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Fuel Optimization in Multiple Diesel Driven Generator Power Plants*

Jesper Knudsen[1], *Student Member*, *IEEE*, Jan Bendtsen[2], *Member*, *IEEE*, Palle Andersen[2], *Member*, *IEEE*, Kjeld Madsen[3], Claes Sterregaard[3], and Anthony Rossiter[4], *Member*, *IEEE*

***Abstract*— This paper presents two fuel optimization approaches for independent power producer (IPP) power plants consisting of multiple diesel driven generator sets (DGs). The optimization approaches utilize assumed information about the fuel consumption characteristics of each individual DG in an effort to demonstrate the potential benefits of acquiring such information. Reasonable variations in fuel consumption characteristics are based on measurements of a DG during restricted air filter flow operation. The two approaches are (i) a gradient search approach capable of finding the optimal power generation for each DG in a fixed selection of DGs accommodating a given plant power reference and (ii) a genetic algorithm approach further capable of determining the optimal selection of DGs to operate in an IPP power plant. Both approaches show notable potential benefits, in terms of fuel savings, compared to current market-leading solution approaches.**

I. INTRODUCTION

Independent power producers (IPPs), supplying electric power under power purchase agreements (PPAs), have become integral parts of electric infrastructures worldwide due to ongoing deregulation. Whether providing temporary supply during, e.g., musical festivals or sporting events, adding additional capacity in periodically overloaded grids, known as peak shaving, or establishing the main supply in an area without grid connection, IPP power plants must be highly reliable and provide a stable supply. Consequently, diesel driven generator sets (DGs) are widely used as the source of electric power generation by IPPs, providing the necessary overall plant capacity through a number of DGs [1], [2], [3], [4].

Under a PPA, an IPP has direct financial interest in maximizing the efficiency of its power plants as the payments relate to the delivered electric power. Therefore, successful IPPs maintain timely service of their DGs during plant operation. However, several elements affecting the efficiency of each individual DG are not handled by strict attention to service intervals. Such elements include ambient temperature, which may vary significantly across the area occupied by an entire power plant due to, e.g., shade, wind direction or adjacent DGs. Besides influencing the quality of the combustion through the intake air temperature, power is also consumed by the cooling system of DGs. Cooling systems for IPP power plant DGs often use electrically driven cooling fans as they offer higher flexibility in system design than belt driven fans. Effectively reducing the DG efficiency, electronic cooling systems often use around two to three percent of the rated power output [5], [6], [7]. If the cooling systems run constantly at maximum capacity, any efficiency optimization in that regard is inherently meaningless, whereas regulated cooling systems will allow for further efficiency optimization given ambient temperature differences across the plant.

Another element potentially affecting the efficiency of individual DGs across an IPP power plant is the condition of air filters. Dust in the air caught by the filter builds up, eventually, clogging the filter which limits the air intake, causing decreased fuel efficiency of the diesel engine. This effect is confirmed in Section III by an experimental demonstration. Air filters are replaced or cleaned during service according to the pressure drop across the filter. However, unless continuously monitored, clogging of air filters may occur suddenly, and unnoticed, due to, e.g., a wind gust blowing sand on a group of DGs in one area of the plant. Knowledge of such conditions could be used to optimize the efficiency by automatically redistributing the power demands for the DGs in the plant, until the filters can be physically replaced by a service engineer.

Current market-leading plant controller solutions have a user-specified power generation level for optimum fuel efficiency [8]. Assuming this specified level is valid, its usefulness is limited as it contains no information regarding the actual efficiency at that, or any other, power level. Thus, use of this value is rare. Instead, the number of operational DGs in an IPP power plant is most often determined in order to guarantee a minimum of spinning reserve, to be able to cope with sudden unexpected load changes. In an IPP power plant, the DGs are for practical reasons most often of the same make, type, and rating which in turn implies that the user-specified power level for optimum fuel efficiency will be identical for all DGs in the plant. Therefore, each DG is indistinguishable from the next in a fuel optimization context. In other words, more information would be needed for plant-wide fuel optimization. Uncovering the potential benefit of such additional information would allow IPPs or DG manufacturers to perform a cost-benefit analysis of the investment associated with the acquisition of additional information, e.g., installing additional sensors or developing

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[1]J. Knudsen is with the Section for Automation and Control, Department of Electronic Systems, Aalborg University, Aalborg, Denmark and also with DEIF A/S, Skive, Denmark jek@deif.com

[2]J. Bendtsen and P. Andersen are with the Section for Automation and Control, Department of Electronic Systems, Aalborg University, Aalborg, Denmark {dimon,pa}@es.aau.dk

[3]K. Madsen and C. Sterregaard are with DEIF A/S, Skive, Denmark {kma,chn}@deif.com

[4]A. Rossiter is with the Department of Automatic Control and Systems Engineering, The University of Sheffield, Sheffield, United Kingdom j.a.rossiter@sheffield.ac.uk

identification methods.

Previous work on the area of DG plant optimization is remarkably limited; however, similarities can be found in the area of wind farm control, see for example [9]. Within wind farm control many control approaches as well as modeling methods which could prove relevant for DG plant optimization have been investigated, demonstrated briefly by the following few examples. In [10], authors present a fault tolerant wind farm controller whereas the authors of [11], [12], [13], [14] present various generation control approaches based on interior point, game theoretic, Bayesian ascent, and model predictive control methods, respectively.

In this paper, we propose two fuel optimization approaches for IPP power plants based on an assumed knowledge of individual efficiency characteristics of each DG. The first approach uses simple gradient search to determine the momentary optimal power distribution between a fixed selection of DGs for a given plant power reference. The second approach is a genetic algorithm (GA) further able to determine the optimal choice of DGs to utilize in situations where the plant conditions, including the plant power reference, do not dictate a fixed selection of DGs in the plant.

The remainder of the paper is organized as follows. Section II briefly introduces the structure of IPP power plants and a sufficient, simple representation of individual DG fuel characteristics. In Section III, experiments are conducted to acquire actual information regarding fuel efficiency changes caused by critical air filter conditions. Section IV presents the two fuel optimization approaches, while Section V provides concluding remarks.

II. IPP POWER PLANTS

Introducing the general structure of an IPP power plant, this section presents plant-wide efficiency considerations suggesting a rather simple efficiency representation for each individual DG in a plant.

A. Power Plant Structure

Generally, IPP power plants are structured such that DGs are arranged in so-called feeders, connecting through circuit breakers and a power transformer to the grid. As illustrated in Fig. 1, with a four-feeder example, power transformers are also present in the feeders, either at each DG or for a group of DGs, to increase the voltage and, thereby, reduce cable losses due to the lowered current level.

For a specific power plant, the use of power transformers will typically be identical in each feeder. Further, for practical reasons, the feeder power transformers will most often also be of the same make, type, and rating. Depending on the application of the power plant, there might be more than one connection to the grid, or none at all. The power plant might simply supply the load directly, or in combination with delivering power to the grid.

B. Efficiency Representation

Looking at the fuel efficiency of each DG in an IPP power plant, a few reasonable assumptions allow a rather simple individual DG fuel efficiency representation.

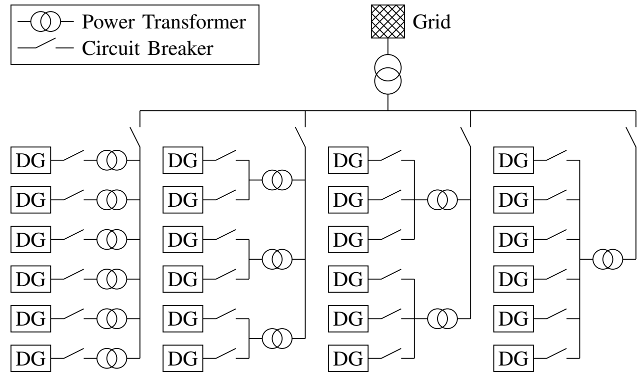

Fig. 1. Structural diagram of an IPP power plant with four feeders utilizing different feeder constructions, in terms of transformer placement [1].

Any loss inside the power plant is a direct financial cost to the IPP, hence, measures are taken to minimize those losses. Such measures include connecting DGs to nearby power transformers and using cable of sufficient capacity and quality. Consequently, cable losses inside the power plant are very small and the difference in losses from one DG to another is negligible. Further, since all power transformers in the feeders are in principle identical, the transformer efficiencies can be neglected in the context of plant-wide fuel optimization.

Following the above assumptions, each DG in the power plant can be represented simply by its individual fuel efficiency characteristics. A DG consists of a diesel engine and a synchronous generator. The efficiency of a generator is, for the purpose of this work, constant when avoiding operation at very low loads [15], leaving the engine as the dominant element in representation of efficiency characteristics.

Data sheets for DG engines provide sparse information about fuel consumption, typically, at three or four different load levels, e.g., 25, 50, 75, and 100 % of rated load. Fig. 2 presents data sheet fuel consumption information of four differently rated DG engines [16], [17], [5], [18]. Additionally, for each engine a least-square fit 2$^{\text{nd}}$ degree polynomial obtained with the MATLAB® function `polyfit()` is shown. The 2$^{\text{nd}}$ degree polynomials inherently match the data sheet information with only three values perfectly, whereas for data sheet information with four values small deviations between the polynomial and the values occur. However, in this work, 2$^{\text{nd}}$ degree polynomials are considered sufficient fits to represent fuel consumption of each DG in a plant.

III. EFFICIENCY VARIATIONS

In an effort to demonstrate the potential efficiency variations on individual DGs in an IPP power plant and validate the use of least square fit 2$^{\text{nd}}$ degree polynomial representations, this section presents measurement results obtained by limiting the flow through the air filter on a DG.

A. Experimental Setup

The output of a Titan OG1-SSS-SSQ-B oval gear flowmeter, mounted in the fuel supply path, as shown in Fig. 3,

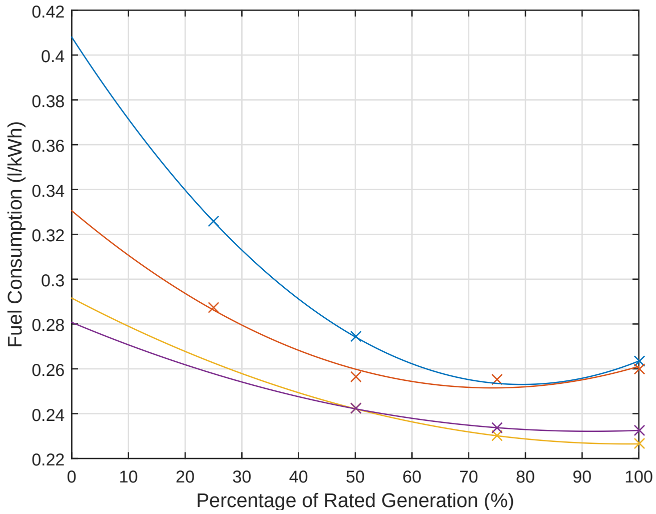

Fig. 2. DG engine [16] (blue), [17] (red), [5] (yellow), and [18] (purple) data sheet fuel consumption values as crosses, with dotted lines showing corresponding least-square fit 2nd degree polynomials.

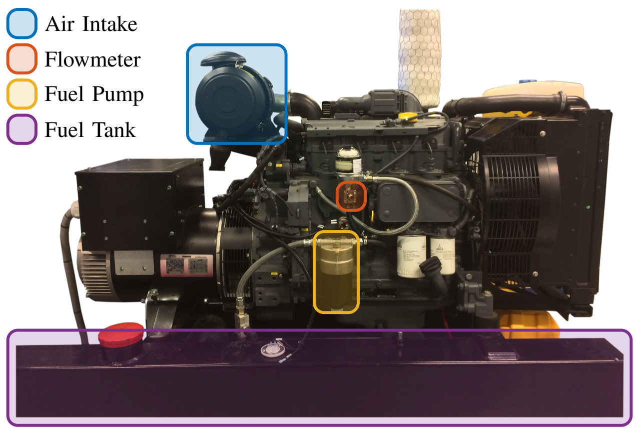

Fig. 3. Diesel driven generator set utilized during air filter experiments. The air filter is inside the air intake (blue), the burned fuel is pumped from the fuel tank (purple) by the fuel pump (yellow) and measured by the Titan OG1-SSS-SSQ-B oval gear flowmeter (red).

is sampled at 1 kHz by a HIOKI Memory HiCorder 8861 using a High Resolution Unit 8957 input module to collect information about the fuel consumption during experiments.

The DG consists of a Deutz BF4M2012 diesel engine driving a 60 kVA/48 kW Leroy-Somer LSA 42.3 L9 C6/4 synchronous generator. During experiments, the DG supplies a controllable load consisting of resistive JEVI heating elements mounted in a 10 m^3 water tank. With a 400 V phase-to-phase RMS voltage each heating element constitute a 10 kW load. Multiple heating elements are coupled in parallel for increased load levels.

B. Experimental Procedure

The experiment is conducted as a two-part process. The conditions of the DG are, to the best of our ability, kept constant during both parts, except for the state of the air filter. Each part of the experiment is performed after an identical warm-up period of the DG from a cold starting point, i.e., both the DG and the ventilated room in which it is contained. Consumption measurements are then collected at various levels of constant load. These applied load levels are 20, 30, 40, and 50 kW.

A brand new air filter is fitted for one part of the experiment. For the other part of the experiment, a used air filter is covered in duct tape, to a state where the air pressure drop across the filter at 50 kW load reach service level.

C. Experimental Results

The presented measurements all represent average consumption values over 10-minute steady-state periods. Fig. 4 provides the results for both air filter conditions along with corresponding 2nd degree polynomial least-square fits obtained with the MATLAB® function `polyfit()`.

Tables I and II present the fuel consumption results along with the corresponding air filter pressure drops. The pressure drops were observed using a Testo 435 multifunction meter. The indicated service level pressure drop for the utilized DG setup is 50 mbar.

We remind the reader that the absolute values of these experimental results should be analyzed with caution, both as a consequence of unavoidable measurement tolerances and the simplicity of the utilized experimental setup. That is, manufacturers conducting similar experiments take measures to ensure the repeatability of the experiments which were not possible here, e.g., strict control of ambient air temperature and humidity and engine temperatures, oil pressure, etc. However, these experimental results do indeed confirm the influence of air filter conditions on the fuel consumption of a DG throughout its operating range and the suitability of 2nd degree polynomial representations.

IV. Fuel Optimization

Utilizing assumed knowledge of individual DG fuel consumption characteristics as 2nd degree polynomials, this section presents two fuel optimization approaches to demonstrate the potential benefit of obtaining such information.

The optimization problem is to minimize the total fuel consumption, given a power reference for an IPP power plant consisting of identically rated DGs. The fuel consumption curves in liters per kilowatt-hour are multiplied by the generated kilowatt to yield the consumption in liters per hour, which when summed over all the DGs is the subject of minimization. The fuel consumption curves in liters per hour are, inherently, strictly monotonic increasing 3rd degree polynomials. The inflection point of the 3rd degree polynomials lie around 50 % of rated power generation. Hence, the polynomials are strictly convex functions for power generation above that point, which coincides with the region of highest efficiency. For a plant power reference r, that allows n DGs with identical fuel consumption curves f to operate in the strictly convex region of f, Proposition 1 shows that each DGs should take an equal share of the plant power reference, i.e., $\frac{r}{n}$.

Proposition 1: For any strictly convex function $h(x_1, \ldots, x_n) = f(x_1) + \cdots + f(x_n)$, where the function

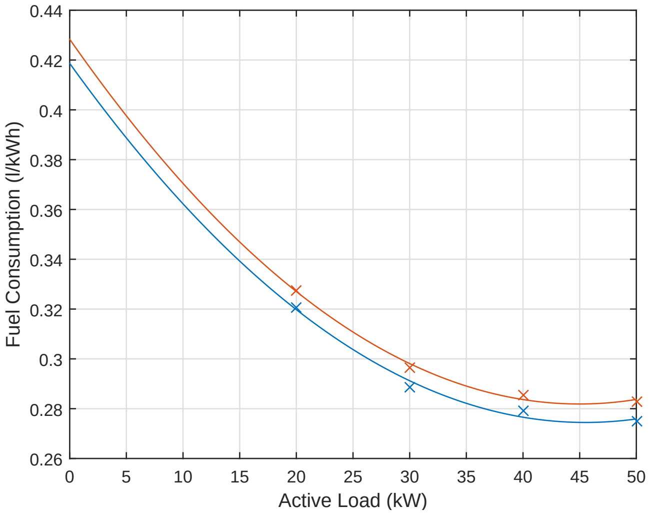

Fig. 4. Measured fuel consumption with new (blue) and taped (red) air filter. Crosses are 10-minute steady-state averages, while the dotted lines are corresponding least-square fit 2nd degree polynomials.

TABLE I

EXPERIMENTAL DATA WITH NEW AIR FILTER.

Load	Fuel Consumption	Air Filter Pressure Drop
20 kW	0.3206 l/kWh	4 mbar
30 kW	0.2886 l/kWh	5 mbar
40 kW	0.2792 l/kWh	5 mbar
50 kW	0.2750 l/kWh	6 mbar

TABLE II

EXPERIMENTAL DATA WITH TAPED AIR FILTER.

Load	Fuel Consumption	Air Filter Pressure Drop
20 kW	0.3277 l/kWh	33 mbar
30 kW	0.2963 l/kWh	39 mbar
40 kW	0.2855 l/kWh	44 mbar
50 kW	0.2831 l/kWh	51 mbar

$f : \mathbb{R} \to \mathbb{R}$ is strictly convex, if $\operatorname{dom} h$ is constrained by $x_1 + \cdots + x_n = r$, the minimum of $h(x_1, \ldots, x_n)$ is at $(x_1, \ldots, x_n) = (\frac{r}{n}, \ldots, \frac{r}{n})$.

Proof: By construction, the strictly convex level sets of $h(x_1, \ldots, x_n)$ are symmetric around the n-dimensional line $x_1 = \cdots = x_n$ and the unconstrained (global) minimum is on this n-dimensional line. If $\operatorname{dom} h$ is constrained by the surface $x_1 + \cdots + x_n = r$, the function $h(x_1, \ldots, x_n)$ attains a constrained minimum where the surface $x_1 + \cdots + x_n = r$ intersects the n-dimensional line $x_1 = \cdots = x_n$ which is at $(x_1, \ldots, x_n) = (\frac{r}{n}, \ldots, \frac{r}{n})$. ■

Presenting the proposition in a simple manner, Fig. 5 provides a sketch of the proof for $n = 2$.

Following the argumentation in the Introduction and the confirming results shown in Section III, we assume differences in fuel efficiency characteristics of the DGs in the plant. For simplicity, let each DG in the plant belong to one of five groups where the groups are distinguishable by their fuel efficiency characteristics only. Based on the combined information from data sheets and the results shown in Section III, Fig. 6 presents five different fuel consumption curves which relate to DGs belonging to the corresponding group.

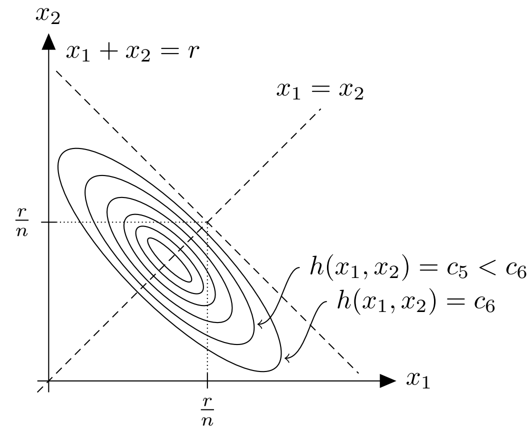

Fig. 5. Sketch of the constrained minimum $(x_1, x_2) = (\frac{r}{n}, \frac{r}{n})$ for the strictly convex $h(x_1, x_2) = f(x_1) + f(x_2)$ where $\operatorname{dom} h$ is constrained by $x_1 + x_2 = r$.

A. Gradient Search Approach

For a given power reference to an IPP power plant, the optimum power distribution between a fixed selection of DGs with assumed 3rd degree polynomial fuel consumption characteristics can be found using a gradient search approach, if the selection of DGs meet one straightforward condition. Remember, the 3rd degree polynomial fuel consumption curves in liters per hour are strictly convex functions above their inflection points and the sum of convex functions is a convex function. The condition on the selection of DGs is therefore, that the selection must be one which allows every DG to operate in the convex region of fuel consumption while collectively accommodating the plant power reference.

The fuel optimization problem, for a selection of n DGs and a plant power reference r, is given by

$$\min_{x} \sum_{i=1}^{n} f_i(x_i) \tag{1a}$$

s.t.

$$0 \leq x_i \leq \bar{x}_i \qquad \forall i \tag{1b}$$

$$\sum_{i=1}^{n} x_i = r \tag{1c}$$

where x_i is the power generation of DG i, $f_i(x_i)$ is the fuel consumption of DG i with power generation x_i in liters per hour, and $\bar{x}_i$ is the power generation rating of DG i, which for the typical IPP power plant is identical for all DGs. We find the solution to the minimization problem (1) with the MATLAB® toolbox YALMIP [19], utilizing the interior-point method of the `fmincon` solver.

With a selection of 30 DGs in total, consisting of six DGs belonging to each of the five groups, characterized by the fuel consumption shown in Fig. 6, we demonstrate the potential benefit of fuel optimization for a plant power reference of 55 MW when the rating of each DG is 2 MW.

Note, Proposition 1 extends to groups of identical fuel consumptions curves, that is, all six DGs of a group will generate the same amount of power in the optimal solution, whereas DGs of different groups will operate at different power generation levels.

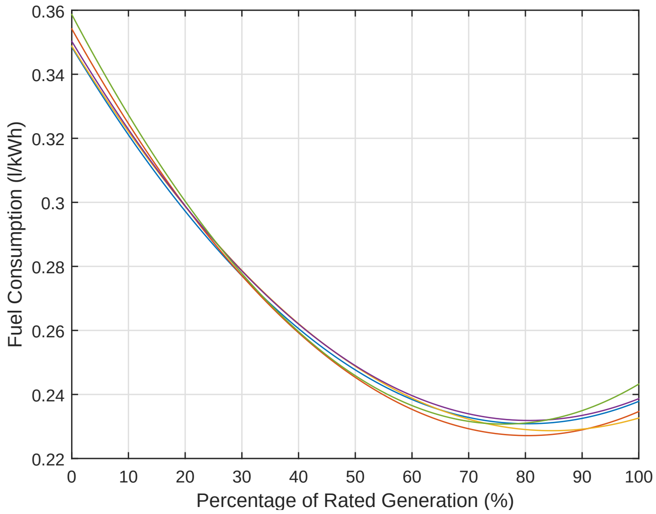

Fig. 6. Assumed fuel consumption curves of DGs in group 1 (blue), group 2 (red), group 3 (yellow), group 4 (purple), and group 5 (green), respectively.

Table III presents the power generation and fuel consumption results for the case described above. The optimal solution requires least power from DGs of group 5, which is in accordance with the fuel consumption curves in Fig. 6, where the green curve is the highest in the region of utilization for this specific plant power reference. Table IV presents the power generation and fuel consumption results for a solution where the plant power reference is distributed evenly among the 30 DGs, as current market-leading solutions do due to lack of individual fuel characteristic information.

In comparison to the even distribution approach, the gradient search approach reduces the fuel consumption by approximately 15 liters per hour due to the simple redistribution of power generation among the DGs.

B. Genetic Algorithm Approach

If the selection of DGs operated to accommodate the plant power reference is not predetermined, the gradient search approach losses its convexity property, which complicates the search for the solution. As an alternative, a genetic algorithm approach is proposed, which is able to find the optimal selection of DGs to operate in an IPP power plant, when accommodating the plant power reference requires less than all the available DGs to optimize the total fuel consumption.

Generally, the structure of a GA is as shown in Fig. 7 [20], [21]. The prerequisite for formulating a GA is the ability to find the fitness of any individual in the population, i.e., calculate the worth of any possible solution. In our particular case, this is the calculation of total fuel consumption of any possible power generation distribution, among the DGs in the plant, which accommodates the plant power reference. With the assumed 3$^{\text{rd}}$ degree polynomial fuel consumption information, that calculation is straightforward. GAs handle many possible solutions simultaneously and the collection of all these possible solution are denoted a population. The number of solutions in the population is a design parameter of the GA, referred to as the population size.

TABLE III

FUEL OPTIMIZATION RESULTS UTILIZING THE GRADIENT SEARCH APPROACH FOR A FIXED SELECTION OF 30 DGS.

Group	DGs†	Power Generation‡	Fuel Consumption‡
1	6	1.8341 MW	427.68 l/h
2	6	1.8371 MW	422.00 l/h
3	6	1.9376 MW	447.95 l/h
4	6	1.8339 MW	429.31 l/h
5	6	1.7239 MW	401.59 l/h
Total	30	55 MW	12771.18 l/h

†operational in Group, ‡per DG in Group

TABLE IV

RESULTS OF AN EVEN DISTRIBUTION APPROACH FOR A FIXED SELECTION OF 30 DGS.

Group	DGs†	Power Generation‡	Fuel Consumption‡
1	6	1.8333 MW	427.46 l/h
2	6	1.8333 MW	420.98 l/h
3	6	1.8333 MW	420.76 l/h
4	6	1.8333 MW	429.14 l/h
5	6	1.8333 MW	432.71 l/h
Total	30	55 MW	12786.35 l/h

†operational in Group, ‡per DG in Group

1) Initialize Population: The first element in the GA is to form an initial population, i.e., come up with a collection of possible solutions. In our GA, the initial population is formed by randomly assigning power to DGs in the plant. Until the total assigned power in a solution goes above the plant power reference r, the power of randomly chosen DGs is selected uniformly in the range from the minimum allowable power to the DG rating. The minimum allowable power is defined as the average power needed from the remaining DGs during the forming of a solution to accommodate the plant power reference. Once the total assigned power goes above the plant power reference, that excess power is removed from the assigned power of the latest randomly chosen DG. The DGs without assigned power at this point, if any, will be part of the solution with zero power generation.

2) Evaluate Fitness: Each solution in the population can be evaluated by finding its total fuel consumption, utilizing the 3$^{\text{rd}}$ degree polynomials.

3) Stop?: The stopping condition of a GA depends highly on the nature of the specific problem. Each successive repetition of evaluation, selection, crossover, and mutation is referred to as a generation. In problems where the optimal fitness value is unknown a priori, the stopping condition can be based on the number of generations, which is the case in our GA. For other problems, e.g., reaching a certain level of fitness or a certain level of change in fitness between generations can be the stopping condition [20], [21].

4) Selection: At this point, the population is repopulated by systematic selection of solutions in the existing population to eliminate some of the solutions with the worst fitness. We utilize so-called tournament selection with replacement in which two solutions from the existing population are picked at random and the one with the best fitness is placed in the new population [20], [21]. This process is repeated until the new population is of the same size as the old population.

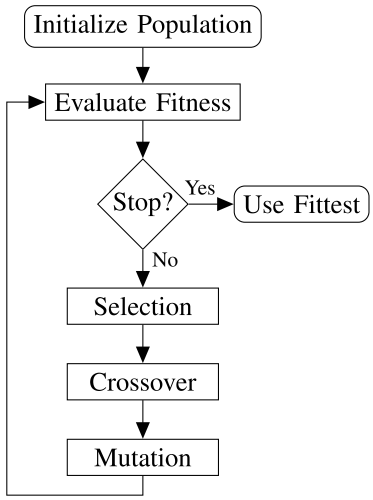

Fig. 7. General structure of a genetic algorithm [20], [21].

Referred to as elitism [20], [21], a number of the most fit solutions are carried straight to the new population to guarantee survival of the fittest. In general, no guarantee is given that the most fit nor the least fit solutions will be picked during the tournament selection with replacement process.

5) Crossover: Also known as mating, crossover is the process of mixing solutions in the population in hope of discovering solution with better fitness [20], [21]. The crossover in our GA takes its inspiration from the so-called single-point crossover [20], [21]. First, we pick two random solutions α and β from the population. With each solution containing the power generation of n DGs, we randomly choose a number c between 1 and $n-1$. As a fifty-fifty chance, we choose whether to manipulate DGs 1 to c or DGs $c+1$ to n and denote the chosen set of DGs m. If the total power generation of the m DGs is zero in solution α or β, we choose a new random c until this sum is non-zero in both α and β. Equations (2) show this, in an example where the set m contains DGs 1 to c.

$$\alpha = \big[\underbrace{x_{\alpha 1} \cdots x_{\alpha c}}_{\alpha m} \cdots x_{\alpha n}\big] \quad , \sum_{i=1}^{c} x_{\alpha i} \neq 0 \tag{2a}$$

$$\beta = \big[\underbrace{x_{\beta 1} \cdots x_{\beta c}}_{\beta m} \cdots x_{\beta n}\big] \quad , \sum_{i=1}^{c} x_{\beta i} \neq 0 \tag{2b}$$

We then calculate the power distribution of the m DGs for both α and β. Finally, we apply the power distribution of the m DGs in solution α to the m DGs in solution β while maintaining the total power generation of the m DGs in β, and vice versa, yielding two new solutions which both accommodate the plant power reference. However, some of the m DGs in the two new solutions might violate DG ratings due to the new combination of power distribution and total power generation. To prevent potential rating violations, the excess power of any such DG is removed and then added randomly to another of the m DGs until no violations occur in both of the two new solutions. A design parameter, referred to as the crossover probability p_c, is utilized after picking two random solutions α and β from the population. With the probability of $1-p_c$, α and β will go through the crossover process without manipulation whereas α and β has p_c probability of going through the entire crossover process, as described above, to form two new solutions. Random solutions are picked successively for crossover until a new population of the same size as before the crossover process began has been produced.

6) Mutation: To increase the diversity of the population, each solution in the population has p_m probability of mutation [20], [21]. If a solution is subject to mutation, the power generation of a randomly picked DG in that solution is set to zero. The power removed by that mutation is added to the power generation of another randomly picked DG in the same solution. If this yields DG rating violations, the excess power is added randomly to another DG until no rating violations occur.

For a 50 DG power plant, consisting of ten DGs belonging to each of the five groups, characterized by the fuel consumption shown in Fig. 6, we demonstrate the potential benefit of selecting the optimal DGs to operate for a 55 MW plant power reference when the rating of each DG is 2 MW.

Table V presents the power generation and fuel consumption results using the GA with a population size of 1000, a crossover probability of 0.75, a mutation probability of 0.9, a stopping condition of 7500 generations, and carrying 10 solutions straight to the new population in accordance with the elitism principle. Table VI and VII present the power generation and fuel consumption results for two solutions resembling current market-leading solutions with lack of individual fuel characteristic information. These two solutions determine the necessary number of operational DGs through a requirement for spinning reserve, set to 2 MW in this case. A spinning reserve matching the rating of one DG is rather common for IPP power plants. For the case of a 55 MW plant power reference and 2 MW spinning reserve, a total capacity of 57 MW requires 29 operational 2 MW rated DGs. The two solutions differ by representing the most fortunate and most unfortunate selection of 29 DGs possible with respect to the fuel characteristics, which are unknown in current market-leading solutions.

The GA approach achieves a spinning reserve of 13 MW which for an IPP power plant with a scheduled plant power reference might seem rather high. Five additional DGs are operated by the GA approach, in comparison with the even distribution approach, to achieve higher fuel efficiency. For the most fortunate choice of DGs the even distribution approach uses 161 liters per hour more than the GA approach, while the most unfortunate choice uses 394 liters per hour more than the GA approach.

V. CONCLUSIONS

In this paper, two fuel optimization approaches for IPP power plants consisting of a collection of DGs have been presented. The optimization approaches utilize assumed information regarding individual DG fuel characteristics to

TABLE V

FUEL OPTIMIZATION RESULTS UTILIZING THE GENETIC ALGORITHM APPROACH FOR AN IPP POWER PLANT OF 50 DGS.

Group	DGs†	Power Generation‡	Fuel Consumption‡
1	5	1.6035 MW	370.17 l/h
2	10	1.6277 MW	369.76 l/h
3	10	1.7026 MW	389.36 l/h
4	0	0 MW	0 l/h
5	9	1.5200 MW	350.74 l/h
Total	34	55 MW	12598.58 l/h

†operational in Group, ‡per DG in Group

TABLE VI

FORTUNATE EVEN DISTRIBUTION APPROACH RESULTS WITH 2 MW SPINNING RESERVE FOR A 50 DG IPP POWER PLANT.

Group	DGs†	Power Generation‡	Fuel Consumption‡
1	9	1.8966 MW	445.01 l/h
2	10	1.8966 MW	438.52 l/h
3	10	1.8966 MW	437.00 l/h
4	0	0 MW	0 l/h
5	0	0 MW	0 l/h
Total	29	55 MW	12760.29 l/h

†operational in Group, ‡per DG in Group

TABLE VII

UNFORTUNATE EVEN DISTRIBUTION APPROACH RESULTS WITH 2 MW SPINNING RESERVE FOR A 50 DG IPP POWER PLANT.

Group	DGs†	Power Generation‡	Fuel Consumption‡
1	9	1.8966 MW	445.01 l/h
2	0	0 MW	0 l/h
3	0	0 MW	0 l/h
4	10	1.8966 MW	446.69 l/h
5	10	1.8966 MW	452.13 l/h
Total	29	55 MW	12993.29 l/h

†operational in Group, ‡per DG in Group

demonstrate the potential fuel savings achievable by acquiring such information. Realistic variations in fuel characteristics have been found by measuring on a DG subject to critical air filter conditions, confirming the air filter influence and the suitability of least square fit 2^{nd} degree polynomial fuel efficiency characteristic representations.

A gradient search approach demonstrates potential fuel savings in comparison to the current market-leading approach for a fixed selection of DGs. Additionally, a GA approach demonstrates potential fuel savings for IPP power plants where the selection of DGs operated to accommodate the plant power reference is not predetermined.

Genetic algorithms are well-established as an approach for finding solutions to non-convex problems; however, many different GA strategies exist, and there are no common methods that work well for all problems. The methods utilized in the selection, crossover, mutation, and for establishing the initial population all impact the usefulness of the designed GA and there is no guarantee that the optimal solution is found. The presented GA solves the investigated case in around eight minutes on a standard modern 2 GHz Intel® Core™ i5 laptop; in comparison, the simple gradient search approach solves its case in around three seconds. While the presented GA is rather consistent in terms of total fuel consumption of the best solution, the power generation for individual DGs vary in tens of kW between consecutive GA runs. For the investigated case, we utilize Proposition 1 and assign the DGs of each group equal power generation, totaling the group power generation found by the GA. However, if each DG had unique fuel consumption characteristics either designing alternative selection, crossover, or mutation methods, or combining the strengths of the GA with the gradient search approach could be a better approach. The GA is capable of finding the optimal selection of DGs for a specific plant power reference and individual DG fuel consumption characteristics. Once the selection of DGs is determined, the gradient search approach is capable of quickly finding the exact optimal power generation for each of those DGs.

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