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REPORT

Contract: OPTIWELLS-2

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SYNTHESIS REPORT

Project acronym: OPTIWELLS-2

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for
Kompetenzzentrum Wasser Berlin gGmbH

Preparation of this document was financed through funds provided by Veolia

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Recherche & Innovation

Berlin, Germany
2016

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Title

Optiwells-2 Synthesis report

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Deliverable number

OPTIWELLS-2 D4.1

Final version

31.08.2016

Acknowledgement

The project team is grateful to *Veolia Eau* and to *Veolia Environnement Recherche et Innovation* for sponsoring and supporting the project *OPTIWELLS-2.*

We thank all involved persons at the technical divisions and research and development departments as well as the technical committee for the valuable discussions and provided information. Many thanks also to the reviewers for their constructive remarks.

Un grand merci & thank you!

Executive summary

Objective of this synthesis report is to summarise the main achievements of the OPTIWELLS-2 project. Based on a preparatory phase OPTIWELLS-1 (2011-2012), the main project phase OPTIWELLS-2 (2012-2015) included the development of two different optimisation modelling methodologies (data-driven, process-driven) for minimising a well field's specific energy demand whilst satisfying both, water demand and water quality constraints.

Chapter 2 gives a short overview on the technical background on pipe hydraulics and the general methodology used within the project.

The general workflow of the testing and application for the three case study well fields investigated within OPTIWELLS-2 is summarised in Chapter 3. For the first two case studies (Chapter 3.1 and 3.2), a process-driven modelling approach was used, which enabled the assessment of three different management strategies (smart well field management, pump renewal or a combination of both) on the specific energy demand. This approach was more time and data-demanding (Chapter 2.5) compared to the data-driven approach used for the third case study (Chapter 3.3).

The cross-case analysis (Chapter 4) showed, that the energetic prediction accuracy of process-driven modelling (Chapter 4.1.3) was improved significantly by using pump characteristics derived from audits instead of relying on manufacturer data, whilst including steady-state well drawdown compared to assuming a static water level in the production well was much less important. This can be explained by the fact, that well drawdown contributed to less than 3% of the required pump head (Chapter 4.1.1), whilst the offset between audit and manufacturer pump characteristics is much more relevant because of pump ageing during long usage periods (up to 40 years). The data-based modelling approach used for Site C has yielded energy consumption forecasts with a similar accuracy, but is more robust as it relies on operational data, thus requiring no calibration.

Optimisation modelling results (Chapter 4.1.3) obtained for three case study well fields indicate that optimised well operation reduces energy consumption up to 20%. The supplementary replacement of particularly aged pumps increases the savings even up to 50%, in case that very aged pumps were formerly operated at high priority. A newly developed pump database comprising the relevant facts of submersible pumps of different manufacturers can be used for the selection of suitable pumps (Chapter 6.1.2).

Testing the methodology developed in OPTIWELLS-2 for minimising the well field's specific energy demand was limited to three small to medium sized well field sites ranging from 6 to 18 submersible pumps. However, the methodology should be also scalable, i.e. applicable for larger well field sites without being too expensive. Currently this is not possible, because important parameters required for assessing the in-situ pump characteristics (pumping rate, pressure head and power demand of pump, water level in well) are typically not logged by the operators with a sufficient temporal resolution. To overcome this data shortage, time-consuming pump audits were required, but these provide only a snapshot that in addition can be fast outdated (for example if that the pumps are renewed). Thus, future research in the field of energetic well field optimisation should focus on:

- the identification (or equipment) of a bigger well field with data loggers
- testing of the data-driven approach for this (large) well field

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Chapter 1
Introduction

1.1 Background

Fresh water aquifers act as a safe drinking water resource for a majority of the European population (75 %). Groundwater abstraction is energy demanding, represents thus a significant cost factor in drinking water production and is also responsible for (indirect) greenhouse gas emissions. For instance, groundwater abstraction was estimated to account for 35 per cent of the energy demand of water utilities both in Germany and Switzerland (Plath & Wichmann 2010). Although groundwater abstraction represents only about 1% of the European electricity consumption, rising energy prices and growing public concern on environmental issues urge water utilities to increase the energy-efficiency of water services.

Many factors influence the energy demand of a well field, for example the geometrical elevation (i.e. height difference between static groundwater level and pipe inlet to waterworks), well drawdown and punctual (e.g. at bends, valves, fittings) and length-dependent pressure losses in the raw water pipes. In addition, the pump characteristics (e.g. offset to manufacturer pump and global efficiency curves due to ageing or cavitation) as well as the well field operation influence the operating point of each single pump and thus its energy-efficiency and specific energy demand. OPTIWELLS-1 identified key energy drivers and quantified their contribution to the total energy demand for a case study well field (Staub et al. 2012). However, this quantitative information cannot be generalized and additional investigations on well fields with different hydrogeological settings and design are necessary to derive more general conclusions about the relative weight of the different drivers.

Current optimisation strategies include either very general operational guidelines or very site-specific “trial-and-error” approaches, but lack comprehensive and applicable global assessments. Meanwhile, there are several management options for minimising the well field’s specific energy demand for water abstraction whilst satisfying predefined boundary conditions (water demand, raw water quality) such as: smart well field management (operating the pumps with the lowest specific energy demand at highest priority), pump renewal or a combination of both.

The energetic optimisation of a well field is complex, since the different system components (aquifer, well, pump, pipe, operation schemes) interact with each other, and the water demand may vary, thus leading to a complex hydraulic optimisation problem with varying system operating points. The large number of well field operation schemes (e.g. on-off switching of pumps) adds to the complexity of an optimising approach, explaining that only very few similar optimisation studies have been conducted so far (Hansen et al. 2013; Hansen et al. 2012; Madsen et al. 2009). In addition, numerous boundary conditions need to be considered to deliver applicable results (water demand, water quality requirements). This complexity requires adequate modelling tools for assessing the saving potentials (e.g. energy, costs for abstraction) from smart well field operation and/or design (e.g. investments in new pumps).
Veolia Eau DT developed a tool (OPTIM’Hydro) by coupling the pipe network model EPANET with a genetic optimiser (NGSG-II algorithm; (Deb et al. 2002)) for improving the system performance. However, this tool, which focuses on water distribution, is currently only able to consider wells as infinite reservoirs (i.e. constant water level, no drawdown due to pumping). MADSEN et al. (2009) developed the WELLNESS tool, coupling a pipe model (EPANET), a complex numerical groundwater model (MIKE-SHE) and a well model (Konikow et al. 2009) with a genetic optimiser (SEPA-2 algorithm; (Zitzler et al. 2001)) by using the open modelling interface OpenMI (www.openmi.org).

This approach enabled a detailed, physical representation of the whole abstraction system, but is very time-consuming due to the sophisticated numerical groundwater model and thus not easily adaptable to other sites. The two approaches described above either completely neglect the energy driver well drawdown (OPTIM'Hydro) or consider it using a very complex, distributed time-dependent numerical model chain (WELLNESS: MIKE SHE plus well model), thus reducing the predictive model performance due to over-simplification (OPTIM'Hydro) or over-parameterisation (WELLNESS). Consequently, there is a lack of an approach that is able to simulate production well drawdown with sufficient accuracy, but is less complex than the numerical groundwater model MIKE SHE in the WELLNESS tool. Analytical functions actually exist to compute local drawdowns in wells for different hydrogeological boundary conditions and well designs (Kresic 2007).These could be integrated in a modelling tool in order to take into account drawdown in a more realistic way while avoiding over-parameterisation and too long calculation times.

Based on findings of OPTIWELLS-1, smart well field management can yield up to 20% energy savings at the well field scale in comparison to classical operation schemes. The investment in newer, more efficient pump technologies, pump and well maintenance actions, or the use of Variable-Speed Drives (VSD) may enable further savings. Besides, while several operators and pump manufacturers pledge for a wider use of variable-speed drives (Boldt 2010; BPMA 2002), the conditions where the use of VSDs provides additional savings for a well field system are yet unclear as they strongly depend on the ranking of the energy drivers - and thus on site characteristics and hydrogeological boundary conditions (Staub et al. 2012). To date, no general assessment method exists to assist operators with the decisions of installing VSDs for a given purpose.

1.2 Objectives

The objectives within the OPTIWELLS-2 project were accordingly:

- **Development of a methodology for modelling and optimising the well field's specific energy demand** by means of smart well field management or pump renewal (of same type) whilst satisfying pre-defined boundary conditions (water demand, water quality).
- **Pump audits** for three small to medium sized case study well fields (6 to 18 pumps) to assess current pump characteristics (i.e. pump and global efficiency curves), which can show a offset to the manufacturer pump catalogues due to ageing or cavitation
- **Sensitivity analysis** to assess how simplifying the structure of the process-driven model, for example neglecting well drawdown (static water level in production well) and using manufacturer pump characteristics (no pump ageing), impacts its' capability to accurately predict the well field's specific energy demand.
- **Testing of the developed modelling and optimisation methodology** for the three audited case study well fields and providing energetic optimisation recommendations to the well field operators

Chapter 2
Energetic Well Field Optimisation

2.1 System boundary and components

Water abstraction from drinking water well fields typically starts at the production well that is equipped with a submersible pump and ends at the pipe inlet to the waterworks. Here, the abstracted raw water is treated before being distributed to the end-users (industry, households).

Within OPTIWELLS-2, the energetic optimisation was limited to the water abstraction process (Figure 1), which comprises the following system components:

- Pipe (network) system
- Wells
- (Submersible) Pumps

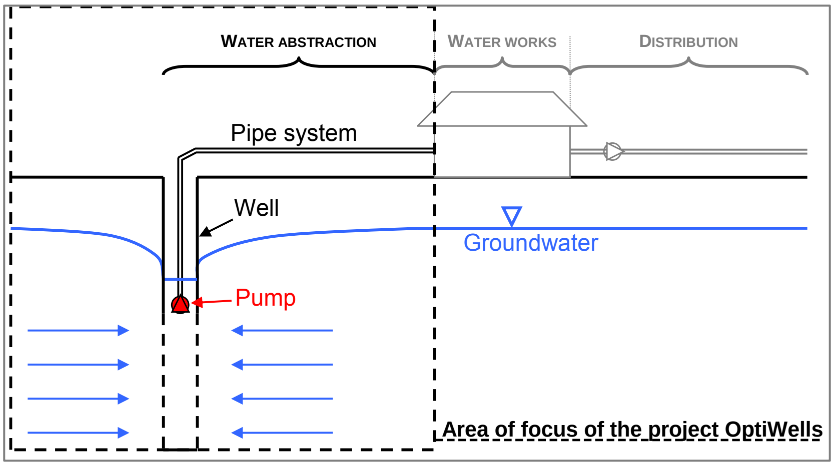


Figure 1 System boundary and components (Staub et al. 2012)

The key prerequisite for optimising the energetic performance of water abstraction is the concept of the pump's operating point, i.e. the pumping rate of the pump at a given manometric head (discharge- total dynamic head curve), and thus the global efficiency of the system (discharge- global efficiency curve).

The operational point of a pump is defined by two components (Figure 2):

- the pump head curve, and
- the system head curve.

While the **pump head curve** (as well as the global efficiency curve) is well defined from manufacturer's catalogues for new pumps, the **system head curve** for an operating pump is depending on the following system components:

1. **Geometrical elevation ($H_{geometrical}$)**: is the height difference between static groundwater level and delivery point (e.g. geometric height of the pipe inlet at waterworks, minimum pressure in pipe network at a certain point). This height difference needs to be overcome in any case, thus it is also called static head.
2. **Well drawdown (H_{well})**: is the lifting height difference between dynamic groundwater level and static water level from pumping (drawdown). Technical details on how pumping rate, pump duration, well construction and aquifer characteristics as well as well interference impact the drawdown were provided within deliverable D1.1 (Rustler et al. 2013) and D2.1 (Rustler & Sonnenberg 2014b).

3. **Pipe losses ($H_{network}$)**: are due to friction or turbulence in the pipe network, which increases depending on the flow velocity by the power of two (i.e. doubling the pumping rate leads to four times higher pipe losses; see also D.2.1 of the OW-1 project). In detail, one can distinguish:
    a. Length-dependent losses ($H_{network,length}$): function of pipe length, diameter and its roughness
    b. Point losses: dependent on loss coefficients (e.g. valves, bends, fittings)

Drawdown and pipe losses are summarized in the **dynamic head loss component**. Dynamic head losses due to pipe losses occur in any pipe system, but in case of well fields, an additional head loss due to well drawdown (i.e. increasing depth to the groundwater table in case of pumping) has to be taken into account. In case of multiple operating pumps in the same pipe, the system head curve will further be impacted by increasing pipe losses, which may shift the operational point and thus influences the global pump efficiency.

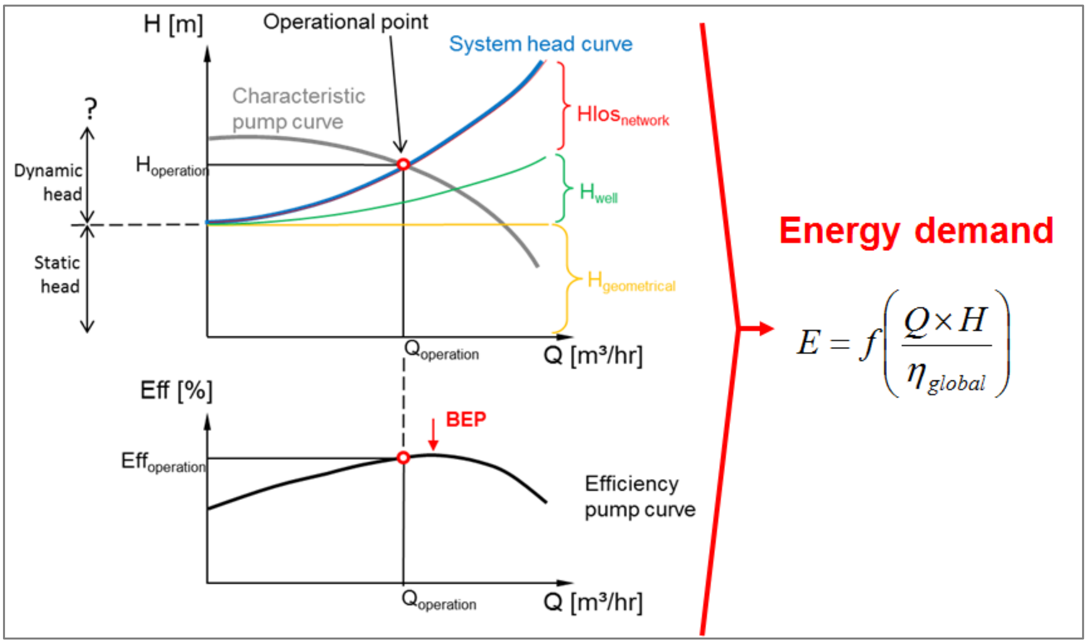


Figure 2 How system components (pipe network losses, well drawdown) impact the operational point. The relevance and shape of each head component is site-dependent and thus not to scale. [modified after (Strybny & Romberg 2007)]

The hydraulic behaviour of the abstraction system (pump, well, pipe network) can thus be defined by the two variables H and Q and the energy demand can be described as a function of these two variables and the global efficiency by the following equation:

$$E = f\left(\frac{Q \times H}{\eta_{global}}\right)$$

<u>where</u>:

- E energy consumption (kW),
- Q discharge(m^3/h),
- H total dynamic head (m) and
- η global efficiency (dimensionless).

The closer the operational point from the discharge-head-curve is to the best-efficiency point (BEP), which is the maximum of the discharge- global efficiency curve (Figure 2), the more efficient is the pump in terms of specific energy cost for abstraction [typically kWh/m^3].

The relation between discharge rate (Q) and length-dependent pipe loss (in meters) can be described by the Hazen-Williams equation:

$$H_{network,length} = \frac{L \cdot 10.67 \cdot Q^{1.85}}{C^{1.85} \cdot d^{4.87}}$$

with:

- *L* length of pipe (meters)
- *Q* volumetric flow rate, m^3/s (cubic meters per second)
- *C* pipe roughness coefficient
- *d* inside pipe diameter (meter)

Figure 3 shows exemplarily the pipe loss component (m/km) on a logarithmic y axis for varying pipe roughness coefficients and diameters depending on a) the discharge rate and b) the flow velocity as calculated during model calibration. This visualisation shows the importance of these parameters on predicting the pipe head loss in the abstraction system, thus pointing out that it is necessary to know each of these parameters as accurately as possible for increasing the predictive model performance.

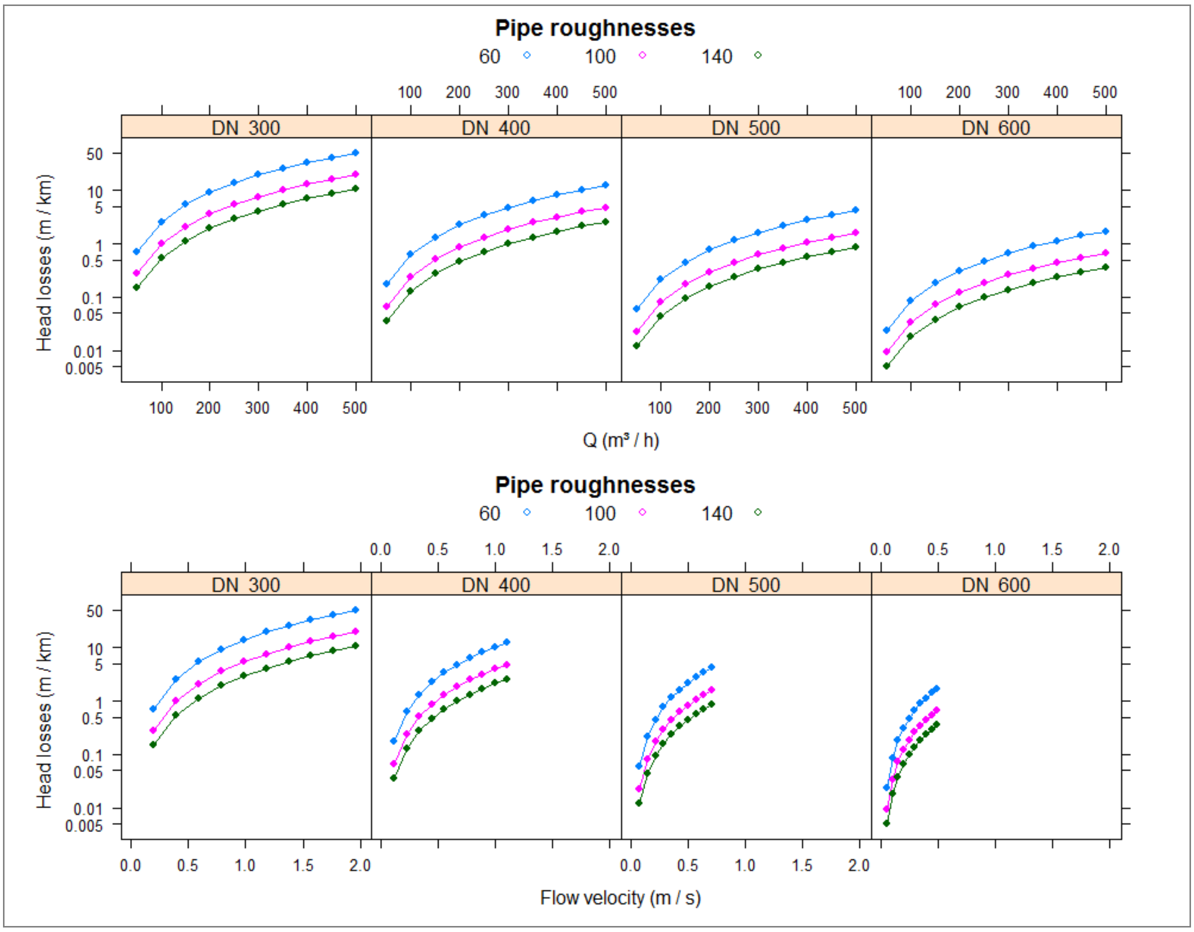


Figure 3: Hazen-solution for different pipe roughness coefficients and diameters under variation of Q (top) and variation of flow velocity (bottom); calculated with R

2.2 Smart well field management

Pumps operate in a given hydraulic head-flow range defined by their pump curve, but are not equally efficient for all possible operation points. To maximize their efficiency, they should be operated as close as possible to their BEP. Operating all possible pumps of a well field in this manner is called "smart well field management".

Operating a well field in this way is complex, since the different components of the system interact with each other, and the water demand may vary, leading to a complex hydraulic optimisation problem with varying system-operating points.

Within the OPTIWELLS-projects, the main energy-drivers within a well field were identified and prioritized for the investigated case studies. These were (with decreasing impact)

(i) static head: geometrical elevation determines up to 75% of a well field's energy demand

(ii) pump age: offset between manufacturer's and current pump characteristics (i.e. pump and global efficiency curves)

(iii) pipe head losses: as detailed in the previous chapter, having several pumps operating within the same pipe network is changing the system head curve depending on the number and placement of pumps in operation

(iv) well drawdown: the drawdown component accounted in median between 2 to 12% of the well field's energy demand for the studied well fields, whilst the sum of the other energy demand drivers (static head, pipe head losses and pump aging) accounted for 88% to 98%.

For the optimization of well field management, as envisaged within OPTIWELLS-2, pump age and well operation schemes, i.e. on-off-distribution of wells, were targeted, while the static head remains the biggest, but inalterable energy driver.

2.3 Modelling

As for the single system components models are available, the objective within the OPTIWELLS-projects was to develop a coupling scheme to optimize well field management by taking into account drawdowns (aquifer & well component), the pipe network and the pump characteristics in an energetic well field optimisation tool.

Two different approaches to implement and couple these system components were considered and tested as will be detailed below:

(i) **Process-driven**: numerical hydraulical pipe network model (EPANET), which is based on physical principles (continuity equation and mass conservation) and coupled with a (steady-state) well drawdown model

As soon as the model is implemented and calibrated, unknown scenarios can be calculated and compared to base scenarios to predict system behaviour.

(ii) **Data-driven**: prediction and optimisation of well field's specific energy demand by using available datasets (e.g. pumping rate, abstracted volume per pump) from continuous monitoring on a high temporal resolution (~ minutes).

As only past and current conditions are considered, this approach is able to describe current system behaviour but cannot be used to predict unknown scenarios.

2.3.1 Process-driven

Objective of process-driven modelling was to represent all system components by numerical or analytical models. In the case of OPTIWELLS-2, these were:

- a drawdown model (WTAQ-2 versus static and steady-state approach), and
- the pipe network model EPANET.

As described within deliverable D1.1 (Rustler et al. 2013) WTAQ-2 was able to consider quasi-transient well drawdowns and account for well interferences. However, calibration demand was high and for most parameters sensitivity was in the range of uncertainties. Therefore, for the case studies (see also Chapter 3), a well interference matrix was derived from monitoring data and implemented into optimization instead of using WTAQ-2 to account for time-dependent drawdown development. This energetic well field optimisation model ("Optimizer") was then run with two scenarios:

(i) static conditions (as in OPTIM'Hydro operated by Veolia DT), and

(ii) steady-state conditions (data-based regression model as developed within OW-2)

The programming language R (Ihaka & Gentleman 1996) was used for the optimiser to be coupled with EPANET (Rossman 2000) in order to automatically run the pipe-drawdown model multiple times. The results were post-processed using R's data analysis and visualisation capabilities.

Figure 4 shows the components of the finally implemented tool. The process-driven modelling approach within OPTIWELLS accordingly comprised the following procedure:

- model setup under local boundary conditions (EPANET)
- integration of steady-state well drawdown (based on multiple-step pumping tests)
- model calibration with pump audit data (best-fit using R)
- sensitivity analysis to quantify the impact of the different levels of model simplifications on the predicted energy demand (multiple calculation runs using R)
- optimization (multiple calculation runs using R)

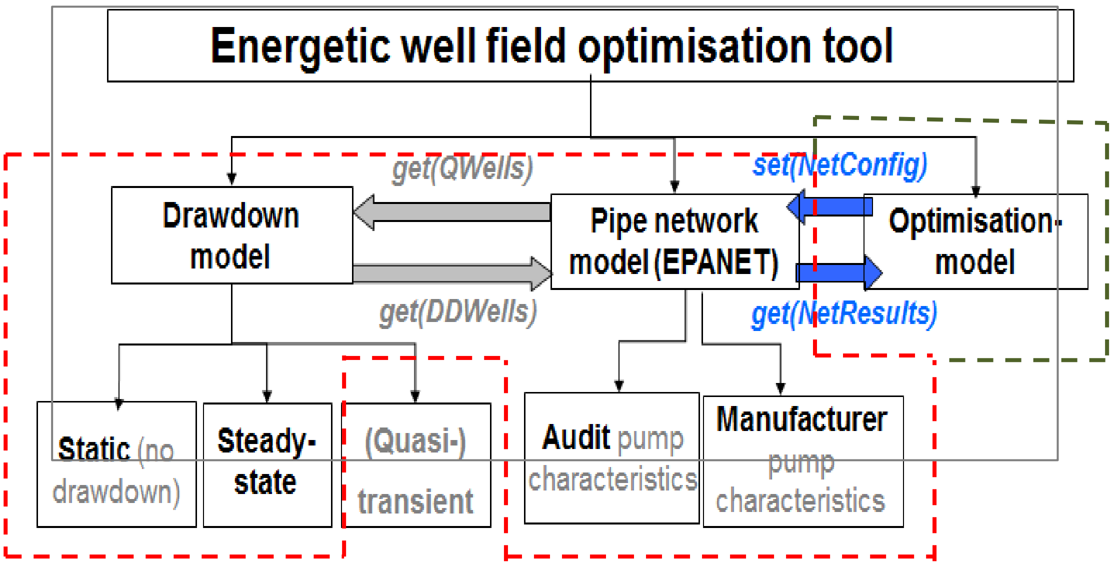


Figure 4: Components of process-driven modelling

with:

Model setup:

- Network geometry (derived from scanned map or EPANET model provided by operator).
- Pipe head loss coefficients (derived from literature)
- Boundary conditions: water quantity, water quality constraints (derived from data analysis of operator data)
- Pump characteristics: (derived from audit)
- (Steady-state) GW drawdown (derived from data analysis or audit)

Calibration:

- Only calibration parameter: pipe diameter
- Neglecting of other (minor) losses

The aim of model calibration was to reproduce the hydraulic well field behaviour (i.e. pumping rates) as accurate as possible by only changing the pipe diameters until modelled and measured pumping rates showed the lowest root mean square error. The model setup used for model calibration included not only the pipe network model and audit pump characteristics (i.e. pump and global efficiency curves) for all pumps but also a steady-state well drawdown model for all wells.

Using the calibrated model, a sensitivity analysis was carried out for each case study in order to assess the impact of different levels of model simplifications (e.g. no well or pump ageing) on the accuracy of the predicted specific energy demand. In total, four different model setups were tested. Table 1 summarizes the resulting level of impact of the model simplifications.

Table 1: Sensitivity analysis: impact of model simplification level (high, medium, low) on the modelled specific energy demand. ***** indicates the calibrated reference model used for model comparison

	Steady-state well drawdown	**Static (no well drawdown)**
Audit pump characteristics	Low*	Medium
Manufacturer pump characteristics	Medium	High

Finally, the calibrated model implementing audit pump characteristics and steady-state well drawdown (low simplification level) was used for energetic optimisation modelling in case of different management strategies. These comprised:

1) Only **smart well field management**: former studies showed that this strategy could save up to 10-20% of energy compared to the routinely applied operation scheme (Staub et al., 2012). Smart well field management is based on identifying the most energy-efficient pumping schedules in order to minimize the specific energy demand of the well field operation. For this objective, the optimizer simulates all possible pumping configurations within the well field and calculates the specific energy of each scenario, defined as the energy needed to provide one cubic metre of raw water (depending on number of pumps n with on/off operation, i.e. 2^n possible combinations minus 1 considering that at least one pump is on).

2) Only **pump renewal**: if the pumping schedule cannot be modified due to additional constraints (water quality, water demand, maintenance, etc.), a “smart pump renewal” can be a good option to reduce the energy demand. Within this study, pump renewal is defined as followed: the currently installed pump is replaced by a new pump of the same model (i.e. the current pump characteristics obtained from the audit are replaced by the manufacturer pump characteristics). For identifying the most suitable pump(s) to change, the optimizer simulates all possible pump renewals (combinations as above) and calculates the specific energy of each one.

3) **Combination** of smart well field management (1) and pump renewal (2)

The boundary conditions for optimising the specific energy demand were always to satisfy an average hourly water demand whilst also taking into account possible water quality constraints. Both boundary conditions were derived for each case study by performing a data analysis with the software R.

2.3.2 Data-driven

Objective of data-driven modelling was to evaluate the feasibility of optimizing well field management by taking into account operational data on drawdown development within the well field without model components. Thus, all system components needed to be represented by data sets. The exact approach had to be developed based on the extent and temporal resolution of available data.

First step was a sensitivity analysis with regard to the impact of transient conditions in drawdown modelling on the energy demand prediction error. As for the worst-case (high drawdown component) an error of 4.9% was calculated, which is in the range of measurement uncertainties, considering transient conditions in the case study approach was abandoned and instead, data-driven modelling should help to identify

(i) the most efficient and most inefficient pumps of a well field, and

(ii) the optimum combination of pumps with regards to total energy demand.

Representing all system components by data was implemented by considering

- the pump system curve from manufacturer and audit data,
- the energy demand per pump from audit and operator data, and
- the current pumping scheme (incl. energy demand of well field) from operator data.

In order to answer the questions above, the following stepwise approach was developed and tested within the third case study as further described in Chapter 3 of this report.

i) Determination of offset between manufacturer and audit data: Identification of inefficient pumps, i.e. operating outside their best-efficiency point (aged or wrongly dimensioned)

ii) Calculation of specific energy demand-curves (E_{spec}-Q) by extrapolating from manufacturer data and offset from audit pump curves

iii) Calculation of total energy demand for the well field by summing up discharges, operating hours and energy demand per pump with satisfaction of the water demand as stop criterion

iv) Prediction of base scenario (current pumping scheme) and plausibility check

v) Optimisation by means of “smart well field management”: development of more energy-efficient pumping scheme

All visualization and data aggregation and modelling tasks were again performed with R (Ihaka & Gentleman 1996).

2.4 Pump audits

The pump characteristics of new pumps are available from manufacturer pump catalogues quite accurately with well-known uncertainty levels depending on the pump's tolerance class according to ISO 9906 (1999). However, due to **aging effects** (iron-ochre formation in the impellers) or **cavitation** (pump operation in overload, outside optimal range) the derived values do not need to be true especially for older, highly used pumps. Both can lead to an offset from the manufacturer characteristics, which in turn may lead to an increased specific energy demand. Thus, prior to assessing the energy demand of the well field pump audits are recommended to derive the current pump characteristics.

Within OW-2, the following parameters were measured within the pump audits that were carried out for all three case studies (Figure 5):

- **Power demand (E):** power demand of the pump (measurement device FLUKE 1730; assumed measurement error: 2%)
- **Pumping rate (Q):** clamped-on ultrasound device (FLEXIM F601, assumed measurement error: 5%)
- Total pressure head (TDH): sum of the
    - ***Pressure* head in the pipe** (**P**, measurement device: VEGABAR 51) and the
    - ***Distance to the groundwater table*** (**H**, measurement device: STS DL70) below that point

The error of the total pressure head is assumed to be 1%. Furthermore, this approach neglects possible head losses in the rising pipe, because the pressure head of the pump was not measured directly at the pump but behind the rising pipe.

During the pump audit, only the audited pump was operated, i.e. all other pumps of the well field were turned off. In addition, the pump characteristics were assessed for at least five different steps (i.e. pumping rates) that were kept constant for approximately five minutes by opening (or closing) a preinstalled throttling valve. In case no throttling valve was installed (a few pumps of the third case study), only one pumping rate could be measured. The duration of the pump audit for each pump (including installation of measurement equipment) took between 60 to 90 minutes.

The logger data were then imported into R for data analysis (Figure 6) and aggregated for each pumping step by using the median values during a time period of quasi-constant pumping rates. This enabled the calculation of audit pump characteristics, i.e. audit pump and global efficiency curves, which were then compared against the manufacturer curves (Figure 7).

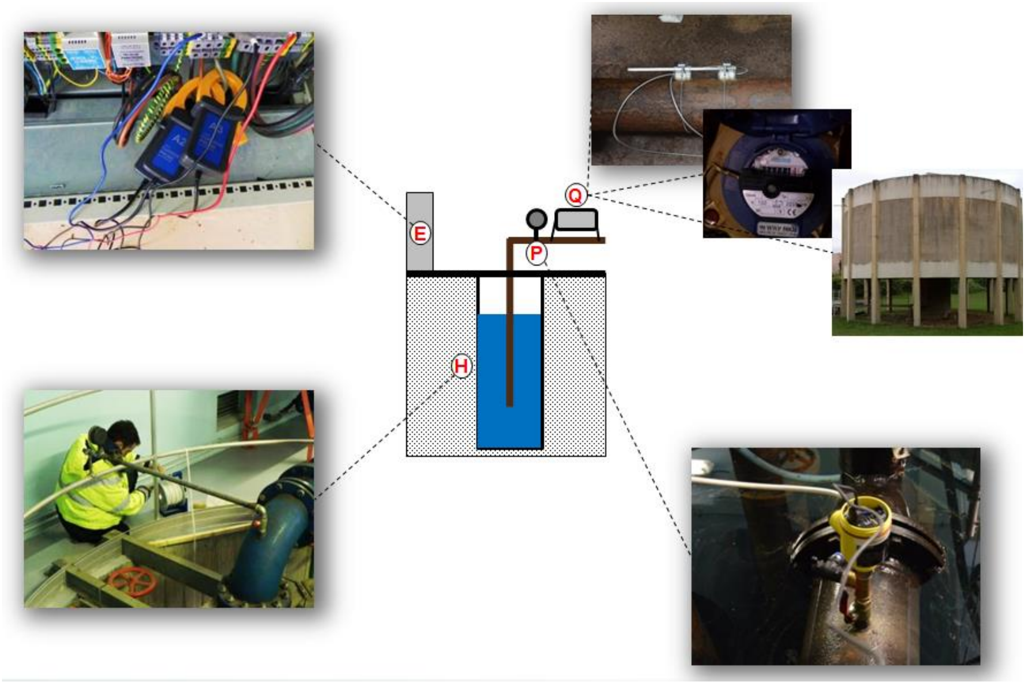


Figure 5 Pump audit and measurement devices for determining pump characteristics (pictures: TUB, KWB)

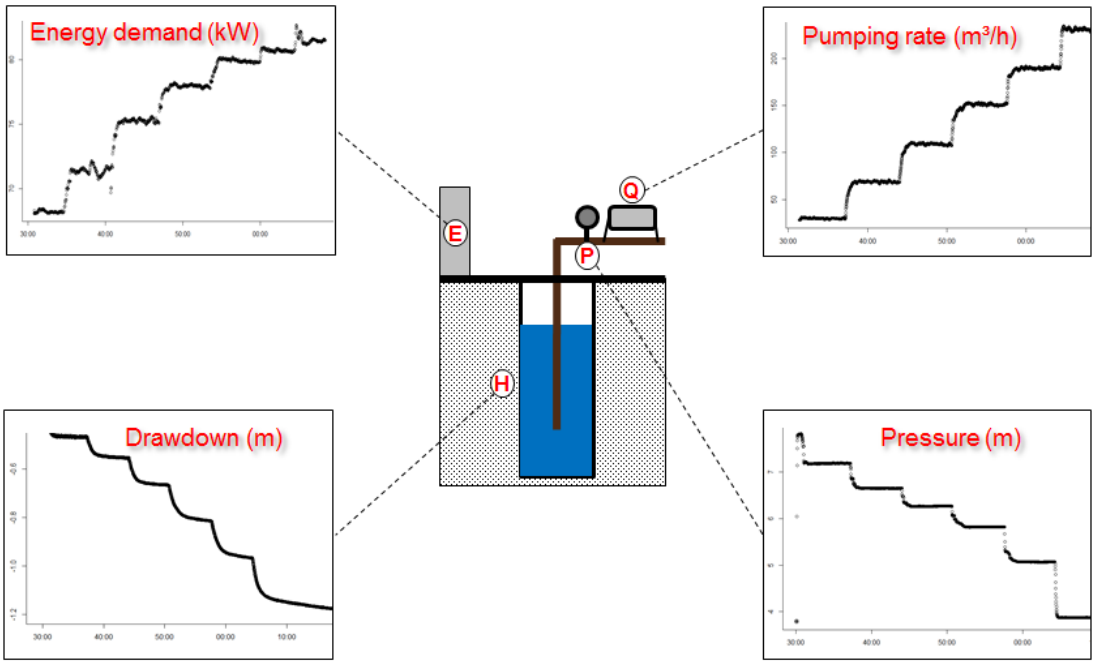


Figure 6 Assessed parameters during pump audit for determining “real” pump characteristics

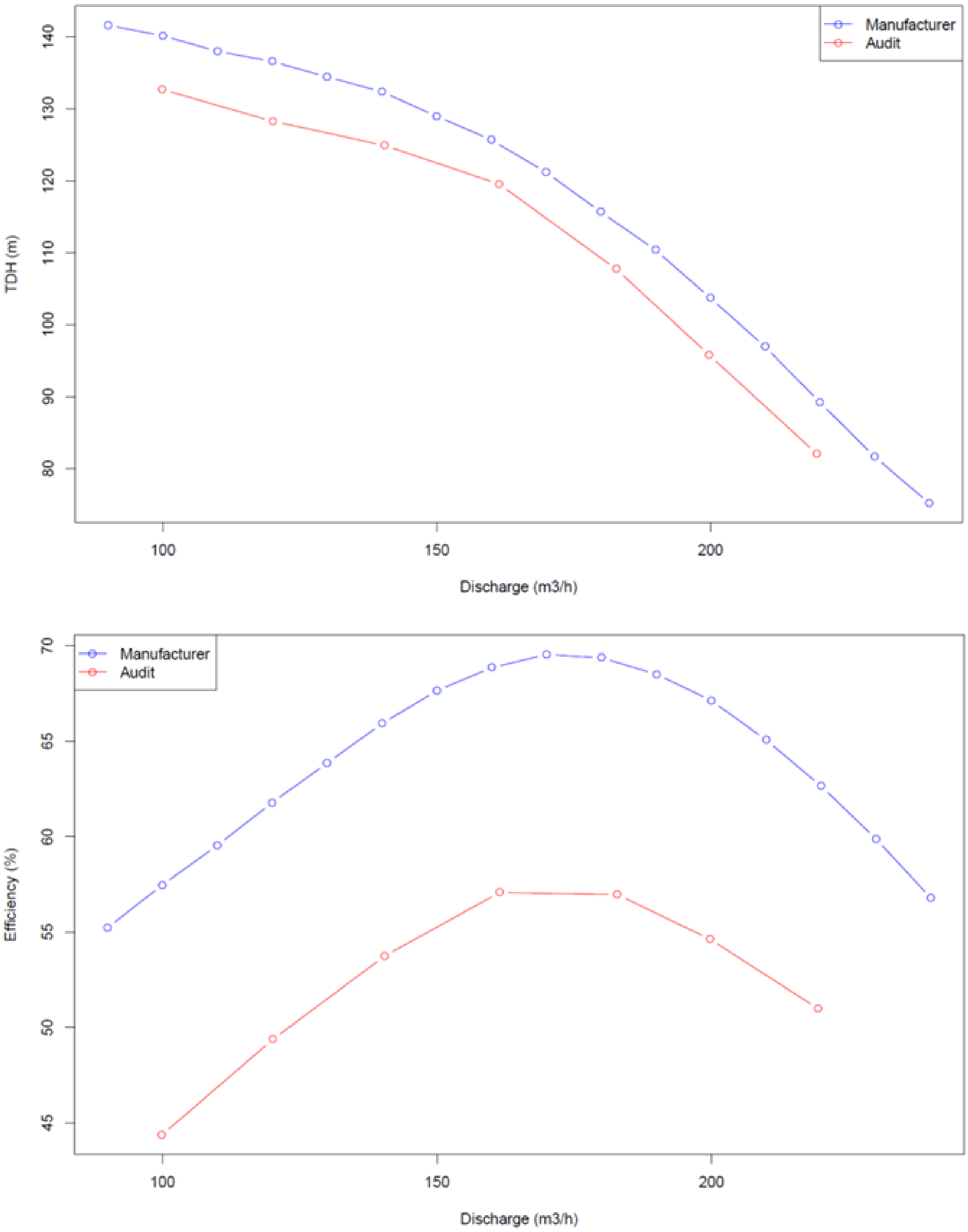


Figure 7 Comparison of manufacturer pump characteristics (blue lines with dots) and "real" pump characteristics based on audit data

2.5 Data prerequisites & uncertainties

The different modelling approaches, process-driven (Chapter 2.3.1) and data-driven (Chapter 2.3.2) have different data prerequisites, which are summarised in Table 2.

Table 2 Data requirements for the different modelling approaches

Data requirements	Modelling approach: Process-driven	Modelling approach: Data-driven
Pipe network	yes	no
Well drawdown curves for each well	yes	no
Pump characteristics		
Pump curves (Q, TDH)	yes	no
Global efficiency curves per pump (Q, TDH, E)	yes	no
Specific energy demand curves per pump (Q, E)	no	yes
Operational data		
Abstracted volume per pump (V)	yes	yes
Pumping rate per pump (Q)	yes	yes
Power demand per pump (E)	yes	yes
Total dynamic head per pump (TDH)	yes	no
Specific energy demand of well field (E/Q)	yes	yes

Accordingly, only for process-driven modelling detailed maps of the abstraction pipe network are required, which should include information on pipe diameters, installed features (valves, fittings, bends), and geometrical elevations of system boundaries (e.g. static groundwater level in wells, geometrical elevation of pipe inlet at waterworks), so that a digital model of the well field abstraction system can be constructed.

In addition, discharge-dependent (steady-state) well drawdown curves need to be included in case that well drawdown contributes to a significant share of the pump's total dynamic head at its operating point, which is true for field sites with low static head but large well drawdowns. For integrating discharge-dependent well drawdown data, recently carried out multiple step pumping tests can be used.

Pump and global efficiency characteristics for each pump are required input parameters in case of the process-driven model, which was used for the first two case studies (Chapters 3.1 and 3.2), while in case of the data-driven modelling approach, as used for the third case study (Chapter 3.3), specific energy demand curves (based on power demand and pumping rate) for each pump are the only required inputs. For acquiring these data, there are generally two options:

1) **Pump audits:** in case that no real-time monitoring of the required parameters for assessing the pump performance is available (see 2.4) and pump ageing or cavitation cannot be ruled out, pump audits are recommended. The uncertainty of the measured parameters depends on the measurement equipment and systematic errors (e.g. in case of improper installation of the monitoring equipment)

2) **Manufacturer pump characteristics**: if neither pump audits nor real-time monitoring are available but the pump is quite new, the pump characteristics can be deduced from manufacturer pump catalogues. The uncertainty of the pump characteristics derived from pump catalogues depends on the pump tolerance class (Table 3) and on the degree of conformity between the installed pump and the manufacturer pump curve.

Table 3 Uncertainty of pump characteristics based on manufacturer catalogues (ISO 9906 1999)

Norm	Pumping rate (%)	Total dynamic head (%)	Pump efficiency (%)	Power demand (%)
Class 1	4.5	3	3	
Class 2	8	5	5	
Appendix A	9	7	7	9

Finally, operational data are required for both modelling approaches, but for different purposes:

- **Process-driven:** in case no pump audit is carried out, operational data are required for assessing the current pump characteristics (pumping rate, total dynamic head, power demand). In addition, operational data (pumping rates per pump) are required for hydraulically calibrating the model (e.g. by changing either the pipe diameter or roughness, see also Figure 3).
- **Data-driven:** this approach requires no model calibration, but operational data (pumping rate and abstracted volume per pump) are required as model input parameters. In addition, in case no pump audit is carried out, operational data are required for assessing the specific pump characteristics.

For both modelling approaches, operational data on the specific energy demand of the well field should be available at least on a monthly basis, so that the predictive model performance can be compared with measured data.

In general, as can be seen from Table 2, process-driven modelling has not only higher data requirements compared to data driven modelling, but also its application requires more technical steps (e.g. model parameterisation, calibration, validation). However, the more technical steps are needed the higher is the predictive uncertainty of the model (e.g. due to overfitting during calibration). Thus, the predictive uncertainty in case of data-driven modelling is much lower, but at the expense that it is not possible to assess the system behaviour for different boundary conditions (e.g. assessing the impact of pump replacement on the well field's future energy demand).

Chapter 3
Case studies

Within Optiwells-2, three cases studies were assessed concerning their energy demand optimization potential. In order to do so, detailed data analyses, pump audits, modelling and optimisation of the specific energy demand were performed. Details are given in the following chapters. Reports or presentations are available individually for each case study, thus only brief descriptions are given here.

3.1 Site A

3.1.1 Site characteristics

The first case study was a small well field in north-eastern Germany (Figure 8) with a total of 8 production wells, of which six wells were operated with a total average hourly pumping rate of 74 m^3/h (data: January - May 2013). Raw water is transported in a main pipe (DN 400) approximately 3.5 km to the pipe inlet of the waterworks, which was set as system boundary for this study. Water treatment consisting of aeration and filtration within the waterworks as well as distribution of the purified drinking water were not taken into account within this study. Static lifting height, i.e. from the static groundwater table to the pipe inlet at the water works, adds up to 30 meters. The age of the six operable pumps varied between one to six years (median: 4.5 years). The pumping rate of the pumps was comparably low with a median of 35 m^3/h (minimum: 14 m^3/h; maximum: 66 m^3/h), which can be explained by the low specific capacity of the wells having well drawdowns up to 10 meters at the given discharge rates.

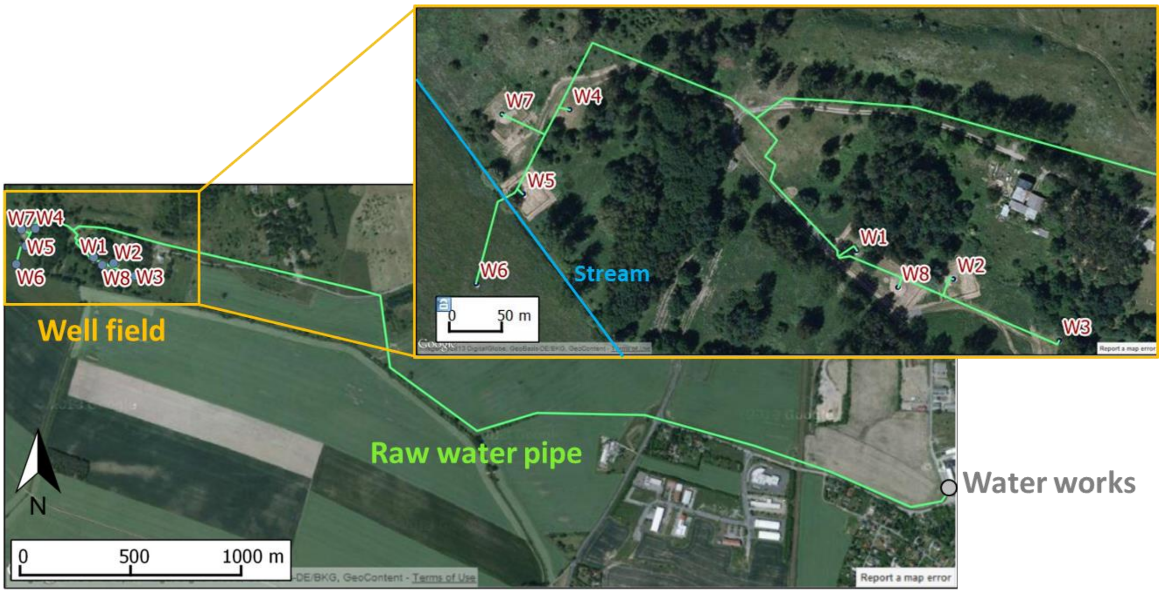


Figure 8 Case study well field

As between 2004 and 2013 the energy price has tripled, considerable efforts were dedicated to optimising the specific energy demand of the well field by the operator already in the past, which decreased by approximately 20% in the same time period (Figure 9).

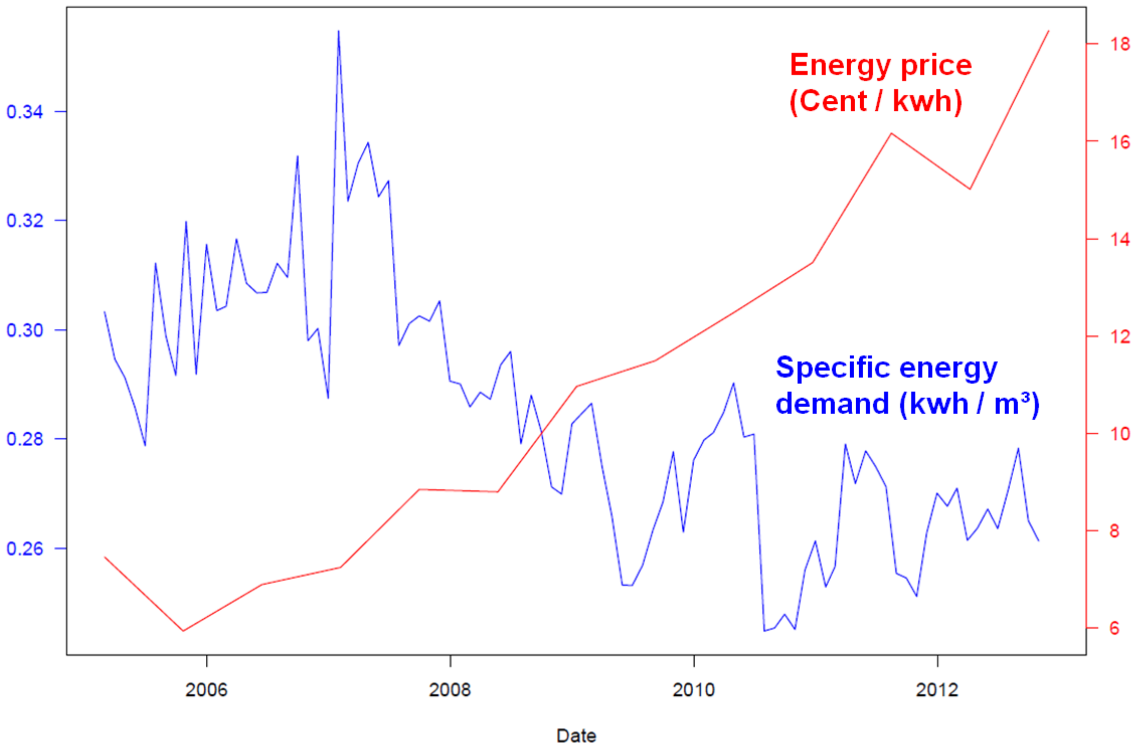


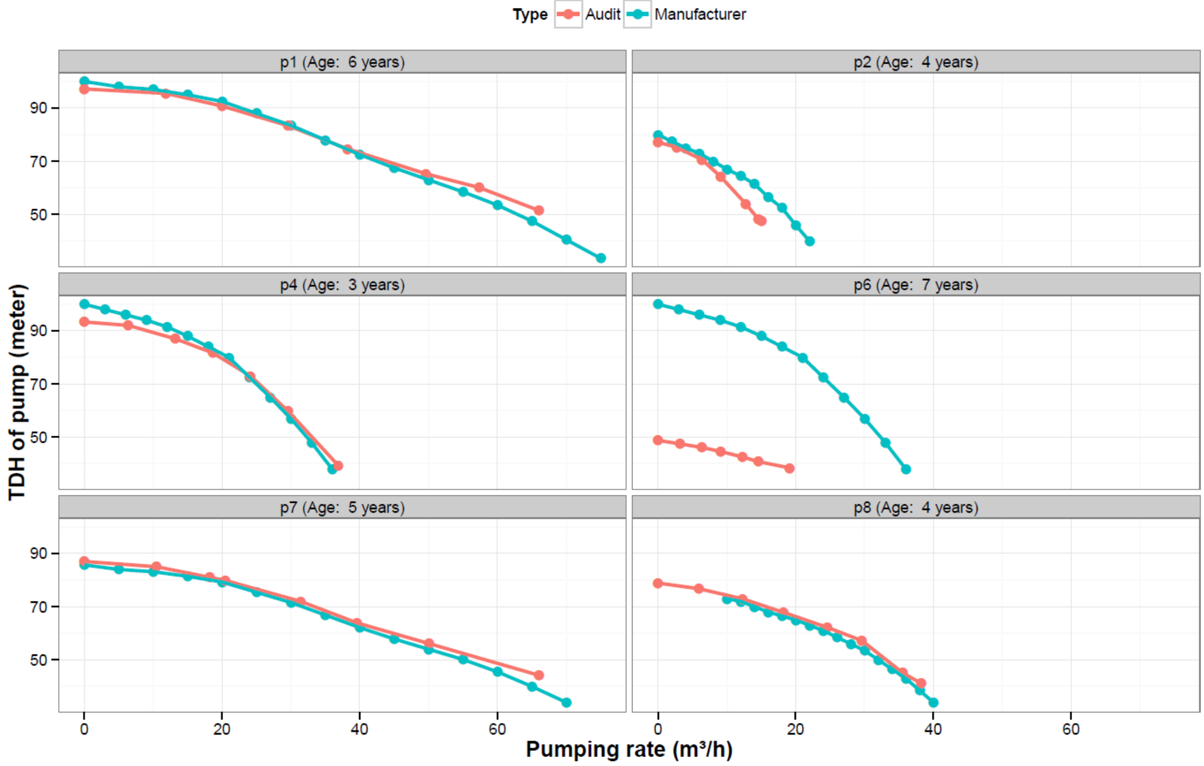
Figure 9 Energy price and specific energy demand of the well field

3.1.2 Pump audit

The pump audit was performed within four days (8th - 11th of April 2013) by KWB and TU Berlin together with the local well field operator in order to assess the current pump and global efficiency curves of the six operable pumps in the production wells W1, W2, W4, W6, W7, W8 of the studied well field. The pumps p3 and p5 (in W3 and W5, respectively) were not audited because these wells were not operated due to their low specific capacity.

During the pump audit, only one pump was operated at a time while all other pumps were turned off. For each well, the pumping rate was increased every five minutes by successively opening the initially fully closed valve in at least five steps with quasi-constant discharge until it was fully open.

The audit results are summarized in Figure 10 and Figure 11. Comparing audit and manufacturer data shows that for both, total dynamic head and global efficiency there is a large offset for pump p6 and a minor offset for pump p2 whilst all other are pumps very close to the manufacturer curves (Figure 10). Interestingly the picture is different for the specific energy demand of the pumps (Figure 11), because even pump p6 fits nearly perfectly with the manufacturer data. This can be explained by the fact that for this pump obviously both, total dynamic head and global efficiency dropped by the same order of magnitude, thus having nearly no impact of the specific energy demand.



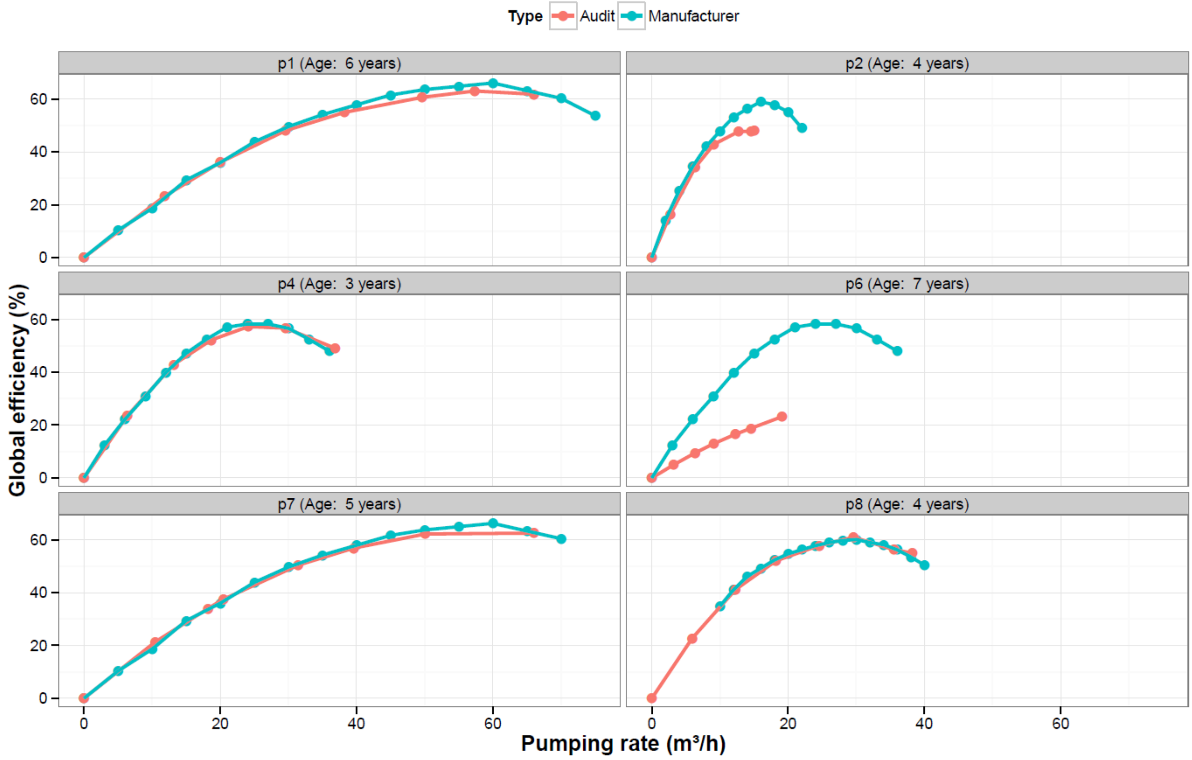


Figure 10 Comparison of audit (red lines with dots) and manufacturer (blue lines with dots) pump characteristics for both, total dynamic head (top panel) and global efficiency (bottom panel). Each dot represents one pumping step.

However, despite the fact that the specific energy demand curves (Figure 11) are very similar for all pumps, the pump with the highest specific energy demand is pump p6 (0.5 kwh/m³ at maximum audit pumping rate). At the maximum audit pumping rate it is 250 % higher compared to the specific energy demand of the other pumps. Thus, it is recommended to check whether the pump is connected electrically correct (i.e. that the phases are not shifted so that the impeller is turning in the wrong direction) and potentially to renew the pump p6.

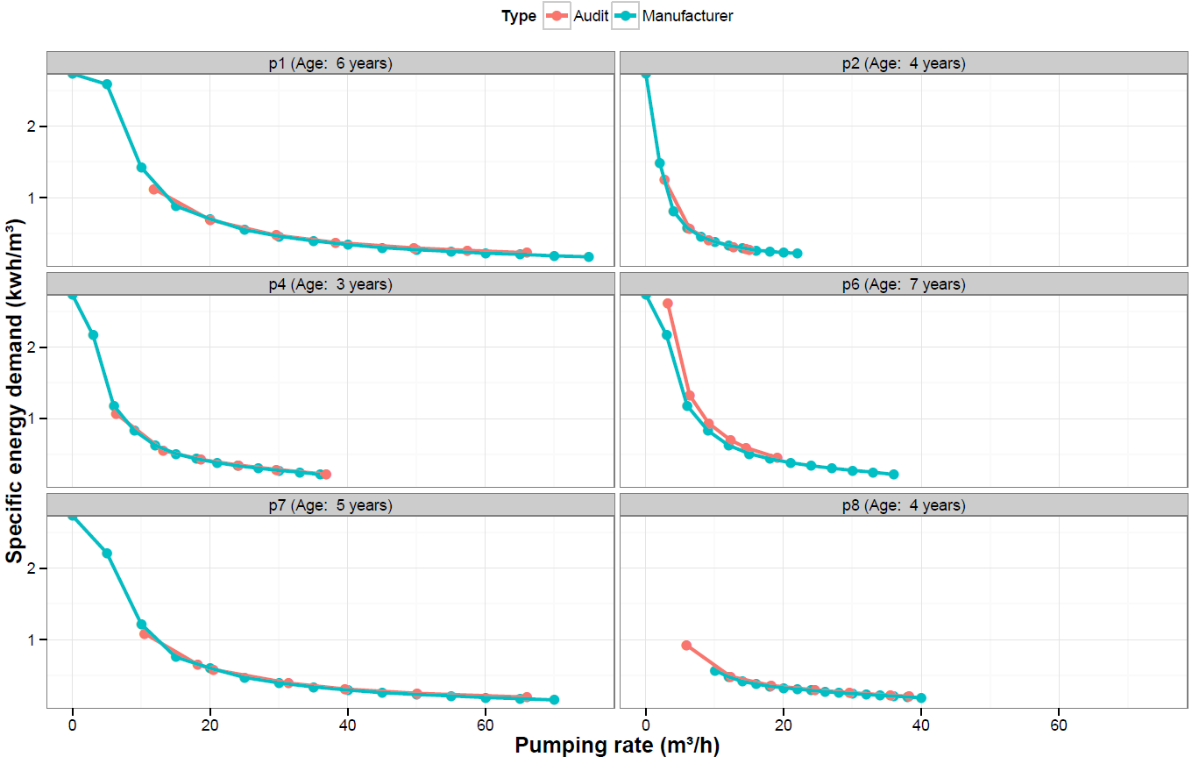


Figure 11 Impact of changed pump characteristics: audit (red) versus manufacturer data (blue)) on the specific energy demand

3.1.3 Process-driven modelling

The raw water pipe network was digitalised as EPANET input file based on maps provided by the well field operator. For using the model in process-driven optimization, the following model features needed to be included additionally:

- **Pump characteristics:** pump and global efficiency curves (derived from the pump audit as described in Chapter 3.1.2)
- **Well drawdown:** steady-state drawdown for different pumping rates (based on the audit data)
- **Boundary conditions:** average water demand and water quality (derived from the analysis of operational data)

3.1.4 Results

Model calibration & validation

The process-driven EPANET model, which included steady-state well drawdown and audit pump characteristics (i.e. pump and global efficiency curves) was hydraulically calibrated by fitting only the unknown pipe diameter for the main pipe between the well field and the waterworks (3.6km) for all wells pumping in parallel. With this approach, the real pipe diameter is potentially underestimated because no minor pipe losses are assumed.

The objective function to be minimised was defined as average error between measured and modelled pressure and discharge in the pipe, in case that all six pumps in the wells of the well field were operating in parallel. For the best calibration run, the pipe diameter was adjusted to 371 mm, which resulted in an error of less than 0.3 % for both parameters (Table 4).

In a next step, model validation was performed by checking the model results for single well operation to the data measured during the audit. The average error for both, discharge and pressure increased up to 6% (Table 4). However, given the measurement uncertainties for discharge (clamped-on ultrasound device, assumed error: > 5 %) and pressure measurement (assumption: 1%), such a value is acceptable and the model was thus assumed to be well calibrated.

Table 4 Results of model calibration & validation

	Discharge measured (m^3/h)	Relative error (in %) *modelled – measured*		
		Discharge	Pressure	avg(discharge, pressure)
Calibration (W 1 | **2** | 4 | **6** | 7 | 8)	212.64	-0.26	-0.32	-0.29
Validation (W 1)	66.02	-2.35	-10.04	-6.19
Validation (W 2)	15.03	2.93	-6.98	-2.02
Validation (W 4)	36.88	-2.60	-1.50	-2.05
Validation (W 6)	19.12	7.95	-3.50	2.23
Validation (W 7)	66.02	-4.26	-7.28	-5.77
Validation (W 8)	38.25	0.08	-5.28	-2.60

Sensitivity analysis

In a second step, the calibrated model was used to test the impact of the model structure (i.e. including audit pump curves and measured well drawdowns instead of neglecting well drawdown and using manufacturer pump curves) and uncertainty (i.e. missing operation data) on the predicted specific energy demand of the well field. Figure 12 shows the resulting deviation between predicted (model) and measured (operator, reference value) energy demand with regard to:

(i) **Model structure (difference between the four different box-whisker plots):** the most simplified model structure, assuming static groundwater levels (GW) during well pumping and manufacturer pump characteristics (right box in Figure 12) underestimates the operator's measured specific energy demand by 28% in median. However, the most realistic model-structure, taking into account audit pump curves and steady-state well drawdown, underestimates operator's measured specific energy demand by 13% in median (left box in Figure 12). In case only one feature is considered in the model structure, the median underestimation of the specific energy demand varies between 22% (in case of neglecting well drawdown, second box from left in Figure 12) and 19% (in case of assuming manufacturer pump curves, third box from left in Figure 12).

(ii) **Uncertainty (range of each box-whisker plot):** due to the unknown temporal distribution of the pump configuration schemes (e.g. how much of the time all wells are pumping in parallel), the box-whisker plots indicate the specific energy demand for all different 63 well field operation schemes (i.e. 2^6-1= 63 pumps on/off combinations for the six pumps). This uncertainty could only be ruled out, if data on the real temporal distributions of the used pump configuration schemes would be available.

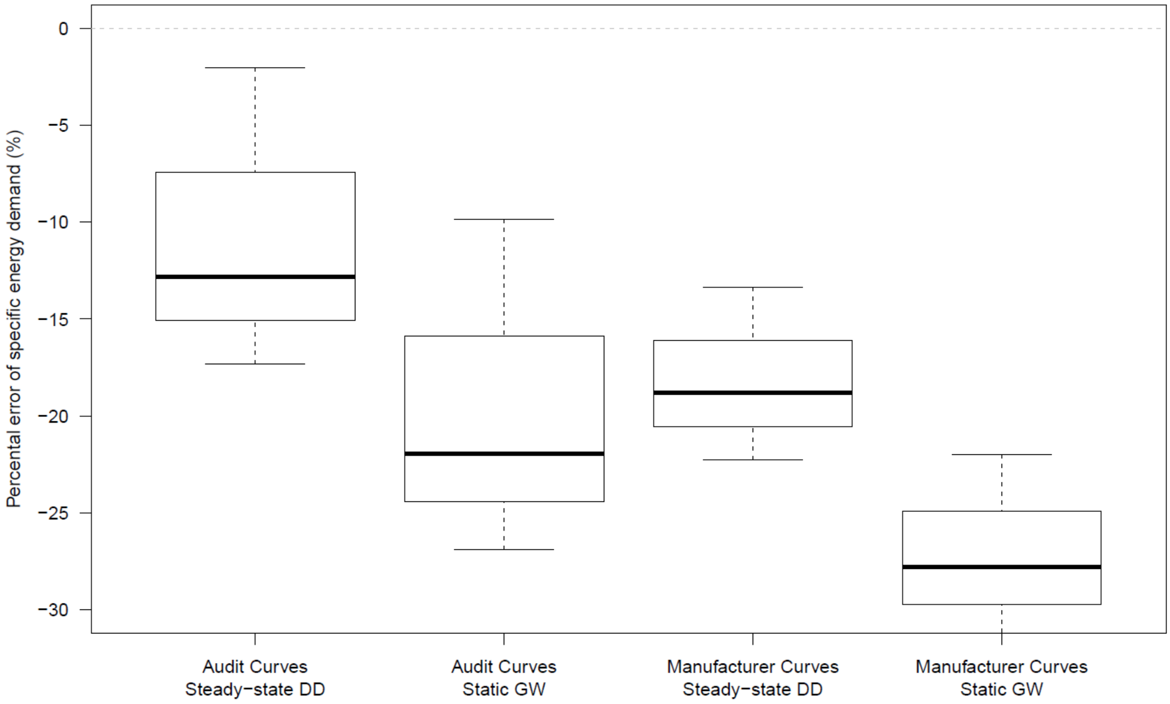


Figure 12 Sensitivity analysis: model structure (different boxes) and uncertainty concerning the real operation schemes (range of box-whisker plots) on predicted specific energy demand

Energy optimisation

For the first case study, the optimisation objective was to minimise the specific energy demand of raw water abstraction under the following two constraints:

- **Satisfying an average hourly water demand** (here: 75 m³/h, dashed grey line: Figure 13)
- **Maintaining a predefined minimum raw water quality** only by means of dilution either by mixing water of different wells within the studied well field or by diluting the raw water of the studied well field with raw water from a second well field with better water quality.

The impact of the three investigated management alternatives (chapter 2.2) for minimising the specific energy demand of the well field under the constraints defined above is shown in Figure 13. By applying smart well field management alone or in combination with the renewal of two pumps (p2 and p6), the specific energy demand could only be reduced by 3 % to 12 % for the best-case pump configurations compared to the current operation scheme (Table 5). While investing in new pumps had no impact in terms of energy savings for the best-case pump configuration scheme compared to smart well field management only (top panel in Figure 13), it significantly minimised the specific energy demand variability of the 63 different pump configuration schemes (middle panel in Figure 13), thus reducing the risk of using highly energy demanding pumping configurations.

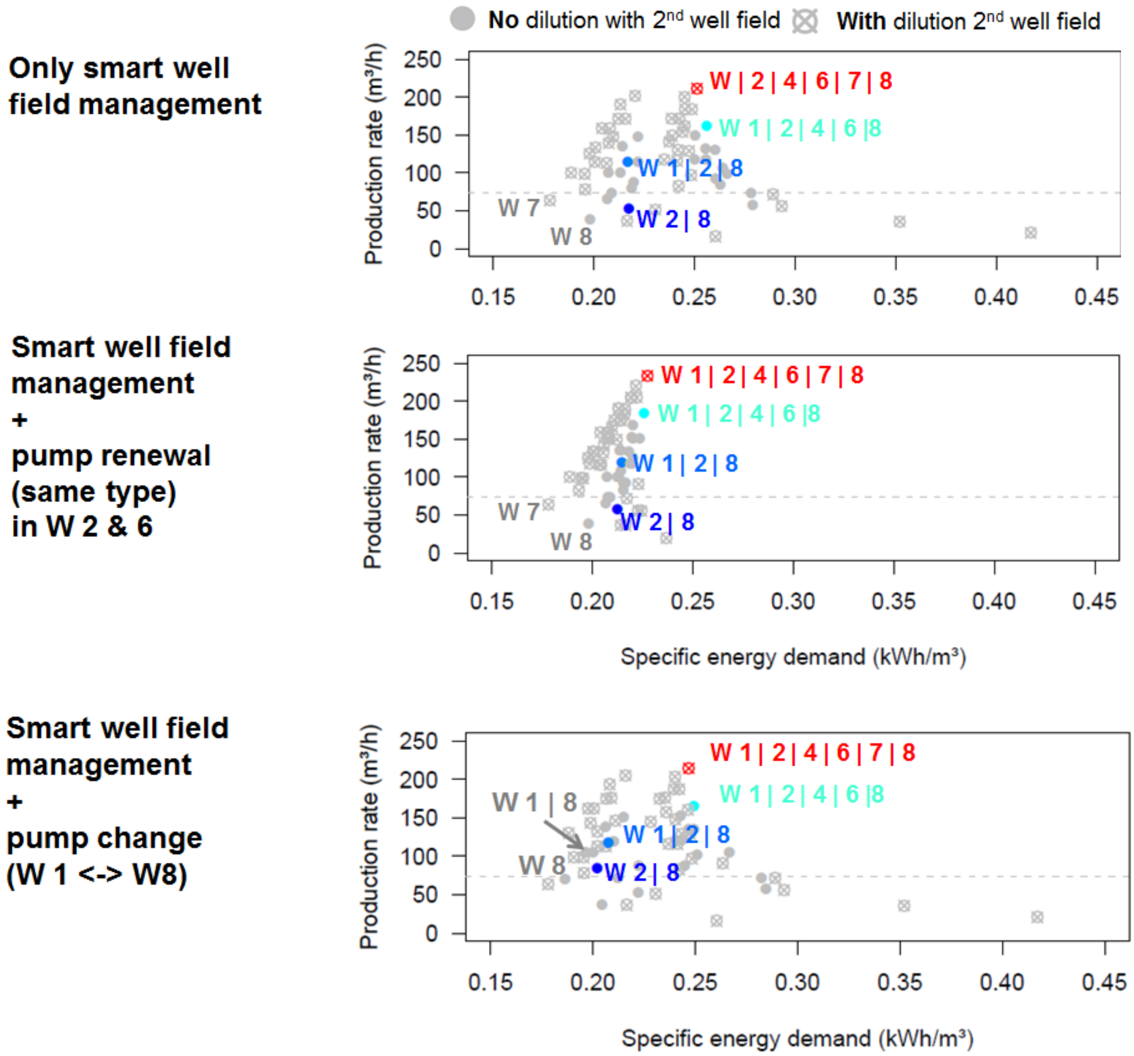


Figure 13 Optimisation modelling results for three different management strategies. Pump configurations used by the operator are marked from dark blue (base load) to red (peak load configuration).

The third management alternative combined smart well field management with swapping the currently installed pumps in well 1 and 8, but did not consider investing in pump renewal (bottom panel in Figure 13). In this case the specific energy demand could be reduced by 11.1 % compared to the current best-case operation scheme. This is similar to the second strategy (smart well field management plus pump renewal) but still satisfying the predefined raw water quality without mixing with better quality water of the second well field.

However, despite the fact that this third alternative would yield a good solution in terms of satisfying water quality and water demand whilst minimising the specific energy demand its implementation would not be an easy one. This is due to the additional legal constraint of a “maximum allowed pumping rate per well” defined by the water authority (not taken into account for this scenario) which further limits the solution space. In a nutshell, the energetic optimisation potential for this case study site was very low. This can be attributed to the fact that the current operation scheme chosen by the operator is nearly as energy-efficient as the best-case operation schemes for the three management alternatives assessed within optimisation modelling. Table 5 summarizes the results in terms of energy costs per year.

Table 5 Best-case optimisation results for the case study Site A. Operation schemes in bold do only satisfy the minimum water quality in the raw water when the abstracted water is diluted with raw water from the second well field (not taken into account in the energetic study) with significantly better water quality.

	Operation scheme	**Annual energy costs (k€/a)**
Jan.- May 2013	Unknown (0.261 kWh/m³)	30.7
Current operation (since 11/2013)	W 2 | 8 (0.217 kWh/m³); W 1 | 2 | 8 (0.217 kWh/m³)	25.7 (- 16.6 %) 25.7 (- 16.6 %)
Smart well field management ***(+ pump renewal of p2 and p6 with same type in W2 and W6)***	W 4 | 8 (0.209 kWh/m³) ; W 1 | 4 | 8 (0.213 kWh/m³) **W 7** (0.178 kWh/m³); **W 7** | 8 (0.188 kWh/m³)	24.7 (- 19.9 %) 24.7 (- 18.4 %) **21.5 (- 31.8 %)** **24.7 (- 28.7 %)**
Smart well field management & pump change (W 1 <-> W 8)	W 8 (0.186 kWh/m³); W 8 | 1 (0.196 kWh/m³)	22.2 (- 27.7 %) 22.2 (- 27.7 %)

3.1.5 Conclusions

For the given case study setup, the initial data analysis showed that the specific energy demand of the well field already decreased within the last ten years by 20%. It is very likely that investment in new pumps had contributed to this reduction as the median age of the submersible pumps lied at 4.5 years only (ranging from 3 to 7 years). This hypothesis was further confirmed by the pump audit, which showed that significant offsets between manufacturer and audit pump characteristics were limited to two (p2, p6) out of six pumps, which are current candidates for pump renewal.

The energetic optimisation modelling further demonstrated that combining smart well field management with:

- **Switching pumps in well 1 and 8:** would be a pragmatic solution for minimising the specific energy demand by nearly 12 % compared to the current operation scheme for the best-case operating scheme whilst still satisfying the predefined raw water quality without mixing. However, implementation was rated to be unlikely because the maximum pumping rate per well is restricted by the water authority, a criterion that is not satisfied by this solution
- **Investing in new pumps (p2 and p6):** would improve the operational flexibility while not significantly decreasing the specific energy demand compared to the best-case operation scheme. Replacing these two pumps reduced the variability in total energy demand of the well field for all possible pump configuration schemes, which however varied by less than 15% (0.21 +- 0.03 kwh/m³).

In a nutshell, the pump with the lowest specific energy demand (p7) is currently installed in the well with the lowest water quality, thus limiting the solution space for reducing the specific energy demand. This case study thus served as an example how the consideration of multiple constraints (water demand, water quality and water authority regulations) led to solutions which are energetically sub-optimal but satisfying the given restrictions.

3.2 Site B

3.2.1 Site characteristics

The second case study focused on a well field in eastern France consisting of five production wells with six operable submersible pumps (W3 w equipped with two pumps, WK is equipped with three pumps, but only pK_2 is operated). The average hourly production rate of the well field is 400 m³/h (data: year 2013). Wells W1, W2 and W3 are located in the same area and distant of about 500 m from each other, WA and WK are located in distinct and more remote areas (Figure 14). The static head is about 80 meters for the pumps in wells W1, W2, W3 and WA and 40 meters for the pumps in well WK. However, the latter has operational constraints due to water quality issues and can thus not be operated at all times. Since only chlorination is required as water treatment, four wells (W1-3 & WA) are directly connected to the distribution network, while abstracted raw water of WK is conveyed into a tank. In case that the production rate of the four wells W1-3 & WA is higher than the water demand, water is delivered to the tank, too.

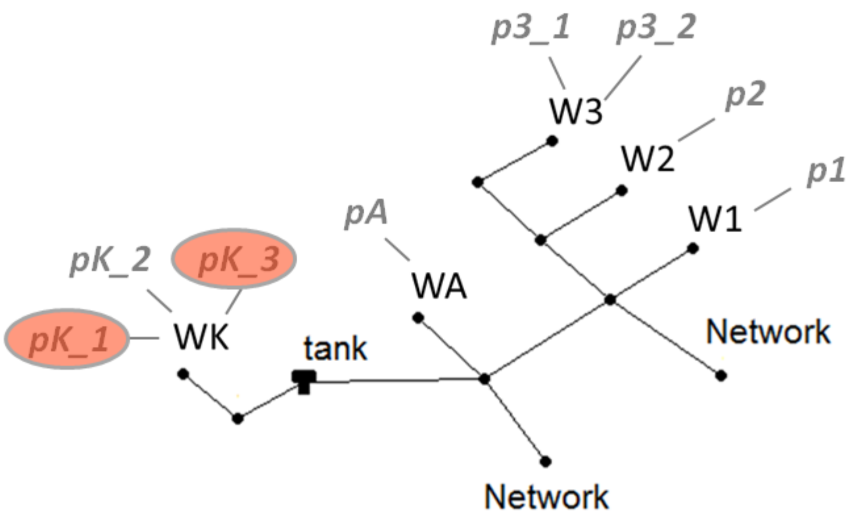


Figure 14 Simplified map of the case study well field. The pumps pK_1 and pK_3 in well WK were not used by the operator at the time of investigation and were thus not audited in September 2013

3.2.2 Pump audit

The pump audit was performed in four days (9th – 12th September 2013) by KWB and TU Berlin together with the local well field operator in order to assess the current pump and global efficiency curves of the six operable pumps in the five production wells (W1, W2, W3, WA, WK) of the well fields. The pumps pK_1 and pK_3 in well WK were not audited because these pumps were out of operation during the audit in September 2013. During the pump audit, only one pump was operated at a time while all other pumps were turned off. The pumping rate was increased every five minutes by successively re-opening the initially fully closed valve in at least five steps with quasi-constant discharge until the valve was fully open.

The audit results in comparison to the additionally evaluated manufacturer pump data are shown in Figure 15 and Figure 16. Both, total dynamic head (top panel, Figure 15) and global efficiency (bottom panel, Figure 15) indicate that in general the oldest pumps (pA, pK_2, p3_1) showed the largest offsets between current and initial values. The younger pumps (p1, p3_2) had a reduced global efficiency, whilst the most recently installed pump p2 showed no significant offset.

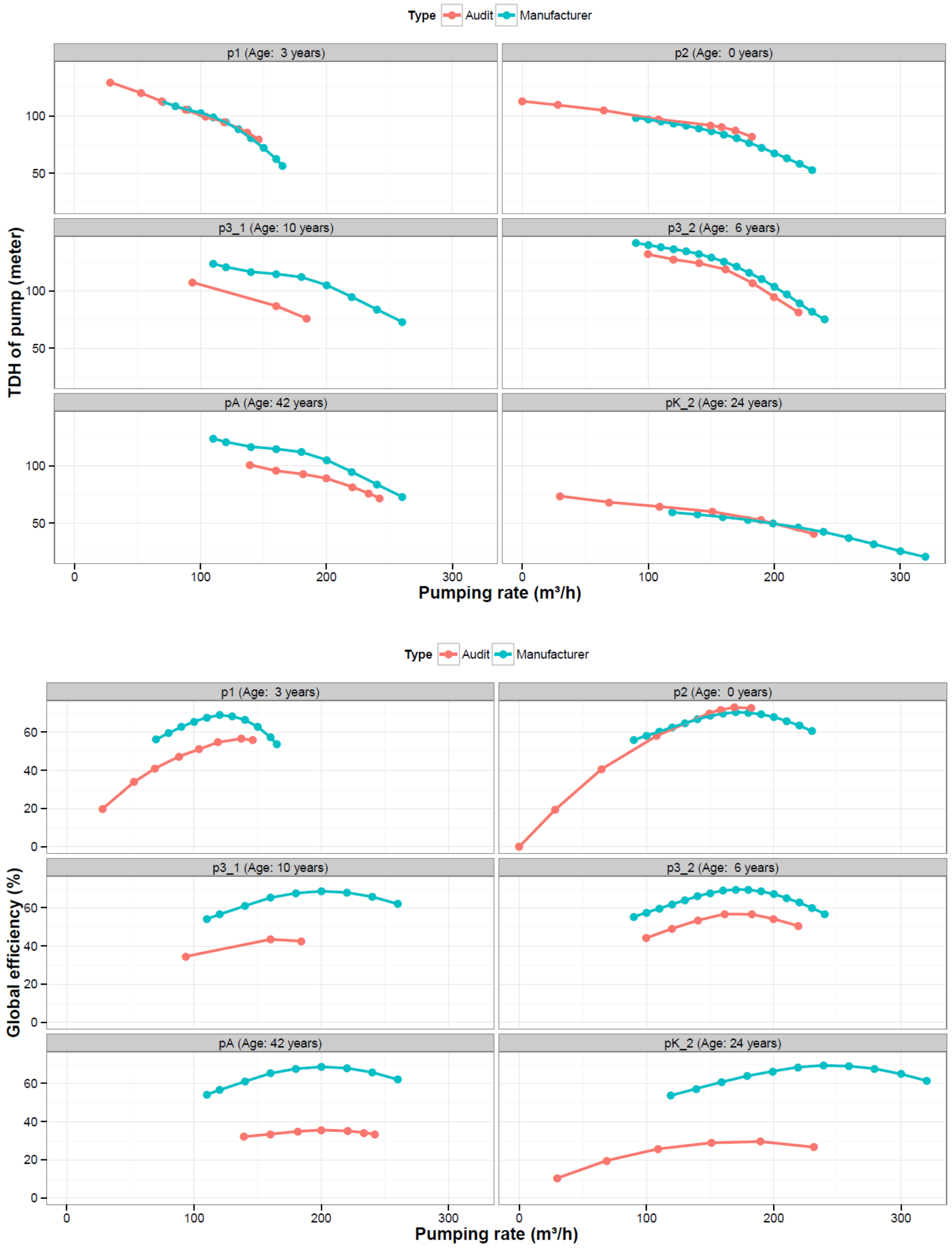


Figure 15 Comparison of audit (red lines with dots) and manufacturer (blue lines with dots) pump characteristics for both, total dynamic head (top panel) and global efficiency (bottom panel)

In order to determine how these changed pump characteristics impact the specific energy demand of each pump, the specific energy demand curves are shown in Figure 16. Again, the two oldest pumps (pA and pK_2) showed the largest offset to the manufacturer data, while all other pumps did not significantly differ from the manufacturer curves. However, in terms of specific energy demand, the 24 years old pump pK_2 is still comparable to three much younger pumps (p1, p3_1, p3_2). This was attributed to the fact that the well WK is located on a higher geometrical elevation, requiring only half of the total head of the other pumps (see chapter 3.2.1 and top panel, Figure 15).

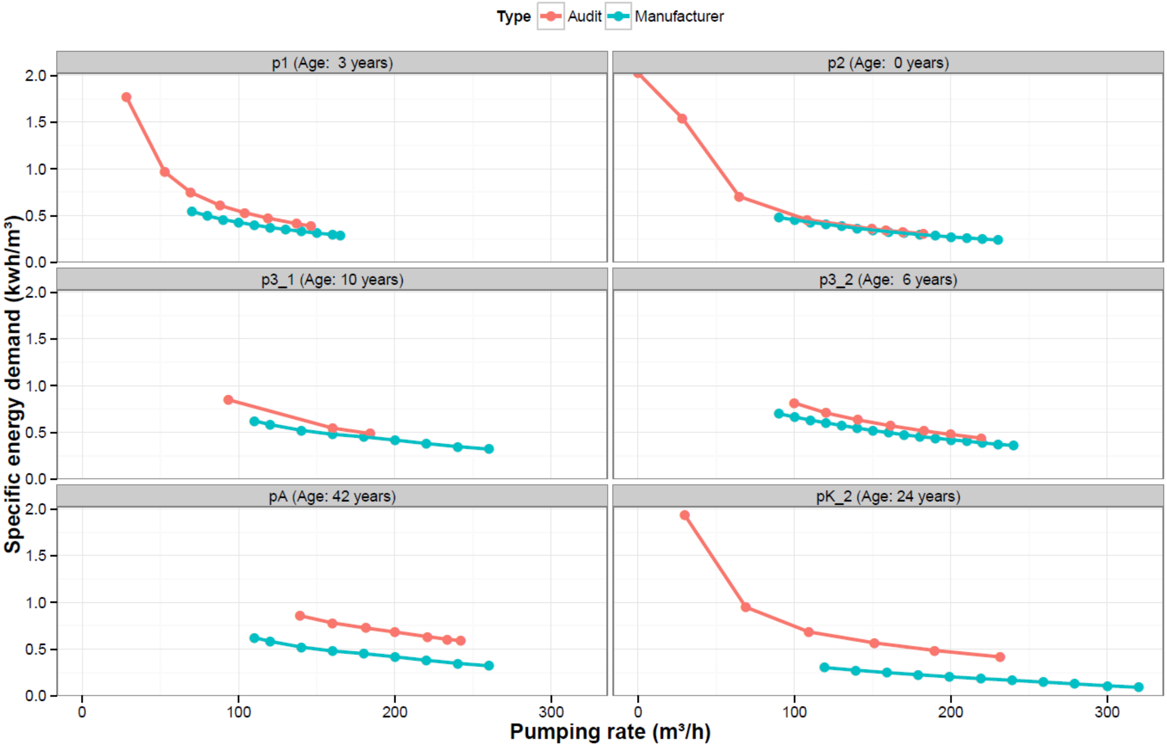


Figure 16 Impact of changed pump characteristics (e.g. due to ageing, cavitation) on the specific energy demand

3.2.3 Process-driven modelling

The pipe network (including reservoirs) was provided digitally as EPANET input file by the well field operator. However, for using the model the following model features needed to be included:

- **Pump characteristics:** derived from pump audit (Chapter 3.2.2)
- **Well drawdown:** steady-state drawdown based on audit data
- **Boundary conditions:** water demand pattern and water quality (both derived from data analysis)

Subsequently, the process-driven model was hydraulically calibrated by changing the pipe diameter so that the root mean square error between modelled and measured pumping rate was minimised for a two weeks period. The workflow was described in detail within deliverable D2.1 (Rustler & Sonnenberg 2014a). As stated there, calibration ended with an average error between modelled and measured pumping rates of 0.2 m^3/h, thus the model was considered to be well calibrated.

3.2.1 Results

Sensitivity analysis

The calibrated process-driven EPANET model using audit pump characteristics and steady-state well drawdown (left boxplot Figure 17), underestimated the measured specific energy demand by only 1 % (for the well field operation of October 2013). Compared against more simplified model structures either neglecting the well drawdown or pump ageing (i.e. offset to the manufacturer data) or both, the accuracy of the calibrated model used for optimization modelling was still satisfying (error of less than one percent) despite the fact that neither transient well drawdown nor well interference were considered. Obtaining this low error can be explained by the following findings:

- the case study well field is not impacted by well interferences and
- a steady-state drawdown model is sufficient since at least 70% of the drawdown is reached after five minutes of pumping for every well and the drawdown is small (less than two percent) compared to the static head.

Figure 17 summarizes the deviation between predicted and measured specific energy demands comparing static and steady-state approach and using audit versus manufacturer data. As the temporal pattern of the pumping scheme was given from operational data, one value was calculated for each model setup and the range of uncertainty of sensitivity analysis, as discussed for the first case study, could be ruled out by applying real data. From the four models (Figure 17), pump ageing (i.e. audit curves instead of assuming manufacturer curves) was identified as the most influencing factors for this case study. In case only manufacturer pump data were used for modelling, the relative error of the predicted specific energy demand was 40 %. The impact of considering well drawdown on the specific energy demand was negligible for the energetic well field modelling as it increased the accuracy by only 0.8 % compared to a static groundwater level in the wells. The high median age of the pumps of 17.5 years further underlined the plausibility. Finally, using the most realistic model (audit curves and steady-state drawdown), improved the prediction accuracy by approximately 43 % compared to the most simplified model (manufacturer curves and static groundwater level). This model was therefore used for energy demand optimisation modelling, which is described in the following chapter.

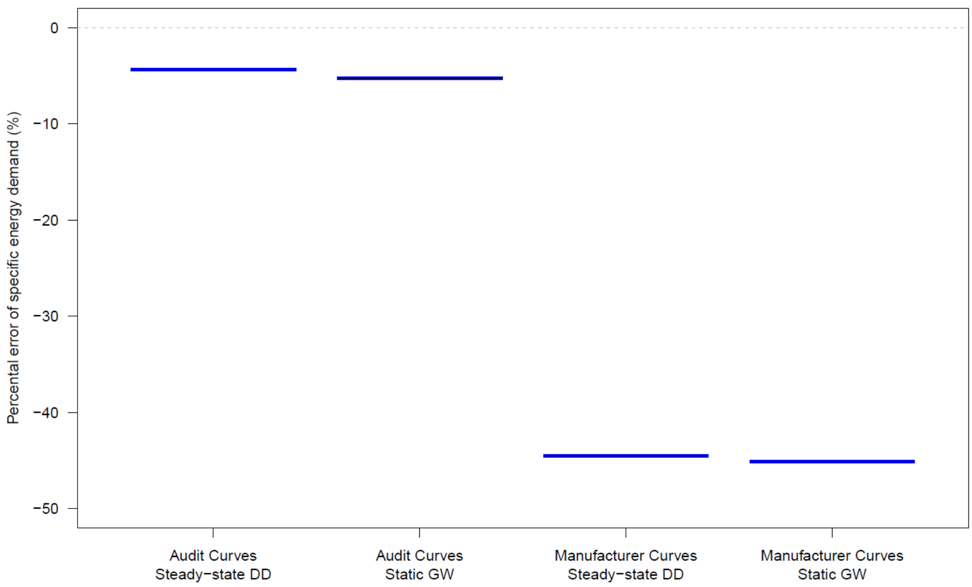


Figure 17 Sensitivity analysis: impact of model structure on predicted specific energy demand

Optimization

Management Option 1: Only smart well field management

The 63 possible pumping configurations were compared with regard to their respective specific energy demand and flow rates (Figure 18). From Figure 18, the operator can not only evaluate the energy demand of the currently implemented well field operation schemes but is also able to identify alternative configurations that are more energy-efficient and fit better to his constraints (e.g. operational restrictions, water quality). For example, considering that the average hourly water demand is 400 m³/h, the pump configuration scheme p2 | pK, as highlighted in Figure 18, would induce an improvement of 17.5% of the specific energy demand compared to the current pumping schedule indicated by the dashed line.

However, quality constraints do not allow this pumping schedule. Thus, a combination of two pumping schemes is required (p2 and p1 | p2 | pK, Figure 18), which limits the maximum energy savings to 16 %.

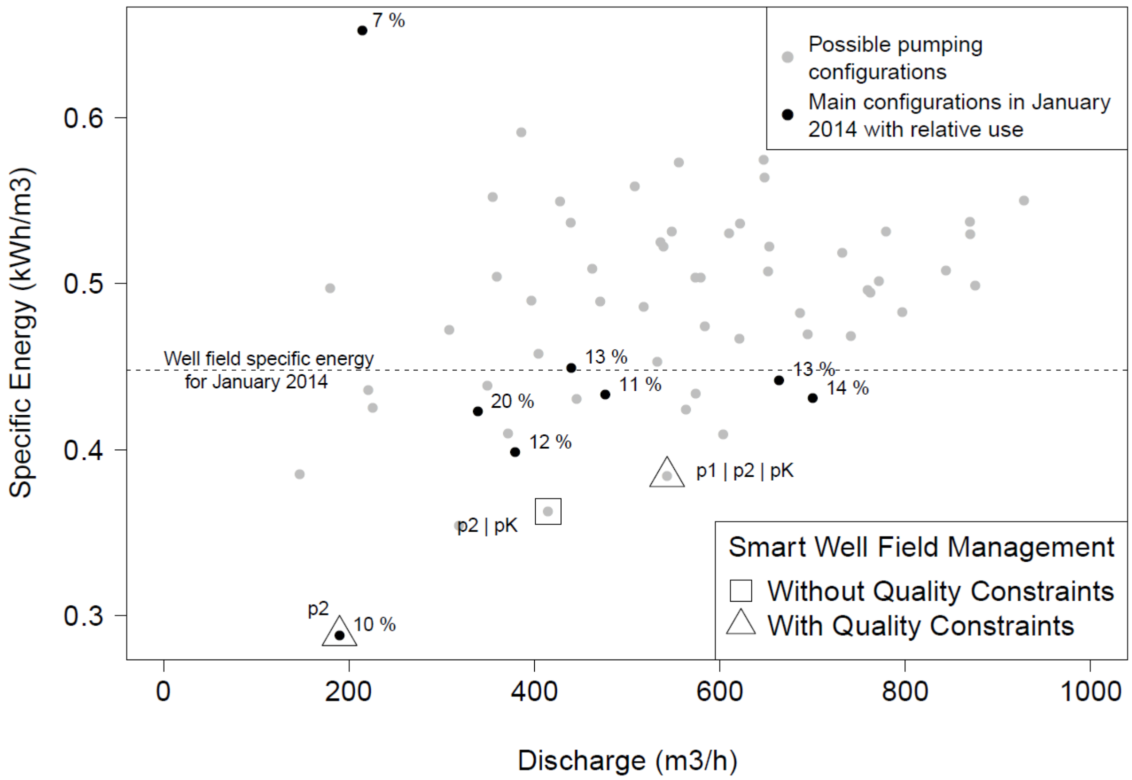


Figure 18 Specific energy demand and production rate for all 63 different well field operation schemes (Philippon et al. 2014)

Management Option 2: Only pump renewal

From the simulation of every pump renewal combination, the optimizer found the best pumps to be renewed that maximize the energy saving potential are in decreasing order pK, pA, p31, p32, p1. The renewal of pump p2 does not bring any energy saving because this pump was changed just before carrying out the study within OPTIWELLS-2. The pump renewal option can bring almost 10% of energy saving for one pump renewal and reaches at maximum 25% of energy saving, if the five pumps cited before are all renewed (black columns in Figure 19).

Management Option 3: Combination of smart well field management and pump renewal

For every potential pump replacement, the optimizer also applied the smart well field management approach. Depending on the approach (only pump renewal or combined strategy), the best pumps to replace were different. For example, the second best pump to be replaced after pK is pA, if the pumping schedule cannot be changed, whereas it is p1, if smart well field management can be applied. After pK and p1 being replaced, the combined approach already reaches the maximum saving potential (49.7% without quality constraints and 47.6% with) because in the best pumping schedule only the pumps p1, p2 and pK were used. Any further pump renewal did thus not increase the energy saving. Figure 19 summarizes the results.

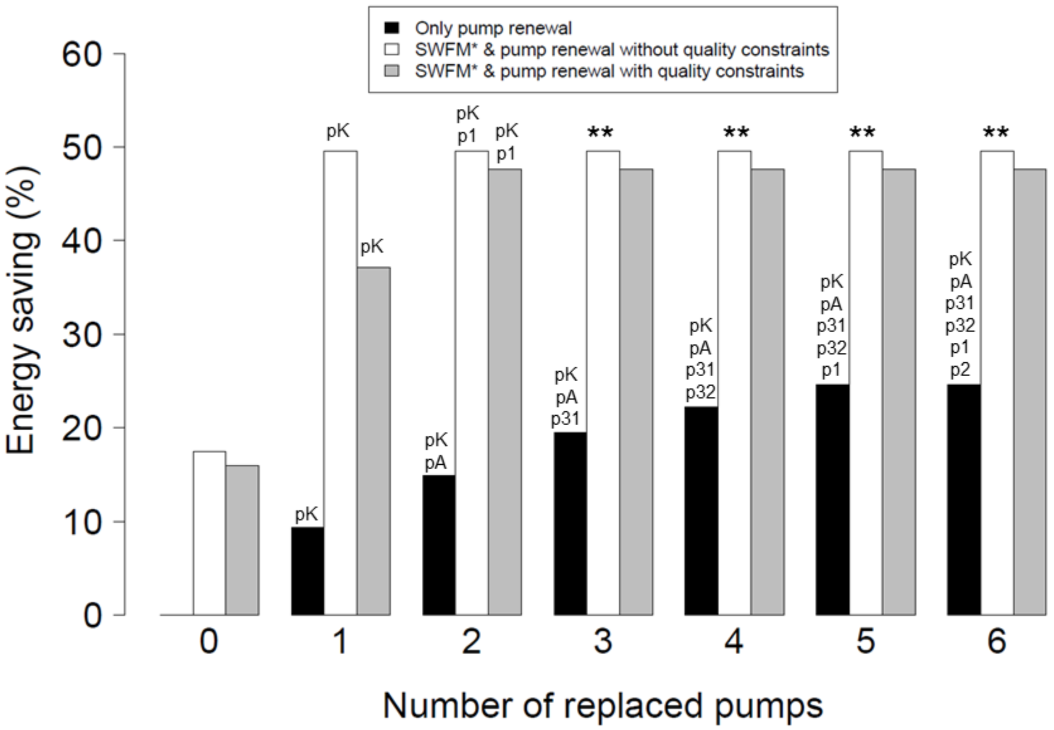


Figure 19 Impact of different optimization strategies on energy saving potential for case study well field (compared to specific energy demand for January 2014), *SWFM: Smart Well Field Management (Philippon et al. 2014)

3.2.2 Conclusions

For the second case study, the process-driven model approach showed an energy saving potential of up to 40% for the well field by taking into account steady-state well drawdown, pump and pipe ageing. Optimisation modelling showed that combining smart well field management with the "smart" renewal of two pumps, the well field`s specific energy demand could be reduced by nearly 50% compared to the well field operation scheme which was in place in January 2014. However, this energy saving is a maximum potential as it bases on the assumption that the identified most energy-efficient pump configuration scheme satisfying water demand and quality constraints would be used throughout the whole year, what in practice is typically not feasible.

3.3 Site C

3.3.1 Site characteristics

The third case study is the largest well field site that has been investigated within OPTIWELLS-2 and is located in France. It consists of 14 different production wells and is equipped with in total 19 submersible pumps (out of them two wells with two and three pumps each, Figure 20). The average hourly pumping rate is 480 m³/h (data: year 2013). Raw water is transported in DN 300 to DN 600 pipes for maximum 1 km to the waterworks. Treatment comprises aeration and filtration, but is not further considered in the study. Water abstraction comprises four pipes connecting different numbers of wells to the raw water tank or in a bypass directly to the waterworks inlet (see Figure 20). Static elevation was 10 m to the raw water tank inlet and 8 m to the waterworks inlet. The median age of the installed pumps (at the time of the audit) is 5.5 years (1st quantile: 1 year; 3rd quantile: 6.75 years). Looking at all 19 pumps, manufacturer pump characteristics for the pumps at the best efficiency point as documented by the operator are:

- **Total dynamic head:** varying by +-120% (median: 17m, min: 11m, max: 27m)
- **Global pump efficiency:** varying by +- 4% (median: 59%, min: 58 %, max: 63%)
- **Pumping rate:** varying by +- 25% (median: 120m³/h, min: 90 m³/h , max: 160 m³/h)

For the site audit, wells W4 and W6 were not operated because of water quality issues and pump p103 was not operated because of pump damage. These wells / pumps were not considered for the field work.

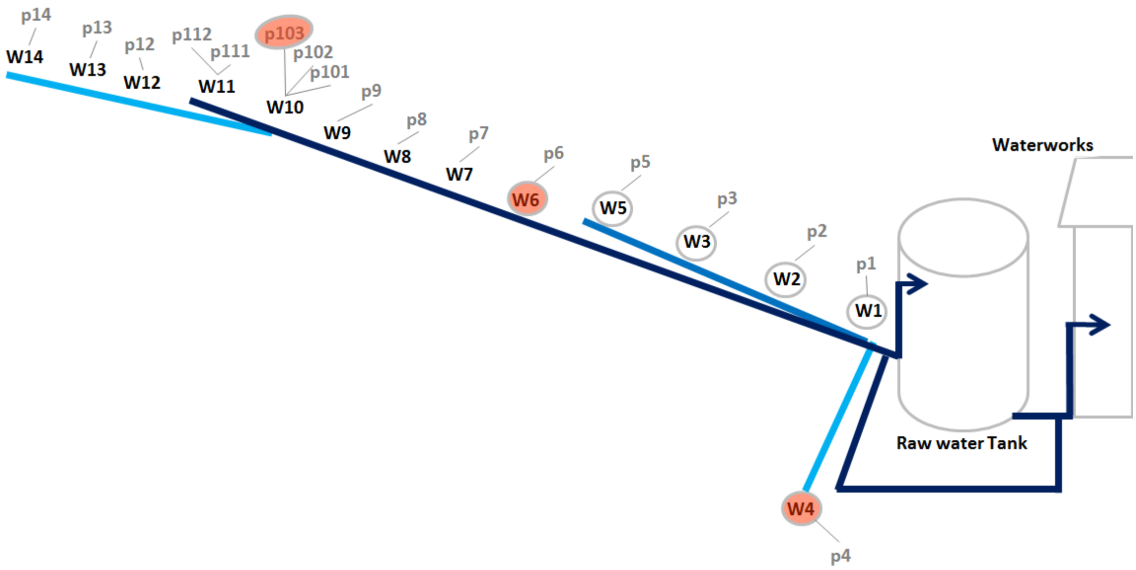


Figure 20 Simplified map of the Site C well field. Note that the pumps in wells W4 and W6 are not operated due to water quality problems. The pump p103 in well W10 was damaged in May 2015 and thus could not be audited.

The well field is usually operated following a fixed pumping scheme responding to the demand variations. In a first data analysis step, the operation scheme was analysed and monthly variations of pumping scheme, abstracted volumes and related specific energy demand of the well field were visualized. The temporal development of the specific energy demand for the period of January 2012 to August 2014 is shown in Figure 21.

While the pump prioritisation (i.e. the order which pumps were put in operation first) was not changed for the well field by the operator within this period, six out of nineteen submersible pumps were renewed within one year (November 2012 until November 2013). These renewals already reduced the specific energy demand by 20% (Figure 22). The highest saving potential was explained by the replacement of pump p101 (-17.7 %) and p2 (-8.1 %) while replacement of the other four pumps had no further significant impact on the specific energy demand (Figure 22).

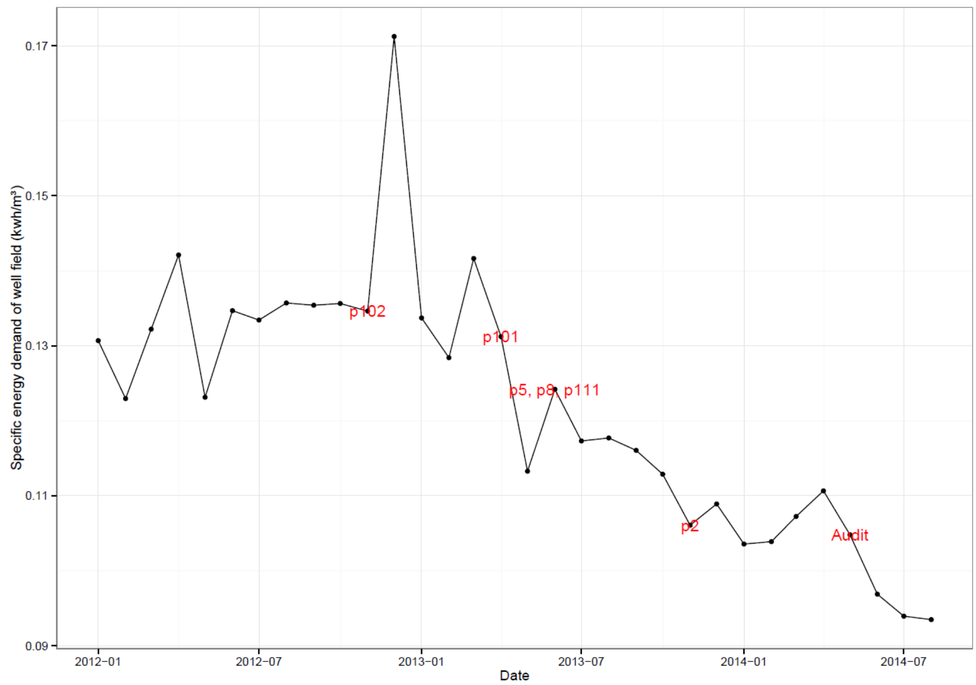


Figure 21 Temporal development of specific energy demand for raw water abstraction for the wellfield. The red labels indicate pump replacements

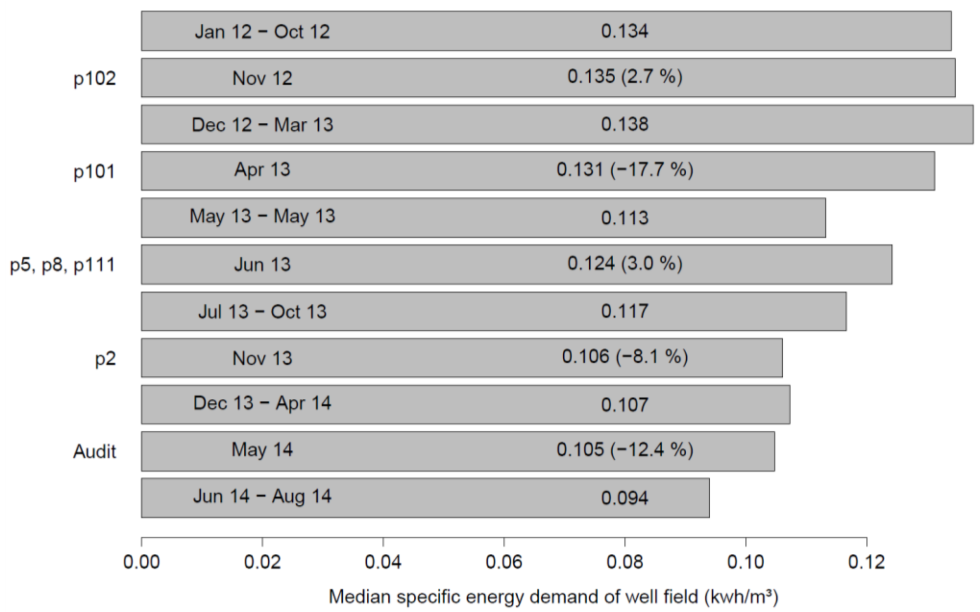


Figure 22 Impact of the pump renewal of six pumps within one year on the specific energy demand of the well field

3.3.2 Pump audit

A pump audit was carried out within four days in May 2014 by KWB in order to assess the actual pump characteristics. During the pump audit, the whole well field was stopped and only the audited pump was operated. The valve to the waterworks was closed and all water was conveyed to the raw water tank (see Figure 20). Furthermore, the valve at the raw water tank outlet was closed. A water level logger was put in reservoir to measure the water level increase over time. The average pumping rate was then calculated by dividing the tank volume increase (multiplying water level increase in tank with the known tank area) with the total pumping time.

In contrast to first two audits, power demand was not measured directly at the pumps but in the building close to the waterworks. Consequently, potential cable losses (assumption: ~ 3%) are already included in the power demand measurement, so that the pump's global efficiency is underestimated (assuming that both, total dynamic head and pumping rate were measured precisely). Within four days in May 2014, two different types of audit were carried out:

- **Specific energy demand ("simple") audit (for all 14 pumps):** only pumping rate and power demand were measured for 10 minutes for each pump at the maximum pumping rate (Figure 23).
- **Pump characteristics audit (for 9 pumps):** pumping rate, power demand, pressure in the pipe and water level in the production well were logged for different pumping rates (if possible) for approximately 30 minutes per pump. This enabled to derive both, pump and global efficiency curves for each pump and each pumping rate (Figure 24 & Figure 23).

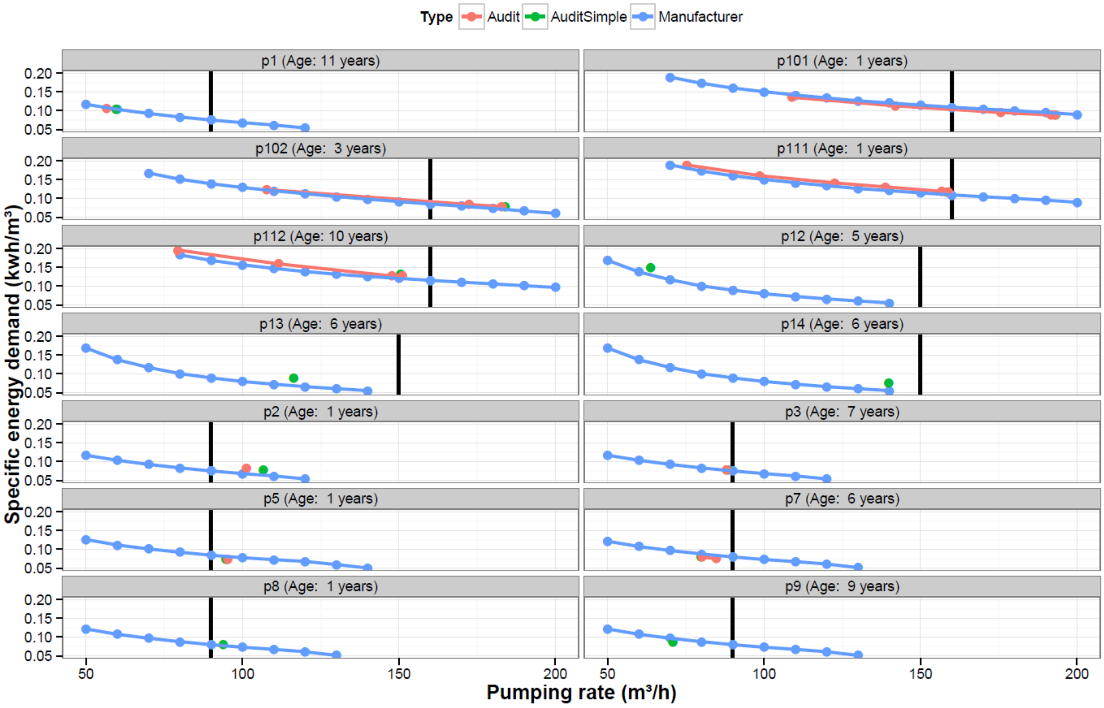


Figure 23 Impact of changed pump characteristics (i.e. due to ageing, cavitation) on the specific energy demand. Note that the specific energy demand was not only measured during the pump characteristics audit (red lines with dots) but also during an additional specific energy demand audit (green dots) for the maximum pumping rate of each pump.

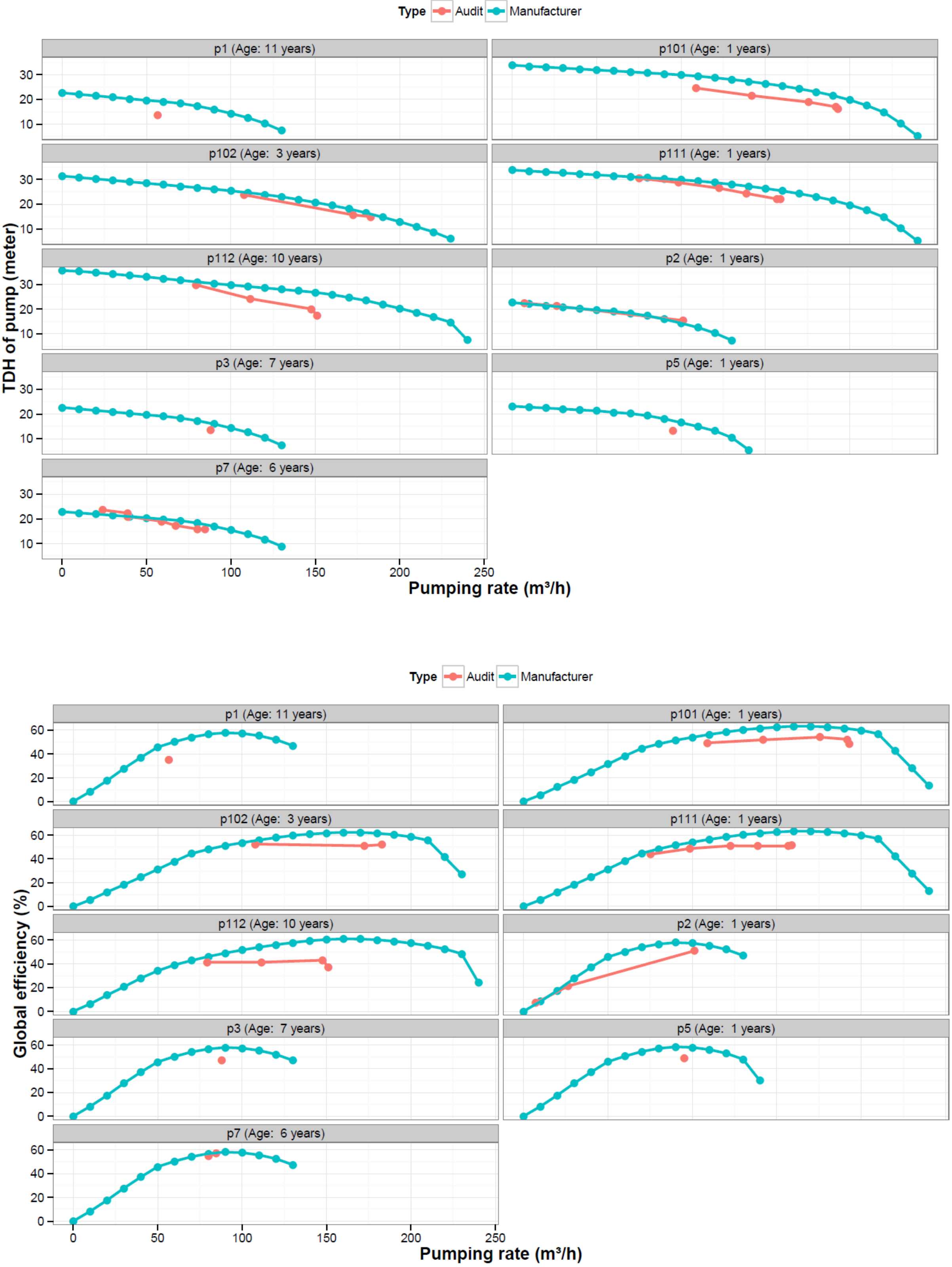


Figure 24 Comparison of audit (red lines with dots) and manufacturer (blue lines with dots) pump characteristics for both, total dynamic head (top panel) and global efficiency (bottom panel)

3.3.3 Data-driven modelling

Instead of applying the process-driven modelling approach by parameterising, calibrating and validating a hydraulic EPANET model (as for the first two case studies), for the third case study, a data-driven approach was developed. It required the following input parameters:

1) ***Audit specific energy demand curves*** E_{spec,p_i} ***(purple lines in Figure 26):*** manufacturer specific energy demand curves (blue lines, Figure 26) are corrected with a constant offset that is derived from the specific energy demand audit for all pumps at maximum pumping rate (Figure 25).
2) ***Monthly median pumping rate of each pump*** Q_{p_1}***(Figure 27):*** from operational data, 10-minute volume meter data for 10 pumps were available. For 5 pumps (p101, p102, p103, p111, p112) in wells 10 and 11, only the operating hours were available. Thus the maximum pumping rate during audit was used as proxy. Multiplying monthly operating hours with the constant (estimated) pumping rate for each pump, the monthly production volumes are calculated.
3) ***Share of each pump to the total monthly abstraction*** $Share_{p_i}$ ***(Figure 28):*** based on the monthly sums of the volume meter for each pump (measured by the operator every 10 minutes) the percental contribution of each pump to the total abstraction volume was calculated.

With the above-described input data, the specific energy demand of the well field can be calculated for each month according to the following equation:

$$E_{spec,wellfield}\left(Q_{p_{1-n}}, Share_{p_{i-n}}\right) = Share_{p_1} \cdot E_{spec,p_1}\left(Q_{p_1}\right) + \ldots + Share_{p_n} \cdot E_{spec,p_n}\left(Q_{p_n}\right)$$

with:

- $Share_{p_i}$ percental abstraction share of pump ***i*** (e.g. 0 -> not operating, 1 -> whole well field abstraction)
- Q_{p_i} pumping rate of pump ***i*** (m^3/h)
- E_{spec,p_i} audit specific energy demand curve of pump i

The above equation was then used for predictive modelling by using the real volume abstraction share of each pump as model input parameter. In case of optimisation modelling by means of smart well field management, this information is not required, but the pumps are re-prioritised. Accordingly, the equation simplifies to:

$$E_{spec,wellfield}\left(Q_{p_{1-n}}\right) = \frac{Q_{p_1}}{Q_{p_1} + \ldots + Q_{p_n}} \cdot E_{spec,p_1}\left(Q_{p_1}\right) + \ldots + \frac{Q_{p_n}}{Q_{p_1} + \ldots + Q_{p_n}} \cdot E_{spec,p_n}\left(Q_{p_n}\right)$$

with:

- Q_{p_i} pumping rate of pump ***i*** (m^3/h)
- E_{spec,p_i} audit specific energy demand curve of pump I (pumps are ordered ascending from low to high specific energy demand)

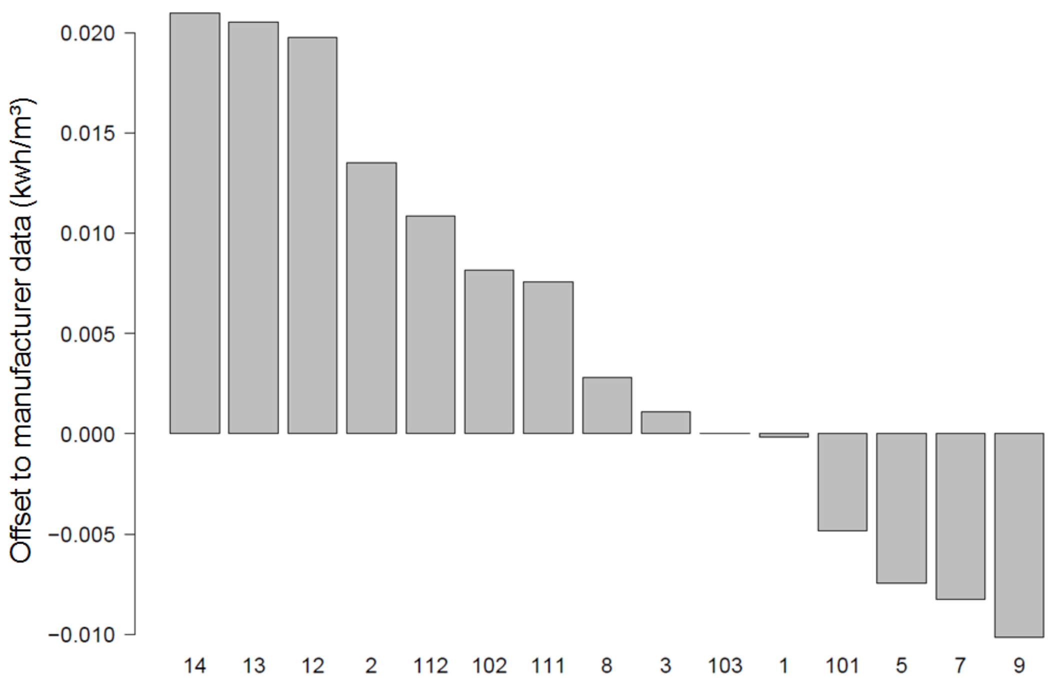


Figure 25 Offset between manufacturer data and audit results for the specific energy demand of the audited pumps (pump p103 was out of operation at time of audit and thus not measured, so that manufacturer characteristics are assumed for this pump (the offset is zero)

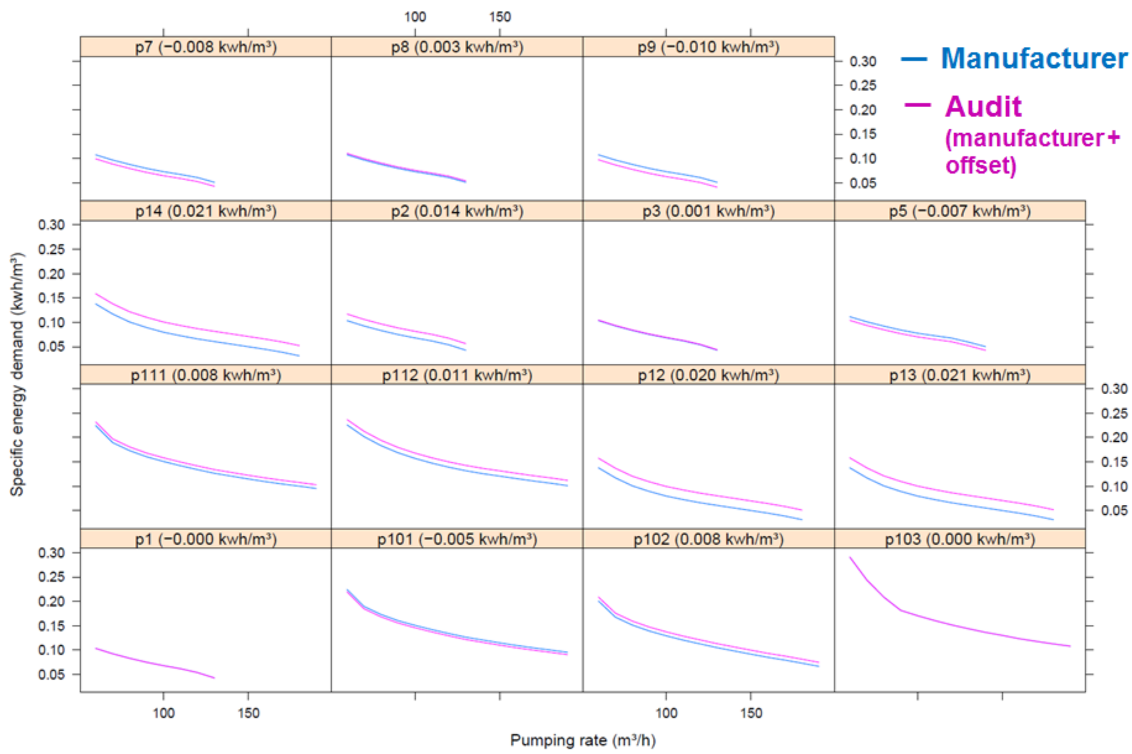


Figure 26 First model input parameter: audit specific energy demand curves from adding the offset value from audit to all manufacturer curves. Note that p103 was renewed after the audit in June 2014. Thus, the offset manufacturer curve is used instead

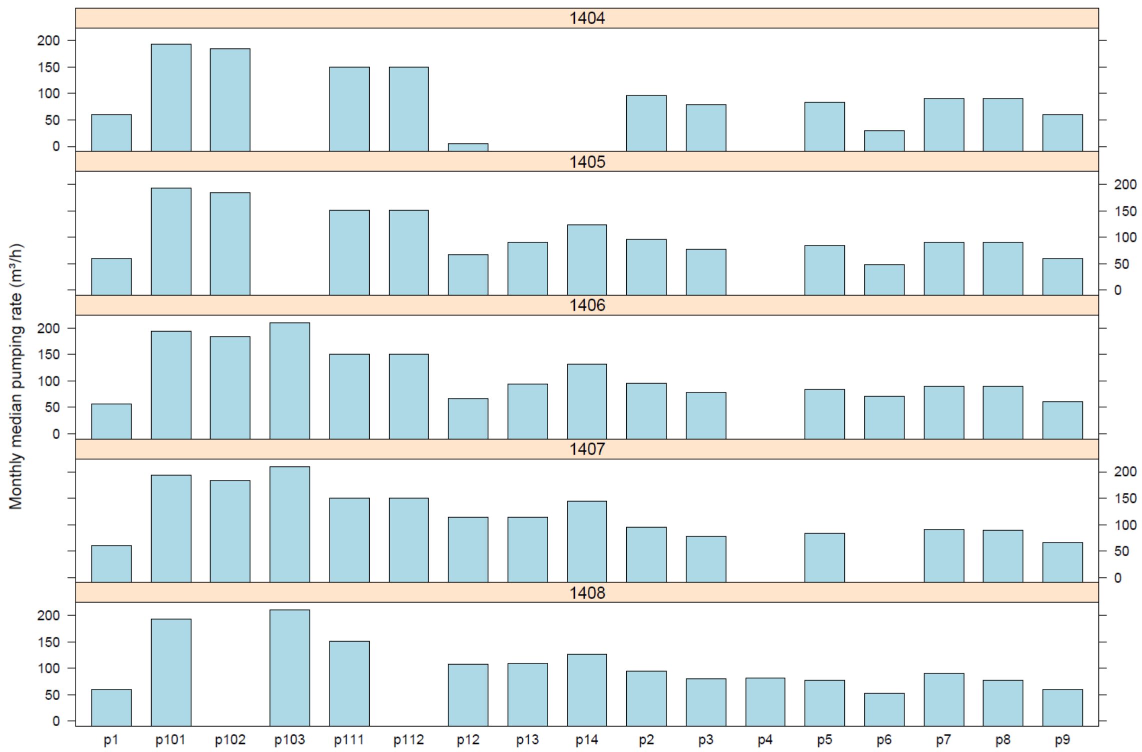


Figure 27 Second model input parameter: monthly median pumping rate for the period April to August 2014 calculated from LERNE data. Note that for four pumps (p101, p102, p111, p112) the maximum pumping rate from the audit was used. For pump p103 (renewed in June), a pumping rate of 210 m³/h was assumed.

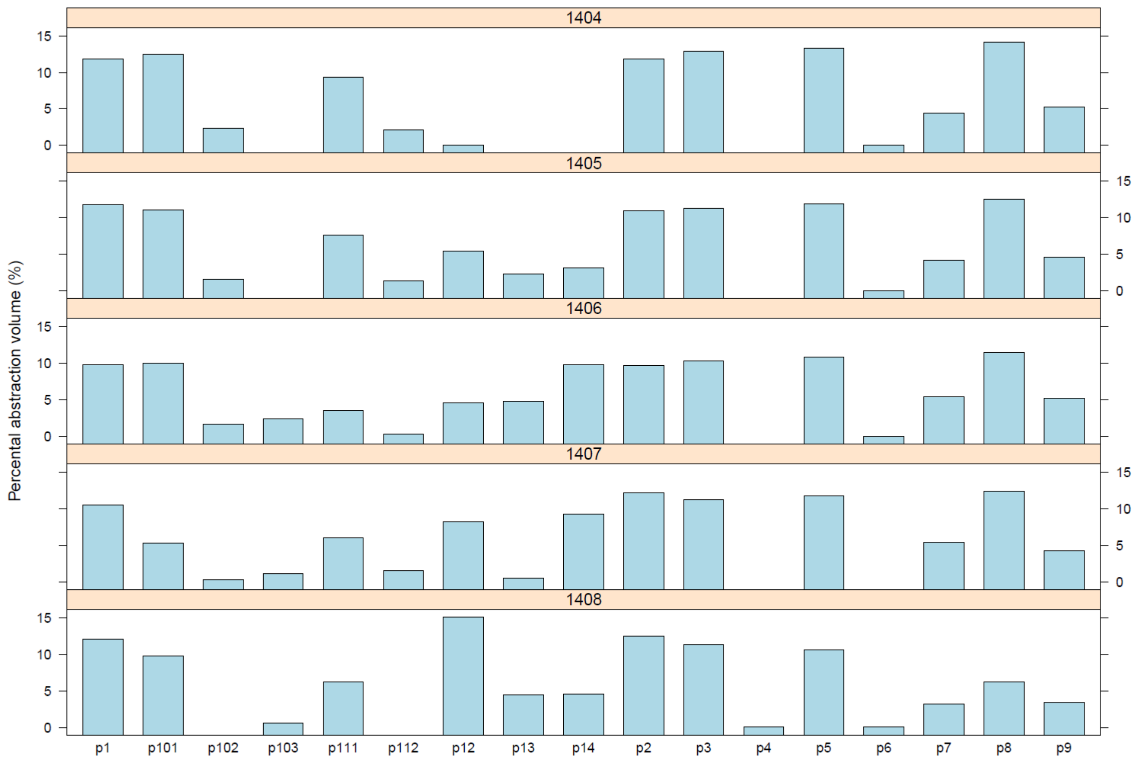


Figure 28 Third model input parameter: percental abstraction volume for the period April to August 2014 calculated from LERNE data. For five pumps (p101, p102, p103, p111, p112), the abstraction share needed to be calculated by multiplying the median monthly pumping rate with the operating hours of each pump.

3.3.4 Results

Predictive modelling

The predictive performance of the data-driven model is shown in Figure 29, indicating a good fit (underestimation varying from 0.5% to 5%) compared to the specific energy demand measured by the operator for the months June to August 2014. Uncertainties in the predictive model performance for this period can mainly be attributed to the following causes:

(i) **unknown volume meter data for 5 pumps (p101,p102,p103, p111, p112) in well 10 & 11**: leading to an increased (not quantifiable) uncertainty for three input parameters

(ii) **lack of continuous energy demand measurements**: extrapolation using a linear offset to the manufacturer curves may be too simplified. However, as no real-time measurement for the power demand for each pump is available, this error is not quantifiable.

Nevertheless, the resulting model prediction error is in the range of the measurement uncertainties for volume, pumping rate and power demand, which indicates an acceptable model performance.

The comparably larger offset for the months April and May 2014 can be explained by the fact that the pumps p12, p13 and p14 (in the wells 12 to 14) were electrically wrongly connected (phase-shifted), so that the pump was running in the wrong direction up to the audit in mid May 2015. Thus, the median monthly pumping rate for at least two out of the three pumps was zero (p13, p14) for this period, so that their operation was not considered in the data-driven model although they were actually operating.

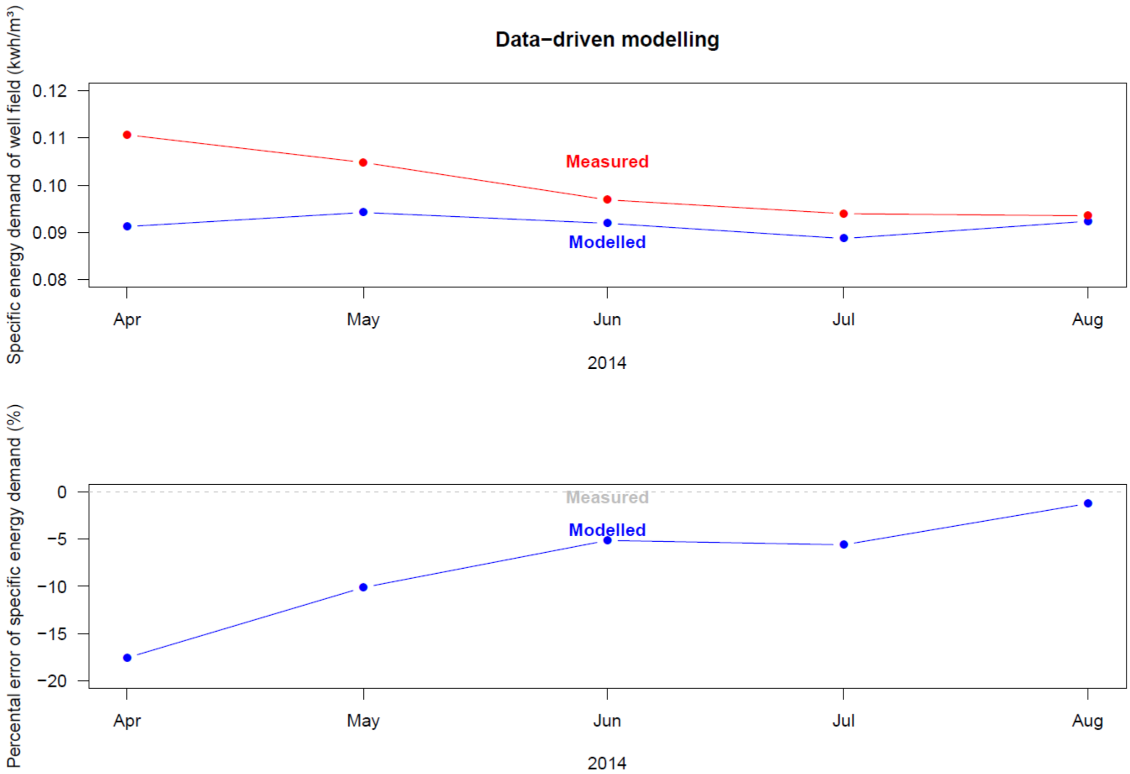


Figure 29 Predictive modelling performance: measured (monthly by the operator) vs modelled specific energy demand for the wellfield abstraction.

Optimisation

Within data-driven modelling, only energetic optimisation by means of "smart well field management" was assessed. The "smart well field management" optimisation relies on the following input parameters:

(i) the audit specific energy demand curves (purple lines, Figure 26)

(ii) the monthly median discharge rate per pump (Figure 27)

(iii) the hourly average water demand per month

Using this information, the pumps with the lowest specific energy demand were set into operation first, adding pumps until the hourly average water demand for the respective month was met. The resulting specific energy demand of this strategy was then compared against the base scenario (i.e. operator's pump priorities, Figure 30). From the results, it could be seen that smart well field management highly prioritised the pumps p7, p102 and p14. For the modelled months after the audit, the specific energy demand of the well field could be reduced between 20% (June, July 2014) and 12% (August 2014) compared to the measured real specific energy demand. On the other hand, the evaluation of the pre-audit energy demand showed that the renewal of 6 pumps in 2013 already reduced the total energy demand of the well field by 20% and the correction of phase-shifted pumps p12, p13 and p14 further reduced the total energy demand of the well field by approximately 12% (Dec. 2013 to April 2014 versus June to August 2014).

The pump p14 is highly prioritised in the smart well field management scenario (top three priority within months June to August 2014, Figure 30) but showed the largest offset between manufacturer and audit specific energy demand (+38% for pumping rate of 130 m^3/h, Figure 24 and Figure 25). Thus, it is recommended to replace this 6 years old pump. For the p10 and p11 it is further recommended to verify the total pressure head, which was significantly higher (up to 40%, Figure 25) compared to the other wells, thus leading to increased specific energy demands (Figure 26). Furthermore, the specific energy demand of whole well field decreased by 12% after the pump audit (Figure 22) although the operating scheme was not changed (Figure 27 and Figure 28). To which extent this could be contributed to correcting the phase shift of pump p12, p13 and p14 was not further evaluated.

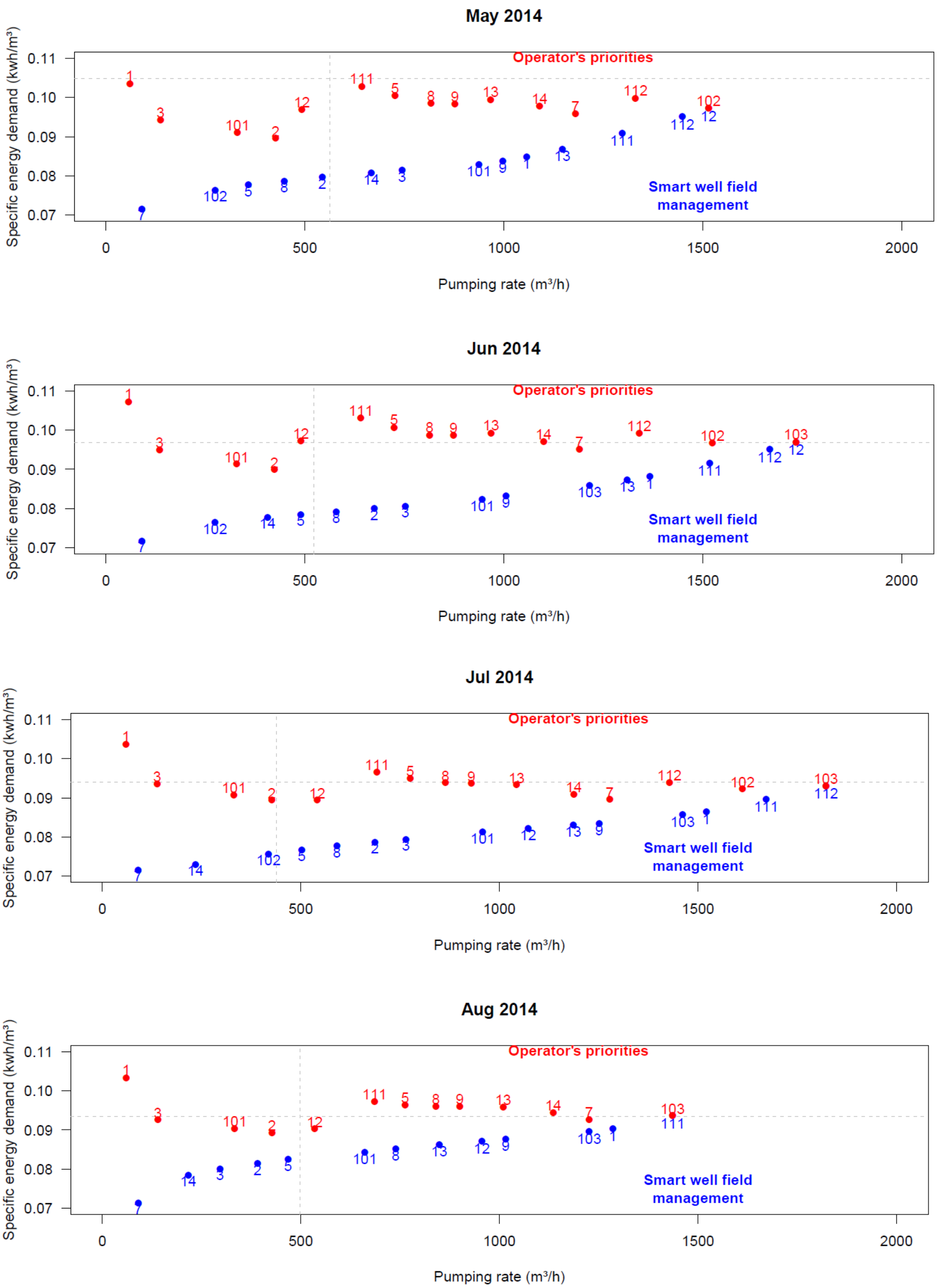


Figure 30 Energetic optimisation potential by smart well field management (i.e. re-defining of operator's current pump priorities). The operator's water demand and specific energy demand for each month are indicated with dashed grey lines.

3.3.5 Conclusions

As described in Chapter 3.3.2, cable losses could not be separated from the specific energy demand of the pumps because of the point of measurement. For the data-driven modelling approach, pipe losses were also not validated. To which extent the modelled specific energy demand of the well field for the smart well field management scenario may be underestimated or overestimated due to the changed priorities of pumps and its effects on pipe losses (from well position within the pipe and operating pumps at lower/ higher demand conditions than before) was not assessed. Lower pipe losses are expected for pumps that had low priority and are now operated earlier, and higher pipe losses for pumps that formerly had high priority (e.g. p1) but have a lower priority in the smart well field management scenario. If significant, these effects lead to a shift in the pumping rate, which in turn impacts the specific energy demand of the pumps in operation.

In general, the data-driven model cannot be taken to predict the energy demand of unknown scenarios with different boundary conditions, as operational data are needed as input. Thus, pump renewal schemes could not be calculated before being really implemented. In order to overcome that limitation, an extended real-time monitoring could be implemented (i.e. logging both, the abstracted volume and the power demand for all pumps).

The advantages of the data-driven modelling approach compared to the process-driven modelling used for the two former case studies can be summarised as follows:

- **Simplicity:** as the model only needs three input parameters for predicting the specific energy demand of the well field, its algorithm is simple and highly transparent, thus this approach is well adapted for being integrated in the operator's information system
- **Scalability:** in case of the availability of data loggers for volume and power demand for all pumps, the data-driven model can be easily scaled to larger well fields. For example, a well field with hundreds of pumps without requiring time-consuming and fast outdated pump audits. In addition, no complex model setup and calibration as required for process-driven modelling is required, which in turn enables real-time forecasting and feedback for the operator on the energetic performance of the well field.

Chapter 4
Cross-case analysis

4.1.1 Case study site characteristics

System boundary

The system boundary of the three case study sites differed between Site B and the other two study sites (Site A, Site C). The Site B well field is directly connected to the distribution network, thus the system boundary inherently included the distribution network. Contrary, the system boundary for the other two sites was limited either to the pipe inlet at the waterworks (Site A) or the raw water tank before the waterworks (Site C), so that it included only the water abstraction process without water distribution.

Manufacturer pump characteristics

On the basis of using manufacturer pump characteristics and assuming that all pumps are operating on their best efficiency point, the submersible pumps of the three different sites can be compared as shown in Figure 31. Both, total dynamic head (TDH, top panel Figure 31) and pumping rates (middle panel Figure 31) at the best efficiency point are highest for the Site B well field, leading to a in median ten percent higher global efficiency (bottom panel Figure 31) compared to the Site A or Site C well field. This can be explained by the fact that pumps with higher hydraulic power demand, i.e. pumping rate multiplied with total dynamic head, usually have a higher global efficiency (Höchel 2012).

The resulting specific energy demand (Figure 32) for the Site B well field is in median four times higher compared to the Site C well field, which can be attributed to the approximately four times higher total dynamic head (top panel Figure 31) in case of the former. However, the Site C well field has the highest variability of the specific energy demand between the pumps (varying by more than 240%, from 0.05 to 0.12 kwh/m^3). This can be explained by the large variability of the total dynamic head (top panel Figure 31) within the Site C well field, which varies in same order of magnitude (by 240% from 10 m to 24 m). This cannot be explained by significantly different geometrical elevations, because the wells are located within a small well field with similar static water and well drawdowns (top panel Figure 34). Thus, in case that the assumption that the current pump operation is close to the pumps' best efficiency points is true (which was confirmed by the pump audit, see Figure 23 in Chapter 3.3.2), the only possible explanation of this phenomena can be either pump ageing or increased pipe head losses (e.g. due to incrustations) for some parts of the well field.

The median pump age (Figure 33) at the time of the pump audits was comparable for Site C (5.5 years) and Site A (4.5 years), but significantly higher in case of Site B (8.5 years). In case of Site B, the pump age variability was much higher, too (ranging from 0 to 40 years) making it more likely that the current in-situ pump characteristics will show a significant offset for these pumps (e.g. due to pump ageing or cavitation).

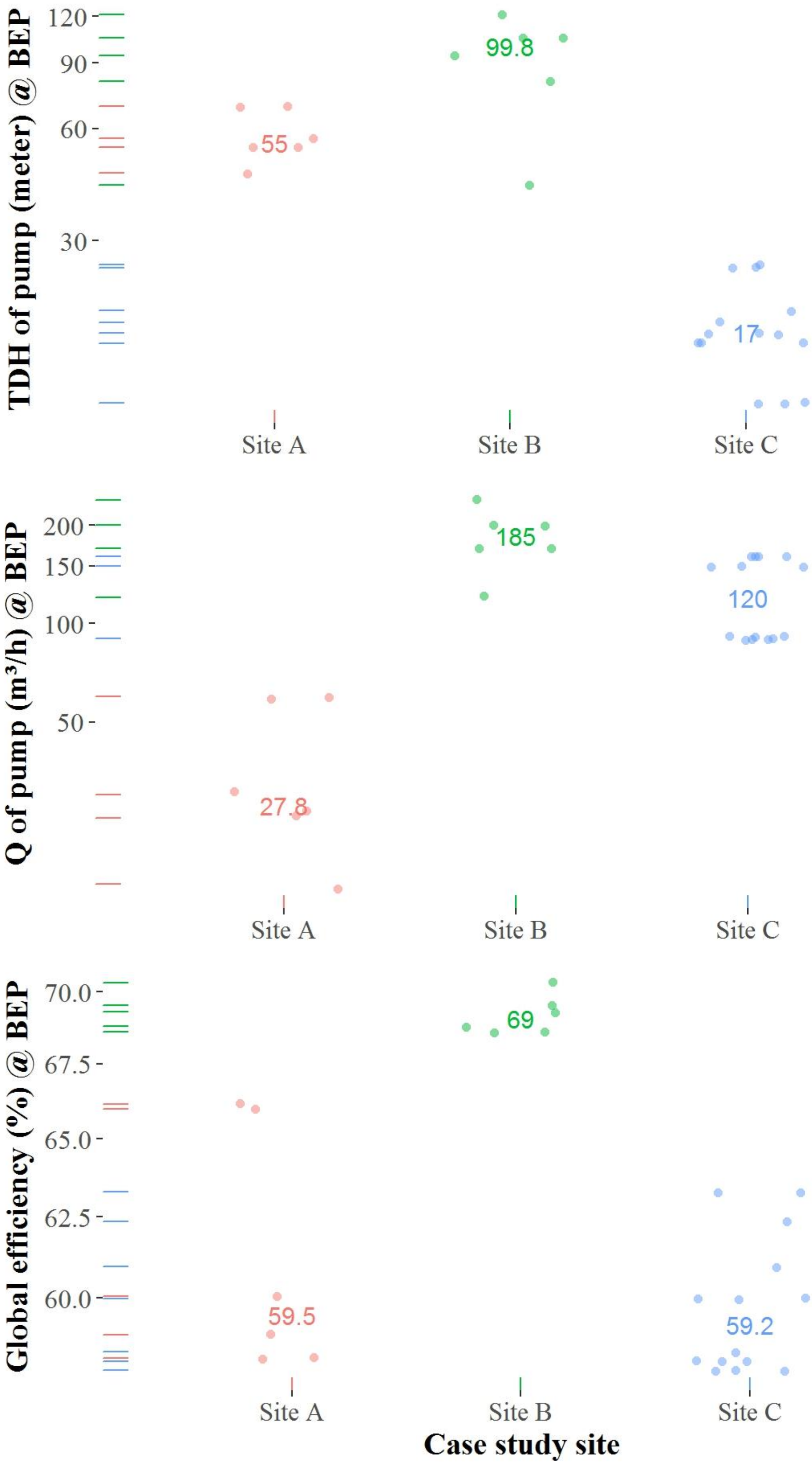


Figure 31 Manufacturer pump characteristics at best efficiency point for the pumps of the three case study sites. The number indicates the median value

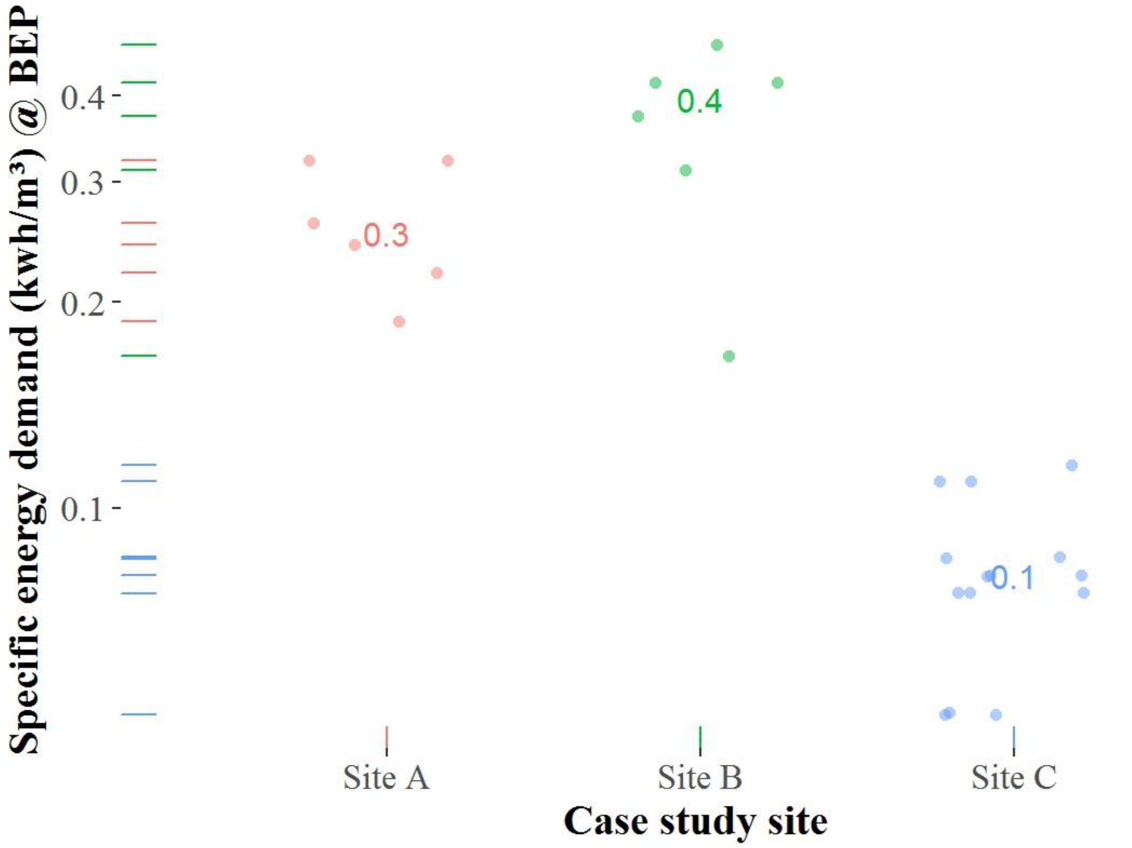


Figure 32 Specific energy demand of the pumps of the three sites due to manufacturer pump characteristics at best efficiency point (Figure 33). The number indicates the median specific energy demand

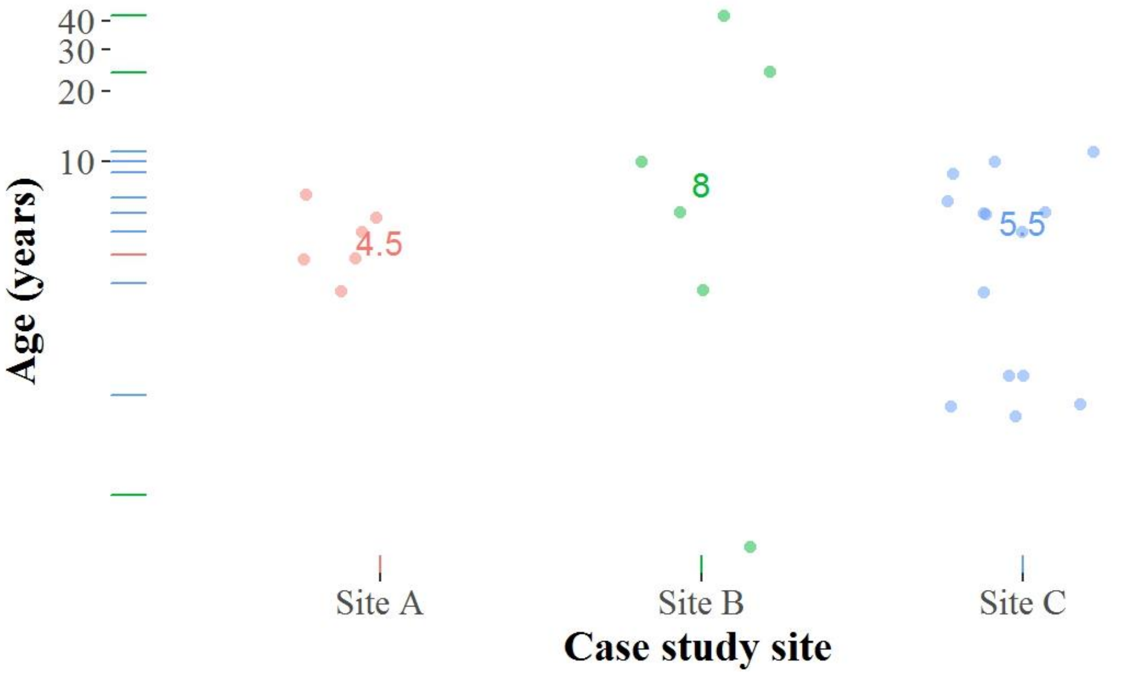


Figure 33 Age of the pumps (at the time of the pump audits) for the three case study sites. The number indicates the median age

Contribution of system components to required pump head

On the basis of using manufacturer pump characteristics and assuming that all pumps are operating on their best efficiency point, the total dynamic head for each pump (top panel Figure 31) was separated into the three system components (Figure 34):

- static elevation,
- well drawdown and
- pipe losses.

As Figure 34 clearly shows, the static elevation is the most important system component, which accounts in median for 60 to 75 percent of total pump head (bottom panel Figure 34), followed by pipe losses (23 to 36 percent of total pump head) and well drawdown (2 to 13 percent of total pump head).

In a nutshell, because 98 percent of the total pump head (Site B, Site A) can be attributed to the two system components static elevation and pipe losses, including steady-state well drawdown into process-driven modelling will not improve the specific energy demand modelling prediction significantly.

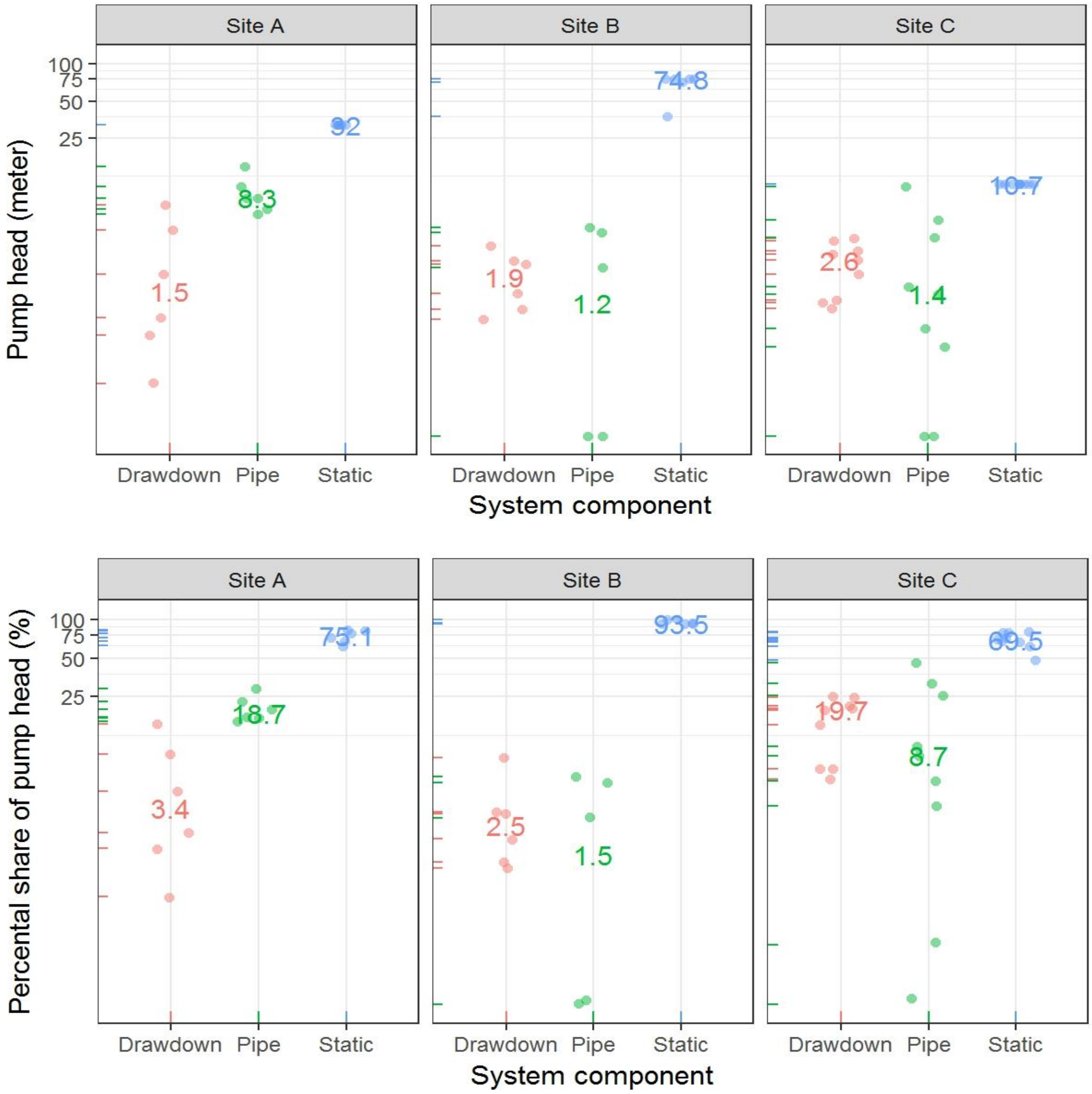


Figure 34 Absolute (top panel) and percental share (bottom panel) of pump head for the different system components. Pipe losses are calculated by subtracting the static elevation and well drawdown (both based on measured data) from the total dynamic head.

4.1.2 Data availability

The data availability for the three different case-study sites differed significantly as shown in Table 6. The four parameters listed in Table 6 are required for assessing the current pump characteristics.

For the two study sites located in France (Site B, Site C), operational data were available on a high temporal resolution (every ten minutes) due to automatic data logging at least for the two parameters pumping rate (derived from volume meters) and water levels in the wells. In case of the Site A well field, these data were only available with an insufficient temporal resolution (bi-weekly manual readings).

Neither pressure head nor the power demand for each individual pump was available for any of the studied case study sites. However, the total power demand was available for the whole well field with sufficient temporal resolution (weekly to monthly), which together with the monthly well field abstraction volumes was used for calculating the specific energy demand for each of the three well fields.

Consequently, operational data availability for all three case study sites was insufficient for optimising the well field's energy demand by means of process-driven or data-driven modelling. To overcome this data bottleneck, pump audits were performed for all three case studies (see Chapter 3.1.2, 3.2.2, 3.3.2), which enabled the assessment of actual pump characteristics. These audit pump characteristics were subsequently used as inputs for process-driven (pump and global efficiency curves of pumps) and data-driven (specific energy demand curves of pumps) modelling, as will be summarized in the following chapter. Note that the information gain due to pump audits is limited, as these are only snapshots of the pump condition (i.e. assuming no change in pump performance over time) and can be quite fast outdated (e.g. in case of pump replacement).

Table 6 Operational data availability for the three case-study sites

Available parameters	**Case study site**		
	Site A	**Site B**	**Site C**
Pumping rate per pump(Q)	bi-weekly (manually)	volumemeter loggers (every 10 minutes)	
Water level in well (H)	bi-weekly (manually)	water level loggers (every 10 minutes)	
Pressure head (P) per pump	no		
Power demand per pump* (E)	weekly	bi-weekly	monthly
	* only total energy demand of well field		

4.1.3 Modelling

For the three case study sites, the modelling results for sensitivity analysis (in case of process-driven modelling), predictive performance and energetic optimisation potentials can be summarized as follows.

Sensitivity analysis

The impact of simplifying the hydraulically calibrated process-driven model based on audit curves and steady-state drawdown (left column Figure 35) on the predicted well field's specific energy demand is studied by means of the sensitivity analysis for the two case studies Site A and Site B. The key results can be summarised as follows:

- **Well drawdown:** including steady-state well drawdown (steady-state DD) improves specific energy demand prediction at maximum by 10 % (Site A) but only less than 1 % in case of Site B. Well interference was not observed at Site B (due to the large distances between wells), and even for Site A it did not play a significant role (maximum additional drawdown due to well interference is 0.4m which is less than 1% of total head) thus not affecting the specific energy demand.
- **Pump characteristics:** using audit instead of manufacturer pump characteristics is much more important for the Site B well field (prediction error reduction of 40%) with older pumps (up to 40 years) compared to the Site A well field (prediction error reduction of 5%), which has much newer pumps (all less than eight years old).

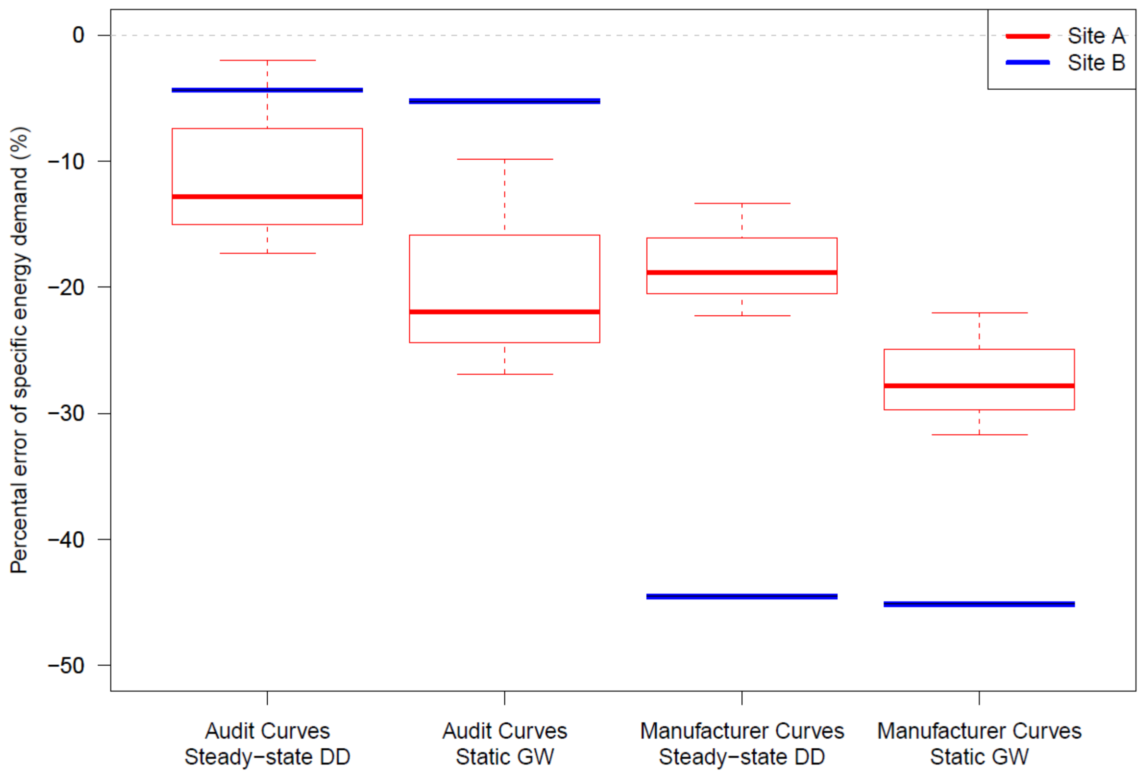


Figure 35 Sensitivity analysis for process-driven modelling case studies. Note the box-whisker plots in case of the Site A case study are due to the unknown pump operation (e.g. which pumps are operated in parallel), which could be only eliminated if data of pump on/off statuses for all pumps were available

Predictive modelling

The predictive performance of the well field's specific energy demand for both, process-driven and data-driven modelling approaches is shown in Figure 36.

In general, the predictive performance of, both process-driven and data-driven modelling approaches is highly accurate: the operator's measured specific energy demand is underestimated by the models between 2 – 17 % (Site A) to 4 % (Site B, Site C). The offset variability in case of Site A (2% - 17%) can be attributed to the fact that no data on the used pump operation scheme of the operator during the study period was available. Consequently, this range covers all possible operation schemes.

All three case studies underestimate the operator's measured energy demand. A possible explanation in case of the two process-driven models is the fact that these pump audits were performed in the production well close to the submersible pump, thus not taking into account additional cable losses (between the well and the main electricity station). In contrast, in case of the Site C case study, the pump audit inherently included the cable losses, because the power demand measurement was performed in the main electricity station. Thus, for Site C the offset between predicted and measured specific energy demand can only be attributed to (i) possible measurement errors during the pump audit (3.3.2) for assessing the specific energy demand curves and (ii) the data-driven model input parameters (Chapter 3.3.3).

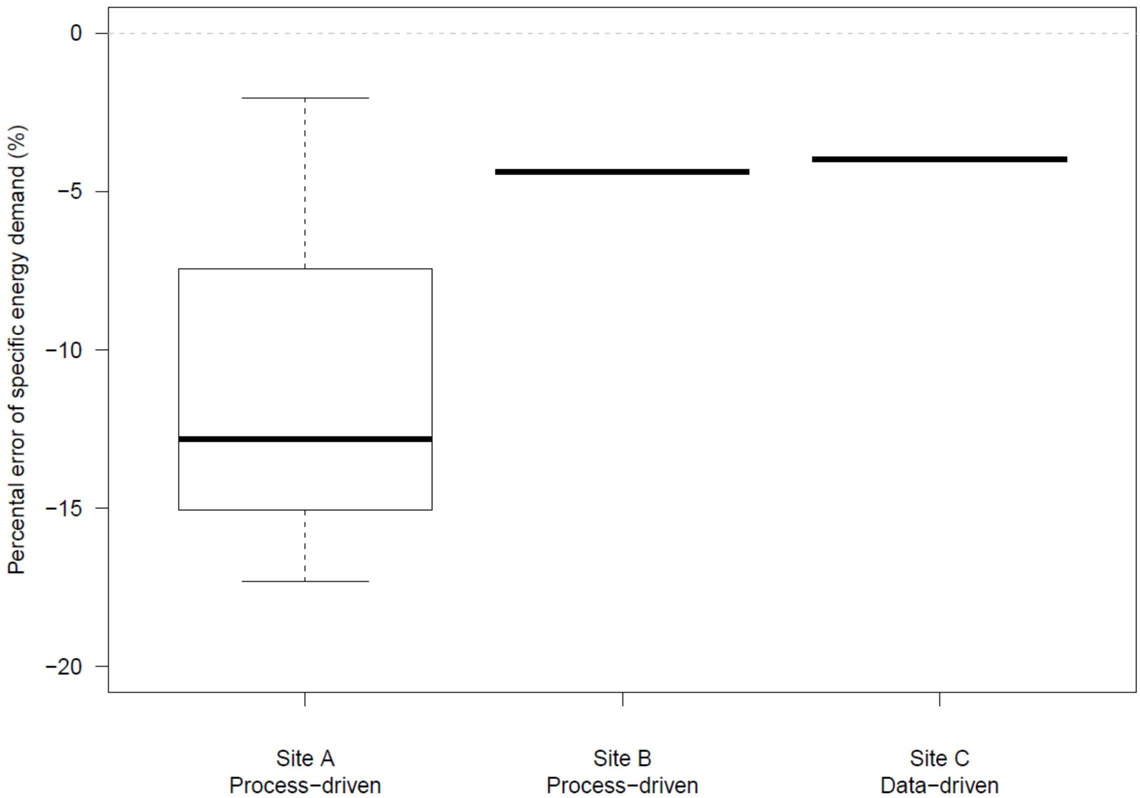


Figure 36 Predictive modelling performance of the hydraulically calibrated process-driven models (Site A, St.Louis) using audit pump curves and steady-state well and data-driven model (Site C). Note the box-whisker plot in case of the Site A case study is due to the unknown pump operation scheme (e.g. which pumps are operated in parallel), which could be only eliminated if data of pump on/off statuses for all pumps were available

Optimisation

Within OPTIWELLS-2, the optimisation objective was to minimise the well field's specific energy demand for water abstraction, whilst satisfying two boundary conditions:

- **Water quantity:** average hourly water production rate required to satisfy water demand
- **Water quality:** raw water quality in line with drinking water guideline threshold value

Taking these two constraints into account,

Table 7 summarises the maximum achievable percental specific energy demand reduction for each of the three case study well fields.

Neither smart well field management alone nor combining it with the renewal of the two aged pumps (p2 and p6) does reduce the specific energy demand of the best-case operation scheme by more than 3% for the Site A well field. However, although investing in new pumps does not minimise the specific energy demand of the best-case pumping configuration, it minimises the risk of selecting a very inefficient pump and is thus reducing the specific energy demand variability of all possible operation schemes (see also Figure 13).

In contrast, the Site B well field has a large potential for specific energy demand reduction ranging from 18 % (smart well field management only) to 48% (in case smart well field management is combined with the replacement of two pumps p_K and p1).

While the first two case studies were performed using a process-driven approach, a data-driven modelling approach was chosen for the third case study well field Site C. In case of smart well field management only, the specific energy demand reduction potential varied between 12 and 20%. However, it was not possible to study the impact of hypothetical pump renewal in the data-driven modelling approach used for Site C, because its application is limited to constant boundary conditions.

Table 7 Maximum percental reduction of specific energy demand for the three case studies taking into account both, water demand and water quality constraints.

Management strategy	**Process-driven modelling**		**Data-driven modelling**
	Site A	Site B	Site C
Smart well field management	3 %	18 %	12 - 20 %
Combination of smart well field management and pump renewal	3 %	48 %	*not possible******

**As data-driven modelling is limited to constant boundary conditions, it is not possible to study the impact of hypothetical pump renewal as this would change the boundary conditions.*

Chapter 5
Critical review of modelling approaches & value of monitoring

Within OptiWells-2, two modelling approaches, data-driven and process-driven, were used for optimizing the specific energy demand of the case study well fields. These approaches differ not only in their data requirements, setup and complexity, but also in their limitations (e.g. is the application of a data-driven model valid in case of changed boundary conditions?).

This chapter provides a critical review on both modelling approaches and proposes a pragmatic step-wise energetic well field assessment methodology (Figure 37) as defined below:

1. **Initial assessment:** if the well field`s actual specific energy demand is significantly higher than the theoretical one calculated using the theoretical specific energy curves of the pumps (i.e. >> 10%deviation), it is recommended to proceed with modelling, otherwise to stop after the initial assessment step.
2. **Modelling:** ***data-driven modelling (see Chapter 2.3.1)*** is valid as long as changing boundary conditions (e.g. well field operation) do not impact the pumps' operating points significantly. If this condition is not satisfied or if predictions are needed for new boundary conditions, which would impact the pumps` operating points significantly (e.g. replacement of raw water pipes), the more data-demanding and more complex ***process-driven modelling (see Chapter 2.3.2)*** needs to be carried out.

The level of data prerequisites for each step is indicated by the size of the blue database symbols in Figure 37. These data prerequisites are explained in more detail in Figure 38, showing that the initial assessment has the least data-requirements, whilst process-driven modelling has the highest data-requirements. Furthermore, process-driven modelling is more time-demanding compared to data-driven modelling, because it requires the setup of the pipe network system as well as a model calibration steps, so that the offset between measured and simulated pumping rates is minimised (by changing the unknown pipe characteristics roughness or/and its effective diameter). Data-driven modelling is sufficient in case that only the impact of smart well field management on the specific energy demand of the well field should be assessed. Whenever energy demand predictions for different boundary conditions are required (e.g. due to pump replacement or pipe renewal), process-driven modelling needs to be performed.

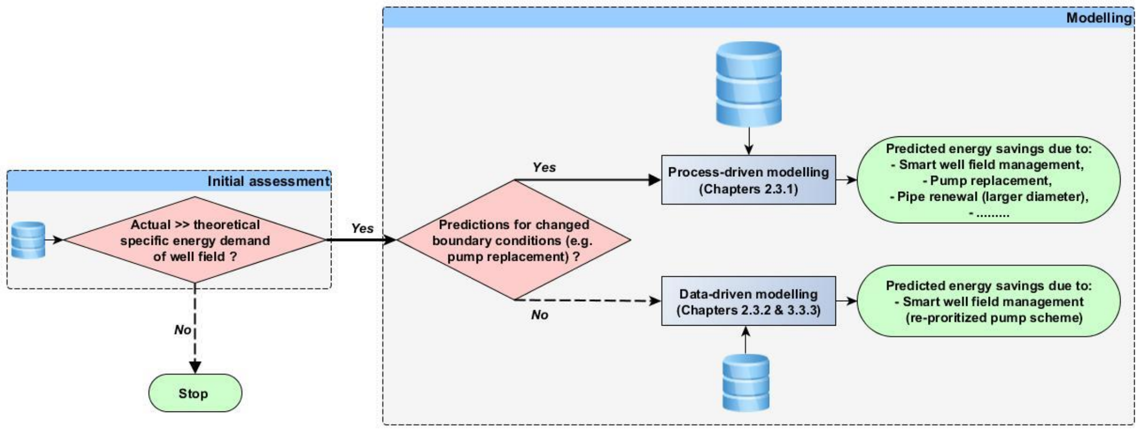


Figure 37 Flowchart for step-wise energetic well field assessment methodology. The level of data-prerequisites for each step are indicated by the size of the blue database symbols and explained in more detail in Figure 38

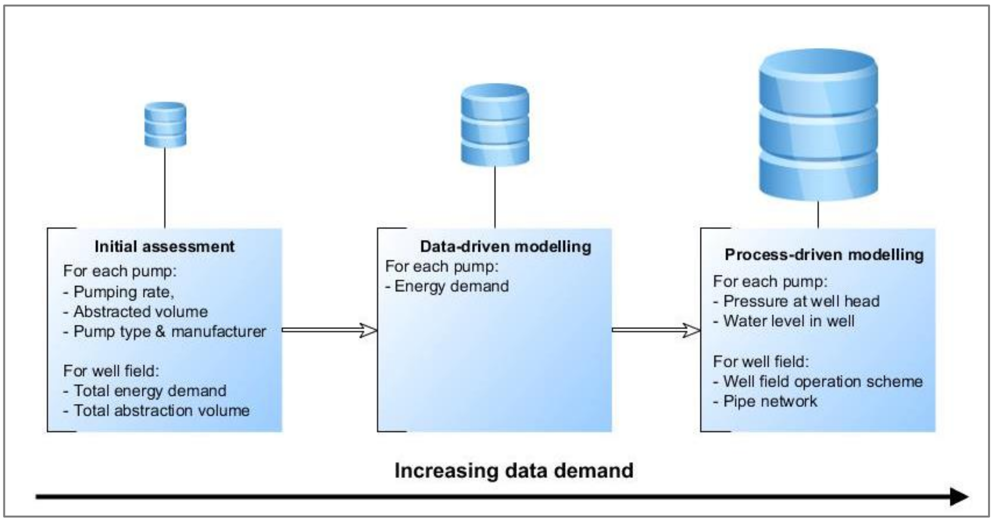


Figure 38 Data-requirements for performing energetic well-field optimisation. Note that process-driven modelling relies on both, data used for initial assessment and data-driven modelling

The value of monitoring data collected during each assessment step (Figure 38) for determining the actual pump characteristics of each pump is shown in Table 8.

The initial assessment assumes that all pumps follow their theoretical characteristics as defined in the manufacturer pump catalogues. The additional data collected for the data-driven modelling step (energy demand per pump) allow to derive the actual specific energy demand per pump, but still do not enable to identify offsets for both, theoretical pump curve and global efficiency curves. In case that data for both, static head and well drawdown curves for each pump are available and that in addition the pipe loss is calculated using the Hazen-Williams equation (see Chapter 2.1), the actual pump curves can roughly be estimated. This enables the identification of pumps with high mechanical ageing potential indicated by a large offset to the theoretical pump curves. Before replacing these pumps with new ones, a cross-check by field measurements of pressure and well drawdown for the concerned pumps is however recommended.

Only in case of the process-driven modelling step, where additional information for each pump (i.e. pressure at wellhead & dynamic water level in well) is collected, the actual pump and global efficiency characteristics for each single pump can be calculated.

Table 8 Value of monitoring data collected during each assessment step (Figure 38) for determining the actual pump characteristics of each pump. Asterisks (*) indicate that actual pump curve characteristics can be at least roughly estimated in case that additional data for both, static head and well drawdown curves for each pump are available and in addition the pipe loss is calculated using the Hazen-Williams equation (see Chapter 2.1).

		Pump characteristics		
		Pump curve	Global efficiency curve	Specific energy demand curve
Initial assessment		Theoretical*	Theoretical	Theoretical
Modelling	Data-driven	Theoretical*	Theoretical	Actual
	Process-driven	Actual	Actual	Actual

In the following, each step of the general flowchart (Figure 37) is explained in more detail.

Initial assessment

The initial assessment is based on the operator's data for each pump (abstracted volume, pumping rate, pump type & manufacturer) and for the well field (total abstraction & energy demand) in combination with theoretical pump characteristics derived from manufacturer pump catalogues. Consequently, the theoretical specific energy demand of the well field can be calculated using a data-driven approach (see Chapter 3.3.3) and compared to the operator`s current specific energy demand at the well field scale.

In case that the actual specific energy demand shows more than 10 % deviation compared to the theoretical one, it is recommended to proceed with modelling, otherwise energetic well field optimisation is not required.

The initial assessment needs to answer the following three questions:

1. Do the pumps with the lowest theoretical specific energy demand abstract most of the water? (***if no***: reprioritise pumping operation to place pumps with lowest specific energy demand in operation first and redo initial assessment)
2. Is the pumping rate for any of the pumps varying more than 40% compared to the pumping rate at the best efficiency point? (***if yes*:** check whether VSD pumps are beneficial compared to fixed speed pumps and if so equip these pumps with VSDs in the well field and redo initial assessment)
3. Are there pumps that are always operated with a pumping rate lower than 80% of the pump's theoretical best-efficiency point pumping rate? (***if yes*:** replace these under-dimensioned or mechanically aged pumps and redo initial assessment)

If question (1) is answered with 'yes', and (2) and (3) with 'no', the well field's energy saving potential can be regarded as low. Otherwise, the recommended countermeasures for each of the options above need to be implemented first before redoing the initial assessment to check the impact of these changes on the well field's specific energy demand. Figure 39 summarizes the procedure.

Limitations of this approach:

It needs to be noted that the initial assessment relies heavily on measured data (pumping rate and abstracted volume per pump). Consequently, the impact of proposed measures (e.g. pump reprioritisation) can only be evaluated once these measures are actually implemented for the well field and the initial assessment is repeated (i.e. comparing theoretical and actual specific energy demand).

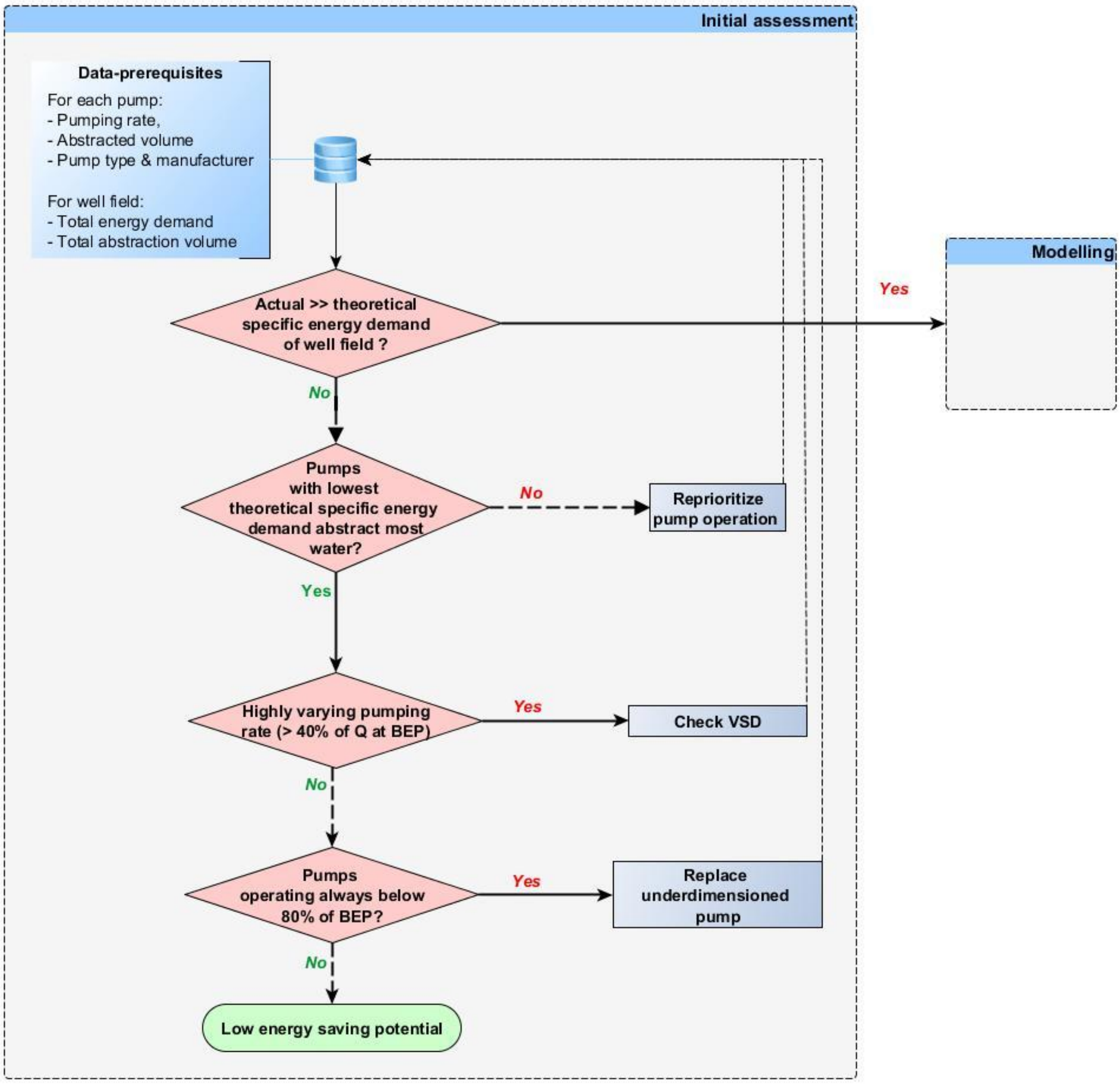


Figure 39 Initial assessment flowchart

Data-driven modelling

Data-driven modelling is performed if (i) the initial assessment yielded that the actual specific energy demand of the well field is significantly higher than the theoretical one (rule-of thumb: >> 10%) and (ii) investment in new pumps or pipes is not planned (smart well field management, only). The general steps for data-driven modelling are explained in Chapter 2.3.2, whilst an example for applying this approach is summarised in Chapter 3.3.3 for the third case study site. The advantages of using data-driven modelling compared to process-driven modelling is that it requires much less input data, no spatial model parameterisation and no model calibration. Consequently, its application is less complex and time-demanding, making it feasible for being integrated into the operator's information system and providing real-time forecasts of the well field's specific energy demand for different operating schemes. Figure 40 summarizes the procedure.

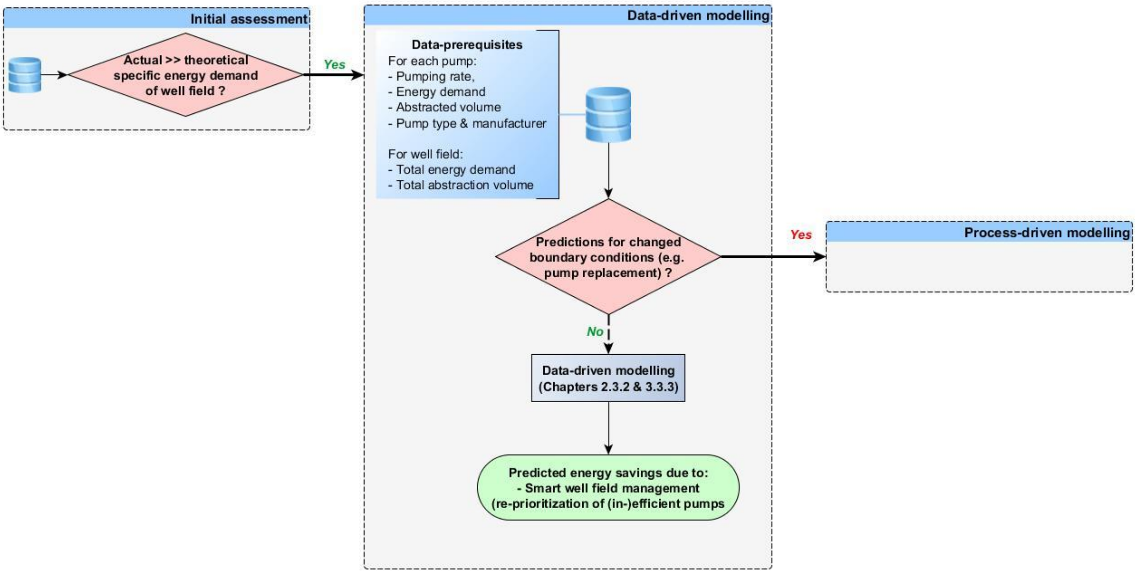


Figure 40 Data-driven modelling flowchart

Limitations of this approach:

As the initial assessment, the data-driven modelling relies on measured data only. Thus, its application is limited to comparable boundary conditions. For example, smart well field management reprioritizes the well field's pump operation to prefer pumps with low specific energy demand for a given pumping rate (e.g. median monthly from operator's data). However, changing formerly low prioritized pumps (i.e. pumps only used during peak well field abstraction conditions) to high priority pumps will also impact the pumping rate and pipe losses because of their positions in the well field and number of pumps in operation etc. Thus, the approach is recommended for small well fields with large pipe diameters and comparable low median well field pumping rates, only. In any case, after implementing the new pump operation scheme proposed by the data-driven model for the well field, a possible offset of the pumping rate is immediately visible in the operational data. Consequently, the data-driven model can be re-run, leading to more precise specific energy demand forecasts.

Process-driven modelling

Process-driven modelling is performed in case that the initial assessment yielded that the actual specific energy demand of the well field is significantly higher than the theoretical one (rule-of thumb: >> 10%) and that energetic saving predictions are required for management measures with capital investments (e.g. pump renewal or pipe replacement with larger diameter) leading to changed boundary conditions (i.e. different pump or system characteristics).

Prior to calculating energy demands, the level of detail for representing the groundwater component needs to be estimated. This includes well drawdown as part of the dynamic head and well interference. Well drawdown measurements from multiple-step pumping tests are compared to the static head component:

1. *Well drawdown at maximum pumping rate is >> 10% of static head*

   if yes: well drawdown should be considered by adding a discharge-dependent head loss term

   if no: well drawdown can be neglected, considering static groundwater levels is sufficient

2. *Well interference at maximum pumping rate is >> 10% of static head*

***if yes**:* well interference should be considered by adding the maximum observed interference at the end of the pumping test to the static groundwater level, whenever interfering wells are operated parallel

***if no**:* well interference can be neglected

Consequently, process-driven modelling is performed (see Chapter 2.3.1 for more details) considering the groundwater component as described above. Finally, it enables not only to predict the energetic saving potential for different management strategies (smart well field management, pump renewal or combination of both), but also to calculate the actual performance of each pump (global efficiency, specific energy demand and pump curve offset to theoretical one) for a given well field operation scheme. Figure 41 summarizes the procedure.

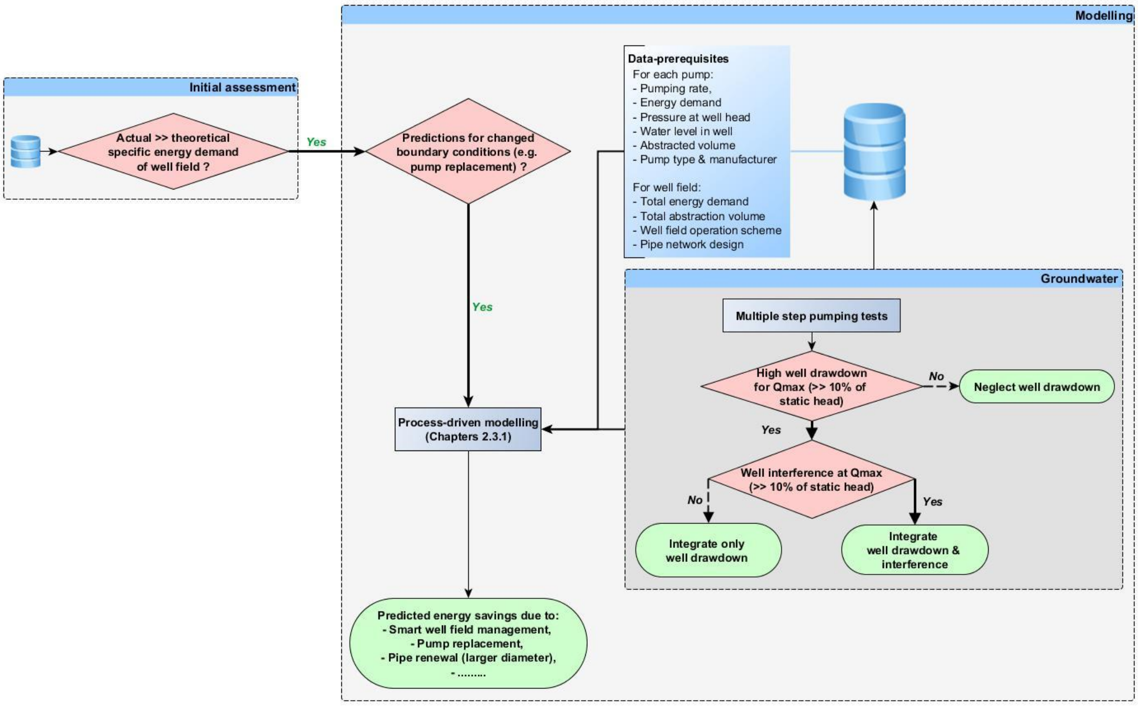


Figure 41 Process-driven modelling flowchart

<u>Limitations of this approach:</u>

Besides the fact that process-driven modelling is the most flexible approach, it is also the most data- and time-demanding one, requiring at least five operational parameters for each pump (pumping rate, energy demand, pressure at well head, water level in well and abstraction volume). In case these data are not available, process-driven modelling is still possible, but with uncertain predictive accuracy. The second case study site (see Chapter 3.2) showed for example that especially in case of well fields with aged pumps the use of theoretical pump curves can underestimate the actual specific energy demand by more than 40%.

In addition, process-driven modelling is only possible if the whole pipe network of the well field is digitalised and calibrated (i.e. by modifying the pipe network characteristics until the error between measured and simulated pumping rates is acceptably small, usually < 5%). This is not only a time-demanding, but also a non-trivial task due to the non-linear increase of pipe losses (if the pipe diameter is reduced). Furthermore, calibration is not scalable and needs thus to be repeated for each new well field.

Chapter 6
Conclusions & Outlook

6.1 Recommendations for energy optimisation of well fields

"I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind." (Lord Kelvin)

6.1.1 Data prerequisites

A key characteristic of all case study sites is the lack of operational data. These data are either completely not available (e.g. pressure in the pipe(s), power demand of pumps) or do not have the adequate temporal resolution (e.g. bi-weekly water level readings for Site A well field). Within OPTIWELLS-2, this lack of real-time data was overcome by performing pump audits. These typically took 60-90 minutes per pump including installation of measurement equipment and enabled assessing the current in-situ pump characteristics (i.e. pump and global efficiency curves). The obtained data were a prerequisite for setting up a process-driven EPANET model of the well field abstraction systems.

Furthermore, as pumps are replaced in frequent intervals (e.g. Site C: six pumps within a year), any prediction based on models using these "snapshot" pump characteristics from audits as input parameters are quite fast outdated. In order to overcome this problem, the implementation of more data loggers for real-time monitoring is recommended, which would in future allow to assess the following operational parameters for each pump with an adequate temporal resolution (depending on the pump switching frequency):

- Pumping rate (or volume meter) of each pump
- Power demand of each pump

These data are the minimum requirements in case of the data-driven modelling approach used for the third case study (Chapter 3.3) and in case of process-driven modelling (Chapters 3.1 and 3.2) the following additional input parameters are required:

- Pipe network geometry
- Pump characteristics (pump and global efficiency curves) and
- Well drawdown (only in case that this contribution is significant compared to the sum of static head and pipe losses)

Based on these data, the process-driven hydraulic model (EPANET) needs to be parameterised, calibrated and validated before it can be used for predicting and optimising the specific energy demand of the well field. Compared to the data-driven modelling approach, these additional steps in case of process-driven modelling are not only more time-consuming, but also its predictive model performance is less robust. This is due to the fact that (i) the process-driven workflow relies on much more data prerequisites that are all potential sources of uncertainty (Chapter 2.5) and (ii) in addition, model calibration may lead to overfitting, thus reducing the model generalisation (i.e. low predictive model performance in case of unseen data).

Thus, only in case that a quantitative assessment of the impact of a hypothetical pump renewal (i.e. new pump with different pump characteristics) is required, process-driven modelling is advantageous because by using a data-driven modelling approach it is not possible to vary the pump characteristics hypothetically.

6.1.2 Development of advanced pump catalogue database

Within OPTIWELLS-2, optimisation modelling for minimising the specific energy demand of the case study well fields was limited to three management strategies: smart well field management, pump renewal (of the same type that is currently installed) or a combination of both. However, this neglects two further possible management strategies:

- **Pump replacement with different pump type:** this measure may be indicated in case that the currently installed pump is either wrongly dimensioned (rule-of-thumb: not operating within 80 – 120 % of the best-efficiency point's pumping rate) or the pump's global efficiency at the best-efficiency point is significant lower compared to the best currently available pumps from the manufacturer catalogue.
- **Equipment of submersible pumps with variable speed drives (VSD):** in case that the operational data for a given pump shows that the pumping rate is highly variable (rule-of-thumb: operating point varies by more than 40%, i.e. below 80% and above 120% of the pumping rate at the best-efficiency point), equipping the pump with a VSD could be a measure to reduce the specific energy demand (see also deliverable D 1.2, (Bauer et al. 2014). However, at least for the studied case study sites, the pumping rate variability was with less than 10% rather low, thus it is not recommended to install VSDs for improving the specific energy demand.

To overcome this limitation it was decided to further enhance an already existing pump catalogue, developed in MS EXCEL by TU Berlin within OPTIWELLS-1. While the current EXCEL version contains the best-efficiency point pump characteristics of 3200 pump aggregates (i.e. combination of pump types and different number of stages) from ten different pump manufacturers (Höchel 2012), within OPTIWELLS-2 this pump catalogue (Figure 42) was enhanced by:

- **Multiple data points for each pump aggregate:** the pump, global efficiency and net pressure suction head curves for all pump aggregates were digitalised.
- **Transformation into MS ACCESS database:** enabling user-friendly cross-manufacturer comparison of the 3200 pump aggregates based on user-defined filter criteria (i.e. pump head or pumping rate at best-efficiency point, pump size or tolerance class), thus simplifying the operator's workflow for identifying a small set of pumps, which fit his conveying task best (see also deliverable D2.2, (Sonnenberg & Rustler 2015))
- **Meta-information on VSD usage of pump motors:** integration of constraints defined by the pump manufacturer (e.g. minimum/maximum VSD frequency) in the pump catalogues.

Data from the pump catalogue can be exported and used as input data for the process-driven model (e.g. EPANET), thus enabling to directly assess the impact of pump replacement with a different pump type on the energetic well field performance.

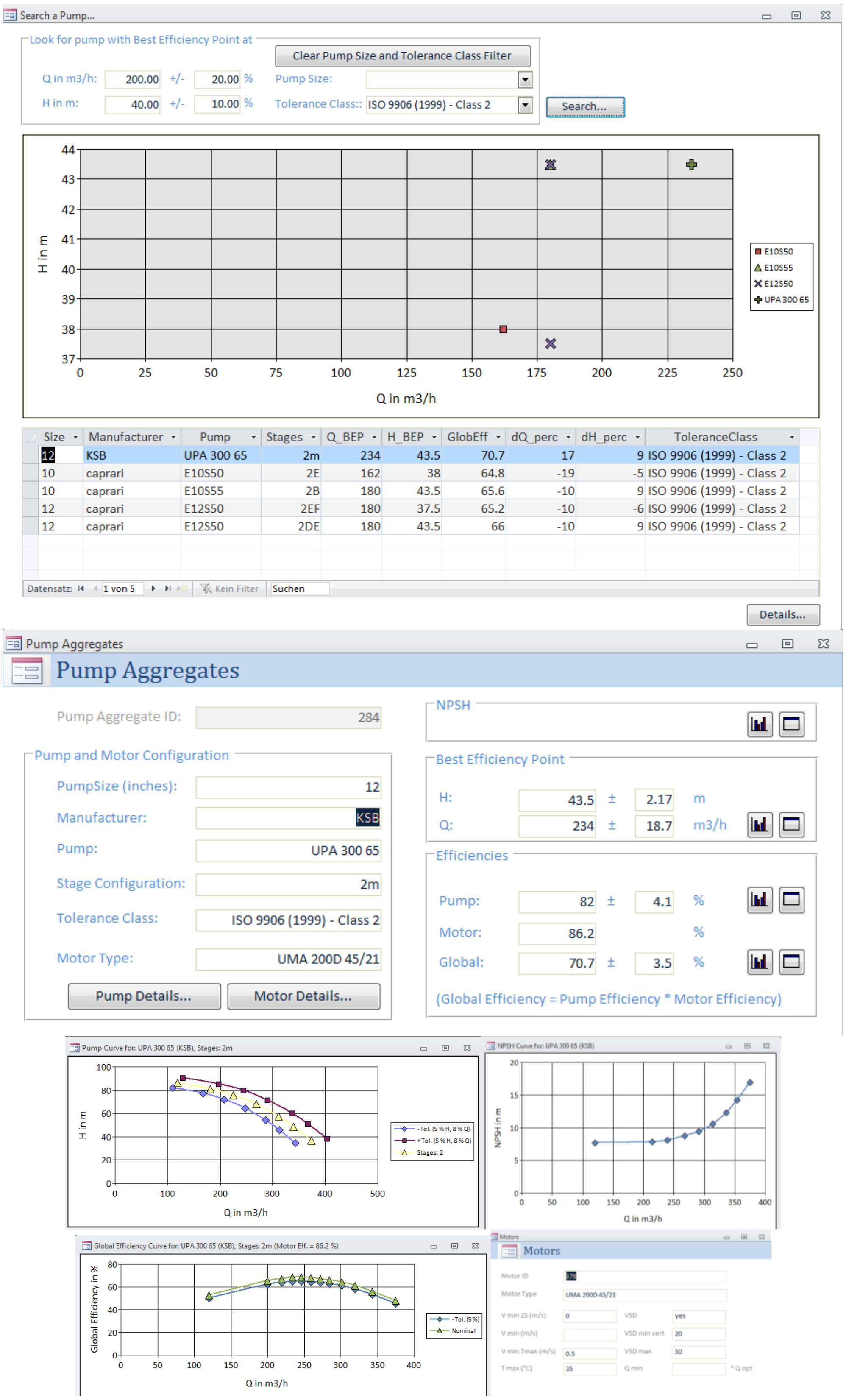


Figure 42 Pump catalogue database (MS ACCESS): characteristics of 3270 pump aggregates (i.e. pump models with different number of stages) from 10 different manufacturers. The user can filter pumps based on pumping rate, total dynamic head at the best efficiency pump, pump size or tolerance class (top panel). After selecting pump technical details on the pump aggregate, its motor (e.g. meta-information if VSD usage is possible) as well as pump, global efficiency and net pressure suction head curves are available

6.2 Further research & development needs

Testing the methodology developed in OPTIWELLS-2 for minimising the well field's specific energy demand was limited to three small to medium sized well field sites ranging from 6 to 18 submersible pumps. However, the methodology should be also scalable, i.e. applicable for larger well field sites without being too expensive. Currently this is not possible, because important parameters required for assessing the in-situ pump characteristics (pumping rate, pressure head and power demand of pump, water level in well) are typically not logged by the operators with a sufficient temporal resolution (ideally: at least twice as high as pump switching frequency). To overcome this data shortage, time-consuming pump audits were required, but these provide only a snapshot that in addition can be fast outdated (for example if that the pumps are renewed).

Thus, future research in the field of energetic well field optimisation should focus on:

- **Identification (or equipment) of a bigger well field with data loggers** for continuous measurement of at least two operational parameters for each pump (volume, power demand per pump) and for the whole well field with high temporal resolution and
- **Testing of the data-driven approach for this (large) well field**, because it can be easier automatized as it requires less data (e.g. no pressure head or well drawdown), less technical steps (e.g. pipe network model setup and calibration) and thus will likely provide more robust predictions compared to a process-driven approach. These features make the data-driven approach very suitable for being integrated in the operator's real-time information system, thus enabling real-time forecasts and feedback (e.g. identification of malfunctions like phase shifted connected pumps) the operator on the energetic performance of the well field.

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