physical representation instead. While performance related difficulties have been largely solved the availability and quality of input data is the main problem for the latter category of models.

In addition to general fitness, the scalability of the energy signature approach was investigated. It can be concluded that very promising results can be reached at different temporal and spatial scales. The limits of scalability depend on both the temporal and the spatial scale. For time and space, aggregating effects can be observed, promoting the use of data driven models. When larger areas are considered, hourly simulation can deliver good results as was shown in the CHP Ops and Blaue Heimat case studies. When the scale of application is reduced to a small number of users, the temporal resolution for simulation should be increased to a daily representation to achieve good results.

The case studies presented show that the selected modelling approach can be used as a quick model to predict monthly and daily energy needs at the neighbourhood scale and can even produce good results, down to a smaller number of users. The results from the Rintheim case study indicate a saturation effect at the size of 20 to 30 similar users (e.g. residential units) for the daily simulation.

The model delivered good predictions of hourly heating energy needs at the scale of urban neighbourhoods and can be applied with very little effort. A simple Excel tool was developed as a by-product of the analysis. Below the scale of building clusters, the quality of the hourly prediction is less certain. The method proved easily applicable and thus suitable for use in early planning stages or for initial energy concepts. Even though the sigmoid method was originally designed based on buildings mostly constructed before the introduction of the German Energy Saving Ordinance EnEV2002 (Hellwig 2003) it proved applicable to low energy buildings.

As outlined in the discussion the application of energy signature models on building clusters or neighbourhoods should include the assessment of annual heating needs for the different use types and climate correction of the values (see 4.1.1). Additionally the non-temperature dependant part of the load should be identified or estimated specific to the application case in order to improve the simulation results. The prediction of domestic hot water consumption and the weekday factors for non-domestic users yield the largest potential for improvement. For the former, the use of average domestic hot water use outside the heating period was successfully tested. The latter was applied in the application case for a mixed-use district heating network. As shown in the Bad Aibling and the commercial zone case study, specific schedules for heating systems should be included where such information is available. This could be done by e.g. overruling the distribution function until the start of the heating period, modification of weekday factors or inclusion of site-specific hourly profiles. Based on these preparatory steps, the energy signature model can be applied using a test reference year (TRY) or a specific meteorological year to simulate heating needs during a specifically hot or cold year. In addition to the generation of hourly and daily time series, due to the good results in terms of correlation and variance, the model resulted in excellent results for simulating annual load duration curves, which are typically used for the planning of district heating and cogeneration systems and for smaller areas, based on an hourly simulation.

A new set of parameters (HMFx) is proposed in order to improve the quality of simulation results for periods of extremely low temperatures that occurred in the year 2012. For the Rintheimer Feld case study, the CV RMSE was reduced by six percent and the prediction of the variance was improved by eight percent. In the Bad Aibling case study, the variance in the 2012 results was improved by seven percent for residential buildings and by nine percent for hotels. The latter also showed a slight improvement of the CV RMSE, while the residential prediction was slightly worse. In this case study, the cold period in February 2012 was compared to the warmer year 2013. In the latter, both parameter sets showed similar performance. The proposed change in the parameter set mainly effects temperatures below minus five degrees. As the model uses a geometric row of days this effect is only visible for a period of consecutive days. The new profile was successfully applied to the data of different case studies. The observations of an underestimation of peak loads based on the original parameter set (BDEW, VKU et al. 2014) for low temperature periods is consistent with results from a recent study on the state of gas load prediction by Roon, Gobmaier et al. (2014). Even though this thesis is focused on the relatively small scale of urban areas, the results contribute to the future discussion on the much larger scale of gas market areas. Based on the results presented, the choice of a linear model for deep temperatures (Roon, Gobmaier et al. 2014) could not be supported. In contrast to this option, measurements from residential and non-residential uses (hotels) show a non-linear development at low temperatures. In the discussed case studies peak loads are higher than predicted by the original sigmoid function (BDEW, VKU et al. 2014) but do not follow a linear trend with decreasing temperatures. A linear substitute at very low temperatures could thus risk overestimating peak loads. The redefinition of input parameters for the energy signature approach therefore should be investigated to improve the gas load prediction in periods of very cold temperatures.

7.2 Simulation and monitoring for urban neighbourhoods

The results show that the model can be a useful component in a combination of monitoring and simulation to predict the aggregated energy needs at hourly scale in the operational phase of an urban development. In this context, the approach can be used, with limited additional effort, as a calibrated model to provide a continuous benchmark for smaller areas or for a smaller number of users.

A four-step approach for local energy planning is proposed (section 6.1.4), in which the discussed energy signature model is proposed in the conception phase to develop realistic benchmarks with an hourly time resolution based on measured or calculated annual energy needs. The data-driven approach is judged suitable for most urban energy planning tasks and can be combined with steady state calculation approaches that are suited to describe individual efficiency measures. For detailed simulation of operation strategies or the representation of dynamic effects in the local energy system it should be replaced by a forward modelling approach. In this way, the energy signature can be used to derive continuous benchmarks for daily or hourly energy use in the operation phase for new or existing buildings.

The investigation at different temporal and spatial scales lead to the paradoxical conclusion that the aggregating effect that allows for the application of the data-driven model at the scale of a neighbourhood also prohibits the use of monitoring data only at the aggregated scale as the sole source of information to make a judgement on the performance of individual users. In other words, specific user behaviour or the unintended inefficient operation of the system is not necessarily visible at the scale of a neighbourhood. Thus, neighbourhood scale monitoring schemes should always be accompanied by the assessment of individual users. This highlights the need of the application of a multi-scale monitoring of urban development projects.

In order to support the application by multi-scale data analysis, an online analytical processing (OLAP) framework was discussed to implement the simulation model. Specifications were developed in the framework of this thesis. The OLAP concept chosen for the implementation meets the main requirement of scalability for monitoring and simulation. Depending on the data source, spatial and temporal aggregation or disaggregation can be applied. This functionality is implemented in OLAP via the concept of slicing not unlike the better-known pivot tables.

7.3 Classification of urban energy system models

The state of the art in urban energy modelling tools was described based on the current discussion in applied research. A classification of urban energy models is proposed in chapter 3.1.5 (Table 9), contributing to the discussion on energy system models at the urban scale. In the context of this thesis, a focus was put on the comparison of physical and statistical models, also regarding their inherent aggregating or disaggregating nature. For this purpose, various demand models were described and classified according to their temporal and spatial scales. For a number of tools, this analysis points out compatibilities in the daily assessment. In this sense, the discussed regression model could be used as an alternative energy demand model in solutions such as EnerGIS or TIMES HEAT.

The development of tools is often driven by individual research and development projects, and shows little incentive to move towards standardisation. This is possibly linked to the fact that often urban development projects are seen as one-of-a-kind actions (Cajot, Koch et al. 2015). To an extent, this is true due to their context-specific nature. However, often similar local energy planning tasks can be identified and are currently discussed in the context of standardisation (IEC/SEG 1-WG2 2015). As a contribution to this discourse, chapter 2 proposes a structure of urban planning tasks related to local energy planning. The structure is based on the review of existing urban energy concepts and follows the widely accepted approach of targeting energy efficiency of building and supply systems first and satisfying remaining energy needs with energy from renewable sources (Malottki, Koch et al. 2013). For each subsequent step requirements for local energy planning tools are identified as well as exemplary approaches.

7.4 Known limitations

While the simulations for the different case studies delivered very good results for all aggregated residential applications, only a limited number of non-domestic load profiles was tested in the case studies CHP Ops, Bad Aibling and the mixed commercial zone. The application delivered good results, yet it is apparent that more work needs to be done to test the reliability of non-domestic simulations. Weekday factors especially, could be calibrated in a pre-assessment of the data.

The results obtained for the year 2012 and 2013 indicate the fitness of the newly developed set of parameters (HMFx profile), which predicts peak loads at low temperatures better than the existing profiles. Yet, larger application tests should be conducted before the results of this thesis can be more generally accepted.

Finally, even though data-driven models are generally described a solution that can be applied without expert knowledge (ASHRAE 2005), optimal or correct system operation should be assured by experts before simulation is carried out, as errors in the operation could be carried forward in the simulation. In other words the strength of data-driven models goes hand-in-hand with the risk of simulating inefficient plant operation as no normative calculation is provided.

8 Outlook

This thesis delivered tests on the robustness but also the limitation of the regression model at the scale of urban neighbourhoods. For residential neighbourhoods or building clusters larger than 30 individual users, good results were obtained. In order to allow a flexible application of the energy signature model, future work should focus on the development of a set of validated sets of parameters for different building uses. For a number of uses tests at the neighbourhood scale were conducted in this thesis.

The model was integrated into the JAVA based simulation language of AnyLogic as part of the EnergyLogic library. The modules are currently tested for a wider application in the context of on-going projects, simulating local energy systems. The library will be published under an open source license in the coming years in order to allow a wider application as well as to collect experiences from further application cases.

The classification of modelling approaches (see section 3) showed the compatibility of different top-down approaches as they use similar temporal aggregation scales. Future work will test the application of the sigmoid regression model in the application of TIMES. While the building typology and the hourly load profiles could be maintained (McKenna 2013, Fehrenbach, Merkel et al. 2014), “steps” in the annual load curve from the direct application of typical days could be avoided.

Based on the developed concept for combined simulation and continuous benchmarking for neighbourhoods and the prototype application developed by SIANI institute, the tested energy signature model and statistic indicators will be implemented in the MONET framework developed by SIANI. The energy signature model will be tested to provide ongoing benchmarks for continuous monitoring and for load predictions based on on-line weather forecast data. The first use cases will apply the energy signature to calculate continuous benchmarks for the heating needs at neighbourhood scale. Thus, the measurements can be compared to daily or hourly values generated automatically based on actual temperature measurements. Deviations from the benchmark beyond the expected uncertainty could indicate malfunctions in the operation of the heating system with little lead-time. The second use case requires the connection to online weather forecast to predict future energy needs. Such an application could provide for the basis to optimise plant operation in district heating systems.

The discussed fields of applications in different planning stages for urban development planning are a core question, which is investigated in the IEA EBC Annex 63: “Implementation of energy strategies in communities”. The work conducted in this thesis seeks to contribute to this discussion by providing an easy to use yet robust model to support decision making in local energy planning and continuous monitoring at the neighbourhood scale and eventually help to realise the ambitious targets set in today’s urban development projects.

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10 Annex

10.1 Annex A: Definitions

Brownfield land

brownfield land is land previously used for industrial purposes or certain commercial uses and that may be contaminated by low concentrations of hazardous waste or pollution and has the potential to be re-used once it is cleaned up. (CEMAT 2007)

Building Energy Performance

"Calculated or measured amount of energy actually used or estimated to meet the different needs associated with a standard use of the building, which may include, inter alia, energy use for heating, cooling, ventilation, domestic hot water and lighting." ISO 16818:2008(E), 3.84

Comprehensive Plan

"Reflects the belief that the planning system should plan towns (or large parts of them) as a whole and in detail." (UN-HABITAT 2009)

Energy and GHG Inventory

"An inventory is a summary of all the energy consumed and GHG emissions produced within a community […] and by what sources and sectors." (CEMAT 2007)

Energy Efficiency

Ratio between an output of performance, service, goods or energy, and an input of energy

Energy Need for Heating or Cooling

"Heat required for delivery to or extracted from a conditioned space by a heating or cooling system to maintain the intended temperature during a given period of time." ISO 16818:2008(E), 3.82; In EN 15603 energy need is referred to as a calculated value

Energy use for space heating and cooling

"energy input to the heating or cooling system to satisfy the energy need for heating or cooling, respectively" ISO 16818:2008(E), 3.87

Energy System

The "combined processes of acquiring and using energy in a given society or economy." (Jaccard 2006, Keirstead, Jennings et al. 2012)

Integrated Planning

A "process involving the drawing together of level and sector specific planning efforts which permits strategic decision-making and provides a synoptic view of resources and commitments. Integrated planning acts as a focal point for institutional initiatives and resource allocation. In the context of integrated (or comprehensive) planning, economic, social, ecological and cultural factors are jointly used and combined to guide land- and facility-use decisions." (CEMAT 2007)

Local Energy Planning (LEP)

An "approach to support the development of a local energy strategy by means of rational planning and management principles." (Jank 2000)

Master Plan

"These are spatial or physical plans that depict on a map the state and form of an urban area at a future point in time when the plan is 'realized'. Master plans have also been called 'end-state' plans and 'blue-print' plans." (UN-HABITAT 2009)

Urban Area

An "area which physically forms part of a town or city and is characterised by an important share of built-up surfaces, high density of population and employment and significant amounts of transport and other infrastructure (as opposed to rural areas)." (CEMAT 2007)

Urban Energy Master Plan

A spatial or physical plan that depicts the individual measures or components that form the future combined processes of acquiring and using energy in a given urban area.

Urban Energy System Model

A "formal system that represents the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area." (Keirstead, Jennings et al. 2012)

Urban Regeneration and Revitalisation

Process that "aims at transforming the obsolete socio-economic base of certain urban areas into a more sustainable socio-economic base through the attraction of new activities and companies, modernisation of the urban fabric, improvement of the urban environment and diversification of the social structure; towards sustainable territorial development."
(CEMAT 2007)

10.2 Annex B: List of own publications

10.2.1 Journal Papers, Book Chapters & Reports

Cajot, S., Peter M., Bahu, J.-M., Koch A., Maréchal F. (under review). Obstacles in energy planning at the urban scale. Sustainable Cities and Society – Special Issue: From sustainable buildings to sustainable cities

Sipowicz, M., David, A., Bahu, J.M., Koch, A.. (under review). Using multivariate analysis in classification of suitable areas for distributed energy system deployment in Great Britain. European Journal of Operational Research

Spataru, C., Koch, A. (2015) **Multi-scale Modelling of Energy Resources, Technologies, Controls and Policies for Future Energy Grids**, in: A.Vesco, F. Ferrero (eds.): *Social, Economic, and Environmental Sustainability in the Development of Smart Cities*, IGI Global

Oldenburg, O. Murshed, S.M., Kremers, E., Mainzer, K., Koch, A. (2015) **Model-based analysis of urban Energy Systems (on the basis of a city's energy Master Plan)**, Journal - Emergence: Complexity & Organization, Vol 17 Issue 2

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Koch, A., J.-C. Kersting (ed.) (2011). **Description of the state-of-the-art of energy efficient projects on the scale of neighbourhoods**

IEA ECBCS Annex 51: Energy Efficient Communities - Case Studies and Strategic Guidance for Urban Decision Makers, EIFER report HN-41/11/018.

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Kersting, J.-C., Koch, A. (2011). **Approche Transverse EcoQuartier, mapping actors et actions – Explorative Study on Transnational City Networks.** EIFER report HN-41/11/017

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10.2.2 Conference proceedings & Online Articles

Cajot, S., A. Koch, Marechal, F., Peter, M. (2015). **Energy planning in the urban context: challenges and perspectives.** 6th International Building Physics Conference, IBPC 2. Torino.

Bahu, J.-M., Koch, A., Kremers, E., Murshed, S.M., **Towards a spatial urban energy modelling approach.** 3D GeoInfo 2013- 8th 3D GeoInfo Conference, 27-29 November 2013, Instanabul.

Erhorn-Kluttig, H. (Fraunhofer Institute for Building Physics), Kaan, H., Borsboom, W. (TNO), Fuhler, T. (SBR), Koch, A. (EIFER), Nyffenegger, U. (Kanton Bern) (2013) **OVERVIEW - Market Trends towards Nearly Zero-Energy Buildings.** http://www.buildup.eu/ 22.1.2013

Heyder, M., A. Huber, A. Koch (2011). **Sustainability in Neighbourhoods through Standardised Planning and Contextual Processes.** In: N-AERUS XII - La Ciudad a escala humana, 2011 Madrid. Faculty of Architecture, Universidad Politecnica de Madrid, 11.

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Boutaud, B., A. Koch, P. Girault (2011). **The Franklin district of Mulhouse: first French experience of low energy building renovation in a historic area of the city centre.** In: WREC 2011 proceedings, Linköping University Electronic Press World Renewable Energy Congress 2011, 8–13 May 2011, Linköping, Sweden.

Koch, A., R. Jank, P. Girault, B. Boutaud (2011). **IEA Annex 51: Energy Efficient Communities – Stand des Projektes und erste Ergebnisse der internationalen Fallstudien**

VDI Expertenforum Energieeffizienz in den Städten und der Industrie von morgen, Karlsruhe, 22./23., KIT Scientific Publishing

Koch, A. (2010). **Heat Demand Modeling at the Scale of Urban Neighborhoods,** Next Generation Infrastructure Systems for Eco-cities Conference, 11-13 November 2010, Shenzhen, China

Markl, L., A. Koch, A. Huber (2009). **Neighbourhood cooperation for energy solutions: removing barriers - First results of an applied research project,** eceee 2009 Summer Study, 1.-6. June 2009, Côte d'Azur.

Koch, A. (2009). **Energy Balances of Urban Quarters for the Development of Energy Efficiency and Management Strategies,** 5th Urban Research Symposium, Cities and Climate Change, 28.-30. June 2009, Marseille.

10.2.3 Oral presentations

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Koch, A. (2013). **Energy Efficient Neighbourhoods - Context and Solutions,** KIC InnoEnergy Generic Master Programme "Energy Technologies" – ENTECH, CC Germany, Energy on the Urban Scale, 30.1.2013, Karlsruhe

Koch, A. (2013). **Energy Efficiency Policies in the German Building Sector** Mastère Spécialisé Immobilier Bâtiment Énergie, École des Ponts ParisTech, Paris. oral online lecture 7.1.2013

Koch, A., Kremers, E. (2012) **Smart Buildings in Smart Grids** - HECTOR School – Building Performance in Smart Grids, KIT, 21.10.2012

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Koch, A. (2012). **La ville du futur… elle sera intelligente et décarbonée,** round table discussion, edf Fédération des epl PACA, EDF Commerce Méditerranée, Martigues. oral presentation 7.2.2012

Koch, A. (2012). **La politique d'efficacité énergétique des bâtiments en Allemagne,** Mastère Spécialisé Immobilier Bâtiment Énergie, École des Ponts ParisTech, Paris. oral online lecture 10.1.2012

Peter, M., Koch, A., Casiani, F., Strittmatter, J. (2012). **Resource efficiency and urban energy demand - new perspectives for urban planning?** 6th Urban Research and Knowledge Symposium 2012. Cities of Tomorrow: Framing the Future, poster presentation, Barcelona, Spain. October 8-10, 2012.

Koch, A., Zech, D. (2011). **Impact analysis of consumption patterns – use of heat energy in residential buildings.** Sustainable Consumption – Towards Action and Impact, 6.-8. November 2011, Hamburg, Germany. oral presentation

Heyder, M., A. Huber, A. Koch (2010). **Sustainability in Neighbourhoods: Between Standardised Planning and Contextual Processes.** Sustainable Consumption – Towards Action and Impact, 6.-8. November 2011, Hamburg, Germany. oral presentation

Koch, A. (2011). **IEA Annex 51: Energy Efficient Communities – first findings from international case studies.** Local Renewables Freiburg 2011 – Green Buildings and Renewable Energy: The Way Forward in Urban Development, 27.-.28. October 2011, Freiburg im Breisgau, Germany. oral presentation

Koch, A. (2011). **Urban Morphology and Heat Energy Demand, LSE Cities / EIFER Studie London, Paris, Istanbul, Berlin,** Clean Tech Insights Konferenz 2011, 29.-30. September 2011, Berlin, Germany. oral presentation

Zech, D., Koch, A. (2010). **Wirkungsanalyse des Wärmekonsums – Nutzerverhalten und thermische Energienutzung,** Workshop: Das Konsumverhalten und seine Folgen, Interfakultäre Koordinationsstelle für Allgemeine Ökologie (IKAÖ), Universität Bern. oral presentation

Koch, A. (2010).**Energy Efficient Communities - Analytical Framework for the Description of Urban Development Projects. The French Contribution to the IEA ECBCS Annex 51,** Delivering Sustainable Cities: The Local Leadership Challenge, 6th European Sustainable Cities and Towns Conference, 19-21 May 2010, Dunkerque, France. poster presentation

Koch, A., L. Markl (2010). **Renovating the building stock in Germany,** Presentation at the International Council for Research and Innovation in Building and Construction (CIB) Task Group 66 Web Event: The Implementation of Energy Efficient Buildings Policies in Europe, 24 February 2010. oral (online) presentation

Koch, A. (2009). **Sanierung mit Passivhaus Komponenten – Überprüfung der Ausführungsqualität und Monitoring**, EffizienzTagung, 13.-14. November 2009, Hannover. Oral presentation

Koch, A. (2009). **Energy Efficiency Strategies for Urban Quarters,** World Sustainable Energy Days 2009, 25.-27. February 2009, Wels. poster presentation

10.3 Annex C: Case Study Description

In the context of the Macro DE project, the author conducted simulations for a district heating system referred to as “CHP Ops”. The full results from the project are published by Woods (2012). For this thesis, reference is made only to the demand model validation case. VOLKSWOHNUNG GmbH, a communal housing association based in Karlsruhe, provided detailed data for residential use from the housing estate “Rintheimer Feld”. Technical data access was made available by the University of Applied Science Karlsruhe for the conducted analysis. This data set was used to test the model’s scalability. Data for a third case study was provided by Fraunhofer ISE measured in the “Blaue Heimat” project. Here, aggregated data for a cluster of buildings was used to test the model. This case study can be seen as a proto-typical application for the model in a realistic application case without in depth knowledge of the underlying variations within the buildings’ operation. Based on the “Nullenergiestadt” project in Bad Aibling, the University of Applied Science Rosenheim supported this thesis with measured data for residential and non-residential uses. A further case study was investigated to test the model’s scalability. Data from individual, single-family houses were used to test the simulation results against individual load profiles. The data was collected in order to monitor the operation of individual heating units for single-family houses. Data was made available by EIFER and previously prepared by Grießbaum (2012) to test simulations for hybrid energy systems. Finally, access to measurements form a commercial zone was granted by Drees & Sommer for the purpose of validation. The individual projects and the data sets are described in the following sections.

10.3.1 CHP Ops site in the Macro DE project

10.3.1.1 Case study description

The Macro Distributed Energy (DE) project was carried out in 2010 in order to assess the potential for district heating systems with a maximum installed power of 5 MW_{el} in the United Kingdom (Woods 2012). In the framework of the project, the energy signature approach was applied by the author supported by the project team to describe hourly heat demand profiles in the United Kingdom for a total of 4,660 statistical zones. These higher density zones are referred to as Middle Layer Super

Output Areas (MLSOAs). The selected zones were clustered into representative zones, classified by attributes such as scale, heat density and the ratio of residential to tertiary demand (Sipowicz, David et al. forthcomming). Further technical and economic analysis was carried out by project partners to assess the suitability for district heating systems for the derived classes. The project was led by Caterpillar with Paul Woods (AECOM) as technical coordinator; other project partner included the University of Manchester, EDF R&D, MK niras, DELTA and WADE. EIFER's contribution was led by Kevin McKoen. The author was responsible for the identification and application of the thermal demand model (Figure 54). The calculation was executed with the help of two students (A. Nichersu and N. Griessbaum). A more detailed project description can be found at www.eti.co.uk. While the demand assessment was carried out for the whole UK, a test of the model's fitness was conducted with data from an individual district heating system, which for reasons of confidentiality was referred to as "CHPS Ops".

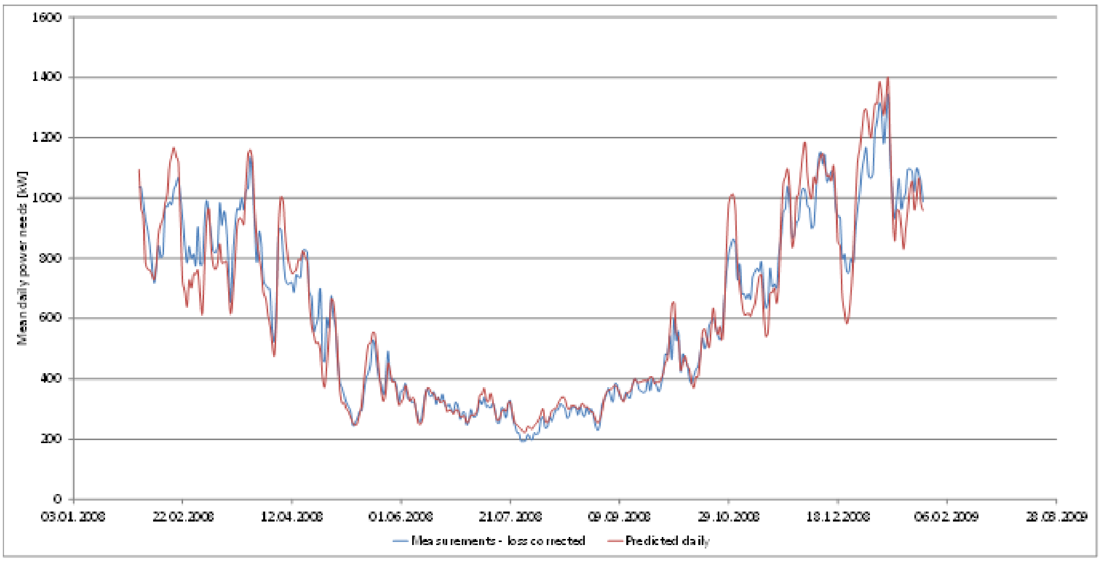

Figure 54: Comparison of measured (blue) and simulated daily heat demand qtd. in (Woods 2012)

In this thesis reference will only be made to the published case study results (Woods 2012) the work will not provide further details on the district heating system.

10.3.1.2 Data Description

Measurement of the mean power output was made available by the plant operator for the project in 10-minute time steps for two measurement periods between 1.2.2008 until 27.1.2009 and 5.7.2009 until 1.7.2010. Data was provided for five individual building clusters of different use types connected to the district heating system. The data contains the delivered energy at each building cluster and therefore does not contain losses in the distribution system outside the buildings.

The data used for model validation consisted of different uses serviced by a central CHP system. In the context of the project, both non-residential and residential use profiles were tested for daily and hourly demand. Seventy-six percent of total demand refers to residential uses. About a third of the apartments were built in 2005. The rest of the residential building stock consisted of buildings from the last century, which, however, were well maintained, and a small number of small multifamily apartments built in the 1970s. For one of the five building clusters, 34 daily measurements were missing. These were added by linear interpolation and compared to the same weekdays of the week before and after.

10.3.2 Blaue Heimat

10.3.2.1 Case study description

Data for this case study was kindly provided by Sebastian Herkel and Florian Kagerer from Fraunhofer ISE. The case study description is based on published project reports (Herkel and Kagerer 2011). The building cluster "Blaue Heimat" originally built 1951 was renovated in 2005 with the target of a net-zero energy building. After renovation, the low energy building contained 40 residential units. The concept includes two adjacent buildings supplied by the same energy system, which were not renovated to the same standard. Planning and construction works were accompanied by Fraunhofer ISE. The external walls, roof and basement ceiling were insulated resulting in a high overall performance expressed in a specific transmission coefficient ($H_{T'}$) of 0.31 W/(m^{2}K). The windows were exchanged for triple glazing. In order to reduce ventilation losses, decentralised ventilation with heat recovery was installed for each staircase. The three-story building is supplied with heat by a gas driven combined heat and power (CHP) system with an installed capacity of 80 kW$_{th}$ and 50 kW$_{el}$. In order to increase CHP running hours, the system also supplies two neighbouring buildings with heat. These are connected via two decentralised hot water storage tanks of 800 litres for domestic hot water and two 325-litre storage tanks for space heating needs. The locally produced electricity is fed into the grid and taken into account for the total primary energy balance of the building. After renovation, the building achieved a very low value of 19 kWh/(m²a) for specific annual space heating needs. With 11 kWh/(m²a), the specific domestic hot water needs are in the range of the assumptions for the German building regulation (12.5 kWh/(m²a)). The central CHP system is connected to existing buildings via a distribution system in the basement of the low energy renovation project. By means of the electricity produced on-site the project nearly reaches a net-zero energy standard (Herkel and Kagerer 2011).

Monitoring was conducted by Fraunhofer ISE in the context of the IEA Task 37 "Advanced Housing Renovation by Solar and Conservation" supported by the BMWi (Herkel and Kagerer 2011). Monitoring began in July 2009 and a full year of monitoring data was provided for the period between October 2009 and September 2010.

10.3.2.2 Data Description

Data was provided for all three buildings at a 15-minute resolution. The data was checked for missing values and provided in a structured format by Fraunhofer ISE. Data was made available for the period between 14.7.2009 until 1.1.2011 and thus contained data for 536 days. In total six measurement failures with 41.6 days were reported as missing values. Data for 365 days was used for the model validation. As a number of consecutive missing values fell in the month of December 2010, the 1st of September 2009 was selected as starting point. The selected year contained 8.2 days as missing values.

As in the other case studies, data from heat meters were used for comparison with the simulation results. These included the aggregated measurement of the heat supply to each of the adjacent buildings, as well as related domestic hot water needs. The load curve for the two existing buildings could be well traced as heat meters were installed at the connection points. The two load profiles were subtracted from the total measured heat supply for the total building cluster. Even though this associates relatively larger circulation losses from horizontal distribution (i.e. connection to adjacent buildings) to the remaining profile of the low energy building, it was judged an acceptable simplification given the external view on the project, which corresponds to the limited amount of information, assumed for many urban energy planning tasks.

The case study thus consists of three distinct data sets for two existing buildings as well as the central low energy building. Figure 55 shows the measured data for space heating and domestic hot water use mapped to the ambient temperature. The energy signatures of the three buildings show typical curves for a well-operated system with clear dependency on the outdoor temperature. Due to its higher performance and lower peak demand the low energy buildings are typically represented by the shallower curve (MFH A).

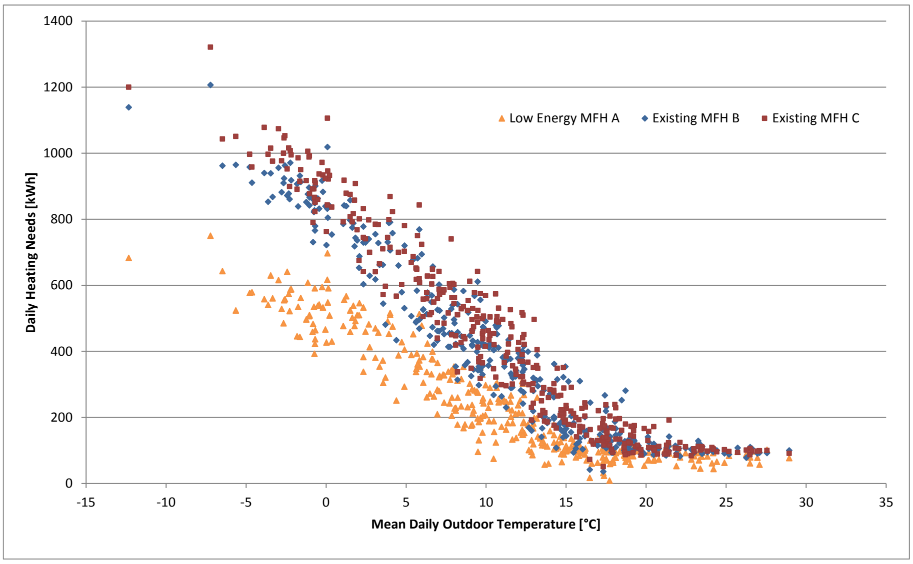

Figure 55: Energy signatures of the three building parts in the "Blaue Heimat" case study

As they represent different performance classes, all three buildings were individually simulated to test the simulation model. In order to describe the total balance correctly, the model was adopted to represent the given amount of energy use in summer as the sum of domestic hot water needs and distribution losses. The monthly balances evaluated by Herkel and Kagerer (2011) showed relatively stable losses throughout the year.

10.3.3 Rintheimer Feld

10.3.3.1 Case study description

Case study data was kindly provided by Dr. Reinhard Jank, Mr. Kuklinski and Mr. Kürsten (VOLKSWOHNUNG GmbH) with the technical support of Prof. Wolfrum

(University of Applied Science Karlsruhe). Information on the project is based on the published reports, project publications such as (Jank 2013) and personal communication. The data is based on the monitoring of three residential buildings with 30 residential units each, organised in three staircases. For the model validation measurement of two of the buildings were used. The three buildings were part of the urban regeneration project Rintheimer Feld that was supported by the EnEff:Stadt research program. The objective of the project was to develop an integrated energy concept combining the renovation of the buildings to an economic optimum with a new supply infrastructure for the neighbourhood. The renovation measures were implemented by VOLKSWOHNUNG GmbH between 2009 and 2015. In addition to the overall targets for the whole neighbourhood "Rintheimer Feld", two buildings were selected to test new technologies, which are currently not part of standard renovation measures. The work was accompanied by the RWTH as research partner in an EnEff:Stadt project. The monitoring concept was developed by RWTH Aachen and the University of Applied Science Karlsruhe and installed by the latter. The monitoring data is evaluated by the RWTH Aachen in an ongoing project funded by the BMWi.

Measurement of two low energy buildings was accessible for testing the fitness of the energy signature model. In addition to a disaggregated data set, this case study can be seen as a test to apply the signature model to high performance buildings as the cases of "Blaue Heimat" and "Bad Aibling". The first building was designed as a "3-litre" building referring to the energy content of 3 litres of fuel. The target value for the heating energy needs that was also reached after renovation in 2012 was 35 kWh/(m^{2}a). The second building was designed with the more ambitions target of 31 kWh/(m^{2}a) which again was confirmed after the renovation measures (Jank 2013). In both buildings, which share the same geometry the renovation, measures included high performance building parts including passive house components. As the objective was to compare the performance of building technologies, a number of different solutions was included in the renovation scheme especially in the second building, characterized as an experimental building. Here also different supply solutions were included such as CO_2 borehole heat exchangers connected to a heat pump as well as an air-water heat pump system. Regarding the application of the data-driven model, a specific challenge was seen in the representation of the latency, which is inherent to low temperature panel heating systems. Detailed technical specifications for the buildings can be found in (Jank 2013), further details on the neighbourhood concept are published in a dedicated publication of the research program EnEff:Stadt by Jank and Kuklinski (2015).

10.3.3.2 Data Description

The demonstration buildings in the Rintheimer Feld project were assessed in comparison to a reference building renovated to meet the standard measures applied in other renovations conducted by VOLKSWOHNUNG GmbH. Monitoring was installed for one staircase in the reference building (10 units) and in all 60 units of the two demonstration buildings.

Each building contains three staircases (entrances) with ten residential units each with a cellar in which the central space heating and domestic hot water provision is located. In the case study a number of different technologies is used (i.e. district heating, CO_2 heat pump and an air-water heat pump), therefore the space heating needs captured by the heat meter of individual apartments were used for analysis. The data was received and treated in an anonymised form, so that no reference is made to individual apartments or users. As the selected simulation approach does not consider specific physical properties of individual apartments, the single objects are not referenced to their specific location. For the monitoring each apartment is subdivided in its rooms and contains a central heat meter for space heating. In each staircase, four apartments are additionally equipped with heat meters for all rooms (living room, kitchen, sleeping room, bath, and children). The installed heat meter measures the amount of energy (kWh) as well as the inlet and outlet temperature (°C) and the volume flow (l/h) at 60 seconds intervals. In addition, within each apartment, domestic hot water use is measured via a heat meter (kWh) as well by its volume flow (l/h) and inlet and outlet temperature (°C). Next to the heat meters in each room (usually living room, children, sleeping, kitchen, bathroom) measurements of room temperature [°C] and relative humidity [%] were taken. In addition, values for luminance [lux] and CO_2 concentration [ppm], as well as volatile organic compounds, (VOC) were measured. Household electricity use is measured in 15-

minute time steps, as well as auxiliary electricity for the heating and hot water systems (i.e. pumps, etc.). A weather station was set up to measure temperature, relative humidity, global radiation, luminosity, wind speed and direction. For each measurement, an absolute value is provided as a timestamp [yyyy/mm/dd hh:mm:ss] every 90 seconds. For the further analysis raw data from heat meters of apartments and data obtained from the local weather station was used.

Reliable measurements on the installed sensors was obtained from September 2011 onwards (Jank 2013). For the model validation, measurements were available for a period of 12 months between January 2012 and December 2012. The temporal resolution is, depending on the sensor, provided in 60 second time intervals; each set of values is provided in relation to an absolute timestamp [yyyy/mm/dd hh:mm:ss] specific to the sensor, as measurements were not synchronised. The raw data was received grouped per day and staircase and further structured with one csv file per heat meter or sensor. The data for the analysis was anonymised so that no reference could be made to individual users. The data was received as continuous measurement from 240 sensors installed in 60 units. The temporal resolution was based on one-minute time steps. As the sensors used individual time stamps, the data was imported into a SQL database. For synchronisation, measurements were aggregated to hourly and daily time series. In total 9 measurement failures longer than four hours were identified as missing days each affecting ten apartments each (90 missing values). The days were substituted by the maximum value of the continuous measurement for that day and checked against the following day’s value. From the sixty samples, two apartments were excluded from further work as the time series delivered implausible patterns. In one case, the main heating load was measured in summer with decreasing loads in winter; in the second case, no significant heating load was measured. As it could not be determined if this was due to malfunctioning heat meters, as reported in other cases (Jank 2013) or due to specific heat demand patterns both apartments were excluded.

To test the proposed approach combining simulation and monitoring, a data warehouse solution was implemented in the framework of a student project with support by the SIANI institute. Data analysis and queries were conducted based on an online analytical processing (OLAP) solution, which will be described in section 5.2).

10.3.4 Single building systems

Data was kindly provided by EIFER for testing the application of individual residential buildings. The data was first prepared by Niklas Grießbaum in the context of his diploma thesis (Grießbaum 2012). The thesis was supervised by the author and Dr. Aurelian Florin Badea (KIT-IFRT). As in the case study “Rintheimer Feld”, the application of the heating needs is investigated for the scalability of the approach. According to the underlying hypothesis, a simplified model should deliver better results for increasing numbers of users and reach saturation when a statistically significant number is reached.

10.3.4.1 Case study description

For the individual building case study, monitoring data from eight individual buildings in South West Germany was used. The data was recorded between the 1st of August 2008 and the 31st of July 2010. For privacy reasons no address specific information is correlated to the datasets and the individual buildings are referred to “building A” up to “building H”. All buildings are situated within a 20 km radius in a village context so that similar weather conditions are assumed for the analysis. All buildings were recently modernised and each was equipped with a new individual heating system for provision of space heating and domestic hot water. The systems were all connected to a storage tank and use radiators for the heat distribution.

10.3.4.2 Data Description

Heat meters were included for the boiler and for the solar thermal system as well as for storage for each building. For total heating needs, these meters were used in connection with the heat meter data for the heating and domestic hot water circuit. Due to the heat meters’ assumed rounding effects, validation from heat measurements was preferred to flow and temperature measurements. The data was available in hourly time steps. Data treatment was carried out in the framework of a diploma thesis (Grießbaum 2012), which found the time steps to not be isochronal, i.e. some hours were assigned none or two values. Data was filtered to ensure each data set contained 17520 values. In the data treatment missing data for periods shorter than four hours were interpolated using a piecewise cubic spline interpolation polynomial (pchip) (Grießbaum 2012) longer periods were reported for manual treatment. Due to long consecutive periods of missing values and implausible values two buildings were excluded from the case study.

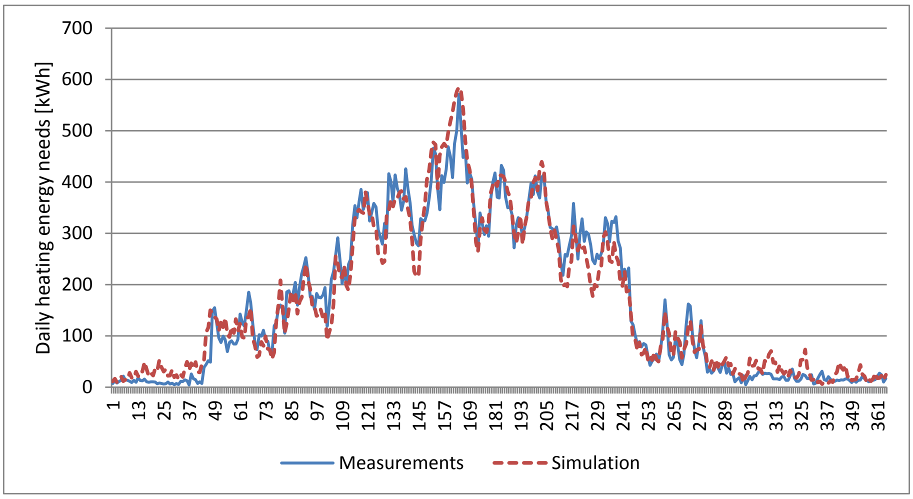

Figure 56: Measurements and simulation of the aggregated daily heating needs of all single-family buildings

Data from the space heating needs of six buildings were selected for comparison with simulated demand in different levels of aggregation. In order to do so, a randomly chosen building was added to the cumulated load for each simulation run. The last case therefore corresponded to the aggregated demand of all buildings. This could be seen as the equivalent of the heating needs supplied by a common heating system without considering the distribution losses outside the buildings.

10.3.5 Bad Aibling

10.3.5.1 Case Study Description

Data for the zero energy development project (“Nullenergiestadt”) in Bad Aibling was kindly made available by Prof. Mathias Wambsganß, Rafael Botsch and Florain Alscher of the University of Applied Science Rosenheim. The case study description is mainly based on published reports and project publications such as (Böhm, Schroeder et al. 2010). The B&O Park Area in Bad Aibling is a conversion of a former military site. The target was defined as zero energy development (“Nullenergiestadt”) for the brown field project. The 70 ha site located 50 kilometres south of Munich and was constructed as a military area for the German air force in the thirties. After the Second World War it was used by the US military and housed 1400 military staff and their families. In addition to barracks, it included a number of services. Energy was supplied by three boilers with a nominal power of 6.5 MW each connected to a district heating system. In 2004 the US Army abandoned the site and thus opportunities arose for the current development (Böhm, Schroeder et al. 2010). During the redevelopment, the existing structure was transformed into residential and recreational buildings as well as hotel facilities and a school building (Table 36). The redevelopment project and accompanied research activities were funded through the EnEff:Stadt research program by the German Ministry for Economics (BMWi). The development aimed at high standards for renovation between EnEV 2007 and Passive House standard, as well as EnEV -50% up to the passive house standard for new construction. The existing district heating infrastructure was maintained and redesigned to comply with the reduced needs. In the northern part of the area serviced by the district heating system mainly residential uses, hotels, school buildings and a small part of office space are located.

Table 36: Summary of the buildings in the north loop, estimation for the initial system layout qtd. in (Böhm, Schroeder et al. 2010)

Use	Net surface m2	Heating needs [kWh/m²a]	Auxiliary energy [kWh/m²a]	Electricity needs [kWh/m²a]
Residential / Housing	1.012	87	5	20
Residential / Housing	1.922	70	5	20
Residential / Housing	2.246	51	5	20
Residential / Housing	2.152	75	5	20
Residential / Housing	116	42	5	20
Residential / Office (ground floor)	1.478	88	5	25
Residential / Office (ground floor)	481	47	5	25
Residential / Office (ground floor)	968	55	5	25
School	2.152	150	25	35
Seminar spaces / Apartment building	1.496	50	10	25
School / Office building	8.092	75	30	45
Hotel	1.202	69	5	20
Hotel / Gastronomy	872	83	30	50
Hotel / Apartment	578	70	5	20
Hotel / Apartment	578	63	5	20
Gastronomy	1.429	69	30	50

During summer, the district heating system is supported by solar thermal systems installed mainly in the northern area which initially connect to decentralised storage units and then, in second instance, to the network. Heat pumps provide the necessary temperature level for domestic hot water when needed. A wood chip boiler installed in the centre of the northern loop is the main heat supply in winter. The renovated gas boiler in the south functions as backup system. In addition to the roof mounted thermal solar collectors, a large PV plant supports the project’s net-zero energy target of the project. In the projected energy balance, the total thermal needs for space heating and warm water were estimated at 2.044 MWh/a, the auxiliary energy amounts to 444 MWh/a with 861 MWh/a total electricity needs including household electricity.

10.3.5.2 Data Description

In order to control the performance of the energy system a monitoring system was defined as part of the EnEff:Stadt research program. The implementation is based on the software “MoniSoft” developed by KIT-fbta. The concept was aligned with the EnEff:Stadt program’s guidelines (Erhorn, Erhorn-Kluttig et al. 2012) and implemented on site by Prof. Wambsganß and his team at the University of Applied Science Rosenheim. The system collects data from the building operation and stores it in a database. Analysis is conducted by the University of Applied Science Rosenheim in order to periodically observe the system and store data, control the correct functioning of the system, check on the plausibility of the data and maintain the monitoring hardware when necessary (Böhm, Schroeder et al. 2010). For the purpose of this thesis, hourly data was provided aggregated at building level and specified per use. It was further assigned to the branches of the local district heating network. For the tests, data was anonymised and treated without reference to specific buildings or users. As the “Nullenergiestadt” contains a number of non-residential buildings, it was of particular interest for model validation to test non-residential parameter sets. The data was provided as synchronised data at an hourly time scale. From the provided data, the years 2012 and 2013 were providing for two nearly complete annual time series for different uses. Hotels represented an especially large share of the available data. In total, measurements for 2012 and 2013 contained five missing days. Furthermore, a residential cluster along with office and school buildings were also used. Over the course of the two years 15 days were reported as missing data. With regard to previous tests, measurements from 2012 were of specific interest when testing the newly proposed parameter set for low temperatures, as February 2012 included a period of subsequent days with very low temperatures, reaching hourly values below -20 °C. Site-specific weather data was provided. As the hourly temperature data contained a number of missing values, it was compared to the hourly and mean daily temperature measured at the DWD station 1262 located at Munich airport (Figure 57).

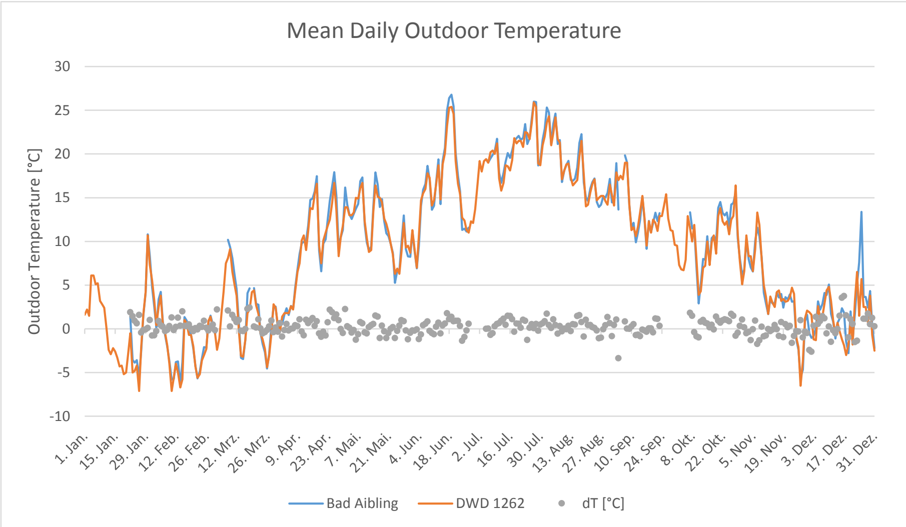

Figure 57: Comparison of the site-specific mean daily outdoor temperature measured in Bad Aibling and Munich (DWD station 1262) for the year 2013

This comparison was done to complete missing values in the temperature data and to test the sensitivity of the simulation results to site-specific temperature data. The comparison showed good agreement between the two temperature measurements. Figure 57 shows the comparison of data from 2013. This is of interest for future application cases as when modelling energy needs for urban areas most cities can provide for global meteorological measurements, while data at smaller scales such as postcodes or districts will be difficult if not impossible to obtain in most cases.

10.3.6 Commercial Zone District Heating System

At a high aggregation level, the total load of a district heating system supplying heat for a commercial zone was used as a case study. Data was kindly made available by

Sven Reiser and Gregor Grassl of Drees & Sommer. For confidentiality reasons no reference to the exact location or the specific user or processes was provided. The site located in the south of Germany consisted of two-third light industrial use and one-third office spaces. The absolute energy use in 2013 was 291 MWh and 222 MWh in 2014. The climate corrected values are 271 MWh and 249 MWh using the DWD (ww.dwd.de) climate factors for the respective years. Based on annual benchmark values (BMVBS 2009) it can be estimated that the site hosts approximately 1000 m^2 of office buildings and 1500 m^2 of light industrial use. Data was provided as complete time series of hourly energy use for the years 2013 and 2014. Given the limited amount of information, the case study lends itself as a test for a real application case. Simulation based on the default parameter set were carried out for the year 2013. The resulting errors were analysed in comparison with the measurement data. Findings from this comparison were used to improve the parameter of the simulation. The modified simulation was rerun for 2013 and for 2014. Such an application could be imagined for site-specific simulation or in cases were the method should be adapted for continuous application after an accompanying research.

Table 37 summarises the case studies used for the model validation. In all cases, data was used at the lowest scale of measurement and further used for aggregated buildings or building clusters up to a complete neighbourhood or zones.

Table 37: Summary of the case studies

	Case Study	Building Use	Scale
1	CHP Ops	Residential, School, Recreational facility	Building cluster, Neighbourhood
2	Blaue Heimat	Residential	Buildings, Building Cluster
3	Rintheimer Feld	Residential	Buildings, Building Cluster
4	Single family buildings	Residential	Buildings
5	Bad Aibling	Residential, Hotel, School, Office	Building Cluster, Neighbourhood
6	Commercial Zone	Office, Light Industrial	Building Cluster, Commercial Zone

10.4 Annex D: Complete statistic results

10.4.1 Case Study "CHP Ops"

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Residential building cluster 1	8.44%	13.53%	-	0.91	0.96	-	0.88	0.94	-
2	Residential building cluster 2	5.58%	17.26%	-	0.91	0.94	-	1.07	1.13	-
3	Residential building cluster 3	18.13%	23.88%	-	0.91	0.97	-	1.53	1.55	-
4	Tertiary buildings GBH	8.22%	19.57%	-	0.91	0.96	-	1.02	1.03	-
5	Tertiary buildings GKO 1	9.63%	50.54%	-	0.91	0.83	-	0.88	0.76	-
6	Tertiary buildings GKO 2	10.55%	63.95%	-	0.91	0.78	-	0.89	0.68	-
7	Aggregated residential buildings	5.98%	12.33%	29.71%	0.91	0.97	0.87	0.95	1.01	0.94
8	Aggregated tertiary buildings	6.65%	19.72%	37.25%	0.90	0.91	0.79	1.00	1.00	0.87
9	All buildings	3.62%	11.18%	24.13%	0.91	0.97	0.91	0.97	1.02	0.98

10.4.2 Case Study "Blaue Heimat"

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Multifamily Building A	9.35%	18.30%	-	0.91	0.96	-	0.91	0.93	-
2	Multifamily Building B	8.88%	13.65%	41.61%	0.91	0.98	0.85	0.90	0.92	0.89
3	Multifamily Building C	14.09%	20.74%	46.67%	0.91	0.98	0.81	0.93	0.94	0.89
4	All buildings A-C	7.36%	11.05%	36.27%	0.91	0.99	0.87	0.92	0.94	0.94

10.4.3 Case Study "Rintheimer Feld"

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Multifamily Building 1 unit	89.51%	143.08%	-	0.76	0.73	-	0.51	0.42	-
2	Multifamily Building 5 units	24.12%	44.56%	-	0.87	0.85	-	1.14	0.98	-
3	Multifamily Building 10 units	20.27%	39.37%	-	0.89	0.92	-	0.88	0.81	-
4	Multifamily Building 15 units	12.47%	27.39%	-	0.91	0.96	-	0.88	0.85	-
5	Multifamily Building 20 units	12.74%	23.66%	-	0.91	0.97	-	0.87	0.87	-
6	Multifamily Building 30 units	14.28%	23.60%	-	0.91	0.97	-	0.86	0.87	-
7	Multifamily Building (complete)	13.74%	26.11%	-	0.91	0.96	-	0.89	0.88	-
8	Multifamily Building (complete)	8.24%	20.27%	-	0.91	0.97	-	0.94	0-96	-

10.4.4 Case Study “Single dwelling units”

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	SFH A	26.40%	34.81%	-	0.88	0.93	-	1.09	1.10	-
2	SFH B	11.74%	25.22%	-	0.91	0.96	-	1.02	1.02	-
3	SFH C	15.30%	24.10%	-	0.91	0.98	-	0.86	0.85	-
4	SFH D	13.82%	30.22%	-	0.90	0.94	-	1.00	1.00	-
5	SFH G	20.55%	44.12%	-	0.91	0.91	-	0.81	0.78	-

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	SFH A	26.40%	34.81%	-	0.88	0.93	-	1.09	1.10	-
2	SFH A. C	16.13%	22.67%	-	0.88	0.93	-	0.99	1.01	-
3	SFH A. C. G	13.72%	21.77%	-	0.91	0.97	-	0.94	0.95	-
4	SFH A. C. G. D	26.40%	34.81%	-	0.91	0.97	-	0.95	0.97	-
5	SFH A. C. G. D. B	11.98%	19.14%	-	0.91	0.97	-	0.96	0.98	-

10.4.5 Case Study “Bad Aibling”

	Series	CV RMSE			ρ			σ_s/σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Residential (2250 sqm)	10.97%	24.34%	-	0.90	0.94	-	0.99	0.97	-
2	Residential (2250 sqm) 2012	16.95%	24.36%	42.54%	0.90	0.96	0.88	0.86	0.89	0.89
3	School & Boarding (2150 sqm)	16.01%	31.03%	-	0.90	0.93	-	0.89	0.92	-
4	School (8090 sqm /partial)	20.41%	29.41%	-	0.90	0.95	-	0.82	0.85	-
5	All School buildings	6.77%	26.08%	-	0.91	0.95	-	0.99	0.91	-
6	Office Buildings	35.85%	44.75%	-	0.91	0.83	-	0.88	0.89	-
7	Hotels (580 sqm)	14.21%	49.14%	-	0.79	0.87	-	0.88	0.74	-
8	Hotels (1160 sqm)	11.41%	27.44%	-	0.89	0.93	-	0.98	0.93	-
9	Hotels (2030 sqm)	7.81%	22.42%	-	0.91	0.95	-	0.94	0.95	-
10	All Hotels	6.77%	20.01%	32.32%	0.91	0.96	0.91	0.99	0.99	0.97
11	All buildings NW	10.08%	22.73%	-	0.91	0.95	-	0.96	0.99	-
12	All buildings NE	10.08%	20.01%	-	0.91	0.96	-	0.96	0.99	-
13	All buildings loops NW & NE	17.97%	19.55%	-	0.95	0.96	-	0.98	0.98	-

10.4.6 Case Study “Commercial Zone”

	Series	CV RMSE			ρ			σ_s / σ_m		
		mon	d	h	mon	d	h	mon	d	h
1	Sim 2013	-	19.02%	47.74%	-	0.97	0.84	-	0.98	0.94
2	Modified Sim 2013	-	14.97%	29.33%	-	0.98	0.94	-	0.97	0.94
3	Sim 2014	-	22.25%	53.92%	-	0.97	0.79	-	1.01	0.96
4	Modified Sim 2014	-	19.24%	36.20%	-	0.97	0.91	-	0.97	0.93
5	Annual load duration curve 2013	-	-	14.00%	-	-	0.99	-	-	0.94
6	Annual load duration curve 2014	-	-	9.29%	-	-	0.99	-	-	0.96

10.5 Annex E: Urban energy planning tools

Table 38: Local energy planning tools

Tool / Method	Application	Modelling approach (demand side)	Developer	References
Forward models				
R-C models				
CitySim, Suntool	District scale energy demands simulation	R-C model statistic subroutines for user beaviour	EPFL, University Nottingham	(Starkovic, Campell et al. 2006), (Robinson, Haldi et al. 2009)
OSAKA model	City wide energy demand simulation	R-C model applied to building archetypes	University of Osaka	(Shimoda, Fujii et al. 2004), (Shimoda, Asahi et al. 2007)
Energy balance models				
District Energy Concept Advisor	Development of district energy concepts	DIN 18599 based on building archetypes	Fraunhofer IBP	(Erhorn-Kluttig, Erhorn et al. 2013)
CITY GML based building simulation	Large scale energy demand modelling	ISO 13790 steady state energy balance	TU Munich, HfT Stuttgart, EIFER	(Nouvel, Schulte et al. 2013), (Bahu, Koch et al. 2013)
RETScreen (CHP module)	Potential assessmetn for RES & CHP	Annual load duration curve based on monthly energy balance	NRCan	(Natural Resources Canada 2005)
Heating / Cooling Degree Days	Heating demand assessment	simplified forward building representation	multiple	(Day 2006)
Data driven models				
Energy signature models				
EnerGIS	District scale heat demand assessment	linear regression model	EPFL	(Girardin, Dubuis et al. 2008), (Girardin, Marechal et al. 2010)
District Heating models	District scale heat demand assessment	multiple linear regression model	Dotzauer, Heller, Nielsen	(Dotzauer 2002), (Heller 2002), (Nielsen and Madsen 2006)
Gasload prediction (DE, AT)	Gas load prediction	sigmoid regression, statistic hourly profiles	TU Munich, TU Graz	(Hellwig 2003), (Geiger and Hellwig 2002), (Eichlseder 2008), (BDEW, VKU et al. 2014)
Static Load curves				
POLIS, URBS	District heating system assessment	Measured or statistic load annual load profile	Max-Planck-Institut for Plasma Physics, GEF Ingenieure	(Richter 2004), (Richter, Graf et al. 2007), (Zhivov, Liesen et al. 2010)
BHKW Plan	Layout planning for mid-scale CHP systems	statistic profile for annual load duration curve	Steinborn innovative	
Type day				
COPRA	Layout planning for mid-scale CHP systems		Dr. Valentin Energiesoftware GmbH	(Dr. Valentin Energie Software GmbH 2002)
Deeco	Urban energy system modelling		TU Leipzig, TU Berlin	(Bruckner, Morrison et al. 2003), (Bruckner 2001), (Wittmann and T. 2007)
TIMES HEAT	Optimisation for national and individual heat supply systems	Typical days per weekday and period coupled to hourly load profiles	KIT IIP, EIFER	(Merkel 2012), (McKenna 2013), (Fehrenbach, Merkel et al. 2014)
VDI 4655	Reference load profiles for residential buildings	Typical days per weekday and period coupled to hourly load profiles	VDI	(VDI 2008)
GOMBIS	Development of district energy concepts	Typical days per weekday and period coupled to hourly load profiles	Korb Systemtechnik	(Saadat 2000), (Saadat 2003)

Table 38 provides an overview on local energy planning tools and methods categorised according to the applied demand side model. A tool is understood as a software solution combining different functionalities for a specific purpose and user. Table 38 is limited to specific tools, yet a large number of relevant case studies can be found that are based on generic modelling frameworks or languages such as Modelica (Fritzson 2006, Huber and Nytsch-Geusen 2011), TRNSYS (Nußbicker-Lux 2010, TRNSYS 2011) or INSEL (Schumacher 1991).