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ICE Simulation – Calibration and Optimization

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Simulace spalovacího motoru – kalibrace a optimalizace

ICE Simulation – Calibration and Optimization

Summary

The document concerns application of optimization approach when dealing with thermodynamic modelling in internal combustion engine using detailed 0-D/1-D model. Three different possibilities are mentioned – calibration of ICE mathematical model, engine setting optimization and engine control from system simulation point of view (controller optimization is not meant by this term). These possibilities are listed in order of importance (based on author's opinion).

Calibration is critical phase of engine model work-flow – only properly calibrated model can provide sound conclusions. Optimization is supposed to provide a great help due to the fact that an error between prediction and measurement can be minimized. This is in line with main goal of calibration which is to find the values of calibration parameters so that the mathematical model matches experimental data as closely as possible. On the other hand, user's experience is invaluable as each calibration is a unique process – there is no general method to calibrate engine model properly, moreover there might be significant errors in experimental data.

Optimization of engine setting under steady-state operation is a standard task. Due to increase in computer power, complex multi-variable multi-target multi-constraint problems can be solved within reasonable time – this allows to perform optimizations of higher quality as internal combustion engine features strong non-linear interaction of many input parameters.

Engine control optimization is very challenging task due to the need to simulate transient response and the fact that optimization is more difficult from theoretical point of view. Strong development is expected in this application field before it becomes an industry standard task. At present time, a common approach is to derive a model which is much simpler from complexity level point of view. Such model is significantly faster however it usually *'looses'* most of its physical meaning hence its predictive ability is limited or even lost.

Some examples are briefly presented to show application of optimization in all three above-mentioned categories. Some results are shown in each example so that the quality of optimization/calibration process can be estimated.

Souhrn

Předložený dokument se zabývá použitím optimalizačního přístupu pro případ termodynamických simulací spalovacího motoru užitím detailního 0-D/1-D modelu. Tři různé možnosti jsou zmíněny – kalibrace matematického modelu motoru, optimalizace nastavení motoru a řízení motoru z pohledu celkové systémové simulace (nejde o optimalizaci regulátoru). Tyto možnosti jsou řazeny dle své důležitosti (podle názoru autora).

Kalibrace je kritickou fází při tvorbě modelu – pouze řádně zkalibrovaný model může poskytnout rozumné výsledky. Očekává se, že optimalizace zde může významně pomoci, neboť je možné minimalizovat odchylku mezi výsledky simulací a naměřenými daty. To je v souladu s hlavním cílem kalibrace, což je najít takové hodnoty kalibračních parametrů, aby matematický model odpovídal co nejlépe experimentálním poznatkům. Na druhé straně zkušenost uživatele je neocenitelná, protože každá kalibrace je unikátní proces – neexistuje obecná metoda jak korektně kalibrovat model motoru, navíc naměřená data mohou obsahovat chyby.

Optimalizace nastavení motoru odpovídající ustálenému stavu je dnes již standardní úlohou. Díky nárůstu výpočetního výkonu je možné řešit komplexní problémy (víceparametrická optimalizace omezená mnoha limity s cílem optimalizovat více výstupních parametrů) v rozumném časovém úseku – to umožní provádět optimalizace vyšší kvality, protože spalovací motor se vyznačuje silnou nelineární interakcí mnoha vstupních parametrů.

Optimalizace řízení motoru je velmi obtížný úkol, neboť je třeba simulovat přechodový režim a tato optimalizace je mnohem náročnější z teoretického hlediska. Značný vývoj lze očekávat v této oblasti předtím, než se tato optimalizace stane standardním úkolem. V současné době je běžným postupem řešit tyto obtíže za pomoci značně zjednodušených modelů z hlediska fyzikální složitosti. Takovýto model je výrazně rychlejší avšak obvykle ztrácí mnoho ze své fyzikální podstaty, a tedy jeho prediktivní schopnost je omezena nebo dokonce ztracena.

Stručně jsou zmíněny příklady, aby demonstrovaly použití optimalizace ve všech třech výše uvedených oblastech. Jsou ukázány některé výsledky, takže je možné posoudit kvalitu optimalizace/kalibrace.

Klíčová slova: spalovací motor, detailní termodynamická simulace, optimalizace, kalibrace modelu motoru, přeplňování, řízení motoru

Keywords: internal combustion engine, detailed thermodynamic simulation, optimization, calibration of engine model, turbocharging, engine control

Contents

1 Introduction

An internal combustion engine (ICE) has been used widely as a source of mechanical energy. Its application is dominated by automotive industry, mainly passenger cars and light/heavy duty vehicles. Despite the fact that its *'age'* is more than one century, it is still an important machine, which is expected to be the main power source in vehicles during the next decades. Its main advantages are high power density, high efficiency and reasonable prices. However, limited supplies of oil, increasing oil prices and significant pollutant production have been leading to an increased social pressure to improve ICE efficiency while decreasing emission of pollutants.

Simulation has been an important tool to achieve these ambitious goals. Its importance has been ever increasing during the course of the whole development process. Many different tools – ranging from simple algebraic ones up to 3-D CAE tools – are available to enhance the development procedure. These tools differ in physical complexity, moreover different tools are applied in different phases of development process (simple tools are used usually at early development stage while detailed 3-D tools are applied during later stages). All these tools require some kind of a calibration to improve confidence in predicted results. There is a clear trend to apply more profound models (i.e., level of physical complexity is higher) during early development stages. This leads to the situation in which these models have to be reliable although there are no experiments to verify them as the machine might not even exist at that time. That requires highly qualified users with profound knowledge and extensive experience with similar engines. Moreover, 3-D CAE tools might be applied as initial source of calibration before any experimental data are available. Such procedure is clearly very demanding, however advantages are obvious – improved design is available sooner, hence development process can be shortened.

One of the main advantages of any simulation tool (once properly/reasonably calibrated) is the potential for relatively fast optimization. The possibility to optimize is very important as it enables to find a potentially promising designs for a following detailed analysis – it can save a lot of time due to the fact that *'dead-end'* designs are avoided.

As mentioned above, reliable simulation results cannot be achieved without proper calibration. Once the confidence in predicted results is high, optimization approach is usually applied to find an optimal design. The following text deals with application of optimization approach in different phases of ICE model creation and usage. As the author deals with thermodynamic simulation of ICE, all below mentioned text and examples concerns thermodynamic simulation tools. However many conclusions (presented below) are generally valid, i.e., they do not hold for thermodynamic modelling cases only.

2 Application of Optimization Approach

It is well known that one of the main reasons why to build a thermodynamic model of ICE is to perform some kind of optimization. It is a very important feature as theoretical thermodynamic analysis is usually much faster and much cheaper when compared with experimental one. It was already mentioned above that each thermodynamic model needs some kind of calibration – the more precise calibration, the higher confidence in predicted results. When using the word *'calibration'* in this document, it is meant to calibrate a mathematical model of ICE (it does not mean to calibrate a control unit). The author's experience is that the calibration phase of model creation is usually the most important one. That is why sufficient amount of time is required to perform this critical step in a best possible way. Based on that, both the optimization and the calibration are important phenomena regarding ICE thermodynamic modelling. The following text is aimed at describing them in detail.

When dealing with thermodynamic simulation of ICE, the optimization approach might be typically applied in three different ways – the first one is the calibration of ICE model, the second one concerns engine setting/design optimization (this is a typical standard application) and the third one deals with engine control optimization from system point of view. Each of them has its own specific features that is why they are dealt separately in the following sections – general comments and example(s) are presented to demonstrate main features. The examples concern engine models built in 0-D/1-D code (c.f. [1, 2]) – such models are suitable for engine system simulations.

It was mentioned above that the standard task is to optimize engine setting/design – that usually means to search for optimum solution under steady-state operating conditions. Such approach is described in section 2.1. However, if a mathematical model of ICE is supposed to provide reliable prediction, it has to be properly calibrated – this is a complex issue which is commented in detail in section 2.2. It is also well known that engine control (from system point of view) is a critical factor. There is a lot of potential to improve engine control by means of both simulation and optimization, however it is relatively difficult task as engine transient response has to be considered. This is briefly described in section 2.3. It is obvious that transient simulation is more difficult (from the physics point of view) when compared with steady-state one – this makes calibration even more important (and more difficult).

The optimization methods can be divided into three different categories – deterministic, stochastic and combined. The deterministic methods are based on deterministic approach, their output is usually only single optimum design. The following methods belong to this category – mathematical analysis (calculus), simplex method, linear/quadratic programming. In ICE applications, gradient based methods are widely applied. The stochastic methods are based on certain random features, the Monte Carlo method is example from this category. These are not applied frequently in ICE optimization tasks. The combined methods combine both approaches. Special sub-category of such methods consists of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. Genetic algorithm is one possible method from this sub-category – recently it has been widely used to solve complex optimization problems (multi-variable multi-target multi-constraint optimization). It is surprisingly effective in the field of ICE applications. However its main disadvantage is that it is *'method only'* – it is not based on principles of the ICE physics which means that analysis of optimal population evolution cannot generate hitns/advices how to improve ICE design from general point of view.

2.1 Optimization of ICE Setting/Design

It was mentioned above that one of the main reasons why to create a thermodynamic ICE model is to perform optimization which is supposed to be faster and cheaper when compared with experimental optimization. Development/research based on application of thermodynamic ICE model has been done for a long time and model-based optimization has been ever present. That is why it is a standard task to perform optimization when thermodynamic ICE model is available. Initially optimization tools were relatively simple (e.g, gradient-based methods, design of experiments). However as more computer power was available it was possible to run multi-variable multi-target multi-constraint tasks, which are relatively complex. Due to non-linearity of equation set 2.1 (located below in section 2.2) to be solved, there are many local optima. Moreover, there is strong non-linear interaction of input parameters. All these facts lead to a conclusion that simple optimization methods are not suitable for such complex tasks. At first full factorial combination of all input parameters were calculated so that a user can obtain robust optimal solution – it is clear that such approach is very time consuming. The author was surprised that genetic algorithm, which is suitable for describing *'live'* system evolution, is very good tool in such complex optimization tasks (described above). It was proven that genetic algorithm [3] is both reliable/robust and relatively time effective tool. At present time, it has been widely used at Department of Automobiles, Internal Combustion Engines and Railway Vehicles at Faculty of Mechanical Engineering at the Czech Technical University in Prague to perform various optimization tasks.

From mathematical point of view, more detailed description of a general thermodynamic ICE mathematical model is presented in section 2.2, equations 2.1-2.5. Application of a optimization approach is also described in that section, equations 2.6-2.7. When performing optimization of engine setting/design, mathematical model is run in a *'normal'* way. That means that unknown variables y_i are determined by solving 2.1 numerically. The calibration procedure (section 2.2) is finished, hence the vector c_n is known and the mathematical problem 2.1-2.4 is properly defined. The optimization task 2.6 (or its simplified version 2.7) is solved with respect to engine design parameters, i.e., certain components of k_m (equation set 2.3) are optimized.

From optimization point of view, typical variables to be optimized are the following – compression ratio, intake valve open/close timing, exhaust valve open/close timing, turbocharger matching (selection of the best possible turbochargers to provide required boost pressure), etc. These parameters can be considered as engine design ones. There are usually other variables to be optimized – they may be regarded as control ones as they can be *'adjusted'* during engine operation. Injection/ignition timing, turbocharger setting (waste-gate, variable geometry position), air excess are typical examples of them. Their optimized values correspond to ICE steady-state operation (transient response is dealt with in the following section 2.3). The targets of optimization depend on ICE application. There are usually two typical examples, which can be considered as single-target optimization task – the first one is to find the lowest possible brake specific fuel consumption (BSFC) while satisfying engine power requirement*, the second one deals with maximum achievable engine power. Regarding multi-target optimizations, typical example concerns minimization of BSFC while minimizing pollutant production (or at least not exceeding certain limits). Optimization constraints are very important in a case of engine setting/desing optimization – they limit achievable optimal solution considerably. It may also happen that there is no solution due to them. Typical constraints are the following – maximum in-cylinder pressure, minimum air excess, maximum inlet turbine temperature, maximum turbocharger speed, compressor surge, knocking, maximum/minimum exhaust gas recirculation (EGR), etc.

Due to limited extent of this document, no detailed example is presented in this section. As the engine setting/design optimization has been a standard task for a long time (at least two decades), almost every paper, which deals with ICE thermodynamic modelling, contains information regarding optimization using ICE model – c.f. [13–18], some papers concern an application of complex optimization methods (c.f. [4, 7, 20]). However, Figure 2.1 shows a comparison of different charging concepts of unspecified spark ignition (SI) engine. Each engine concept is fully optimized at each engine speed including (turbo)charger matching while taking into account many constraints including knocking. This example demonstrates a possibility to perform huge complex optimization tasks (genetic algorithm was applied as optimization tool) including selection of proper design concept.

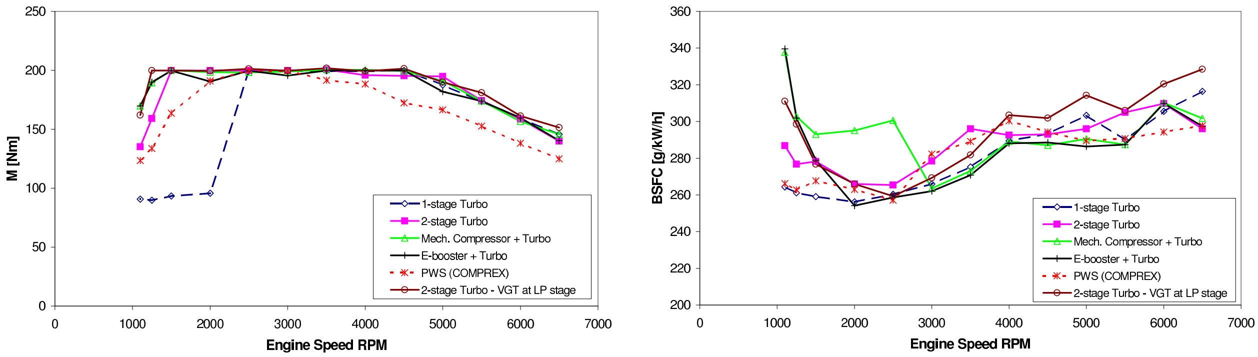


Figure 2.1: *Comparison of different charging concepts –* **best variant** *of each concept is presented; engine torque (left sub-figure) and BSFC (right sub-figure).*

*The requirement to obtain desired power is usually achieved by a controller which is directly built-in thermodynamic model. It may happen that the required output cannot be reached – if this is a case, a properly defined constraint is supposed to ensure that the design is dropped.

It has been verified many times in the past that theoretical optimization (using thermodynamic ICE model) is powerful tool to verify potential of proposed design and to understand the complex links of interaction between ICE and other thermodynamic devices (e.g., 2-stage turbocharger system). Both of these features are valuable. It should be stressed that genetic algorithm produces an optimal solution in such a way which is not straightforward from the physics point of view – in this sense, genetic algorithm is simply only a robust method to find optimal solution. If understanding of thermodynamic links is of primary interest, it is recommended to perform sensitivity studies – it is a sweep of results when only one variable is varied while all remaining ones are set to be constant.

2.2 Calibration of ICE Model

When applying 0-D/1-D thermodynamic model, it is based on 1-D fluid dynamics [5, 6] – it means that non-linear partial differential equation set 2.1 is solved to take into account basic conservation laws (mass, momentum and energy).

$$\mathcal{L}_i(t, x, y_i, k_m, c_n) = 0 \tag{2.1}$$

Where y_i, for $i = 1, 2, ..., N_i$ is the vector of unknown thermodynamic properties to be solved by numerical integration of 2.1. Unknown thermodynamic functions are supposed to be dependent on time and and single space coordinate, i.e., $y_i = f(t, x)$. User has to define vectors k_m and c_n, where k_m, for $m = 1, 2, ..., N_m$ is the vector of constants/functions which are supposed to be known (material properties, machine design including geometry, etc.) while c_n, for $n = 1, 2, ..., N_n$ is the vector a calibration parameters. Initial/boundary conditions 2.2 have to prescribed to be able to solve the equation set 2.1.

$$\mathcal{J}_j(t, x, y_i, k_m, c_n) = 0 \tag{2.2}$$

The sub-models are supposed to add particular relations among y_i, k_m and c_n to be able to solve 2.1 and 2.2. In-cylinder heat transfer, which may be modelled by Woschni empirical formula [19], can be considered as an example of such a sub-model – it defines heat losses via combustion chamber walls. From mathematical point of view, these sub-models consists of differential equations* and algebraic ones.

$$k_m = \mathcal{K}_m(t, x, y_i) \tag{2.3}$$

$$c_n = \mathcal{C}_n(t, x, y_i, k_m) \tag{2.4}$$

Hence the whole equation set to be solved, namely 2.1, 2.2, 2.3 and 2.4, is relatively complex – generally speaking, it is a non-linear hyperbolic system. However, there is still too many unknown parameters (y_i and c_n) – the calibration procedure is supposed to assign values of c_n, which means to define a particular form of 2.4.

The above-mentioned equation set is supposed to represent a particular thermodynamic machine – this is achieved by appropriate structure of the model and calibration

*Typically ordinary differential equations are used, however there are some sub-models which are based on partial differential equations (e.g., multi-zone direct diesel injection model in [1]).

procedure. The former one means that suitable sub-models are selected for each part of the machine, the parts are properly linked to represent real flow of mass/momentum/energy and to consider interaction among the parts. As mentioned above, the latter one is supposed to assign all necessary parameters so that the equation set can be solved by numerical solver – it may sound simple but it is actually difficult.

Before calibration process is started, some parameters have to be known – without that knowledge, calibration is much more difficult or even impossible. Complete geometrical information is needed to build all important parts from geometrical point of view, moreover appropriate links among the parts are created to take into account mass/momentum/energy fluxes. Chemical species have to be known as well to assign correct thermodynamic properties to fluid mixtures which are passing through the parts of the machine. Knowledge concerning engine control has to be available as well. From mathematical point of view, all that means that values of k_m in equation set 2.3 are known. It may happen that due to *'conversion'* of complex 3-D parts into 0-D/1-D simulation tools, some geometrical properties have to be calibrated during calibration procedure so that volume and *'equivalent'* length is preserved to predict proper interaction of pressure waves.

The calibration of 0-D/1-D model *cannot be avoided*. This is very important phase (perhaps the most important) of the simulation work. Without proper calibration, it is difficult to trust the model. Moreover, the calibration process is generally very time consuming as many iterations are needed. There is no general procedure how to calibrate 0-D/1-D model as it strongly depends on particular application and available experimental data of existing thermodynamic machine. User's experience with similar cases is very important and helpful as it can speed up the whole process significantly.

From mathematical point of view, there are many parameters (of selected sub-models) to be assigned, namely c_n in 2.4. To achieve that, experimental data have to be available so that the mathematical model is capable of representing the considered thermodynamic machine. The vector of measured values is denoted as r_k^{meas} while the corresponding vector of values calculated from the solution of 2.1 is written in 2.5.

$$r_k = \mathcal{R}_k(t, x, y_i, k_m) \tag{2.5}$$

Where $k = 1, 2, ..., N_k$ and N_k is the amount of available measured properties. To match model with experimental data, prediction should equal measurements, i.e., $r_k^{meas} = r_k$. The user needs at least so many measured values to match the amount of unknown parameters, i.e., $N_n \leq N_k$.

When taking into account a typical model of ICE at present day, there are really many sub-model parameters (c_n) – these parameters are usually labelled *'tuning'* ones due to the fact that after tuning their values, the mathematical model represents the considered machine. It is usually not easy to measure so many different thermodynamic properties in ICE when only single engine operating point* is considered – it is obvious that only certain thermodynamic properties can be measured at ICE with reasonable accuracy while the

*It is usually sufficient to define each ICE operating point by means of two parameters only – engine speed and engine load.

measurement itself is not too expensive*. That is why $N_n > N_k$ which means that there is not enough information to assign c_n. Typically the following information is available when performing standard ICE experiments at engine test bed – average values of pressure, temperature and mass-flow rate at different locations of ICE, in-cylinder pressure pattern (with sufficient resolution in time domain) and integral parameters which represent the whole engine cycle (power, speed, efficiency, pollutant production, etc). Unfortunately, the averaging procedure means that some information is lost – e.g., average 4-stroke engine torque is calculated as $M_{t,avg} = \frac{\eta_m}{4\pi} \int p(t)\, dV$ ($p(t)$ is instantaneous in-cylinder pressure, $V = V(t)$ is inst. in-cylinder volume, η_m is mechanical efficiency and the integral operation is performed over the whole engine cycle – 2 engine revolutions for 4-stroke engine), where $p(t)$ is thermodynamic property which is solution of 2.1 while $V(t)$ is known parameter from 2.3. The average torque is measured at test bed in different way (taking into account torque balance of test bed rotor). It is obvious that the loss of information is not desired due to the fact that if model predicts correct engine torque, it does not necessarily mean that in-cylinder pressure $p(t)$ is predicted correctly. It would be better to measure instantaneous values, i.e., $r_k = y_k$ to avoid any transformation from y_k to r_k, so that calibration procedure avoids comparison of average values. It is obvious that such measurements are much more demanding, hence more expensive.

To get enough information (at least to match the amount of unknown tuning parameters), the experiments are repeated for different operating points. This usually leads to a status that there are more equations than unknown tuning parameters ($N_n < N_k$). Moreover due to non-linearity, there is strongly varying sensitivity of mathematical model with respect to tuning parameters – in other words, some tuning parameters are more important than other ones. On top of that, there is no guarantee that any reasonable solution† of the problem exists (especially when there is more equations than variables), i.e., that it is possible to find c_n so that $r_k^{meas} = r_k$. All these features make the calibration procedure more difficult.

It is clear from above-mentioned text that there are some difficulties from mathematical point of view. That is why an efficient method to find the tuning parameters c_n is required. At present day standard approach to perform calibration procedure is to to use *'trial-and-error'* method. Usually the calibration is divided into many steps – in each step, only single sub-model (e.g., in-cylinder heat transfer model) is being calibrated/tuned while all other ones are kept unchanged – this means that only certain values of c_n are modified while all remaining ones are kept constant during the step. Due to non-linearity, modified properties of any sub-model result in changes of performance of almost all other sub-models, c.f. equation set 2.4. This leads to requirement to adjust slightly their

*The selection of measured parameters cannot be random – the measured properties have to respect important physical links among parts of considered thermodynamic machine (only such information is valuable for calibration procedure) and obviously these properties have to be measurable.

†The author is aware that the term *'reasonable'* is not suitable for mathematical description. However it is obvious that when there is more equations that unknown parameters ($N_n < N_k$), it is very unlikely that a solution exists from mathematical point of view. That is why the term *'reasonable'* solution is introduced – it means that such a solution is a set of calibration (tuning) parameters c_n which causes that difference between mathematical model prediction and experimental data is within reasonable limits, i.e., $|r_k^{meas} - r_k| \leq \varepsilon_k$.

tuning parameters to compensate that effect* – iterations are necessary. Fortunately, the sub-model interaction is usually not too strong, hence iterative procedure converges in relatively fast way. It is obvious that this approach is not very effective – user's experience is invaluable and it can speed up the procedure significantly.

It seems that optimization approach may provide a great help. Theoretically, all sub-model tuning parameters c_n may be considered as variables to be optimized while minimizing the difference between predicted data and experimental ones. This is written in 2.6.

$$r_k^{meas} - r_k = \min \tag{2.6}$$

The amount of targets is N_k while the amount of optimized variables is N_n. Hence 2.6 defines a multi-variable multi-target optimization task. It is possible to slightly simplify 2.6 by means of creating multi-variable single-target optimization problem 2.7, however a user has to define weight factors β_k.

$$\sum_{(k)} \beta_k \left(r_k^{meas} - r_k\right)^2 = \min \tag{2.7}$$

If the optimization procedure (using either 2.6 or 2.7) is applied to the whole engine model (0-D/1-D model of engine system simulation), it leads to too many variables to be optimized (N_n) and too many optimization targets (N_k in a case of 2.6) – this would result in too long computation times. As far as the author's knowledge is concerned, this has not been done yet (when dealing with system simulation using 0-D/1-D ICE model). Moreover, there is no guarantee that it will produce realistic results in terms of the values of calibration parameters – there are many of them which can compensate errors caused by other ones. This leads to the fact that there is usually not single *'reasonable'* solution. Typically there might be more of them and a user has to decide which of them is really reasonable – if the set of variables is too large, it is difficult for a user to check all relations and consequences. That is why the application of optimization approach during calibration phase has been limited to calibration of certain sub-models only. The author believes that application of optimization during calibration will increase significantly in near future.

From optimization point of view, the variables to be optimized are the tuning parameters (c_n) of sub-models. The optimization criterion is defined in 2.6 means to minimize a difference between model prediction and measured data taking into account all considered engine operation points† – this usually leads to multi-target optimization (each measured property is taken into account). It is obvious that if multi-target optimization is performed, the output of the procedure is a Pareto set (c.f. Figure 2.2 which concerns example of 1-D

*Typically each tuning parameter has different influence on predicted results – some of them are more important than the other ones. This enables to fix the values of the less important parameters and to modify only the most important ones when performing adjustments due to non-linear effects.

†The considered set of operation points may not necessarily be the whole set of measured data – sometimes it is of advantage to split the operating points into smaller domains and perform calibration in each domain separately. By doing that, tuning parameters c_n may vary with engine speed/load. Such approach is usually applied when calibrating simple combustion models, knock model or pollutant production ones.

turbine model calibration based on [10–12]; more information is also presented in the text below including Figures 2.4-2.5) – a user has to select final particular solution from the Pareto set using his/her experience. It has to be stressed that a formulation of multi-target optimization 2.6 is not simple – each measured property has its own specific meaning and its influence on calibration quality is different. E.g., combustion model is critical one while heat transfer in pipes located downstream of turbine has only minor significance. When using single-target optimization problem 2.7, the different importance of r_k^{meas} components can be taken into account when assigning values of β_k. Moreover, certain domain of engine operation may be more important than other ones (e.g., full load at low engine speeds is clearly more important than low load at high engine speeds). It is a user's experience which is important when selecting the final solution from a Pareto set (or setting values of β_k). On top of that, experimental data usually feature a *'noise'* or even significant errors – they may be difficult to detect but they have usually non-negligible consequences when performing calibration procedure. Regarding the constraints of optimization procedure, there are usually no direct constraints.

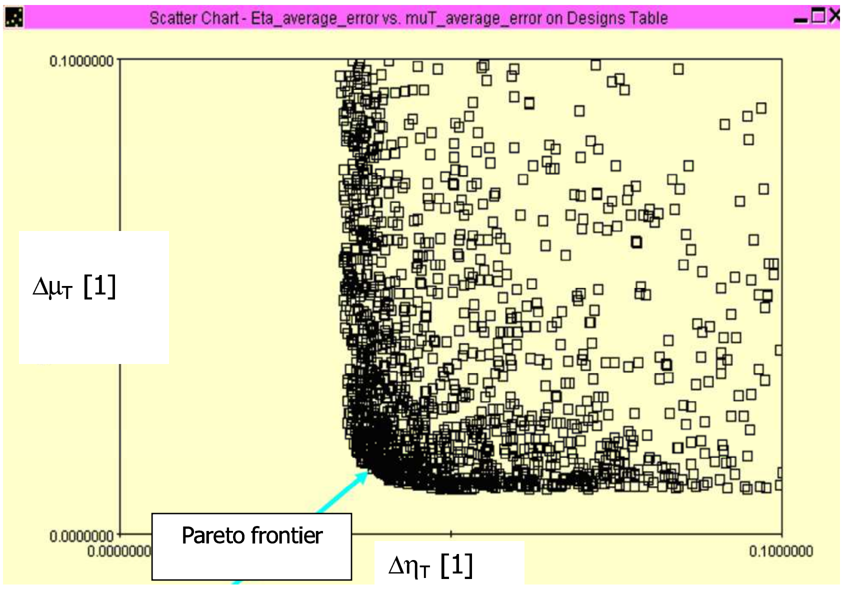


Figure 2.2: *Pareto front and the trade-off between turbine efficiency and discharge coefficient for constant calibration parameters in the whole pressure ratio / BSR ratio range. [1] means dimensionless parameter.*

Based on above-mentioned text, the calibration is complex and difficult task which has many specific features depending on considered thermodynamic machine and available experimental data. Optimization approach may offer improvements to speed up the whole process while improving its quality. However the author doubts that an automatic procedure can be developed in near future – it is too complex and too specific. On the other hand, it is a user who acts as limiting factor – his/her influence has to be minimized. Perhaps certain procedures for calibration of specific sub-models can be developed which can run automatically using either iterative approach or even optimization – they can produce high quality outputs while the amount of user inputs is minimized (hence the probability of user error is decreased). An example of such procedure may be the three pressure analysis (TPA) briefly mentioned in the text below.

It should be stressed that there is one feature of calibration which is similar to optimization of engine control (section 2.3). It is the way how a curve of chemical heat release is derived. Even if the engine operates at steady state, the rate of heat release (ROHR) has to be known. The output of a ROHR model is curve (not a single number). This curve is a critical factor which influences heat transfer in the cylinder, indicated efficiency and temperature of exhaust gases – all these parameters have strong consequences with respect to engine performance. That is why special attention has to be paid to calibration of ROHR. There are many ROHR models (ranging from simple Vibe approach up to relatively complex turbulence-driven multi-zone models). However the first step of ROHR calibration is usually evaluation of experimental in-cylinder pressure traces – the output is a table of data which corresponds to instantaneous rate of heat release with respect to engine crank angle. Once this curve is known, considered ROHR model is calibrated to match that curve as close as possible while checking also the difference between measured and predicted in-cylinder pressure. Unfortunately, the ROHR is strongly influenced by heat transfer model and in-cylinder species composition. That is why it cannot be done separately – iterations are needed again. Moreover, when calculating ROHR curve using measured pressure traces, the mathematical model 2.1 is solved with respect to different variables – it is usually called *'inverse'* run* and the goal is to find mass/energy source terms to obtain measured in-cylinder pressure. This causes some troubles and there are usually special executables which run the mathematical model in inverse mode. These executables are often simplified to avoid too high complexity (e.g., there is only simple model of wall heat temperature) – this simplification leads to additional errors. The way how to avoid all these troubles is to use the three pressure analysis (TPA), c.f. [2]. It requires three measured pressures – intake, in-cylinder and exhaust, hence the name, three pressure analysis. For this analysis, no estimation of the residual fraction, trapping ratio and other thermodynamic parameters are needed as inputs. This approach requires an engine model including valves and ports at a minimum. The simulation is run for multiple cycles until the model has converged. As a result, in-cylinder species composition (based on trapping ratio, residual fraction and other trapped quantities) will be calculated, which is why it is not needed as input. All that means that mathematical model is run in normal mode and all selected sub-models are applied in the calibration procedure as well (hence no additional errors are introduced). The TPA is not based on optimization – it still uses iterative approach in automatic way while there are no additional simplifications. The improvement of calibration quality is obvious, however it is not for free – additional information is needed, namely intake/exhaust pressure. More details can be found in [2].

An example of engine model calibration is presented in [15] – it is a standard procedure of calibrating turbocharged engine. In this case, optimization approach is used only rarely.

*When 0-D/1-D solver runs in *'normal'* mode, it has to know all source terms in 2.1 and the outputs of numerical solution are density, velocity, internal energy and species mass fractions in each control volume (all other properties can be calculated using additional equations, e.g., perfect gas equation of thermodynamic status).

Typically, *'manual'* calibration done by a user is sufficient. If optimization is needed, full factorial combination is computed and a user selects the best possible combination – example of engine knock model tuning is presented in [15], Section 3.2.

The importance of users's experience is clearly shown in Figure 2.3 – this example deals with unspecified diesel engine calibration. The first attempt (labelled *'Calib_1'*) corresponds to application simple sub-models (which may seem to be calibrated in easy way) while the second one (labelled *'Calib_2'*) represents application of more complex sub-models (which are usually more difficult to be calibrated). Moreover, the first attempt was done by a less experienced user. The fist attempt of calibration took more iteration steps (hence longer time) and yet the calibration quality is lower. It is the author's experience that when high-complexity sub-models with predictive ability are selected to be applied, it brings many advantages. It may be slower at the beginning, however it is usually sufficient to take into account *'border'* operating points only (definitely not all measured data) and the models can *'interpolate'* due to their predictive ability (they can be used for *'reasonable'* extrapolation as well).

The example presented below concerns calibration procedure of advanced 1-D turbine model [10–12], which is also described in detail in [15], Section 4.2. The 1-D turbine model is relatively complex one and the relations among all calibration parameters (more than 10) is not straightforward while there are only two properties to be matched with experimental data (efficiency and discharge coefficient). Moreover, due to fine discretization (which is needed due to physical reasons), computation times are relatively long. All these facts cause *'manual'* calibration to be difficult and not time effective.

The calibration procedure of 1-D turbine model (which represents a variable geometry turbine) is very time consuming*. Genetic algorithm [3] is applied to find the best combination of the model calibration parameters to fit the experimental data (efficiency, mass flow) – approach based on equation 2.7 is applied, i.e., simplified multi-variable single-target problem. The best fit may be sought for in every measured point of a map or it can be evaluated from grouped results. In this case, the proven way is to substitute the range of blade speed ratio (BSR) 0.4 - 0.8 at certain pressure ratio by the common calibration parameters, which are functions of pressure ratio only. The optimized deviations can be evaluated between measured and simulated product of discharge coefficient (mass flow rate) and isentropic efficiency, because turbine power depends on them.

As it is demonstrated in Figure 2.4, the results of calibration feature reasonable stability. They are dependent on pressure ratio in some cases, which is well-known feature of the loss-coefficient model due to low Reynolds and Mach number dependence of losses. The dependence on BSR was excluded by finding the best fit for all measured points at the same pressure ratio. Most of pipe diameters are almost constant except for the impeller exit one where outlet velocity-dependent flow separation occurs. Angles of flow at nozzle are reasonably constant, as well, including the deviation *delta alpha2N* between mass

*Algebraic turbine model (steady state model build in MS Excel – details can be found in [10–12]) can be used to speed up the procedure. Genetic algorithm is applied to calibrate this simplified model. The results of that (the values of calibration parameters) provide a good estimate for 1-D model calibration, thus enabling to reduce the search range for each calibration parameter.

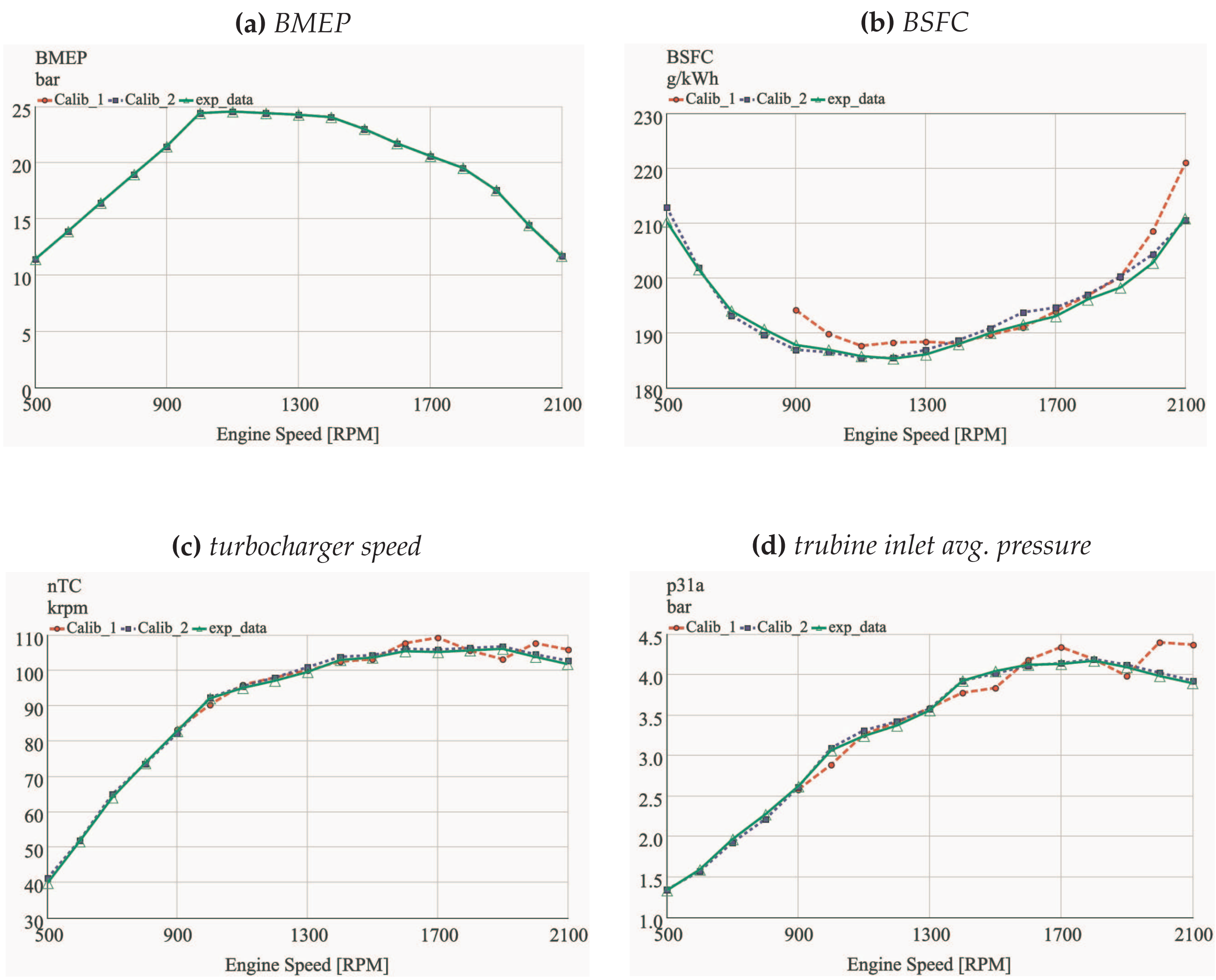


Figure 2.3: *Comparison of different results in terms of engine model calibration under full-load operation – green curve (labelled* 'exp_data'*, symbols: empty triangles) represents experimental data while red curve (labelled* 'Calib_1'*, symbols: circles) resp. blue one (labelled* 'Calib_2'*, symbols: squares) corresponds to the first calibration data set resp. the second one.*

and momentum averaged exit angles. Leakage discharge coefficients and correction of incidence angle loss are negligible for this case.

This experience was repeated – Figure 2.5 – for the case of opened stator vanes. The trends are mostly logical (compare, e.g., the outlet angles for both rack positions in Figures 2.4 and 2.5 – the impeller outlet angle without changes, the nozzle outlet angle changed according to the rack, reduced impeller losses due to more suitable nozzle angle for opened turbine). It is promising for the future development of the model. The traces of calibration parameters can be smoothed by repeated optimization where the less significant parameters are kept at fixed values. The other parameters can be approximated by simple regression dependence on pressure ratio without significant loss of accuracy then. In the case of current turbine, the loss of accuracy is negligible if smoothing of the parameters found by optimization is done using additional regression.

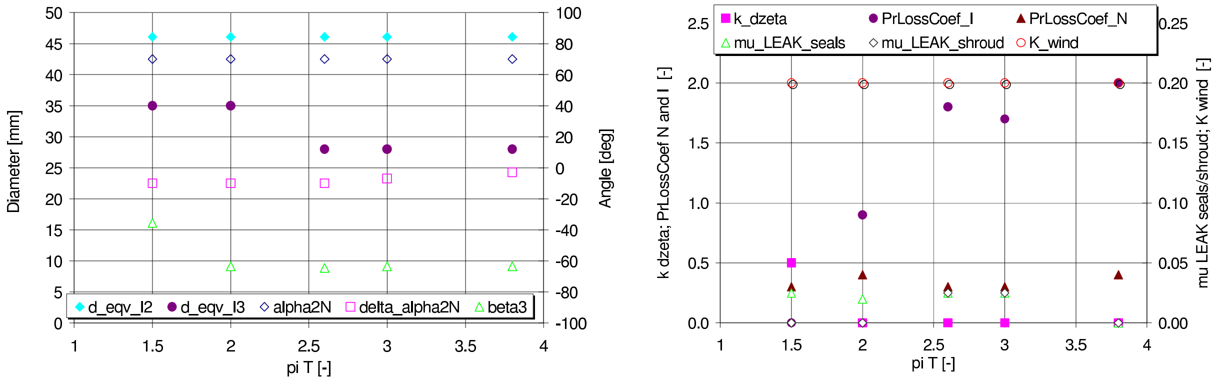


Figure 2.4: *Turbine model parameters found by optimization procedure using genetic algorithm without additional smoothing procedure, variable geometry turbine, rack position R0 (closed vanes).*

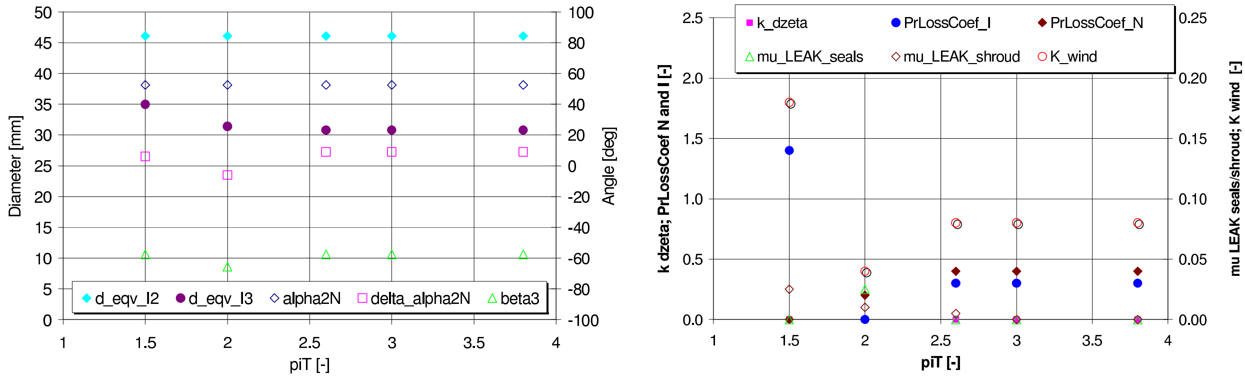


Figure 2.5: *Turbine model parameters found by optimization procedure using genetic algorithm without additional smoothing procedure, variable geometry turbine, rack position R1 (opened vanes).*

The overall comparison of simulation and measurements smoothed by regression for a variable turbine is presented in Figure 2.6 through Figure 2.7. The *'dispersion'* of parameters is caused by different BSR at the same pressure ratio or vice versa. The 1-D model was operated under steady conditions at a virtual turbocharger test rig. The data include all turbine losses. The discharge coefficients are evaluated for fixed reference cross-section of blades, namely 4.52 cm^2, which is physically valid for *'open'* vanes.

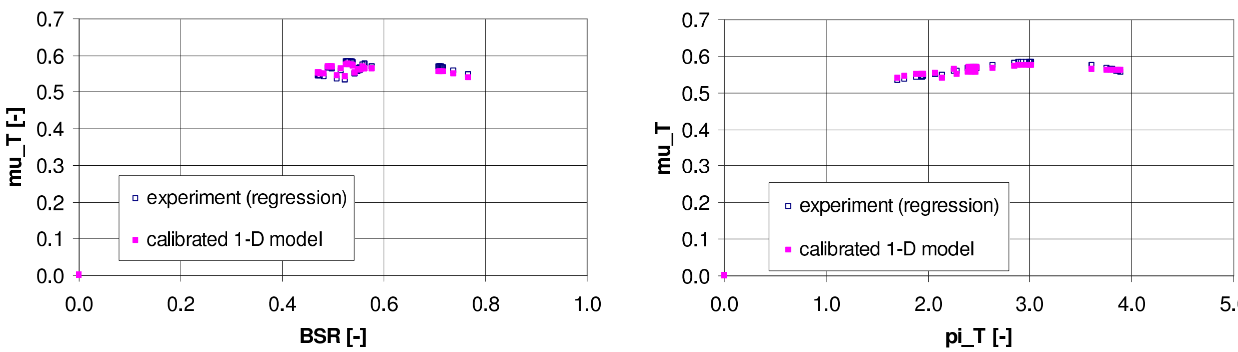


Figure 2.6: *Turbine model calibration results with rack position R0 (closed vanes), turbine discharge coefficient normalized by fixed reference turbine area 4.52 cm^2 – comparison of measured smoothed results and simulated ones.*

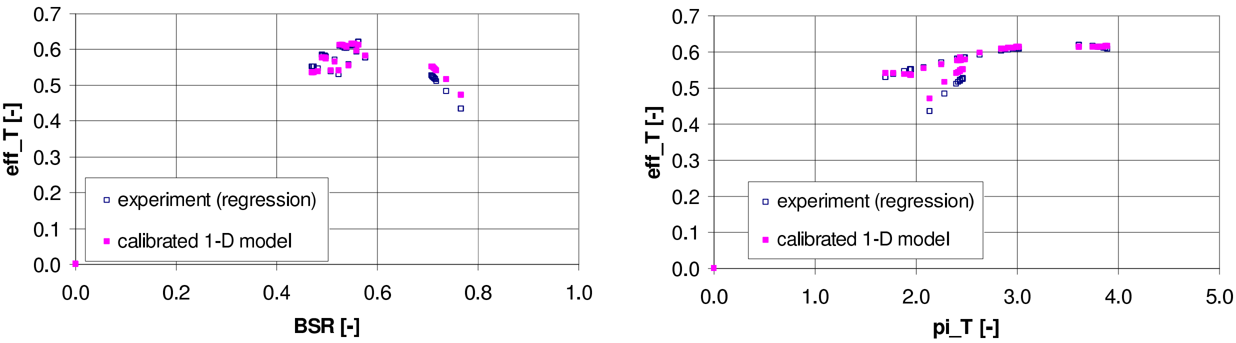


Figure 2.7: *Turbine model calibration results with rack position R0 (closed vanes), turbine isentropic efficiency – comparison of measured smoothed results and simulated ones.*

It was proven that optimization approach (genetic algorithm in this case) is powerful tool for calibration of complex sub-models (e.g, advanced 1-D turbine model). After gaining experience with reasonable ranges of calibration parameters, it can run automatically while producing reasonable results. It was verified that for such a case, *'trial-and-error'* method is not effective – it is difficult to get such a good match (between predicted results and experimental data) which was achieved by application of optimization approach. The downside is that optimization takes relatively a lot of time to find the optimal solution.

2.3 Optimization of ICE Control

It is well known that engine control (from system point of view) is a critical factor – even if the ICE design is good, a poor control will most likely lead to sub-optimal engine performance. That is why modelling of ICE control has become very important especially in the last decade. It is obvious that engine control is strongly connected to ICE transient behavior – control unit has to adjust engine setting continuously to deal with changeable operating conditions. Based on that, engine transient performance has to be simulated if engine control is to be tested/optimized by simulation tools. It is clear that such approach is much more demanding when compared with steady-state simulations – it leads to a fact that simulation times of ICE transient response are at least one order of magnitude longer. Due to recent increase in computer performance, it has been possible to perform such simulations. Once engine model is amended by a model of control algorithm, there are many possibilities how to use such a model to improve ICE performance.

Optimization of engine control is one of them. It has to be stressed that the term *'optimization of engine control'* is supposed to mean to find optimal way of engine control in time domain. It does not mean to optimize setting of certain controller (e.g., PID) to obtain the best possible engine response. Based on that, optimization of engine control is considered from system simulation point of view.

It is necessary to emphasize that optimization of engine control is significantly more demanding when compared with steady-state engine setting optimization. When dealing with steady-state case, the output of optimization procedure is a set of numbers which represents engine optimal setting/design under considered ICE operating conditions. Concerning engine control, the output of optimization is a set of curves – each curve represents an optimal time-dependency of one engine control parameter under considered change of engine operating conditions. If steady-state setting is applied during relatively fast transient change, engine may perform poorly (e.g., turbo-lag) – this is valid especially for turbocharged ICEs due to *'pneumatic'* connection between cylinders and turbocharger(s). When engine is about to reach steady-state operating conditions, control variables are supposed to approach the values from steady-state optimizations. It is obvious that such general approach is significantly more complex, thus more demanding. If both limiting factors are taken into account, namely the need to simulate transient response and the fact that optimization is more difficult from theoretical point of view, it is no surprise to state that engine control optimization using full 0-D/1-D thermodynamic ICE model has been limited up to now. There are many methods and approaches how to deal with that – each method/approach applies a kind of simplification. It is out of the scope of this document to describe them. Relatively simple example is shown in the text below to demonstrate a potential to use a simulation as a tool to optimize ICE control. Other examples of engine control optimizations are shown in [8, 15] – they deal with combination of 0-D/1-D model with 3-D CFD tool to minimize engine transient response time while pollutant production is also taken into account.

From mathematical point of view, it is the same status as in section 2.1, i.e., the equations set 2.1-2.4 is solved numerically with respect to unknown variables y_i. Generally speaking, the optimization problem can be defined by means of the equation 2.6 (or the simplified version 2.7). The variables to be optimized are certain components in vector k_m (equation 2.3) – these variables are usually regarded as control ones. It may seem that it is a similar case as described in section 2.1. However there is one significant difference – when dealing with engine control, the importance of time dependency is high. On the other hand, the time variable t in definition of 2.3 can be neglected in a case of steady-state optimization. Optimization of ICE control emphasizes the dynamic feature of equation set 2.1 – this was not so important when dealing with calibration (section 2.2) or engine setting/design optimization (section 2.1).

From optimization point of view, optimized variables are the ones which can be adjusted by ICE control unit. Depending on ICE application, the following properties are usually optimized – injection/ignition timing, air excess, turbocharger setting (waste-gate, variable geometry position), injection strategy. The target of optimization is usually a single one – to minimize ICE transient response time. In a case of more complex optimization tasks, additional target(s) might be to minimize pollutant production during transient. Concerning constraints, they are usually few of them – maximum turbocharger speed, engine knocking (if applicable) or minimum air excess.

The example presented below is based on the application of fully calibrated detailed 0-D/1-D model of 2-stage turbocharger gas SI engine – it is described in [16] and also in [15], Section 4.5. It is a rather simple case – the main target was to evaluate the potential of different control strategies (not to apply the general approach described above to find optimal time-dependency of control variables) from ICE response time point of view. *'Pseudo-transient'* simulations were calculated to verify engine transient performance. The word *'pseudo'* means that engine speed was kept constant during the course of such simulation while all other parameters can be varied in the time domain (e.g., engine load, throttle angle position, VTA* setting). Starting point of such simulation is usually steady operation at 1.5 MW†. The optimization of engine control is very easy in this case – different strategies of engine control were simulated, each strategy being clearly different in certain aspect(s) – more details can be found in Table 2.1. These strategies are combined (if possible) and then compared, finally some general conclusions are drawn – the author is aware of the fact there is still some potential to improve each control strategy. The main target was to verify thermodynamic potential of each strategy. Engine control in time domain is represented by single PID controller which controls engine power by means of controlling variable geometry setting of HP turbine (PID may adjust throttle flap if necessary).

Strategy Label	**Description**
Throttle Control	Standard control – it is a combination of VTA control and intake throttle control. The former one is always active while the latter one is applied only in the case that the VTA is limited by its application range and hence it cannot be actuated any more. Once the *'pseudo-transient'* simulation starts, the throttle is fully opened and the VTA is set to its lowest possible turbine effective area position (the VTA is *'fully closed'*).
WG Control	Standard control – it is a combination of waste-gate control and intake throttle control. It is similar to *Throttle Control*, the only difference is that the applied HP turbine has no VTA, that is why it is control by waste-gating (instead of VTA).
Lambda=1.5	It means that air excess is kept at the value of 1.5 for both steady state calculation‡ at engine power of 1.5 MW and *'pseudo-transient'* calculation.

Table 2.1: *Large-bore SI engine: description of different strategies of engine control during* 'pseudo-transient' *simulation (table continues on the next page).*

*VTA stands for variable turbine actuation – it is a way to control turbine effective flow area, however it may not necessarily be achieved by rotating stator blades.

†When performing *'pseudo-transient'* simulation, the calculation always consists of 2 cases. The first case is performed to obtain steady state for all important engine parameters, the power level equals the initial value of that for transient cycle. The second case is the transient simulation itself.

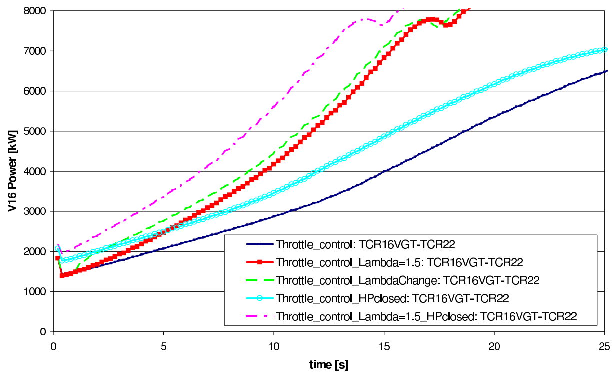
‡The steady state calculation always precedes the *'pseudo-transient'* calculation itself. The main reason is to obtain steady state status of the engine from which the transient load change can start. Most important parameters, which need to be stabilized before change of engine load, are pressures (they react fast), temperatures, mass-flow rates and turbocharger speeds.

Strategy Label	**Description**
HPclosed	If this strategy is applied, the VTA control is switched off during steady state calculation. The VTA is set to the position of the lowest possible turbine effective area. This leads to the fact that the boost pressure is relatively high and a significant throttling is necessary to obtain 1.5 MW. Once the *'pseudo-transient'* calculation is started, the intake throttle is fully opened (the opening of intake throttle is infinitely fast – no time constant for this process is taken into account). This approach can be described as pressurizing both intake manifold and exhaust one to keep turbocharger speeds at high level. Increased boost pressure at the beginning of the *'pseudo-transient'* simulation improves the situation significantly.
ExhThrottling	It is the same as the variant *Throttle Control*, the only difference is that there is exhaust throttle (instead of intake throttle) which is located downstream of LP turbine.
LambdaChange_X	This means that for steady state calculation, air excess is kept at the constant value of X (default value is 1.8). Once the *'pseudo-transient'* simulation starts, air excess is changed to the value of 1.5. The change of air excess takes place at the mixing device which is located upstream of LP compressor. Therefore, it takes some time (approximately 1s) till the enriched mixture gets to the cylinders and the engine power starts to increase more significantly when compared with air excess of 1.8. The value of air excess 1.5 is kept constant during the course of the whole *'pseudo-transient'* simulation. The main advantage of this strategy over *Lambda=1.5* strategy is that there is higher boost pressure at the initial phase of the *'pseudo-transient'* simulation which enables higher fuel flow into the cylinders.

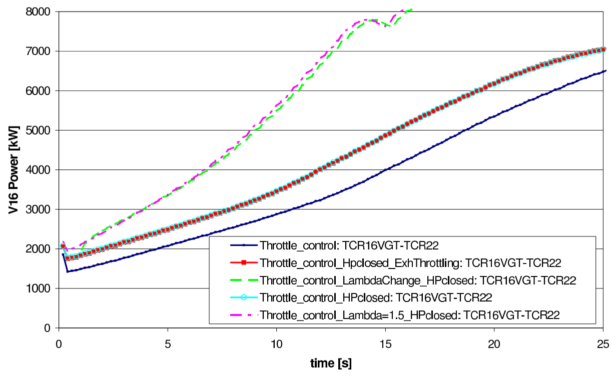
Table 2.1: *Large-bore SI engine: description of different strategies of engine control during* 'pseudo-transient' *simulation (final page of the table).*

The most important results are presented in Figure 2.8. Different strategies to control the engine during the *'pseudo-transient'* simulation are compared. The best strategy is to keep the VTA fully closed under steady operation at low engine loads (to keep both boost pressure and turbocharger speeds at high level). However, this leads to higher BSFC. Low air excess is also suitable for the faster increase of the engine power (higher turbine inlet temperature). Intake throttle can be easily used as a control means to keep the required (low) engine power if the VTA is fully closed. Once there is a need for engine power increase, the throttle can be opened while the VTA is kept closed to build up boost pressure as fast as possible. Air excess should be at the lowest possible value*.

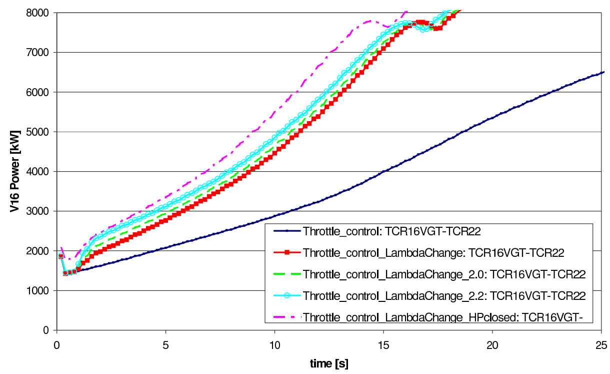
(a) *engine power – detail: basic comparison*



(b) *engine power – detail: basic comparison*



(c) *engine power – detail: basic comparison*



(d) *engine power – detail: basic comparison*

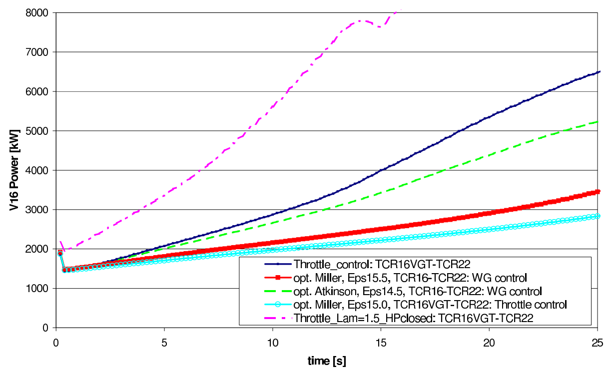


Figure 2.8: *Comparison of different strategies of engine control under 'pseudo-transient' operation, turbocharger configuration* **2xTCR16VTA + 1xTCR22***, realistic turbocharger maps applied, engine power is controlled by means of* **VTA + intake throttle** *(if not stated otherwise), constant air excess, engine setting:* $\varepsilon = 14$ *(if not stated otherwise), Atkinson timing applied if not stated otherwise (IVMult* $= 1.8$*).*

It was verified that optimization of ICE control is possible when using detailed 0-D/1-D engine models – c.f. [8, 16]. However it is very time consuming which limits application of optimization tools to simple cases only. At present days, it can be used to find suitable strategies for further detailed analysis or to understand complex links of interaction among different ICE parts – such information is still valuable, however there is some unexplored potential. It is expected that optimization of ICE control using detailed 0-D/1-D model will be applied more often in the future due to further increase in computer power.

*Knocking can be problem during higher engine loads. This causes the necessity to increase air excess. For fast engine power increase, air excess should be kept at the lowest possible value while avoiding engine knocking and possibly not allowing HP turbine inlet temperature to get too high.

3 Conclusions

It is well known that the thermodynamic simulation tools have necessary features to address many important issues of contemporary internal combustion engines (ICEs). As the simulation tools/methods become more *'advanced'*, it is possible to apply them for more complex cases. This allows higher quality of optimization, hence a better design. Moreover, the confidence in predicted results has been ever increasing – this leads to possibility to apply the simulation tools at earlier stages of ICE development process, hence cost saving can be achieved (due to shorter development time). It has been proven many times that the simulation is both powerful and effective approach when dealing with thermodynamic optimization of ICE. Important issues of ICE simulation including both calibration and optimization are discussed in detail in [9, 15].

For the case of ICE, typically there are three different possibilities how to apply optimization approach. The first one concerns calibration of certain sub-models. The author believes that the calibration (of ICE mathematical model) is the most important part of the work-flow when dealing with thermodynamic ICE models. It was shown that optimization approach can deal with complex calibration problems while being relatively time effective and still the results are meaningful from the physics point of view – the author took an active part in the procedure to develop 1-D turbine model (c.f. [10–12]) including its effective calibration procedure based on optimization. The author has also been involved in activities to enhance/improve quality of engine model calibration – this mainly concerns application of sub-models which are based on principles of the ICE physics. Such sub-models feature improved predictive ability, hence they enable certain extrapolation outside the domain of calibration data – this is very valuable. However, these sub-models are more difficult to calibrate. Such approach was applied in [8, 16–18] and in many cases of co-operation with industrial partners.

The second possibility is to optimize engine setting/design under steady-state operation. This task has been performed for a long time and it is an industry standard now. Due to recent increase in computer power, relatively complex multi-variable multi-target multi-constraint optimization can be performed. It is expected that the trend is going to continue and optimization tasks of higher complexity will be performed. However the downside of complex optimization tasks is that due to a way how an optimization algorithm (e.g., genetic algorithm) finds optimal solution, physical links among input variables are less clear. If understanding of these links is of high interest, it is strongly recommended to perform sensitivity studies of considered input parameters. The author deals with optimization of engine setting/design for more than a decade. A lot of results were published (c.f. [16–18]), moreover many calculations were performed for industrial partners (VW, MAN Diesel, PBS Turbo, Škoda Auto, Porsche Engineering Services, John Deer, CZ Strakonice, etc.) – these data are obviously not available for public access due to non-disclosure agreement. Almost every student at Department of Automobiles, Internal

Combustion Engines and Railway Vehicles, who deals with ICE simulation, is supposed to perform certain optimization of ICE setting/design.

The third possibility is optimization of an engine control from system point of view. This is the most challenging task from theoretical point of view, moreover it is very time consuming. It has been increasingly performed mainly in the last decade. It is expected that strong development in this field (regarding suitable methods to find optimal solution) is going to continue in near future before it becomes an industry standard. The term *'optimization of engine control'* also means to select properly both control strategy and control means – such approach enables to perform a configuration design. It is obvious that simulation approach can save a lot of money as experimental optimization of engine control is very expensive. The author has certain experience with issues of engine control from system point of view (c.f. [8, 16, 18]).

The outlook is that optimization will play ever increasing role in terms of both ICE design and ICE control. More complex optimization tasks have been performed – this trend will continue. It will enable to exploit fully a potential of a certain ICE design in complex transient test cases, e.g., NEDC (new European driving cycle) including fuel consumption and pollutant production. This is in line with one of the main general targets of ICE development which is to improve engine efficiency while decreasing pollutant production.

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Research Activities

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Scientific Work	Article in Impact Journal: 1 (c.f. [11]) Paper in a Reviewed International Journal: 7 Paper in a Proceedings: 16 SAE Paper: 13 Authorized Software: 13 Citation in SCOPUS: 15