GENETIC ALGORITHM FOR FINDING MULTIPLE VIEBE FUNCTIONS DESCRIBING HEAT RELEASE RATE IN ICE

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Abstract

From indicated pressure in engine cylinder the real heat release rate (HRR) can be derived. Such HRR itself is substantial source of in-cylinder combustion process data. These data are useful for numerical simulations of similar in-cylinder processes. Instead of single Vibe function much better representation of the same process is achieved with the sum of multiple Vibe functions with various starts, durations and Vibe exponents. The paper presents genetic algorithm method approach to find these multiple Vibe functions. From such derived Vibe functions a lot of additional informations of combustion process is achieved, for example multiple fuel injections with smeared combustion effects, which are not detectable in HRR.

1 Introduction

Complex physical and chemical processes during the in-cylinder combustion are expressed through the addition of the reaction heat. The derivation of heat addition by crank angle is called the heat release rate (HRR) $dQ_f / d\varphi$, where Q_f is heat due to fuel combustion, and φ is the crank angle. This is presented as [1]:

$$\frac{dQ_f}{d\varphi} = H_f \frac{dm_{fb}}{d\varphi} \tag{1}$$

where m_{fb} is the mass of fuel burnt, and H_f is the fuel lower heat value.

The heat release rate can be derived from the pressure change, as indicated in cylinder, by various methods. Simple ones use the assumption of ideal isentropic compression at already known isentropic exponent. The more complex methods use the derived model for detailed energy balancing by the crank angle stepping through the engine process for the indicated in-cylinder pressure data. Diverse influences of the real process may be taken into account when determining the appropriate heat release rate. Examples include heat exchange on cylinder walls, the variation of temperature dependent properties etc. The latter method was applied in this research [4].

2 Viebe and multiple Viebe functions modeling

The heat release rate is a very important source of information on the combustion process properties. In the beginning, Viebe had proposed a simple function for the time evolution of energy release from certain chemical process, with a designated start, evolution, culmination and consecutive slow-down to final extinguishing. Such a simple Viebe combustion function may substitute the real heat release rate with very rough approximations. The function coefficients are scaled to assume the same content of the heat of the combustion, but the discrepancies between the real and simulated combustion rates are evident.. More accurate models were proposed by using two or more overlapped Viebe functions. The published scientific papers deal with very complicated methods for scaling the coefficients propose the use two Viebe equations. This paper presents a method for finding scaling coefficients for more than two overlapping Viebe functions. This effort may result in further research on finding the right functional connection between engine operation parameters and appropriate heat release rates obtained from a proper combination of several Viebe functions.

The application of accurate heat release rate is a prerequisite for reliable numerical simulations regarding pollutant emissions, specifically NO_x emission predictions. It also enables elaborate research on finding ways to reduce engine emissions, while maintaining the engine power and lowering specific fuel consumption.

At the same time, the data obtained from a set of simple Viebe functions and their scaling factors provides more insight into the combustion process than just the heat release rate. This may be used in future expert systems in real time analysis of engines in operation. As the heat release rate represents the result of various influences, it could be used to detect erroneous influences. At the moment, this analysis may help in finding the best fuel economy for the engine while keeping pollutant emissions below the allowed threshold.

Other important applications are in the field of new fuel injection strategies. To lower the engine noise and NO_x emissions in diesel engines, the fuel injection is split to more injections: pilot injections, main injection and post-injections. One of the important diagnostic tools for obtaining insight in these processes is the heat release rate analysis.

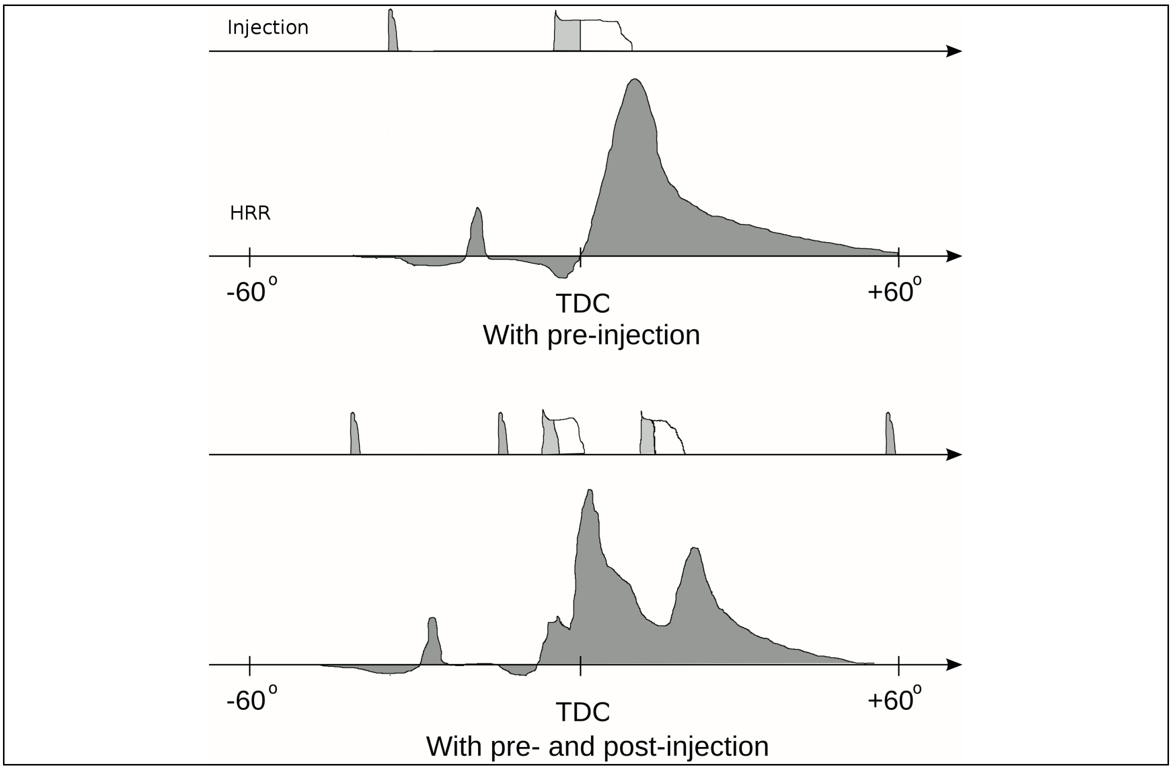

Figure 1: Injection strategy and its influence on HRR [5]

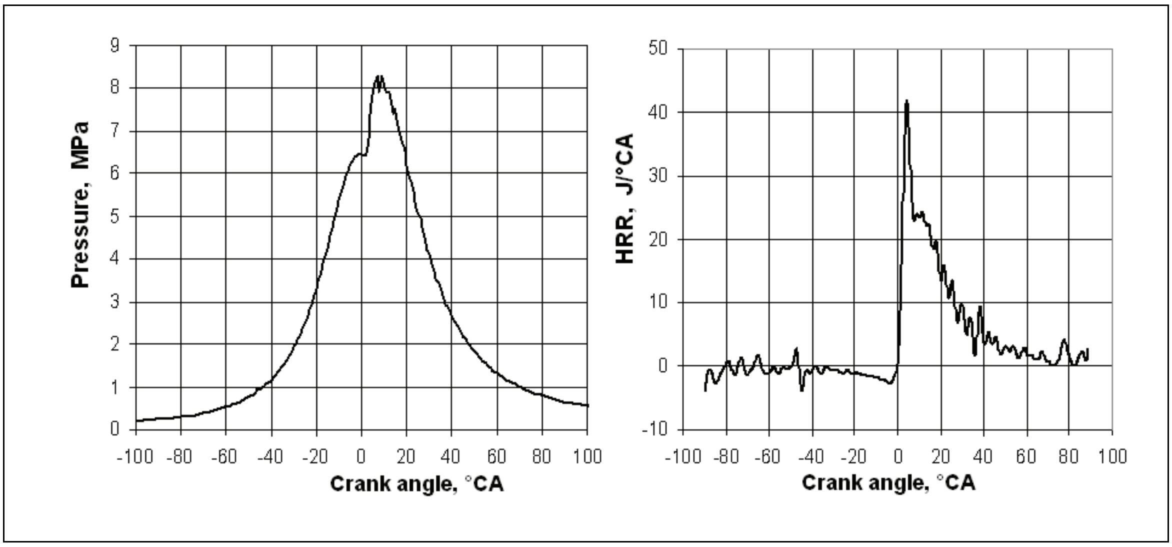

Figure 2: Indicated pressure in cylinder, and calculated Heat release rate (HRR)

The real heat release rate (HRR) is derived from the indicated pressure in the engine cylinder using in-house software for d*Q*/d*f* analysis [4] as shown on Fig.2.

Viebe function can be written as

$$x_{\mathrm{f}} = 1 - e^{-a\cdot\left(\frac{\varphi-\varphi_S}{\varphi_E-\varphi_S}\right)^{m+1}} \tag{2}$$

$$a = -\ln(1-\eta_C) \tag{3}$$

$$\varphi_S \le \varphi \le \varphi_E \tag{4}$$

η_C - is the combustion efficiency, φ_S is the initial and φ_E is the final angle of the Viebe function.

It's derivative is the speed of heat release rate

$$\frac{dx_{\mathrm{f}}}{d\varphi} = a\cdot(m+1)\cdot\left(\frac{\varphi-\varphi_S}{\varphi_E-\varphi_S}\right)^m \cdot e^{-a\cdot\left(\frac{\varphi-\varphi_S}{\varphi_E-\varphi_S}\right)^{m+1}} \tag{5}$$

The sum of multiple Viebe functions can be expressed as:

$$Q(\varphi) = Q_{v,1}\cdot x_{f,1} + Q_{v,2}\cdot x_{f,2} + \cdots + Q_{v,n}\cdot x_{f,n} \tag{6}$$

$$\frac{dQ}{d\varphi} = \sum_{i=1}^{n} Q_{v,i}\cdot\left(\frac{dx_{f,i}}{d\varphi}\right) \tag{7}$$

Finding the coefficients for $Q_{v,i}$, m_i, $\varphi_{S,i}$ and $\varphi_{E,i}$ for each function is not an easy task, as there is no derivative for those measured values. Standard solutions are not easily implemented for such problems.

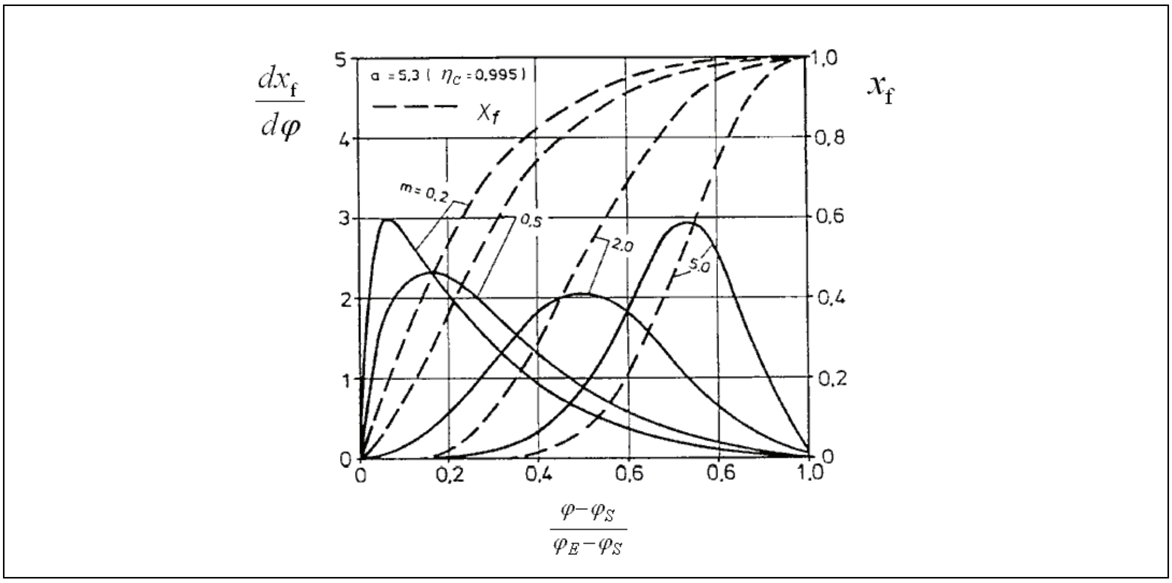

Figure 3: Viebe function and deratives

3 GA (Genetic Algorithms)

Many hard to solve optimisation problems can be solved using GA (genetic algorithms), a heuristic search method that mimics evolution. This method is very robust, does not need a function derivative, just an objective or fitness function associated with input values selected from a defined range. Input values of possible solutions are encoded as genes in chromosomes. There are many schemas that can be used for the encoding of input values.

Each individual, or chromosome, is a potential solution. A population is formed by a number of individuals sharing the same encoding schema, a predefined objective function, and some other parameters depending of setup. The fitness of all individuals (possible solutions) of population has to be evaluated using the objective function in each generation. Some operators are needed for GA to evolve a population. As each individual is given a fitness value there must be a *selection operator* to select the best fitted individuals. Best fitted individuals are more likely to have more fitted children so they are given greater chance to survive and/or recombine parts of their chromosome. If a recombination of chromosomes has to occur, mating of individuals is needed and a *crossover operator* is used. There is a *mutation operator* for improving the gene pool. After a mutation occurs, there is no guarantee that it has improved the fitness of the individual, and can even lower it's chance of survival in the next generations. Each generation contains better fitted individuals through iterations of inheritance, crossover, mutation and selection. Usually the best fitted individuals in the last generation are near optimal solutions. This means that the GA does not guaranty the optimal solution, just a better one. In practice it is almost always a satisfactory solution. The most important parts for effective use of GA are the encoding of chromosomes, the fitness evaluating objective function, population size, crossover probability and mutation probability. The goal in solving a values fitting problem is to minimize the difference between model and target data (measured, from simulation, etc.) by finding optimal coefficients or constants for the model. Coefficients have to be encoded in chromosomes, and the measure of fitness is error minimisation. This means that the objective function is not the value of input coefficients but the measure of error between values produced by the model and target values. Mean square error is usually used as measure of difference, but square root of mean square error gives better performance for some problems.

3.1 Chromosome encoding and decoding of Viebe function parameters

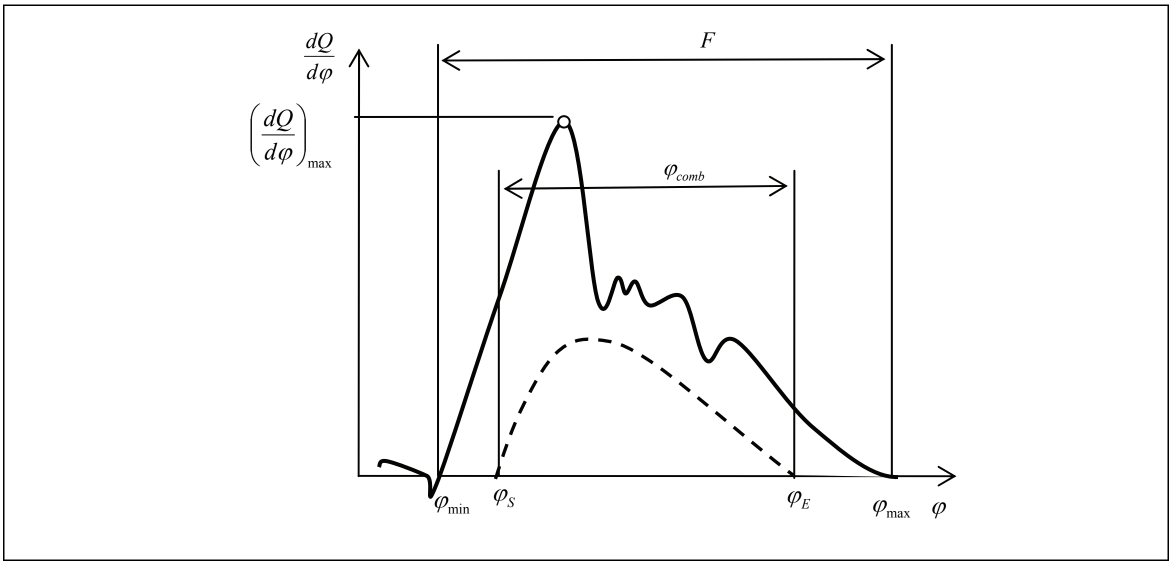

Figure 4: Input search space scaling

A simple genome can be represented as an array of real numbers. Input data values must be efficiently encoded in chromosomes, so there are no input values outside of the scope of Viebe functions. While this is not absolutely necessary, it improves convergence by limiting search space.

Normalization and encoding of data is given for coefficients of Viebe functions (Fig.4).

$$F = \varphi_{\max} - \varphi_{\min} \tag{8}$$

$$\varphi_{comb,i} = \varphi_{E,i} - \varphi_{S,i} \tag{9}$$

$$v_i = \frac{\varphi_{comb,i}}{F} \tag{10}$$

$$z_i = \frac{\varphi_{S,i} - \varphi_{\min}}{F - \varphi_{comb,i}} = \frac{\varphi_{S,i} - \varphi_{\min}}{(1 - v_i) \cdot F} \tag{11}$$

$$c_i = \frac{Q_{v,i}}{\left(\frac{dQ}{d\varphi}\right)_{\max}} \tag{12}$$

$$k_i = \frac{m_i}{4} \tag{13}$$

$$\varphi_{\min} \le \varphi_{S,i} \le \varphi_{E,i} \le \varphi_{\max} \tag{14}$$

$\varphi_{\min}$ is the minimum angle where a Viebe function can start and $\varphi_{\max}$ the maximum angle. New variables v_i , z_i, c_i and k_i are introduced to encode the input search space efficiently.

Each Viebe function can start and finish between angles defined from TDP $\varphi_{\min}$ and $\varphi_{\max}$. All input values in the model are defined in the range from 0 to 1. When calculating the fitness of individuals, input values are not encoded as the GA fitness function uses only the genes decoded from chromosome. The chromosome encoding of a population is shown in Fig. 5

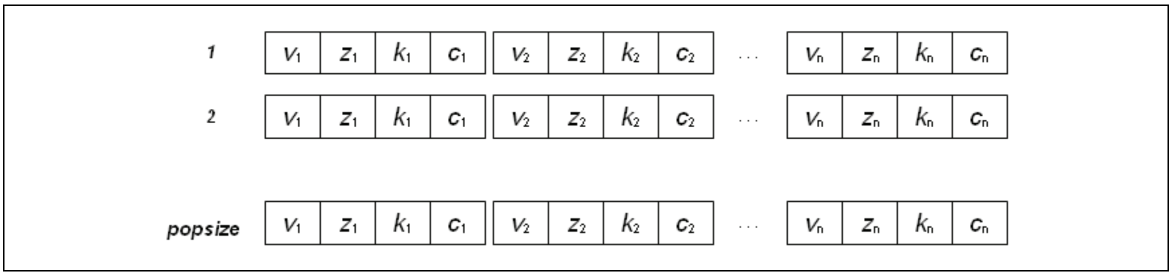

Figure 5: Encoding of population

$$\varphi_{comb,i} = v_i \cdot F \tag{15}$$

$$\varphi_{S,i} = \varphi_{\min} + z_i \cdot (1 - v_i) \cdot F \tag{16}$$

$$\varphi_{E,i} = \varphi_{S,i} + \varphi_{comb,i} \tag{17}$$

$$Q_{v,i} = c_i \cdot \left(\frac{dQ}{d\varphi} \right)_{\max} \tag{18}$$

$$m_i = 4k_i \tag{19}$$

The selected population size is set to 150 individuals, mutation probability 0.1, crossover probability 0.6 and the number of generations 1000.

3.2 Optimization goal and fitness function

To solve the problem, we need to find the coefficients of each Viebe function, the sum of which is also a function:

$$F(\varphi) = \frac{dQ}{d\varphi} = \sum_{i=1}^{n} Q_{v,i} \cdot \left(\frac{dx_{f,i}}{d\varphi} \right) \tag{20}$$

Finding the coefficients means to minimize the difference between the resulting sum of Viebe functions and corresponding target measured or simulated data:

$$Err = \frac{\sum_{\varphi=\varphi_{\min}}^{\varphi_{\max}} \left(F(\varphi) - F(\varphi)_{target} \right)^2}{N} \tag{21}$$

where N is number of target points included in the comparison and φ is angle associated to target value.

Error Minimization can also be expressed as the maximization of its reciprocal value or the maximization of the negative value of a function (usually some sufficiently high offset is used for all data values to appear positive to the GA). The former tactic is very aggressive, but sometimes gives better results, the latter produces stable populations.

$$Err_{\min} = \frac{C}{Err_{\max}} \tag{22}$$

$$Err_{\min} = C - Err_{\max} \tag{23}$$

4 Results

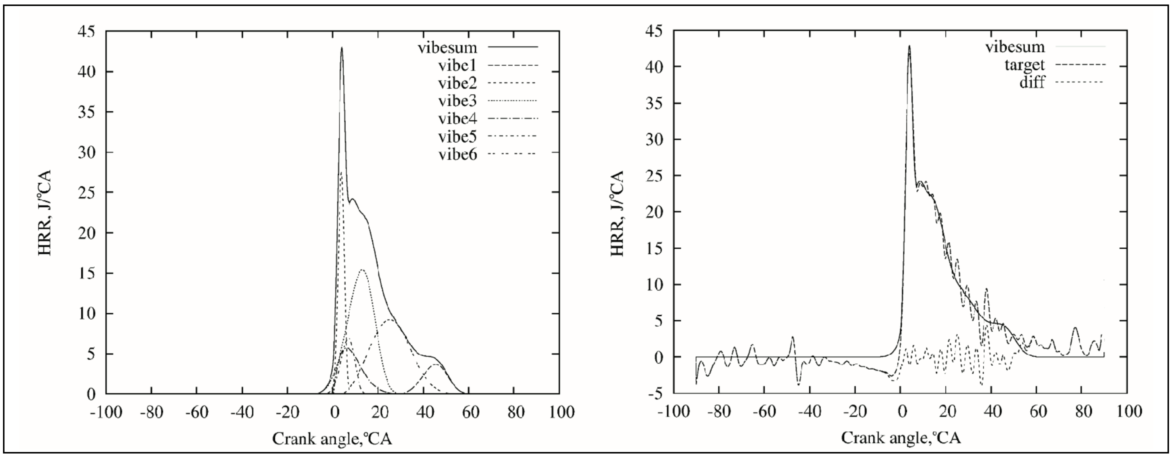

Figure 6: Resulting Vibe functions and comparison between sum of Viebe functions and target data

Figure 6 presents multiple Viebe functions derived from HRR using the presented GA based on indicated pressure change in a cylinder. The actual HRR was split to six Viebe functions. The sum of all 6 presented Viebe functions is compared with HRR showing good correspondence with experimentally derived data.

The homogenous charge combustion part is dominant in this combustion, as evident from the HRR. Similarly, the Viebe function with the highest peak accurately presents this part of the combustion. The diffusion part of the combustion is presented with two Viebe functions indicating non-homogeneity of this part of the combustion process, probably caused by different processes of fuel droplet vapour combustion and soot combustion.

These initial results indicate the capabilities of more detailed combustion process diagnostics when compared with diagnosing only the HRR curve. This may be even more pronounced in cases with multiple fuel injections.

5 Conclusion

Genetic algorithms can be effectively used to find multiple Viebe functions as this paper demonstrates. There is still the challenge of finding the appropriate values for relevant GA properties: population size, number of generations, crossover probability rate, mutation rate etc. The computational demands increase with the search space and solution problem size. Fortunately, GA can be easy implemented for parallel processing on many computers, distributed cores or cloud computing.

The heat release rate decomposed to multiple Viebe functions enables new diagnostic capabilities for analyzing fuel combustion in the cylinder. For example, the improved evaluation of homogenous charge combustion as a part of the whole combustion process allows the possibility of NO_x emissions prediction.

Numerical evaluation of multiple Viebe functions by traditional methods is very demanding and presents a very difficult mathematical task. The application of GA gives an alternative which is better adapted for the same purpose.

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